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THE EFFECT OF VENTURE CAPITAL ON INNOVATION STRATEGIES

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ABSTRACT

We examine a unique dataset of Dutch companies, some of which have received venture financing. The data include detailed information on innovation activities and other company characteristics. We analyse the role of venture finance in influencing innovation strategies. We find that venture capitalists push portfolio companies towards building absorptive capacity and towards more permanent in-house R&D efforts. By contrast, we find that public funding relaxes financial constraints, but does not lead to a build-up of absorptive capacity. Our results thus highlight the special role of venture capital in shaping companies' innovation strategies.

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1 Introduction

Venture capital is a specialized form of financial intermediation whose success in supporting innovative companies through the provision of finance and monitoring and advice services has generated much research.

The active role of venture capitalists in portfolio companies has been documented by several studies (e.g., Bottazzi, Da Rin, and Hellmann (2005), Gorman and Sahlman (1989), Lerner (1995)). In particular, studies have documented that venture capital speeds up product commercialization (Hellmann and Puri (2000)) and the adoption of human resource policies (Hellmann and Puri (2002)), and that it strengthens companies' commercialization strategies (Gans, Hsu, and Stern (2002), Hsu (2006)). However, we still know very little about how exactly venture capital contributes to companies' strategic behavior at the earlier stage when the innovative process at portfolio companies takes shape.

In this paper we contribute to this literature by focussing on one aspect that bridges the industrial organization, management, and finance literatures and that has not been explored so far. This concerns how venture capital influences the way companies integrate new knowledge into the innovation process by combining different inputs. Our study is thus the first to look directly into how venture capital contributes to the innovation strategies of portfolio companies.

The role of venture capital in this context is potentially very important. Venture capital firms are sophisticated investors, whose partners have extensive knowledge of the industry and often previous managerial experience. Their strong commitment to generate high returns in the medium term makes them active investors (Bottazzi, Da Rin, and Hellmann (2007)). They could therefore 'make the difference' by effectively steering portfolio companies' innovation strategy towards commercial success.

There are two possible, though opposite, views of venture capital's role in shaping portfolio companies' innovation strategy. One is that venture investors are particularly good at timing market conditions (see Gompers et al. (2007)). They would invest in companies at the 'right' time with the goal to take them public (or sell them to an industrial acquirer) at the 'right' moment, thus freeing their capital to re-invest it in new ventures (Michelacci and Suarez (2004)). In addition, the certification role of venture investors (Megginson and Weiss (1991)) and their networks of relationships (Hochberg, Ljungqvist, and Lu (2007)) would contribute to attract companies which already have good growth opportunities (Sørensen (2006)), so that venture investors would mainly need to bring them to a successful exit. Venture capital would therefore finance companies whose innovation strategies are already well developed, with the perspective of turning them soon into 'cash cows' (Bottazzi and Da Rin (2002)).

An alternative view is that venture investors are 'company builders' who influence innovation as much as professionalization and commercialization strategies. This view, based on the double moral hazard model of venture capital of Holmstrom and Tirole (1997)[1], stresses the active role of venture capitalists as mentors and monitors of inexperienced entrepreneurs (Baker and Gompers (2003), Gorman and Sahlman (1989), Lerner (1995)). Venture investors would therefore provide teams of entrepreneurs with finance but also with non-financial services like monitoring, support, and advice, in order to create successful commercial ventures. The effect of venture finance would in this case extend across several strategic dimensions, as documented in the case of product commercialization (Hellmann and Puri (2000)), human resource policies (Hellmann and Puri (2002)), and commercialization alliances (Gans, Hsu, and Stern (2002), Hsu (2006)). Whether venture firms would affect strategies at the innovation stage remains an open question.

Verifying which of these two views is closer to reality is important both from a management and from a policy. This is the purpose of our study. We base our analysis on the concept of absorptive capacity. Absorptive capacity, defined as the 'capacity to assimilate and exploit new knowledge,' is a concept introduced by the seminal contribution of Cohen and Levinthal (1989, 1990) and further formalized by Kamien and Zang (2000) and Zahra and George (2002). Particularly important in our context, is that many successful innovation have been favored by the ability to build absorptive capacity. The underlying idea is that R&D activities have two different effects. One is to directly generate new innovations, the other is to provide companies with the ability to identify, evaluate, and absorb internally different forms of know-how which has been generated outside the firm. By investing in the build-up of absorptive capacity through in-house R&D, companies may therefore increase their ability to generate future innovations by remaining actively tuned on what others are doing and ready to exploit the opportunities that scientific and technological advances create.

