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Cross-country differences in the size of venture capital financing rounds: a machine learning approach

by Marco Taboga

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# CROSS-COUNTRY DIFFERENCES IN THE SIZE OF VENTURE CAPITAL FINANCING ROUNDS: A MACHINE LEARNING APPROACH

by Marco Taboga\*

## Abstract

We analyze the potential determinants of the size of venture capital financing rounds. We employ stacked generalization and boosted trees, two of the most powerful machine learning tools in terms of predictive power, to examine a large dataset on start-ups, venture capital funds and financing transactions. We find that the size of financing rounds is mainly associated with the characteristics of the firms being financed and with the features of the countries in which the firms are headquartered. Cross-country differences in the degree of development of the venture capital industry, while highly correlated with the size of funding rounds, are not significant once we control for other country-level characteristics. We discuss how our findings contribute to the debate about policy interventions aimed at stimulating start-up financing.

**JEL Classification:** G24, F0, C19.

**Keywords:** venture capital, financial institutions, country characteristics, machine learning.

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\* Bank of Italy, Economic outlook and monetary policy Directorate.



# 1 Introduction<sup>1</sup>

Venture capital (VC) is widely considered an important factor in stimulating economic growth because it fosters the development of highly productive firms in fast growing sectors, and it spurs innovation and technological progress (e.g., Kortum and Lerner 2001, Bottazzi and Da Rin 2002, Samila and Sorenson 2011, Manigart and Sapienza 2017).

However, the development of VC remains very heterogeneous across countries. In particular, in several advanced economies, especially in Europe, the aggregate amounts of funds channeled to start-ups by the VC industry are orders of magnitude smaller than the amounts recorded in countries such as China, the UK and the US, where VC is very well developed.

We find that the heterogeneity in country-level VC funding reflects relevant differences not only in the number of firms financed by VC funds, but also in the average amounts disbursed by funds in each financing round. As an example, we show some statistics for the three largest euro area countries (France, Germany and Italy) in Figures 1 to 4. Total VC funding in Italy<sup>2</sup> was 230 million euros in 2017, far less than in Germany and France (2.9 and 1.9 billion respectively). Although this difference partly reflects the larger number of financing rounds in the latter two countries, it is mostly accounted for by differences in the average size of the funding rounds (2.4 million euros in Italy, vs 6.1 and 11.6 in France and Germany respectively). We find even more heterogeneity in the average size of funding rounds by analyzing a worldwide dataset comprising more than 80 countries.

In this paper, we analyze the microeconomic determinants of the size of funding rounds. This is an aspect that has been seldom analyzed in the academic literature, but we believe that going deeper on it is a necessary step to understand the cross-country heterogeneity in aggregate VC funding and the policy interventions that could be performed to stimulate it. We outline a theoretical framework in which the size of a funding round is endogenously

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<sup>2</sup>For analyses of the Italian VC market see Generale et al. (2006), Generale and Sette (2008), Bentivogli et al. (2009), Magliocco and Ricotti (2013), Vacca (2013), Bronzini et al. (2017).

determined together with the risk-adjusted expected return on the money invested in the round. The demand for funds by start-ups is shifted both by firm-specific factors (e.g., industrial sector, features of the business plan and the management team, firm’s age, number of employees) and by the characteristics of the country in which the start-up is headquartered (e.g., quality and quantity of infrastructure, ease of doing business, degree of economic development, taxation, features of the labor force, size of the domestic market). All of these firm-specific and country-level factors can affect the productivity of firms and change the risk-adjusted expected return that they can offer to investors for any given level of funding. As far as the supply of funds by VC firms is concerned, we assume that the VC market is at least partially segmented at the international level, so that each start-up faces a supply schedule that is specific to its country. This is motivated by differences in legal systems (Megginson 2004) and informational asymmetries (Nahata et al. 2014) that can hinder cross-border VC financing. In this framework, the characteristics of a country’s VC industry can shift its supply schedule. In particular, previous literature (Elango et al. 1995, Brander et al. 2002, Bernile et al. 2007, Cumming and Dai 2011) has suggested that the dimension of the VC industry can be an important factor, mostly because of diversification needs dictated by risk aversion and because economies of scale in VC funds management allow larger funds to demand lower expected returns on their invested capital.

We use data on VC funding rounds, start-ups and VC firms from Crunchbase, and data on countries’ characteristics from the World Bank’s World Development Indicators (WDI) and Doing Business Indicators. The datasets we use are extremely rich: the WDI databank contains more than one thousand indicators for each country, and the quantitative data we extract from Crunchbase contains more than 700 variables for each funding round. To deal with this wealth of data, we resort to two machine learning techniques: boosted trees (Breiman et al. 1984, Friedman 2001) and stacked generalization (Wolpert 1992). Used together, they allow us to construct three variables that summarize all the information about the characteristics of 1) start-ups, 2) their respective countries of incorporation and 3) the VC



industries in those countries. The three variables are then used in linear regression models in which the size of funding rounds is the dependent variable. Thanks to the stacked generalization methodology, the summary variables provide all the information that is useful to predict the dependent variable, but without introducing data snooping biases. Furthermore, the use of boosted trees allows to reduce the dimensionality of the data in a non-parametric fashion, so that possible non-linearities are taken into account, and it provides a rigorous way to balance the two opposing needs of using all the relevant information and preventing over-fitting.

The lack of exogenous shifters does not allow us to rule out biases due to omitted confounders in our regression analysis. Therefore, we cannot provide a clear-cut causal interpretation of our results. We nonetheless argue that it is not likely that our results are invalidated by omitted variable bias.

We find that the characteristics of start-ups and the countries where they are headquartered are significantly associated with the size of funding rounds, and they account for a relevant portion of the cross-country heterogeneity in average size. In particular, the Doing Business Indicators, which provide objective measures of business regulations and their enforcement, play a crucial role in explaining cross-country variation in funding size.

As far as the characteristics of national VC industries (among which size and degree of development) are concerned, we find that they are not significantly correlated with funding size once we control for other county-level characteristics. Provided one is willing to admit a causal interpretation, this is the finding of our paper that has the most direct policy implications. Over the last decades, several countries have tried to stimulate VC activity by injecting public money into domestic VC funds. From a theoretical point of view, this policy is arguably sound: increasing the financial capacity of VC funds, either directly or via syndication with government sponsored entities, can incentivize the funds' general partners to increase the size of funding rounds, by decreasing their absolute risk aversion and by creating scale economies (see the references above). On the other hand, opponents of this view may

