Chapter 13. Mixing experimentation and targeting: innovative entrepreneurship policy in a digitised world

By

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Innovative entrepreneurship plays a key role in our societies, being an engine of job creation, innovation, and inclusiveness. In light of that, policy makers are aware of the importance of creating a fertile entrepreneurial ecosystem. However, only a tiny minority of new firms eventually becomes a successful innovative business. Improving the prediction of this success ex ante would allow governments to target their support to start-ups, and could alter the balance between targeted and non-targeted (e.g. reducing entry and exit barriers) policy approaches. This chapter first presents the main arguments in favour of public support to innovative entrepreneurship. It then discusses how newly available big data and machine learning techniques could help policy makers design more effective policies through more precise targeting of firms with the highest growth potential. The chapter then focuses on venture capital, which, besides filling the equity gap, also aims to target these innovative firms. It concludes with a discussion of the factors that will affect the balance between targeted and non-targeted policies in the future.

Balancing targeting and experimentation: new developments in policy support to innovative entrepreneurship and venture capital

This chapter critically overviews the policy debate about high-growth and innovative entrepreneurship, addressing the most crucial and timely policy questions. Although they represent only a tiny sub-sample of all new firms, high growth firms are crucial to create new employment, foster innovation, and increase productivity in the long run, taking advantage of the ongoing digital transformation and other disruptive innovations. However, a number of scholars argue that entrepreneurship is following a "secular" declining trend, especially in the United States, although recent evidence show signs of recovery across OECD countries (Decker et al., 2016). At the same time, the range of policy instruments that are available to support start-ups and the associated volume of finance and technical expertise provided to support these firms has probably never been so high. Public intervention in venture capital – one of the most popular instruments to identify and financially support innovative firms – has also become increasingly popular over the last years. A central question is whether these policy interventions are effective, and whether they are targeting the "right" start-ups and entrepreneurs.

These questions – concerning the type of interventions that best support the emergence and development of high-growth and innovative firms – have attracted increasing attention in academic and policy circles. This chapter critically reviews this debate. Considering that only a tiny minority of new firms contribute to economic growth, the effectiveness of untargeted entrepreneurship policy has been questioned by some scholars, who argue that public resources should be concentrated only on firms with the highest growth potential. This in turn poses the related question of whether it may be possible to identify high potential firms ex ante, possibly leveraging on new opportunities provided by big data and innovative predictive analytics techniques (e.g. machine learning). Alternatively, if success proves to be unpredictable ex-ante, ultimately this would lead to an important role of market experimentation to detect successful ventures. In such a case, policy makers should therefore opt for a "let 100 flowers bloom" approach, in which entry and exit barriers are reduced, and entrepreneurs can test their business ideas in the market, growing fast if they prove to be successful, and exiting smoothly and rapidly if they are not.

Of course, this is a stylised framework; in practice, innovative entrepreneurship policies typically attempt to strike the right balance between these two extreme approaches. An illustrative "real world" example is public investments in venture capital (VC), which represents the main instrument for public intervention in innovative entrepreneurship across many OECD economies. This policy typically targets the most successful start-ups, given that VC investments tend to involve less than 1% of new firms. At the same time, the need to complement the private VC market with public investments is often motivated by filling in an equity financing gap in technological areas that require more experimentation and risk-taking. These are often also areas where market success is less predictable and private businesses may contribute to wider social objectives (e.g. climate change mitigation, public health, etc.), thus providing an additional rationale for public policy. But is government VC an effective policy instrument to identify and support innovative and high growth start-ups? While the necessary evidence base to answer this question is still incomplete, this chapter overviews the available evidence. A number of policy trade-offs that should be taken into consideration in the implementation of this policy emerge. The chapter also stresses the need to widen the available evidence base to better inform policy making.

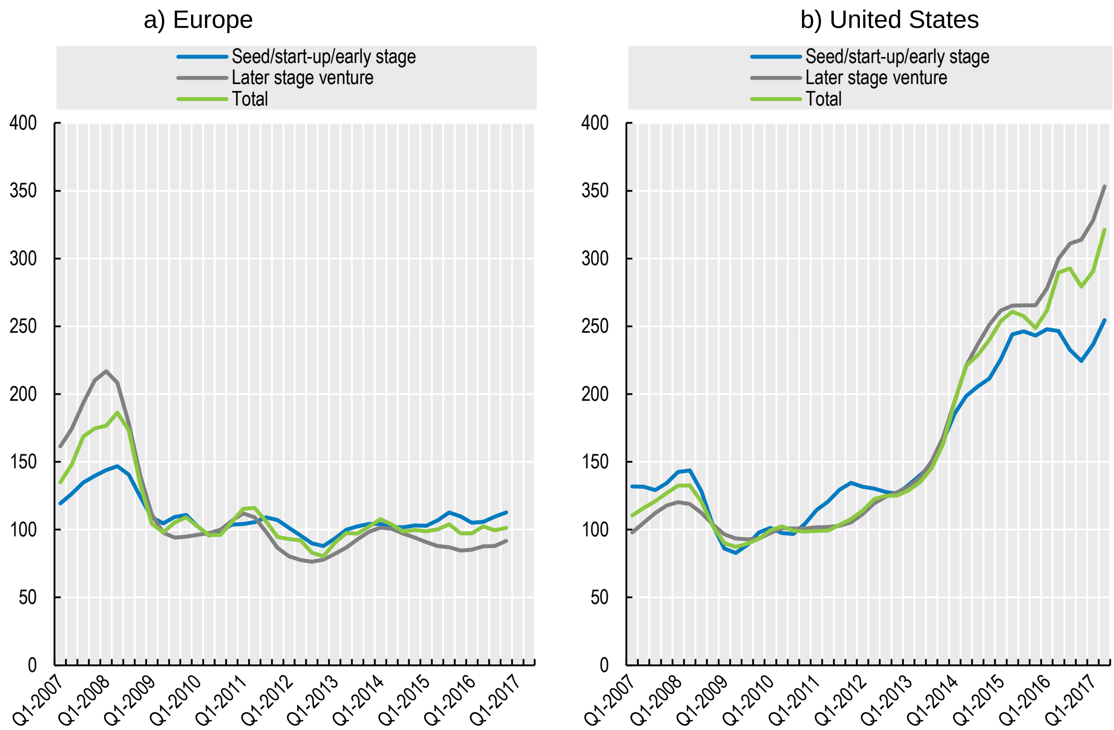
How has innovative and high-growth entrepreneurship evolved in recent years?