From a management perspective, absorptive capacity is then a major factor underlying companies' ability to combine external sources of knowledge for the production of innovative products. As argued by Cockburn and Henderson (1998), Freeman (1991), and Mowery, Oxley, and Silverman (1996), the combination of internal and external sources of knowledge is an important factor in explaining many successful innovations. The econometric analyses of Arora and Gambardella (1990, 1994) further strengthened this point by showing that internal know-how is important both for screening external know-how and for incorporating it into innovations. Moreover, Levin and Reiss (1988) and Veugelers (1997) show that the ability to incorporate external know-how further increases the level

[1] See also Casamatta (2003), Hellmann (2006), and Schmidt (2004).

of internal R&D. As Cassiman and Veugelers (2006) argue, understanding which variables lead to a build-up of absorptive capacity, would then help making the innovation process a 'manageable source of sustainable competitive advantage.' They focus on the role of a company being closely linked to universities and research centers, while we focus on a company's ability to attract venture capital investors.

Understanding factors conducive to the accumulation of absorptive capacity is important also from a policy perspective. Griffith, Redding, and van Reenen (2004) provide country-level evidence of the importance of absorptive capacity for productivity growth. In other words, absorptive capacity matters for the success of the individual firm but also for economic growth. Leahy and Neary (2007) formally model the innovation process to evaluate the effectiveness of alternative public policies, and conclude that absorptive capacity makes subsidies to R&D more efficient than those to research joint ventures.

Many countries spend large amounts of public money on promoting venture capital (Da Rin, Nicodano, and Sembenelli (2006), Di Giacomo (2004)). One of the tenets of such active public policies is that helping the creation of national venture capital industries increases the amount of innovative R&D and contributes to economic growth through the creation of knowledge spillovers (Keuschnigg and Nielsen (2003)). Clearly, a positive role of venture investors for the accumulation of absorptive capacity by portfolio companies would contribute to justify these policies, while the opposite result would suggest a waste of taxpayers' money.

On these bases, we ask how venture finance influences the absorption of new knowledge through the combination of two different innovation activities (R&D 'make' and 'buy'). More precisely, following Cassiman and Veugelers (2006), we define exclusive combinations of these activities which define alternative innovation strategies, and focus on how venture capital affects the *joint* adoption of both make and buy—which corresponds to the build-up to absorptive capacity. This is an important question since it goes to the heart of how venture financing might contribute to the innovation process.

We therefore provide a novel contribution to a recent literature that has so far focussed on the role of venture capital in the commercialization stage of innovations. Recent studies have started examining how venture capital investors contribute to the formation of cooperative alliances for the commercial exploitation of innovations (Gans, Hsu, and Stern (2002) and Hsu (2006), using US data), and in 'explorative' formal R&D alliances by a sample of Italian firms (Colombo, Grilli, and Piva (2006), using Italian data) In a related stand of literature, Cassiman and Veugelers (2002) look at the relationship between R&D cooperation and knowledge spillovers, and Cassiman and Veugelers (2006) look at the determinants of the complementarity among 'make' and 'buy' innovation activities and using Belgian data. We build also on these studies by including venture investors as a relevant determinants of absorptive capacity.

We base our analysis on a unique database of over 7,800 Dutch companies. The Netherlands is a country with both a high level of innovation and a vital venture capital market and therefore represents a suitable case for our study. We assemble our dataset using detailed firm-level information on innovation activities from the Community Innovation Survey data provided by the Dutch Central Bureau of Statistics (CBS). We supplement these data with information on venture financing from VentureXpert, the leading commercial database for venture finance, and with application-level patent information from the PATSTAT database of the European Patent Office.

Our main result is that venture finance matters for innovation strategies. The arrival of venture capital is associated with an increase in 'make' but not in 'buy' R&D activities, and with an increase in the 'make and buy' R&D strategy. This means that venture capital favors the build-up of absorptive capacity, and also results in a more regular R&D effort. Interestingly, we find that the availability of public funds turns out to increase all innovation activities. This stands in stark contrast with the effect of venture finance, which selectively affects those activities which lead to an increase in absorptive capacity. We also find interesting results for other contextual variables. Consistent with Cassiman and Veugelers (2006), we find that firm size is associated with more innovation activities, while firm age tends to have the opposite effect. Firms in high-technology sectors also focus on the build-up of absorptive capacity. Finally, we find that previous patenting activity, whether measured by its quantity or its quality, has a positive effect on the undertaking of innovation activities. This is particularly important, since we cannot observe innovation activities before the arrival of the venture investor.