argue that capital markets are efficient enough to drive money where profit opportunities arise on a risk-adjusted basis: in other words, if investing more money in the start-ups of a given country were profitable, the opportunity would be exploited by investors; therefore, public intervention would be inefficient. Ultimately, the soundness of public intervention is an empirical matter. The existing empirical evidence is quite mixed. Alperovych et al. (2015) find that Belgian government VC-backed firms display significant reductions in productivity. Grilli and Murtinu (2014) find that government-managed VC funds in Europe have a negligible impact on the growth of the start-ups they invest in. Lerner and Watson (2008) instead point out that public intervention was followed by fast development, and ultimately by the achievement of VC market maturity in some countries such as Israel and India. Leleux and Surlemont (2003) find that public funding does not crowd out private investments and that it helps to increase the overall size of the VC market. Lerner (2009) devotes an entire book to documenting that public intervention in VC markets almost always fails, but he argues that the failures may be ascribed to poorly designed policies, and not to the fact that intervention is a bad idea per se. He also admits that more empirical evidence is needed. Our contribution goes at the root of the problem: what public funding ultimately does is to increase the financial capacity of the domestic VC industry, but we do not find evidence that the latter has a positive effect on the size of funding rounds. However, the distinguishing trait of mature VC industries seems to be the ability to inject large sums of money (in the order of hundreds of millions of dollars per funding round) into the most promising start-ups, that is, to provide adequate funding to the Googles and Facebooks of tomorrow. Our analysis provides evidence that if the VC industry of a given country does not have this ability, then it is unlikely to acquire it by public funding. On the constructive side, the results from our analysis emphasize the importance of improving business-friendliness: the Doing Business Indicators capture most of the country-level information that is relevant for predicting the size of funding rounds. This is in line with previous research, which suggests that some of the aspects measured by the Doing Business indicators have a large

impact on entrepreneurship and finance (e.g., Klapper et al. 2007, Van Stel et al. 2007, Buera et al. 2011, Jayasuriya 2011, Cooley et al. 2004, Greenwood et al. 2013).

The rest of the paper is organized as follows: Section 2 presents the theoretical framework; Section 3 presents the datasets; Section 4 explains how machine learning is used to reduce the dimensionality of the data; Section 5 presents the linear regressions; Section 6 concludes.

## 2 A general theoretical framework

The econometric models employed in this paper are based on a simple theoretical framework in which the size  $y$  of a founding round is endogenously determined together with the risk-adjusted expected return  $r$  on the money invested in the round. In our baseline model, these are the only two endogenous variables, but we also present the results from models where entrepreneurs endogenously choose the characteristics of their start-ups.

Entrepreneurs demand funds to invest in their start-ups. The return they can offer the VC fund depends on the size of the investment, for example, because of decreasing returns to capital and limited investment opportunities. For any level of funding the offered return depends on a host of exogenous factors that affect the productivity and the investment opportunities of the start-up. We are going to classify these factors into two groups.

The first group comprises firm-specific factors  $f$ , such as the industrial sector of the firm and its business plan, features of the management team (e.g., education, previous experience as entrepreneurs or executives), how much progress the start-up has already made (e.g., revenue, number of employees, stage of development, number of patents, etc.), how large the total addressable market is. These factors are firm-specific in the sense that they are influenced by the choices made by the founders before accessing the market for VC funds.

The second group of factors  $c$  is made up of the characteristics of the country in which the start-up is headquartered, such as quality and quantity of infrastructure, ease of doing business, type of legal system, degree of economic development, taxation, features of the

labor force, size of the domestic market, degree of investor protection, economic conjuncture at the time of the funding round. All of these factors are outside the direct control of the founders of the start-up.

Thus, given these assumptions, the demand schedule is

$$y = y^d(r, f, c) \tag{1}$$

where  $r$  is endogenous and  $f$  and  $c$  are exogenous (although we will later relax this assumption on  $f$ ).

Let's now turn to the supply of funds. We assume that the VC market is at least partially segmented at the international level. Differences in legal systems and informational asymmetries that arise in cross-border VC operations can hamper the screening mechanisms that lie at the heart of VC contracts (Megginson 2004, Nahata et al. 2014). In particular, the existing literature shows that, while cross-border VC operations are not uncommon, typically foreign VC funds participate in a funding round only if a domestic fund is the lead investor (e.g., Mäkelä and Maula 2008). Therefore, each start-up faces a supply schedule that is primarily shaped by the characteristics of its domestic VC industry. The quantity of funds offered by a VC fund to a start-up can be thought of as the result of a rational portfolio choice process (e.g., Levy 1973), so that the quantity supplied is an increasing function of the risk-adjusted expected return on the invested capital, and of the total wealth of the fund. The latter determinant of supplied quantities has been extensively discussed also by the literature on VC (e.g., Elango et al. 1995, Cumming and Dai 2011, Brander et al. 2002, Bernile et al. 2007): the dimension of VC funds is the primary characteristic that influences their behavior; portfolio diversification needs prevent small funds from investing large sums of money in any individual funding round. But when funds get larger, they can afford to invest sizeable amounts of money in each funding round without compromising the diversification of their portfolios. Furthermore, the screening costs borne by VCs' general

partners are less than proportional to the size of a financing round; in other words, the more money you invest in a single start-up, the lower the incidence of screening costs will be and the higher the expected return net of those costs. In light of these considerations, we assume that the characteristics  $v$  of the domestic VC industry (in particular, the distribution of the size of domestic funds) are an exogenous supply shifter. Furthermore, we assume that also country-level characteristics  $c$  (e.g., taxation) can exogenously affect the supply of VC funds.

Thus, the supply schedule is

$$y = y^s(r, v, c) \tag{2}$$

where  $r$  is endogenous and  $v$  and  $c$  are exogenous.

The equilibrium derived from equations (1) and (2) yields a reduced-form equation for the size of a funding round:

$$y = y(f, c, v) \tag{3}$$

that is, the equilibrium size of a funding round depends on the exogenously determined start-up's characteristics  $f$ , country-level features  $c$  and domestic VC industry's characteristics  $v$ .

In the next sections, we will outline an econometric strategy for estimating the reduced-form equation (3). However, we recognize that there might be concerns about the exogeneity of the characteristics  $f$  of the start-up. In particular, when entrepreneurs start a new firm, choose a sector of activity and formulate a business plan, they might take into account the expected financial capacity of domestic VC funds<sup>3</sup>: in simple terms, if you know that no domestic VC fund will give you enough money to finance a very ambitious project, then you might refrain from formulating such a project, and start out with a less ambitious and financially demanding plan. From a modelling point of view, if the characteristics of the start-up are completely endogenous (as in endogenous quality models, e.g., Motta 1993), we have a third structural equation

$$f = f(c, v) \tag{4}$$

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<sup>3</sup>See also Sannino (2017) who builds a theoretical model in which entrepreneurs direct their search to VCs based on their projects' quality.

and the reduced-form equation for the size of a funding round becomes

$$y = y(c, v) \tag{5}$$

We will estimate versions of both (3) and (5) in what follows and we will show that endogenizing  $f$  does not significantly change the estimate of the effect of  $v$  on  $y$ , which is the primary focus of interest in this paper.

We conclude this section by noting that, although VC characteristics  $v$  likely depend also on investment opportunities (hence on the start-up quality  $f$  that VC funds observe on average), arguably  $v$  can be assumed to be exogenous and, in particular, predetermined with respect to  $f$  at the deal level (our cross-sectional unit) because of the negligible impact that the observation of any single start-up project has on the VC industry as a whole.