A number of recent empirical contributions based on administrative data have shown that entrepreneurship as a whole has been declining before and in the aftermath of the 2007-9 financial crisis. This is particularly evident in the United States, where a "secular" decline in business dynamism and new firm creation since the 1970s has been observed (Decker et al., 2016). Since 2000, the decline in dynamism and entrepreneurship in the US has been accompanied by a decline in high-growth young firms. Although similarly long time-series are not generally available for other economies, the decline in entrepreneurship has also been observed over the 2000s' in other OECD countries (Blanchenay et al., 2016). However, in many OECD economies the number of new firms created appears to have recovered in the aftermath of the financial crisis, reaching in many cases pre-crisis highs.

Furthermore, more recent data on venture capital (VC) and related funding [1] reflecting the dynamism of the tiny share of new entrants with high-growth potential – suggest that VC-funded entrepreneurship has been booming over the last couple of years. The total amount of VC funding granted across OECD countries in 2016 is substantially higher than before the 2007-9 international crisis. This is mainly explained by a steep increase of VC investments in the United States, which more than doubled over the same period (Figure 13.1).

Therefore, the secular decline in entrepreneurship rate and in dynamism that has recently spurred concerns among policy makers may be a rather composite phenomenon, with different indicators pointing to contrasting trends. The mixed evidence is also a consequence of the very different phenomena that are generally referred to as "entrepreneurship". While a slowdown in so-called "subsistence" entrepreneurship may not necessarily be bad news, a decline in high-growth start-ups and in innovative entrepreneurship may have serious long-lasting negative effects, given the role these firms play for aggregate growth and job creation. This chapter finds that a more fine-grained understanding of the heterogeneity of entrepreneurship is also crucial for policy.

Figure 13.1. Venture capital investments over time in Europe and in the United States



Note: Trend-cycle, 2010 = 100.
Source: OECD (2017), Entrepreneurship at a Glance 2017, OECD Publishing, Paris *http://dx.doi.org/10.1787/entrepreneur_aag-2017-en* based on Invest Europe Yearbook 2016 and National Venture Capital Association/PitchBook Report, 2017Q2

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Why and how should innovative and high-growth entrepreneurship be publicly supported?

Deploying effective entrepreneurship policies is a priority across many OECD economies, in the light of the evidence that new and young firms contribute disproportionally to job creation across OECD countries. The 2017 edition of the EC/OECD STI policy survey identified 167 different initiatives in participating countries related to targeted support to young innovative enterprises (EC/OECD, 2017). Several OECD countries are also developing comprehensive and organic policy frameworks to support innovative entrepreneurship. The need for effective policy interventions also rests on the important role that innovative start-ups can play in meeting broader environmental and social objectives. Start-ups are supposed to be more effective in introducing disruptive and breakthrough innovations (e.g. Egli, Johnstone and Menon (2015)) that provide new solutions to long-standing problems, because they do not suffer from the "organisational inertia" that may instead hamper the development of radical innovations by established incumbents (Henderson and Clark, 1990). Innovative entrepreneurship can promote inclusiveness, which is also high in the policy agenda given growing concerns that economic inequality undermines social cohesion.[2]

The fact that innovative entrepreneurship plays a crucial role for economic growth and wellbeing does not alone grant the need for policy intervention. Rather, the motivation for policy intervention to support innovative start-ups arises out of the widespread belief that there are three general types of market failures that may hamper their development:

- Capital market failures which arise from information asymmetries that affect new or small firms in general;
- Knowledge market failures that make it difficult for innovative firms and their shareholders to capture the full value of their innovation efforts; and
- Positive externalities that are not priced and therefore imply that the social value of entrepreneurship is higher than private returns.

These three sets of market failures may reinforce one another, making it particularly difficult for innovative start-ups to attract the necessary inputs to grow. In principle, this justifies the need for policy intervention. However, the fact that there is a *need* for policy intervention does not necessarily imply that any type of policy would *work*. There are many areas in which there is a consensus on the existence of market failures, but very little understanding of which policy levers should be activated to fix them.

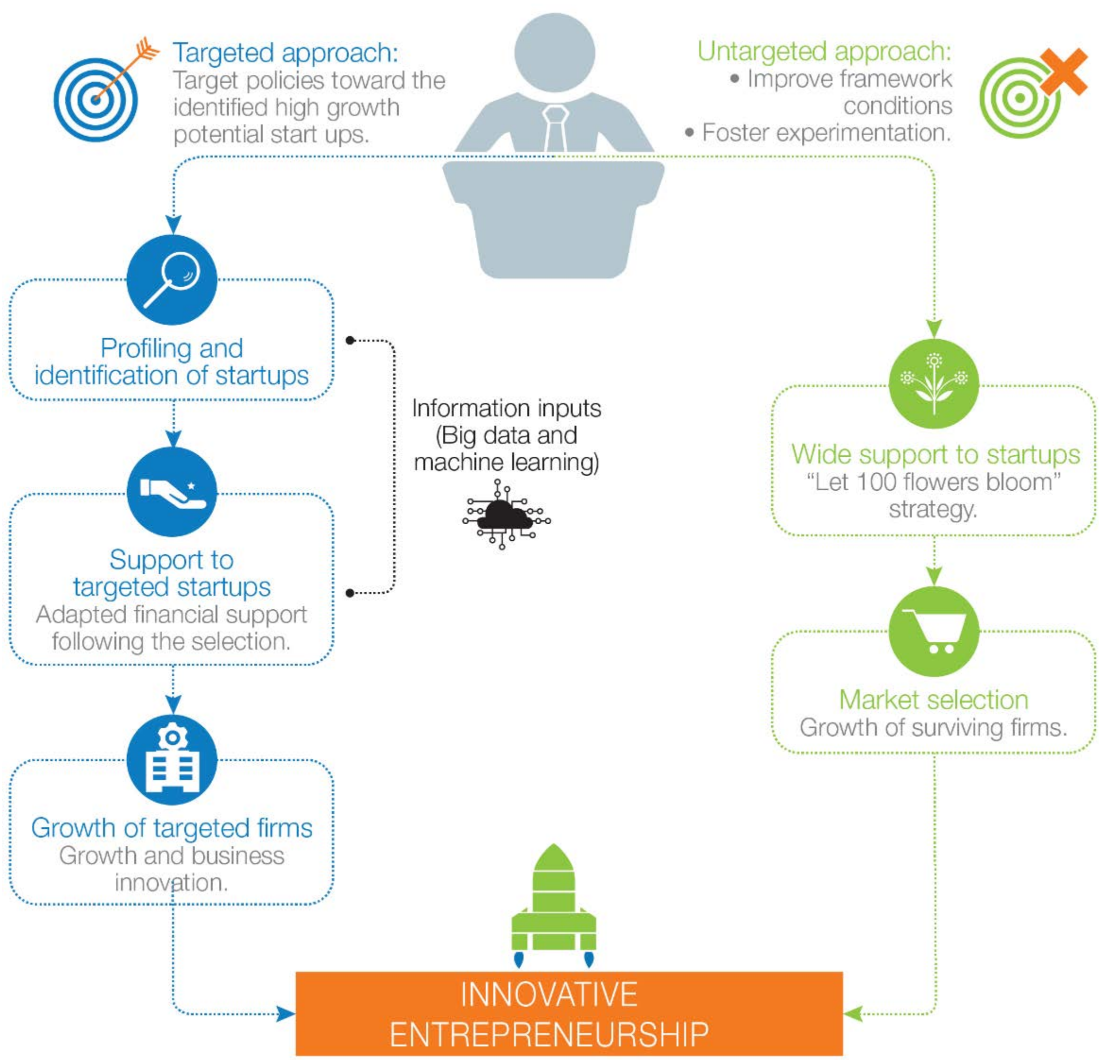
Even more than the type of support and the design of policy instruments essential to the effectiveness of public policies aiming to support high-growth entrepreneurship is the issue of which entrepreneurs and start-ups should be supported. The fact that only a tiny proportion – typically less than 5% – of start-ups eventually grows and innovates (e.g. Calvino, Criscuolo and Menon (2015)) is typically overlooked in the public debate on entrepreneurship. In this context, Shane (2009) argues that encouraging more people to become entrepreneurs is "bad public policy". Rather, "policy makers should stop subsidizing the formation of the typical start-up and focus on the subset of businesses with growth potential".

This narrative, however, should be counterbalanced by the evidence that experimentation is a crucial ingredient of successful entrepreneurship. According to this view, the policymaker should not attempt at "picking winners" and should rather let the market select. A viable alternative approach could thus be "let one hundred flowers bloom". Within this framework, potentially successful entrepreneurs should be enabled to experiment with various innovative strategies and technologies while having the ability to scale up or down, in the event of productivity shocks. There is indeed considerable empirical evidence that suggests that firms need space to experiment with various innovative ideas. Instances of failing in the past are common amongst successful start-ups (Eggers and Song, 2015). Importantly, making room for experimentation may be particularly beneficial for start-ups with a wider societal impact, whose success is not strictly measured in terms of jobs created or profit generated.

The role of the policy maker, in this context, would be to streamline both the entry and the exit of businesses, also by designing an insolvency regime that is not perceived as too "punitive". In practice, however, this entails a number of policy trade-offs which are not easy to solve. For instance, insolvency procedures that are "pro-entrepreneur" and allow for a "fresh-start" would facilitate exit on the one hand, but, on the other hand, they would also increase risk for lenders, thus restricting access to financial resources for prospective entrants. Moreover, because start-ups are small and relatively less organised in comparison to incumbents, it may be difficult for them to communicate their needs directly to policy makers. Although the reality of policy support to innovative start-ups is of course a mix of both, one can distinguish analytically between a targeted and non-targeted approach (Figure 13.2).