### 3 The data

The data on VC funding rounds, start-ups and VC firms is from Crunchbase. We confine our attention to the funding rounds that were announced between January 2014 and December 2017. While the statistics displayed in Figures 1-4, already commented on in the Introduction, refer to all types of funding rounds (pre-seed, seed and Series A-J), we focus on Series A rounds in our econometric exercises (Figure 5), so as to keep our sample as homogeneous as possible. Typically, a Series A round is a start-up's first significant round of VC financing, performed after the business has shown some sort of a track record. The total number of Series A rounds in our dataset is 7,560.

Our dependent variable is the logarithm of the total amount of funding received by a start-up in its Series A round (Figure 6).

In our dataset there are 755 variables about start-up characteristics:

- age of the firm at the time of its Series A round;

- number of founders;
- characteristics of the founders: dummy variables that are equal to 1 if the biography of the founders contains certain words (e.g., executive, experience, consulting, engineer, PhD, Fortune); dummies that are equal to 1 if the alma maters of the founders are in the top 10, 20, ..., 100 universities (according to a ranking of universities made by Crunchbase); dummy for the presence of a woman in the group of founders;
- sectoral dummies (derived from the Category Groups field in Crunchbase);
- textual hints for smart branding: length of the start-up's name, number of words in the name, length of the web address, .com in the web address;
- dummies derived from all the words included in the description of the start-up.

We do not use information on the number of employees available in Crunchbase because it refers to the date of the data download and not to the date of the funding round.

There are 28 variables that provide information about the degree of development of the VC industry in each country:

- number of VC firms in that country;
- quantiles<sup>4</sup> of the distribution of the number of investments made by each VC firm in that country;
- quantiles of the distribution of the number of investment exits (e.g., IPOs, mergers) made by each VC firm;
- quantiles of the distribution of the CrunchBase ranks (a measure of how successful each VC firm is).

Finally, we use the entire WDI database for country-level information. It comprises 1591 annual time series for each country, among which:

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<sup>4</sup>We use the 0.01, 0.05, 0.1, 0.25, 0.5, 0.75, 0.9, 0.95 and 0.99 quantiles.

- total population, its growth rate and composition, mortality and fertility rates;
- GDP and its composition, distribution of income;
- trade (e.g., imports, exports of various goods);
- information about taxation (e.g., incidence on GDP and on different income categories);
- characteristics of the education system (e.g., number of students and teachers and their distribution among different levels of education);
- characteristics of the labor force (education, participation, unemployment, distribution by gender);
- R&D expenditure;
- information about infrastructure (roads, electricity, telephone lines).

The WDI database is complemented by the Doing Business database (204 indicators), which contains country rankings on how easy it is to perform business-related tasks (starting a business, dealing with construction permits, getting electricity, registering property, getting credit, protecting minority investors, paying taxes, trading across borders, enforcing contracts, resolving insolvencies).

## 4 Dimensionality reduction

We now illustrate the strategy for reducing the dimensionality of the data.

Denote the dependent variable (natural logarithm of the size of a founding round) by  $y_i$ , for  $i = 1, \dots, N$ . Denote one of the three blocks of variables (e.g., the block comprising all the start-up characteristics) by  $X_i$ .



Following the stacked generalization methodology (Wolpert 1992), we partition the sample into  $K$  disjoint sub-samples. We denote by

$$I = \{1, \dots, N\}$$

the whole sample and by

$$I_1, \dots, I_K$$

the  $K$  disjoint sub-samples satisfying the property

$$I = \bigcup_{k=1}^K I_k$$

Furthermore, we use the notation

$$I_{-k} = \bigcup_{\substack{j \in \{1, \dots, K\} \\ j \neq k}} I_j$$

that is,  $I_{-k}$  is the union of all sub-samples except the  $k$ -th.

Then, for each  $k = 1, \dots, K$ , we use the sub-sample  $I_{-k}$  to produce a non-parametric estimate of the function  $\hat{f}_k$  such that

$$\hat{y}_i = \hat{f}_k(X_i)$$

for  $i \in I_k$ , is the out-of-sample prediction of  $y_i$  having the lowest root mean squared error. It is crucial to note that the subsets  $I_{-k}$  used to estimate  $\hat{f}_k$  and the subset  $I_k$ , on which predictions are made, are disjoint.

An important condition for the validity of this procedure is that, for any  $i \in I_k$  and  $j \in I_{-k}$ ,  $y_i$  is independent of  $(y_j, X_j)$  given  $X_i$ . This independence condition is violated if there are omitted variables that induce cross-sectional correlation in the errors  $y_i - \hat{y}_i$ . We

expect that the only such omitted variables could be country-level variables<sup>5</sup>. Therefore, we always partition the sample in such a way that the observations pertaining to one country are either all in the estimation set  $I_{-k}$  or all in the hold-out set  $I_k$ . This procedure ensures that the out-of-sample prediction  $\hat{y}_i$  depends on  $X_i$ , but there are no data leakages, that is,  $\hat{y}_i$  does not incorporate any information about the observed realization of  $y_i$ .

Since the process is repeated  $K$  times, we obtain out-of-sample predictions  $\hat{y}_i$  for the whole sample ( $i = 1, \dots, N$ ). For each  $i$ ,  $\hat{y}_i$  is a one-dimensional summary of all the information contained in the vector  $X_i$  that is relevant for predicting  $y_i$ . The summary does not suffer from data leakages, therefore it can be used in a second-level regression in which  $\hat{y}_i$  is used as a regressor to predict  $y_i$ , together with other regressors.

Boosted trees (Breiman et al. 1984, Friedman 2001) are used to obtain the non-parametric functional estimates  $\hat{f}_k$ . We will not go into all the details of boosted trees in this paper, but we refer the reader to James et al. (2013) for an introduction (for economic applications, see Gepp et al. 2010, Döpke et al. 2017, Kim and Upneja 2014, Krauss et al. 2017). In synthesis, the estimator  $\hat{f}_k$  obtained from a boosted tree algorithm can be written as

$$\hat{f}_k(X_i) = \sum_{l=1}^L \beta_l \prod_{m=1}^M \chi(X_i \in A_{lm}) \quad (6)$$

where  $\beta_l$  ( $l = 1, \dots, L$ ) are constant coefficients and  $\chi$  is a dummy variable that takes value 1 when  $X_i \in A_{lm}$  and 0 otherwise. The sets  $A_{lm}$  are derived by using one of the variables in  $X_i$  to decide a sample-split. For example, all the observations for which the selected variable is above a certain threshold are included in  $A_{lm}$  and all the remaining ones are not included<sup>6</sup>. By doing so, the support of  $X_i$  is divided into  $L$  regions such that  $\hat{f}_k(X_i)$  is constant over those regions. The estimator (6) has the same functional form of a local regression estimator derived from the naive density estimator described by Fix and Hodges (1951) and Pagan

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<sup>5</sup>We do not include country dummies in our models because including them would prevent us from analyzing the effects of country characteristics.

<sup>6</sup>Missing values are included  $A_{lm}$  or in its complement depending on which of the two sets is the majority class.

and Ullah (1999). As such, it can approximate any functional form to any desired degree of accuracy when  $L \rightarrow \infty$ . Moreover, it can reproduce any non-linearity in the relationship between  $y_i$  and  $X_i$ .