Policy bottlenecks that are generally detrimental for all businesses can be particularly harmful for small start-ups (Calvino, Criscuolo and Menon, 2016). In some circumstances, the policy environment may have been implicitly designed with the needs and conditions of incumbents in mind, meaning that horizontal structural reforms that are particularly helpful to start-ups are delayed or not implemented. This may also depend on regulation being tailored to the prevailing technology adopted by incumbents, rather than to the innovative technology used by start-ups. Across OECD countries, a number of advocacy groups have been established to help facilitate dialogue between start-ups and government officials. This is commendable, as the policy debate across several OECD economies appears to focus more on saving distressed firms, rather than favouring the birth of new ones. The critical importance of framework conditions, such as civil justice efficiency, open science, fair taxation, free movement of talents across borders, and a dynamic labour market in fostering innovative entrepreneurship, need to be further emphasised.

Figure 13.2. The two approaches to encourage innovative start-ups



Do big data and machine learning applications open new avenues to identify high growth potential start-ups?

Targeting policy interventions only on start-ups with high growth potential poses the crucial policy question of whether policy makers can identify high-potential start-ups. The issue of whether start-ups' growth can somehow be reliably predicted based on observable characteristics is highly debated in the economic literature, particularly following the increased availability of firm-level data (Geroski, 1999; Coad, 2009; Guzman and Stern, 2016). Despite many efforts from econometricians, there has been limited success in identifying firm (or entrepreneur) characteristics predicting subsequent growth dynamics. The combined explanatory power of independent variables is usually low, typically less than 10% (Coad, 2009). A number of academics have argued that the systematic components of growth and performance are by far overshadowed by its randomness (Geroski, 1999; Coad, 2009). Some scholars even suggest that the factors that are expected to explain firm growth path so far are quite erratic and not very meaningful (Coad et al., 2013). Therefore, these scholars maintain that the actual firm level determinants of growth are still somewhat unknown.

One of the difficulties in identifying successful entrants is the lack of detailed data on the characteristics of firms and entrepreneurs "ex-ante", i.e. at the moment in which they create the new company. As many of these firms are very small entities, limited public information is available from administrative sources. In addition, comprehensive measures of "success" are also not readily available from traditional sources, especially when innovation is deemed to be an important component. However, advances in communication technology have opened up an era of big data, making information on both firm characteristics at entry and subsequent performance more accessible. At the same time, advances in information processing hardware and software make it easier for machine learning tools to analyse the growing accumulation of data. This enables the identification of complex relationships and clusters of similar firms, which may be used to more effectively identify successful high growing entrants (Box 13.1).

As a consequence of these improvements on the data side, a rising number of scholars have begun to challenge the idea that growth is random and unidentifiable (Guzman and Stern, 2015; Guzman and Stern, 2016; Åstebro and Tåg, 2017). Guzman and Stern (2015), for example, state that while random factors and unobservable characteristics influence the success of entrepreneurs, the divergence in performance and the effects on various entrants can be explained by observable differences in ex-ante firm characteristics. The authors employ data on entrepreneurs at a similar stage of their entrepreneurial career to design measures of firm characteristics linked to entrepreneur quality. Quality measures include if the founder names the start-up after him/herself, if the start-up purchased or carried out attempts to protect intellectual property (such as a registered trademark or patent) and if the firm has a legal form oriented toward equity financing (i.e. undergoing incorporation or locating in Delaware). Using these measures, they estimate the relationship between growth outcomes (firms that achieve an IPO or high value acquisition within six years of entry) and initial start-up characteristics, and find that a few characteristics allow one to construct a predictive model that determines entrepreneurial quality.

Similarly, Ng and Stuart (2016) apply machine learning algorithms to datasets containing a large set of socio-demographic variables for hundreds of thousands of entrepreneurs in the US tech sector. The authors show that the group of individuals possibly classifiable as "entrepreneurs" actually comprises two distinct clusters (which they name "hobos" and "highflyers") that have diametrically opposed characteristics, namely in terms of social positions and career pathways. Transitions across the two groups are also extremely rare.[3] The authors argue that these findings support a different way to define and study "entrepreneurship", which could take into account the two distinct phenomena that are usually covered by the same term. However, the study also supports the idea that big data and machine learning algorithms could be informative to predict successful entrepreneurship, and possibly also to improve the targeting of entrepreneurship policy.

Box 13.1. Machine learning, econometrics, and economics

Machine learning techniques are becoming increasingly popular in economic analysis as an alternative or a complement to traditional regression analysis to solve practical estimation problems. As Athey (2018) states, "machine learning will have a dramatic impact on the field of economics within a short time frame".

Regression analysis is used to precisely estimate a number of coefficients on a limited number of variables selected a priori based on a model derived from theoretical hypotheses. The estimated coefficients allow the calculation of marginal effects and elasticities, e.g. it is possible to state that start-ups with at least one female founder receive on average 70% less funding, everything else being equal. However, this approach is not informative on whether the linear combination of selected variables is doing a good job in explaining the phenomenon under scrutiny, compared to possible alternative variable combinations and selections.

Supervised machine learning techniques are designed instead, in general, to solve a prediction problem – given all the available information on start-ups, the objective is to identify the variables that are the best predictors of the outcome of interest (e.g. probability of being acquired). The question is not how the variable Y changes with respect to a change of the variable(s) Xs, but rather how the variable Y can be predicted out of a sample based on a wide set of Xs, and possibly which of those are the most important ones. While traditional econometrics has also being dealing with prediction (for instance to estimate economic forecasts), machine learning algorithms perform substantially better. Given that they require large datasets to provide precise predictions, their application suits particularly well "big data" sources that are becoming increasingly available.

The other big difference, compared to traditional econometrics, is that no theoretical model is needed: the analyst can simply "let the data speak". The algorithm is typically fed with the largest available set of variables, and the result is a list of variables ranked by importance, i.e. by their explanatory power in the prediction exercise. The major advantage of machine learning techniques lies in their flexibility. Because no functional form is imposed on the data a priori, these techniques are capable of finding appropriate models for data with varied structure and complexity.

The biggest danger with machine learning algorithms is using them to attach a causal interpretation to the result or to test general economic theories, which can be highly misleading. While the distinction between causality and correlation is prominent in the econometric literature, it is seldom mentioned in machine applications. However, the fact that a set of variables can predict very precisely an outcome does not imply that the same variables are affecting that outcome, as omitted variables or reverse causality could play a role. The classic example of Athey (2018) is the prediction of hotel occupancy rates using room prices. While low prices predict low occupancy rates, lowering the prices further would not lead to lower occupancy rates.

The findings that "highflyers" are systematically different from "hobos" does not necessarily imply, however, that the policymaker should ignore the latter. For instance, this kind of "subsistence" entrepreneurship may still be important to achieve inclusiveness, especially if it creates employment opportunities for individuals who are discriminated against or "red-lined" in the regular labour market. For instance, anecdotal evidence point to Uber having provided a foothold in the job market for thousands of undereducated youngsters of immigrant descent living in French *banlieues*.[4] The lack of transitions across the two groups can also be symptomatic of a lack of opportunities for the "hobos", due to obstacles to social mobility that could possibly be removed. The normative implication of these findings would point to tackling the barriers and the obstacles that hamper social mobility and limit the opportunities for a large set of the population. This is related to a recent US study (Bell et al., 2017) showing that children from high-income (top 1%) families are ten times as likely to become patent inventors as those from below-median income families, while differences in innate ability, as measured by test scores in early childhood, explain relatively little of these gaps.

How to target policies toward the identified high growth potential start-ups?

Once the high growth start-ups have been identified, or at least the scope of potential firms has been narrowed down, policy instruments must be designed to specifically target these firms. In other words, the *analytical* identification of these firms must be translated into administrative and policy *actionable* terms. This points to the challenging issue of how to maximise policy impact by refining policy targeting and the eligibility rules – a topic that has been examined only tangentially by the relevant literature. Even policies with an identical "average treatment effect" on supported firms would have a radically different aggregate effect depending on the eligibility rules, if the way in which firms react to the policy is highly heterogeneous.

Indeed, one important factor driving the success of public interventions is whether the target population reacts to the policy incentives as expected, i.e. in whether it complies with the policy objectives (Andini et al., 2017). Everything else being equal, a policy may fall short of the desired objectives because the eligibility rules are not fully effective in filtering the target population. Policy effectiveness can therefore increase by better targeting the sub-sample that is more likely to take-up and benefit from the policy, i.e. the policy "compliers".

Identifying the observable characteristics of the compliers is a policy prediction problem that suits well machine learning algorithms, which are designed to minimize the out-of-sample prediction error by exploiting all available information (Box 13.1). Machine learning can therefore be used ex-ante to inform the policy design phase, complementing traditional policy impact assessment approaches.

At the same, some factors of complexity should be taken into account. First, the relevant question for the policy maker is not only "*which are the high-growth start-ups*", but also "*which are the high-potential start-ups that do not grow because of the existence of the market failures that the policy is seeking to correct*". The start-ups to be targeted are not those that would grow in any case, but only those for which the policy makes a difference. In principle, answering the latter question requires performing a predictive exercise both in the presence and absence of the market failures, in order to be able to compare the two scenarios. The effectiveness of the policy would be improved if there is a part of the population that is excluded, but that share the same characteristics of the treated sample for which the policy has a positive impact. These considerations are partially related to the emerging literature on the intersection of machine learning with causal impact evaluation in econometrics (Athey, 2018; Chernozhukov et al., 2018).

Despite these challenges, there is huge potential for machine learning techniques to help policymakers to design more effective policies through more precise targeting. Researchers and policymakers should work together to assess the actual feasibility of this approach.

Is government venture capital an effective instrument to select and support high growth start-ups?

Equity financing for innovative start-ups is not only a tool to provide them with the financial resources and expertise needed for their early-stage development; it is also a mechanism to screen and identify high growth innovative start-ups. Governments, especially in Europe, have increasingly used this mechanism to complement their intervention portfolio and influence the type of investments toward those start-ups that most need it from a public mission perspective. This section provides an assessment of the state of the art of knowledge on the effectiveness of public VC and early-stage financing as a policy tool.

Governments are active VC investors in many OECD economies. According to the EC/OECD (2017), equity financing is the most popular instrument to support access to finance for innovative firms across OECD countries. In countries like Canada or Korea, more than 50% of VC-backed start-ups have received some form of public equity support (Brander, Du and Hellmann, 2015). Different degrees of government involvement exist. On the one hand, some programmes entail financial support to existing private VC funds with no direct control over management of the funds (e.g. “funds of funds”). On the other hand, some schemes involve direct government ownership of VC funds.