The estimator (6) can be seen as the result of estimating a linear regression model in which all the regressors are products of dummy variables and  $\beta_l$  ( $l = 1, \dots, L$ ) are the regression coefficients. The regression is built in an additive fashion, by adding one regressor at a time<sup>7</sup>, that is, a sequence  $\{\widehat{f}_{k,\lambda}\}$  indexed by positive integers  $\lambda$  is built, where the  $\lambda$ -th term of the sequence is

$$\widehat{f}_{k,\lambda}(X_i) = \sum_{l=1}^{\lambda} \beta_l \prod_{m=1}^M \chi(X_i \in A_{lm})$$

How  $\lambda$  is chosen is one of the most important details of the algorithm. The general criterion is to prevent over-fitting. This is accomplished by subdividing the estimation sample  $I_{-k}$  into a so-called training sample  $I_{-k,t}$  and a validation sample  $I_{-k,v}$  (the two sets need to be disjoint and their union must be equal to  $I_{-k}$ ). Then, starting from  $\lambda = 0$  and

$$\widehat{f}_{k,0}(X_i) = 0$$

$\lambda$  is increased by one unit at a time and the training sample is used to estimate the coefficient  $\beta_\lambda$  and the sets  $A_{\lambda m}$ . Each time  $\lambda$  is increased by one unit, the coefficients and sets ( $\beta_l$  and  $A_{lm}$  for  $l < \lambda$ ) estimated in the previous iterations are kept fixed. Furthermore, the estimated model  $\widehat{f}_{k,\lambda}$  is used to perform out-of-sample predictions  $y_i$  on the validation set, and the root mean squared error (RMSE) of the predictions is computed. The number of additive terms  $\lambda$  is increased until the RMSE stops decreasing. In other words, we stop adding complexity to the model when its out-of-sample forecasting performance decreases. This kind of stopping criterion (add complexity only as long as it does not cause over-fitting) is used in most machine learning algorithms, and has already been discussed, as far as economic applications

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<sup>7</sup>More precisely, the number of regressors added on each iteration is equal to the number of leaves in the tree that is estimated on that iteration. For the sake of simplicity and for developing intuition, in what follows we pretend that only one regressor is added on each iteration.

are concerned, by Belloni et al. (2014). In their own words, these methods allow "a principled search for true predictive power that guards against false discovery and over-fitting and does not erroneously equate in-sample fit to out-of-sample predictive ability". They also note that techniques for dimensionality reduction that control over-fitting can help to "provide high-quality inference about model parameters" in structural econometric models. Similar considerations can be found in a highly articulate discussion on CrossValidated<sup>8</sup>, e.g., "Over-fitting data is a source of biased parameter estimates, and with no reason to believe that this bias offsets other sources of bias in estimating a particular causal effect, it must then be better, on average, to estimate causal effects without over-fitting the data".

The last missing piece of our procedure is the algorithm for the estimation of the coefficients  $\beta_l$  and the sets  $A_{lm}$ . Among the several different algorithms that can be used to estimate boosted trees, we choose XGBoost (Chen and Guestrin 2016), winner of the Higgs Boson Machine Learning Challenge (Adam-Bourdarios et al. 2015) and several other challenges. It is very popular because of its competitive performance in building high-quality predictive models and it is especially suited to deal with large datasets. As discussing the details of the XGBoost algorithm would take too much space, we refer to the paper by Chen and Guestrin (2016).

The procedure outlined above is repeated three times, so as to construct three variables that summarize all the information about the characteristics of 1) start-ups, 2) their respective countries of incorporation and 3) the VC industries in those countries. The variables thus obtained<sup>9</sup> are then used in the linear regressions discussed in the next section.

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<sup>8</sup><https://stats.stackexchange.com/questions/3893/can-cross-validation-be-used-for-causal-inference/4095>

<sup>9</sup>To further improve the quality of the summary variables, we repeat the entire procedure 100 times with different random partitions  $I_1, \dots, I_K$ , and then take simple averages of the estimates obtained in the 100 runs.

## 5 Regression analysis

The correlations between the explanatory variables are reported in Table 1 and the results from the regression analysis are reported in Table 2.

The dependent variable is the natural logarithm of the amount disbursed in each funding round (displayed by country in Figure 6).

All the three summary variables are significantly correlated with the size of funding rounds (Table 2; columns 1-3). Furthermore, they display substantial heterogeneity across countries (the averages of the three variables by country are plotted in Figures 7-9<sup>10</sup>).

Denote by  $\hat{f}_i$ ,  $\hat{c}_i$  and  $\hat{v}_i$  the summary variables for firms' characteristics, country-level features and country-level VC industry development respectively. According to the framework outlined in Section 2, we estimate both a reduced-form linear regression in which  $\hat{f}_i$  is exogenous:

$$y_i = \gamma_0 + \gamma_1 \hat{f}_i + \gamma_2 \hat{c}_i + \gamma_3 \hat{v}_i + \varepsilon_i \quad (7)$$

an one in which it is completely endogenous:

$$y_i = \gamma_0 + \gamma_2 \hat{c}_i + \gamma_3 \hat{v}_i + \varepsilon_i \quad (8)$$

where  $\varepsilon_i$  is the error term and  $\gamma_0, \dots, \gamma_3$  are the regression coefficients.

Coefficient estimates are standardized, so that they can be interpreted as the percentage change in size caused by a one-standard-deviation change in the associated regressor. Furthermore, regressors are demeaned.

As in Section 2, these reduced-form equations are to be thought of as the result of an economic equilibrium in which the size of a funding round, its risk-adjusted expected return and, possibly, the characteristics of the start-up being financed are endogenously determined. In other words, we do not estimate the supply and demand for funds, but only the equilibrium

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<sup>10</sup>The figures contain only a subset of 27 countries for which there are more than 20 funding rounds in the dataset.

relationship between the size of funding rounds and the exogenous variables in the system.

Our main result (Table 2) is that the development of the VC industry  $\hat{v}_i$ , although significantly correlated with  $y_i$ , is not a significant determinant of funding size once we control for other exogenous variables. Its estimated coefficient is not significantly different from zero both economically and statistically in equations (7) and (8). In particular, from an economic viewpoint, the effect of a one-standard-deviation change in  $\hat{v}_i$  on funding size is to increase it at most by 2 per cent, one order of magnitude smaller than the effects of  $\hat{f}_i$  and  $\hat{c}_i$ .

We note that the loss of significance of  $\hat{v}_i$  in multiple regressions is not due to redundancy, as the  $R^2$  of a regression of  $\hat{v}_i$  on  $\hat{f}_i$ ,  $\hat{c}_i$  and a constant is around 50% (Table 1).