Government intervention in the VC market is justified by the existence of market failures of the private VC market. Indeed, innovations introduced by VC-backed start-ups may bring about important social benefits, often exceeding private ones. Given the public good nature of innovations, start-ups are likely to be underfunded compared to the welfare-maximizing level of funding. This is particularly true for young firms developing innovations that take longer to get to market, or those that generate further social benefits (e.g. inclusive start-ups, start-ups developing green technologies, start-ups in the health sector). Additionally, government venture capital initiatives can target companies for which they have informational comparative advantage (e.g. in the sectors of health and defence) and signal start-up quality to traditional investors (Lerner, 2002).

There are also important risks associated with government VC investments. For instance, government VC may displace private investments if they are targeting the same kinds of start-ups (Brander, Du and Hellmann, 2015). While the evidence on the effectiveness of public VC capital is equivocal, the majority of studies suggest that public VC do not crowd-out private investments. Brander, Du, and Hellman (2015) and Leleux and Surlemont (2003) show that government VC funding seems to cause greater amounts of money to be invested as a whole, both at the industry and firm level. The evidence on the impact of government VC on firm performance is also quite limited, and conclusions are mixed. On average, private VC-backed companies appear to perform better than public VC-backed companies in terms of total investments and successful exits (Brander, Du and Hellmann, 2015), innovation output (Bertoni and Tykvová, 2015), sales and employee growth (Grilli and Murtinu, 2014), although there are also several success stories. However, the form of investment that is associated with the best performance of companies consists of heterogeneous syndicates involving both public and private investors. Given the policy relevance of the topic and the huge amount of public resources invested, additional empirical evidence would be extremely valuable. Innovative sources of data, e.g. Crunchbase, provide new opportunities in this context, despite some limitations (Box 13.2).

Box 13.2. Using Crunchbase for economic and managerial research

Crunchbase (*www.crunchbase.com*) is a commercial database on innovative companies maintained by Crunchbase Inc. The database was created in 2007 within the Techcrunch network, but its scope and coverage has increased significantly over the past few years. As reported by the Kaufmann Foundation, the database is increasingly used by the venture capital industry as "the premier data asset on the tech/startup world".[5] Dalle, den Besten, & Menon (2017) present a detailed discussion of the database and its potential for economic, managerial, and policy-oriented research.

Crunchbase raw data are obtained through two main channels: a large investor network and community contributors. These data are processed by the Crunchbase analyst team with the support of artificial intelligence algorithms, in order to ensure accuracy and scan for anomalies. Additionally, algorithms continuously search the web and thousands of news publications for information to enrich profiles.

Compared to commercial databases covering similar information and frequently used for economic research, Crunchbase has major advantages: it contains cross-linked information on companies, their funders, and their staff; it is partially crowd-sourced, which adds to the comprehensiveness and timeliness of the database; it is updated on a daily basis; and it is structured in an accessible way. The comprehensive information on the profile of founders and the timeliness of the data are two of the characteristics of Crunchbase that make it particularly valuable for policy analysis. The VC industry evolves very rapidly – for instance, China went from having almost no investments in artificial intelligence in 2015 to being the second biggest global player after the US in 2017 – therefore more traditional sources of data may fail to cover the main trend early enough.

Breschi, Lassébie, and Menon (2018) discuss the coverage and representativeness of the database, compared to some benchmark data sources that are more commonly used in the literature. The general message of the benchmarking exercise is that Crunchbase has a better coverage of VC deals and start-ups than comparable data sources. The country-year comparison with aggregated sources on VC investments also suggests that the coverage of Crunchbase is sufficiently exhaustive across OECD member countries and four large emerging economies (i.e. Brazil, China, India, and Russia), with few exceptions.

The database also suffers from a number of limitations. First, the historical dimension of the database is mainly limited to the snapshot of companies that have been active recently. Start-ups that failed and ceased operations are likely not to have left any trace in the database. Therefore, spurious ascending growth trends of deal number or investments may appear in the data. This calls for caution in the examination of trends over time. Second, the amount invested in the VC deal is not disclosed in around 20% of cases. Third, the classification of investors into different groups (e.g. corporate, government, etc.) is not always accurate, and requires additional refinement and cross-validation work. The database has been refined and expanded by OECD in a number of different dimensions. A particularly important addition consists in the matching of patent data from PATSTAT, for both companies (patent applicants) and people (patent inventors) listed in the database (Tarasconi and Menon, 2017).

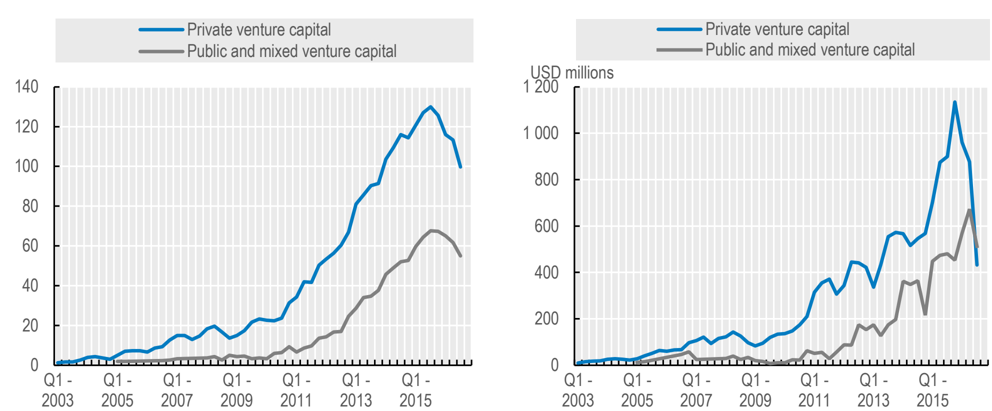
Even if direct positive effects fail to materialise on the "average" start-up, there is reason to believe that under specific circumstances government VC may be an effective complementary policy – at least in some sectors and for a period of time (Breschi et al., forthcoming). For example, government venture capital initiatives can target companies for which they have informational comparative advantage. This would be the case for sectors which are heavily regulated, and thus for which governments have preferential access to information on future market conditions. It would also be true for sectors for which government is a significant source of demand (e.g. in the sectors of health and defence).

Another motivation often put forward to support the role of government VC is its role in kick-starting emerging technologies that are deemed too risky by private investors. If this were generally true, a relatively higher share of government VC should be observed at the beginning of an exponential growth of aggregate investments in a sector. In order to test this hypothesis, Breschi et al. (forthcoming) calculated the total number of deals (upper panel) and investments (lower panel) by quarter in the following rapidly emerging technologies: drones; virtual reality; artificial intelligence; apps; 3D printing; blockchain; and cloud computing (Figure 13.3).[6] The data show that these sectors have experienced an exponential growth in both the number of deals and the total amount of investments. However, private investments appear to anticipate – rather than follow – the inflow of public support, with the latter, however, reaching almost the same level of private investments in 2016. This descriptive evidence therefore seems to suggest that the actual kick-starting of the technology is done by private investors, with public money playing an important role in expanding the market during the consolidation of the technology.

Figure 13.3. Investments in rapidly expanding technologies: public-mixed and private VC

a) Number of deals

b) Investment amounts, USD millions



Note: Data are preliminary. The rapidly expanding technologies are the following ones: drones; virtual reality; artificial intelligence; apps; 3D printing; blockchain; and cloud computing. The identification of the companies is based on keyword search on the company short descriptions. Excludes rounds where the type of investor is unknown.
Source: Breschi et al. (forthcoming), based on Crunchbase data (http://www.crunchbase.com).

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Overall, a complex policy trade-off is emerging. On the one hand, the model that appears to provide more "value for money" is the mixed one, in which public investments follow *pari passu* their private counterparts and mimic their investment strategies. However, inevitably this form of investment is less effective in achieving the "public good" objectives that are mentioned above. It is also the strategy with the highest risk of crowding out private actors. On the other hand, fully public investments – which in theory may be much more effective in filling the equity gap and in providing finance to areas that require more risk-taking and experimentation – appear to underperform their private counterparts, according to the (limited) available evidence. However, private investments may not be the best benchmark in this context, and it is extremely complicated to measure all outcomes of interest beyond market returns. Further research is needed to properly inform this important area of policy making.

Regardless of the model, investments in government VC in contexts in which the market is immature or almost non-existent are unlikely to succeed, as the exiguity of the private VC market is likely to be the symptom rather than the disease. This does not necessarily imply that there is a shortage of innovative entrepreneurial ideas; rather, the main problem appears to be the difficulty of transferring the ideas "from the lab to the market". This may be due to many different factors, e.g. the lack of managerial skills, the difficulty for innovative firms to attract resources (labour and capital) due to market rigidities, a scarce demand of innovative good and services in the local market, policy failures that impose an extra cost on risk, etc. In such a situation, the policymaker should assess carefully the bottlenecks that hamper the development of a dynamic entrepreneurial ecosystem, taking the whole start-up life cycle into account, as the lack of private equity investments may actually be the consequence of very weak growth prospects for start-ups at later stages of their development (Box 13.3).

Box 13.3. In my view: When innovation waterworks are clogged, we should remove obstructions downstream

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I sometimes have the feeling that economists and policy-makers tend to overestimate the role of inputs to the innovation process and the supply side of markets for innovation. The number of patents, of startups, VC investments, are key statistics that are constantly monitored and eventually incentivized, often by pouring public money in the system, "*since private investors will not*". The underlying assumption is that – if the innovation waterworks are clogged – building upstream pressure will solve the problem. As an engineer, I beg to differ, since I would rather try to remove obstructions from downstream.

Metaphors aside, I see a significant risk of neglecting the complexity of innovation systems. Innovation systems do not only comprise multiple tiers of venture capitalists and budding entrepreneurs bearing innovative ideas, but also experienced entrepreneurs, advisers, professional services firms, a talented workforce, suppliers, companies that might acquire startups, open minded regulators and – most important of all – customers, which includes consumers, other businesses, or government entities.

Lacking customers, all the rest loses significance. Even more, in the case of 'corporatist' economies where markets are *de facto* not contestable, unassailable incumbents cannot be competed against by entrant startups, nor will they consider them either as suppliers or as acquisition targets. Now, lacking customers and/or real opportunities for startups to enter markets and grow, why should a dearth of VC investors be considered as a market failure, and not as the proof that markets work very well?