Omitted variable bias is a source of concerns about the lack of significance of  $\hat{v}_i$ . As we explained in the Introduction, in our dataset there are no exogenous shifters that can be used as instruments for  $\hat{v}_i$ . However, we argue that omitted variable bias is implausible if one is willing to assume that improvements in the development of the VC industry cannot decrease the average size of funding rounds (i.e.,  $\gamma_3 \geq 0$ ). Once this assumption is in place, it logically follows that an estimate of  $\gamma_3$  not significantly different from 0 is biased by an omitted confounder only if the true value of  $\gamma_3$  is positive and the omission is biasing the estimate downwards towards zero. This can happen only if the confounder has opposite effects on the size of funding rounds and the development of the VC industry (e.g., on average an increase in the confounding variable increases the size of the VC industry but decreases that of funding rounds). None of the potential determinants of  $y_i$  discussed in the previous sections has this kind of offsetting effect on  $\hat{v}_i$ . Furthermore, in our regressions we do not have a proxy for general partners' skills, which could be an important determinant of both  $y_i$  and  $\hat{v}_i$ . However, the effect of skills should be positive in both cases: a skilled partner helps to make her VC firm successful and to increase its size in the long-run, but she also finds the best investment opportunities, that is, those that attract significant amounts of money, including from syndicated investors. All in all, it is difficult to think of a confounder that

causes financial resources to increase at the deal level and at the same time to decrease at the VC fund level. For this reason, we deem that omitted variable bias on  $\gamma_3$  is implausible.

In Table 3, we show, as a robustness check, the estimates of other two linear regressions where time variables<sup>11</sup> are added to the datasets used to generate  $\hat{f}_i$ ,  $\hat{c}_i$  and  $\hat{v}_i$ , and a fourth predictor  $\hat{t}_i$ , constructed from time variables only with the methodology of Section 4, is added to the regressions. These regressions should capture both time-variation in the dependence among variables and business-cycle fluctuations. The results from these supplementary regressions are not significantly different from those of the baseline regressions of Table 2.

We find that country-level characteristics  $\hat{c}_i$  are highly significant both economically and statistically, they account for the bulk of the predictive power of the regressions, and the coefficient  $\gamma_2$  is very stable across specifications. As these characteristics could be the target of policy interventions aimed at stimulating the venture capital industry, we analyze them more in detail.

The output of the XGBoost algorithm used to construct the variable that summarizes country-level characteristics contains also a measure of the relative contribution of the single variables in the dataset to the summary variable. In particular, the measure of the relative importance of a variable is based on the number of times a variable is used to form a dummy in eq. (6), weighted by the squared improvement in RMSE as a result of adding the dummy to the model (Elith et al. 2008, Friedman 2001).

By analyzing all the runs of the XGboost algorithm, we find that on average each predictive tree includes more than 200 variables and relative importance is quite dispersed (the largest 36 contributions account on average for 50% of the predictive power, the largest 156 for 90%). It is therefore difficult to provide a concise description of the country-level variables that matter the most. However, we note that three of the five largest relative contributions are provided by variables belonging to the Doing Business (DB) dataset<sup>12</sup>. Moreover, the fit

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<sup>11</sup>Year, year-month and month in which the funding round has been announced.

<sup>12</sup>The three variables are two overall measures of the ease of doing business ("DTF global DB17-18 method-

of our regressions and their estimated coefficients do not change significantly if we use only the DB dataset to construct our country-level variable  $\hat{c}_i$ .

We note that the contribution of the underlying variables is rather diffuse also for the other two indicators  $\hat{c}_i$  and  $\hat{v}_i$ , with no single variable weighing disproportionately. Moreover, the contribution of the single variables is characterized by complex patterns of interactions and non-linearities, so that it is difficult to provide easily interpretable economic insights about the main variables that contribute to the results obtained from the regression analysis. We leave a more in-depth analysis of these matters to future research.

## 5.1 Cross-border rounds

As we anticipated in Section 2, it is not uncommon that a funding round sees the participation of a foreign VC fund, although in the vast majority of these cross-border operations the lead investor is a domestic fund. In our dataset, the funding rounds in which at least one investor is foreign are 37% of the total. Furthermore, the average size of these rounds is 44% higher than that of operations involving only domestic investors.

The possibility of syndicating rounds with foreign investors could be one of the reasons why the characteristics of the domestic VC industry are not significant in our regressions. In particular, the limited availability of domestic capital is likely not an obstacle to closing large deals once foreign investors can be involved. To check whether this is the case, we regress a dummy variable that takes value 1 in case a deal is cross-border (and 0 otherwise) on the previously used explanatory variables  $\hat{f}_i$ ,  $\hat{c}_i$  and  $\hat{v}_i$ . We find (Table 4) that the likelihood of involving foreign investors depends significantly on the characteristics of firms  $\hat{f}_i$ , but not on those of countries  $\hat{c}_i$  and VC industries  $\hat{v}_i$ . An explanation for the fact that  $\hat{c}_i$  is not significant (unlike in previous regressions) could be that, as reported by Mäkelä and Maula (2008), funding by foreign investors is often associated with the expansion of the start-up to international markets, so that the characteristics of its headquarters' country become less

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ology" and "DTF global DB16 methodology") and the ease of dealing with construction permits.



relevant.

## 6 Conclusions

We have analyzed a rich dataset on VC funding rounds, covering four years (from 2014 to 2017), more than 80 countries and more than 7,000 financing transactions.

We have found that cross-country heterogeneity in the aggregate amounts of financing provided by VC funds to start-ups is mostly due to international differences in the average size of individual funding rounds. Therefore, we set up an empirical strategy to analyze the microeconomic determinants of the size of funding rounds.

In particular, we focus on the effect of the development of the VC industry (intended as dimension and financial capacity) at the country level. This is important from a policy perspective because in recent decades several governments have attempted to stimulate VC activity by increasing the financial capacity of their domestic VC industries, but the evidence provided by previous academic studies about the effectiveness of these interventions is mixed.

We provide evidence that the characteristics of the domestic VC industry (including various measures of size) are correlated with the average size of funding rounds in a given country. However, this correlation vanishes once we control for other county-level characteristics (e.g., ease of doing business) and for start-ups' characteristics (e.g., activity sector).

We note that the distinguishing trait of mature VC industries seems to be the ability to inject large sums of money into the most promising start-ups. Our main conclusion is that if the VC industry of a given country does not have this ability, then it is unlikely to acquire it by public funding. On the constructive side, the results from our analysis emphasize the importance of improving business-friendliness: the Doing Business Indicators capture most of the country-level information that is relevant for predicting the size of funding rounds.

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## 7 Tables

Table 1 - Correlations between regressors<sup>13</sup>

	$\hat{f}_i$	$\hat{v}_i$	$\hat{c}_i$	Redundancy	
Start-ups' characteristics	$\hat{f}_i$	1.00		3%	
Country-level VC characteristics	$\hat{v}_i$	0.18	1.00	51%	
Other country-level characteristics	$\hat{c}_i$	0.12	0.71	1.00	51%

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<sup>13</sup>The variable  $\hat{v}_i$  summarizes the characteristics (mainly pertaining to dimension) of the venture capital industry of the country in which the funded start-up is headquartered.

The variable  $\hat{c}_i$  summarizes all the other characteristics (excluding those of the VC industry) of the country in which the funded start-up is headquartered.

The redundancy of an explanatory variable is computed as the  $R^2$  of a linear regression in which that variable is regressed on all other explanatory variables.

Table 2 - Linear regressions<sup>14</sup>

Regression models	1	2	3	4	5
Start-ups' characteristics	0.30*** (9.92)			0.27*** (11.8)	
Country-level VC characteristics		0.28*** (4.54)		-0.03 (-0.89)	0.02 (0.76)
Other country-level characteristics			0.38*** (8.71)	0.37*** (7.62)	0.36*** (8.15)
Constant	1.47*** (19.3)	1.47*** (41.0)	1.47*** (38.4)	1.47*** (26.3)	1.47*** (37.5)
$R^2$	8%	6%	11%	17%	11%

<sup>14</sup>The regressions are estimated by OLS. The dependent variable is the logarithm of the size of each funding round. Coefficients are standardized, so that they can be interpreted as the percentage change in size caused by a one-standard-deviation change in the regressor. The t-statistics in parentheses are obtained from robust standard errors (clustering by country). \*\*\*, \*\* and \* indicate p-values below 1, 5 and 10 per cent respectively.

VC characteristics mainly pertain to the dimension of the venture capital industry of the country in which the funded start-up is headquartered.

The other characteristics of the country in which the funded start-up is headquartered exclude those of the VC industry.



Table 3 - Linear regressions with time controls<sup>15</sup>

Regression models	1	2
Start-ups' characteristics	0.23***	
	(10.2)	
Country-level VC characteristics	0.04	0.07
	(0.66)	(1.61)
Other country-level characteristics	0.25***	0.28***
	(4.1)	(4.71)
Time control	-0.13***	0.02
	(-4.51)	(0.82)
Constant	1.47***	1.47***
	(27.23)	(39.7)
$R^2$	20%	12%

<sup>15</sup>The regressions are estimated by OLS. The dependent variable is the logarithm of the size of each funding round. Coefficients are standardized, so that they can be interpreted as the percentage change in size caused by a one-standard-deviation change in the regressor. The t-statistics in parentheses are obtained from robust standard errors (clustering by country). \*\*\*, \*\* and \* indicate p-values below 1, 5 and 10 per cent respectively.

VC characteristics mainly pertain to the dimension of the venture capital industry of the country in which the funded start-up is headquartered.

The other characteristics of the country in which the funded start-up is headquartered exclude those of the VC industry.

The time control variable summarizes all the possible effects, both linear and non-linear, of the time variables (year, year-month and month) on the size of funding rounds.

Table 4 - Cross-border deals - Linear probability models<sup>16</sup>

Regression models	1	2
Start-ups' characteristics	0.03***	
	(2.97)	
Country-level VC characteristics	-0.04	-0.04
	(-0.97)	(-1.32)
Other country-level characteristics	-0.04	-0.04
	(-1.30)	(-0.81)
Constant	0.28***	0.28***
	(7.60)	(7.96)
$R^2$	3%	2%

<sup>16</sup>The table displays the estimated regression coefficients of a linear probability model in which the dependent variable is a dummy that takes value 1 if at least one foreign investor participates in the funding round and zero otherwise. Coefficients are standardized, so that they can be interpreted as the increase in the probability of observing a cross-border operation caused by a one-standard-deviation change in the regressor. The t-statistics in parentheses are obtained from robust standard errors (clustering by country). \*\*\*, \*\* and \* indicate p-values below 1, 5 and 10 per cent respectively.

VC characteristics mainly pertain to the dimension of the venture capital industry of the country in which the funded start-up is headquartered.

The other characteristics of the country in which the funded start-up is headquartered exclude those of the VC industry.

## 8 Figures

Figure 1 - Total amount of funds channeled to start-ups by the VC industry  
(EUR millions)

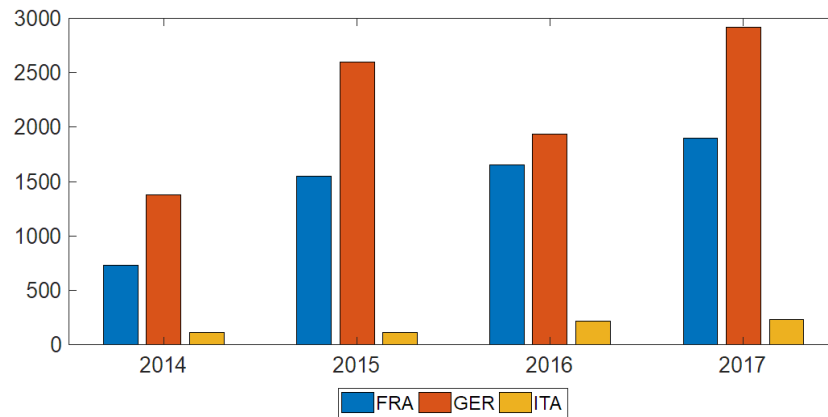


Figure 2 - Number of funding rounds

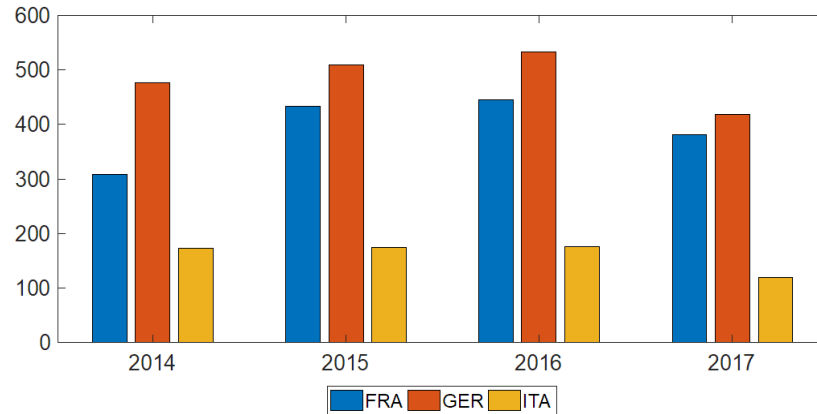


Figure 3 - Average amount of money raised in a funding round  
(EUR millions)