I understand policymakers' willingness to funnel money into VC funds, or in Funds of Funds. It is a direct way to declare they have "thrown money at the problem", but I am sometimes afraid that this may serve as an alibi for sidestepping the much more difficult task of freeing startups from the shackles that hinder their growth. Moreover, this approach tends to support the myth that Venture Capital is simply about money, while it is much more. Allocation of capital to startups is a complex exploratory process, carried out on assets characterized by huge Knightian uncertainty and information asymmetries. The only way to make it work is to ensure a liquid market with multiple VC funds interacting with many startups, combined with a competitive ecosystem able to progressively select the best firms. Moreover, capital allocation is just the first step of the VC process, while the second and most important one is the active support provided by General Partners to founders in growing their firms, recruiting managers, making deals, and structuring the next financing round or exit. In other words, the VC industry will work properly if it is based on a large number of funds, staffed by experienced General Partners. So, while it is likely that a thriving startup ecosystem may nurture an adequate number of such professionals and generate a robust VC industry, I have some doubts that a VC industry may arise out of financial endowments alone, and lead to a thriving startup ecosystem.

Leading scholars like Edmund Phelps and Amar Bhide have argued that the main input to the innovation process is culture: a culture where change and competition are viewed as values *per se* and not as something to be 'managed'. A culture where it is customary to take clear and rapid decisions, without ambiguity and endless deferrals. A culture where not only failure, but also glaring success, are not frowned upon. It is not an easy task, but a worthwhile endeavor indeed.

Future outlook: toward new balances between targeted and non-targeted policies?

Both policy approaches based on targeting or providing wide support to high growth potential firms have their own challenges, costs – actual costs or opportunity costs – and benefits. In practice, policy makers set out to strike the right balance between targeting and fostering experimentation. A number of attributes, including formal and informal institutional set-ups, greatly influence this balance and make it country-specific. This balance also evolves over time with policy learning and changes in preferences.

New empirical evidence, leveraging on big data and machine learning techniques, could influence this balance in the near future. Their potential to fruitfully inform the refinement of eligibility rules of entrepreneurship policy – with a view to focusing on the specific group of start-ups that see their growth potential hampered by market failures – is growing. They therefore hold great potential for better targeting of entrepreneurship policy, which could significantly improve its effectiveness. At the same time, in rapidly changing markets, idiosyncratic and unobservable factors will always play an important role, thus start-up success will preserve a degree of unpredictability. Therefore, direct and targeted policy interventions will certainly always have to be complemented with horizontal reforms in order to ensure an overall business environment conducive to entrepreneurship and experimentation. Start-ups will have to be able to attract resources and to scale-up if successful, and to exit smoothly if unsuccessful.

The balance between targeted and non-targeted approaches will also be increasingly influenced by the need to address the "grand challenges" of our time – from climate change to food security and aging. While the radical innovations brought to life by visionary entrepreneurs are essential to face some of these challenges, these are by nature surrounded by strong ("radical") uncertainties. As shown by studies in economics and sociology of science and innovation, periods of disruptive changes do not lend themselves well to policies aiming to pick the "best" alternatives. Most innovations in these turbulent periods are systemic, emerging from trials and errors of various combinations of technological and social innovations. This makes any attempt to identify ex ante firms with the greatest potential more challenging or, even worse, detrimental to the process of change as it limits experimentation. In such context, a subset of firms with higher growth potential are not "revealed" to the world; their potential for growth emerges and increases through interactions with their environment, allowing faster learning and larger investments in some of them.

Growing inequalities, another mounting concern, might affect the balance in the same direction of a more open and experimental approach for supporting innovative entrepreneurship. The need for inclusiveness will call for policies making high-growth entrepreneurship more accessible to talented "outsiders" in order to foster social mobility.

While big data and machine learning will without doubt improve the capacity of policy makers to identify the sub-sample of start-ups with high growth potential that could critically benefit from targeted policy support, new societal challenges will require more experimentation in years to come. No one can predict the result of this "moving target" process on the innovative entrepreneurship policy in different national contexts. However, it is clear that countries will have to both invest in and monitor progress in techniques targeting firms, and continue to reform their economic system to make the process of experimentation more efficient.

Notes

[1] In this chapter, the term "venture capital" is used with a very general meaning, referring to all forms of equity funding for high-growth and high-risk entrepreneurial venture. The term therefore also encompasses forms of financing that are not properly venture capital, such as angel investments and seed and early stage funding.

[2] For instance, there is evidence that innovative entrepreneurship fosters social mobility in the United States (Aghion et al., 2015), while minority communities, particularly those of South/East Asian origin, have played increasingly important roles in US science and technology sectors (Chellaraj, Maskus and Mattoo, 2008).

[3] In passing, this finding may have important normative implications for the debate on inclusive entrepreneurship, which are not discussed by the authors.

[4] See *the Financial Times*, "Uber: a route out of the French banlieues", 3/3/2016, by Anne-Sylvaine Chassany; available online at https://www.ft.com/content/bf3d0444-e129-11e5-9217-6ae3733a2cd1 (retrieved on 16th July 2018)

[5] http://www.kauffman.org/microsites/state-of-the-field/topics/finance/equity/venture-capital accessed on September 11th, 2017.

[6] The choice of these fields, as well as the procedure to tag the related companies in Crunchbase, follows closely the work done by Crunchbase experts on "buzzword" technologies, available at

https://news.crunchbase.com/news/ahead-buzzword-curve-finding-investors-front-top-tech-trends/ accessed on 12th June, 2018.

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