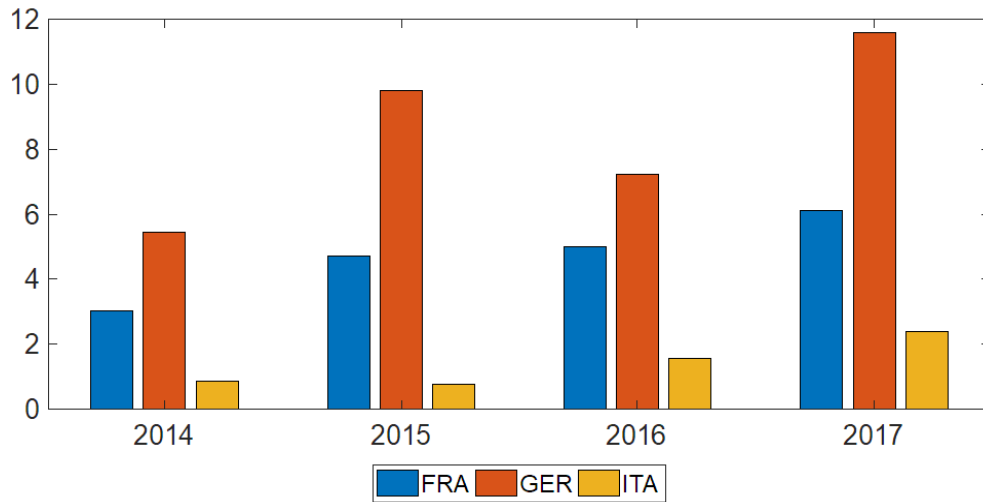


Figure 4 - Number of funding rounds by amount

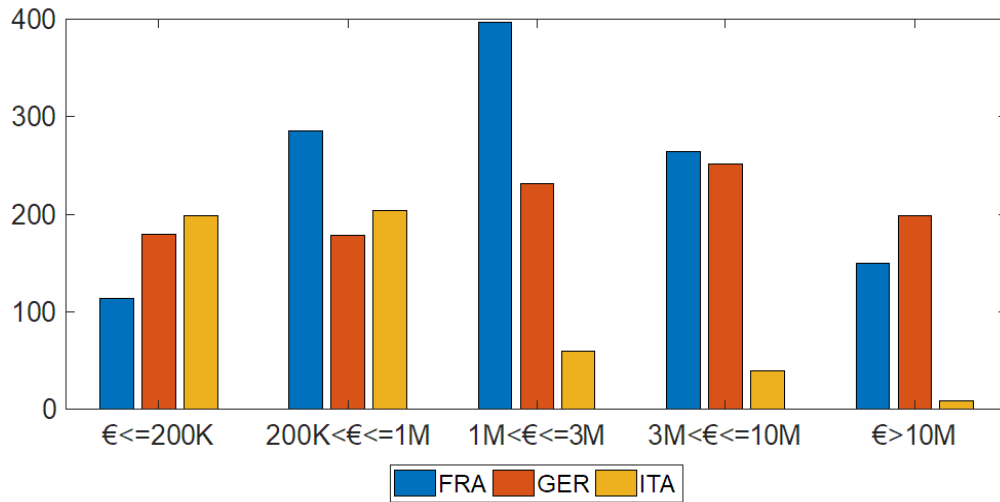


Figure 5 - Average size of Series A funding rounds (EUR millions)<sup>17</sup>

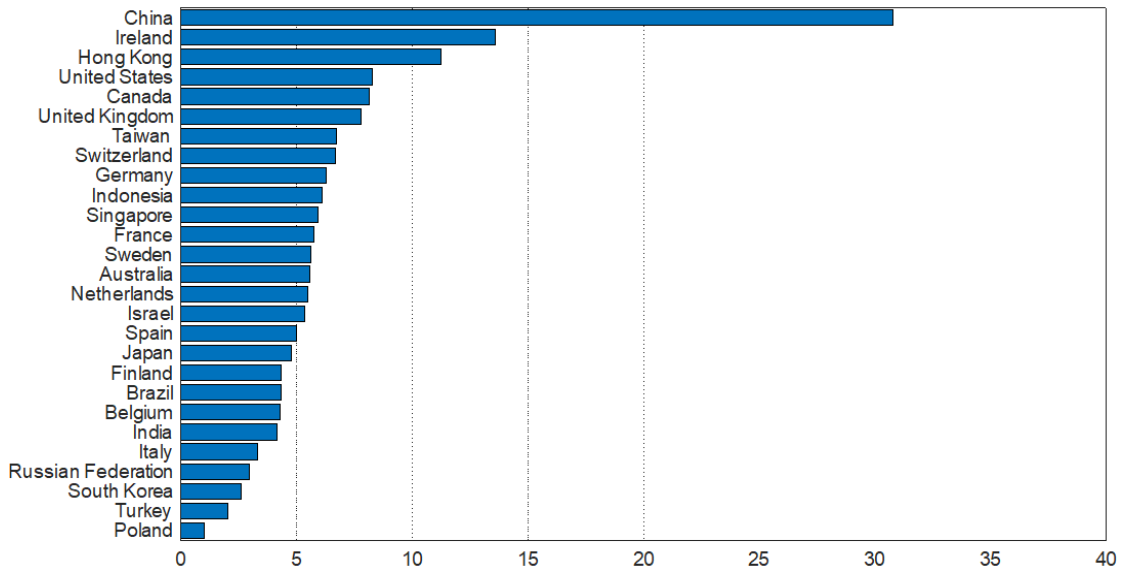
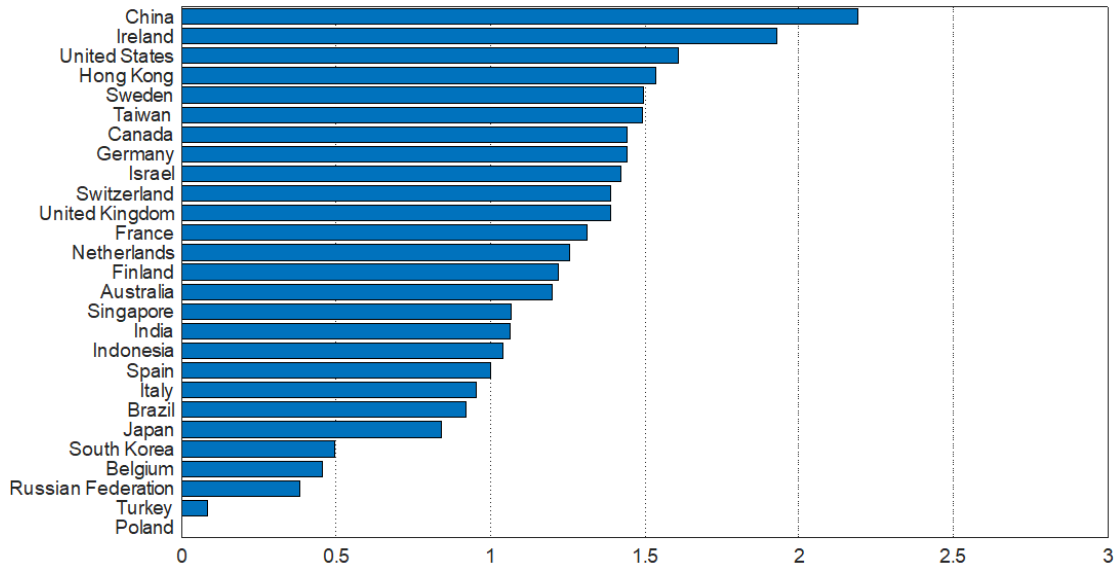


Figure 6 - Average log-size of Series A funding rounds



<sup>17</sup>This chart and the next one plot only the subset of countries for which there are at least 20 funding rounds in the dataset.

Figure 7 - Summary of start-ups' characteristics (country averages)<sup>18</sup>

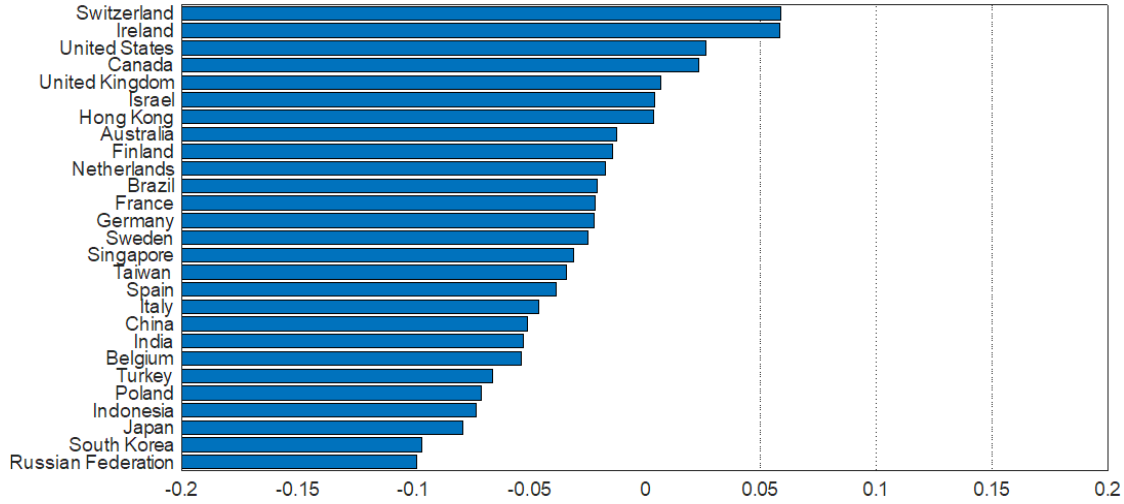
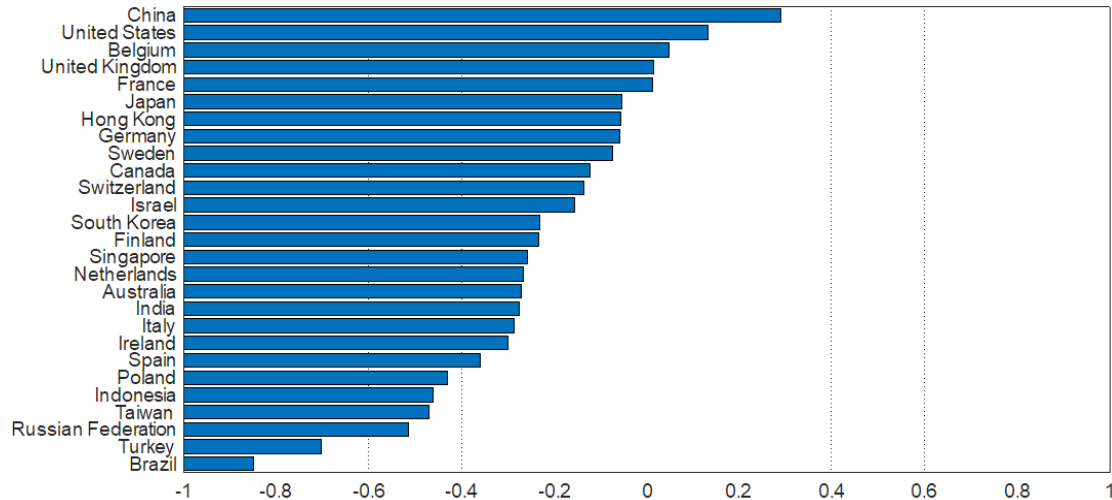


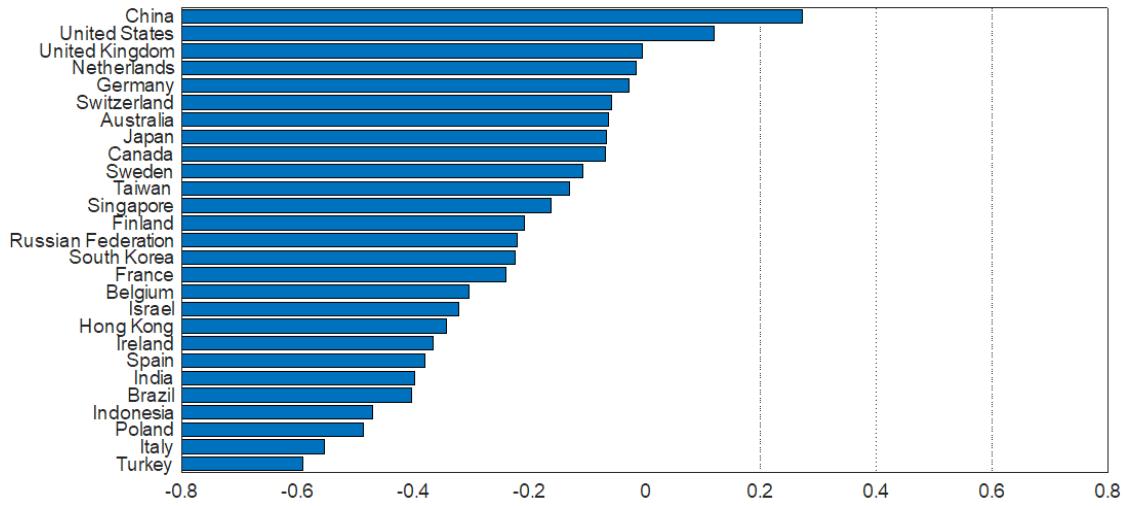
Figure 8 - Summary of country-level VC industries' characteristics<sup>19</sup>



<sup>18</sup>This line chart plots country averages of the variable that summarizes the start-up characteristics that help to predict the size of a funding round. The larger the average for a given country is, the more funding the start-ups in that country are expected to receive because of their characteristics. For example, the first two lines indicate that Swiss and Irish start-ups receive on average 6 per cent more funding than their peers in other countries because of their characteristics. Note that the average value of the bars is not zero because of the cross-country heterogeneity in the number of funding rounds. The chart plots only the subset of countries for which there are at least 20 funding rounds in the dataset.

<sup>19</sup>This line chart plots the variable that summarizes the characteristics of the VC industry in a given country that help to predict the size of funding rounds in that country. The larger the average for a given country is, the more funding the start-ups in that country are expected to receive because of the characteristics of the domestic VC industry. For example, the first line indicates that Chinese start-ups receive on average 30 per cent more funding than their peers in other countries because of the characteristics of the Chinese VC industry. Note that the average value of the bars is not zero because of the cross-country heterogeneity in the number of funding rounds. The chart plots only the subset of countries for which there are at least 20 funding rounds in the dataset.

Figure 9 - Summary of other country-level characteristics<sup>20</sup>



<sup>20</sup>This line chart plots the variable that summarizes all the characteristics of a given country (except those of the VC industry) that help to predict the size of funding rounds in that country. The larger the average for a given country is, the more funding the start-ups in that country are expected to receive because of the characteristics of their domestic country. For example, the first line indicates that Chinese start-ups receive on average 27 per cent more funding than their peers in other countries because of the institutional characteristics of China. Note that the average value of the bars is not zero because of the cross-country heterogeneity in the number of funding rounds. The chart plots only the subset of countries for which there are at least 20 funding rounds in the dataset.

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