One important concern about any study of the effects of venture capital on portfolio companies is that venture firms do not invest randomly, but rather carefully select their portfolio companies on the basis of their likelihood of success. Therefore, one should distinguish between the 'selection' effect (of a company obtaining financing on the basis of its characteristics) and the 'treatment' effect (of the venture firm activism changing the company's situation). We take this methodological issue seriously, and we perform a 'propensity score' analysis which allows us to control for the selection process based on observable company characteristics.[2] We also exploit the fact that for some of the venture-backed companies in our sample we are able to observe innovation strategies both

[2] The small size of the Netherlands and the concentration in our sample of companies which received funding after 1997 prevent us to use instrumental variables based on spatial or temporal availability of funding. Notice that the lack of information on companies before they receive venture funding prevents us to use a Heckman selection model.

before and after venture financing. We find that all our results are confirmed by these additional checks. Nonetheless, the lack of an instrumental variable which may lead to a conclusive analysis warrants some caution in the causal interpretation of our results.

In sum, our paper provides new insights into the positive contribution of venture capital to building successful companies. These findings are relevant for management, as venture investors will affect a company's strategy at an even earlier stage than at the product commercialization phase one which had been documented so far. They are also relevant for a more complete evaluation of public policy towards innovating firms, as they suggest that encouraging forms of finance which are conducive to the build-up of absorptive capacity may be socially more efficient than providing purely monetary support for these companies.

The remainder of the paper is organized as follows. Section 2 presents the data and the construction or our sample and variables. Section 3 discusses our results. Section 4 examines several robustness checks and is followed by a brief conclusion.

2 The Data

2.1 Data sources

We base our analysis on a unique company-level database of Dutch companies. The Netherlands presents two characteristics that make it suitable for our purposes. It is the second European country in terms of patents per capita (European Patent Office (2004)). It is also the second largest venture capital market in the European Union in per capita terms, second only to the UK (EVCA (2007)).

We collect our data from three sources. First, we use innovation and company data from the Community Innovation Survey (CIS). Since 1993, the CIS takes place every four years in all countries of the European Union to investigate companies' innovation activities. Information is gathered by national statistical offices through a survey that covers a representative sample of companies (innovative and not) stratified along the region, sector, and size dimensions.[3] About 10,000 Dutch companies are included in each survey wave.

CIS data is published only in aggregate form to preserve respondents' anonymity. However, qualified researchers can be granted access to anonymized company-level information by the Dutch Central Bureau of Statistics (CBS). In our case, this consists of data from three survey 'waves': the CIS-3 survey, covering 1998-2000, the CIS-4 survey, covering

[3] CIS documentation, which provides a full description of the survey, is dowloadable at the URL: *http://epp.eurostat.ec.europa.eu/cache/ITY_PUBLIC/OSLO/EN/OSLO-EN.PDF*.

2002-2004, and the CIS-3.5 survey, covering 2000-2002 and conducted on a subset of the usual questions.

CIS data have been previously used in both the economics and management literatures. For instance, Mairesse and Mohnen (2002) and Belderbos et al. (2004) use the Dutch survey, while Cassiman and Veugelers (2002, 2006), and Veugelers and Cassiman (2004, 2005) use the Belgian survey.

Our second source of data is the VentureXpert database published by Thomson Financial. VentureXpert is the main commercial source of venture capital and private equity investment data, with substantial European coverage from the late 1990s (Da Rin, Nicodano, and Sembenelli (2006)).[4] The database is compiled from information provided directly by venture capital firms, and contains data at the level of the individual investment ('deal'). For the Netherlands it includes (for the period under study) more than 1,000 deals in over 600 companies, originated by over 300 venture firms.

Our third source is the PATSTAT database recently developed by the OECD and the European Patent Office (EPO).[5] From PATSTAT we obtain information on all the individual patent applications filed with the European Patent Office by Dutch companies. For each patent application the database reports standard measures of patent quality, such as backward citations, forward citations, and patent scope ('family size'). To the best of our knowledge, this is the first study which employs such detailed firm-level information for innovations, financing, and patent quality.

2.2 Sample definition

Our sample comprises two sub-samples. One is the set of venture-backed companies which participated in at least one CIS wave after receiving funding. We have 110 such companies. In the analysis we lose 19 of them due to missing values of the dependent variables.

The second subset is the control sample of CIS respondents which did not receive venture funding. We build the control sample balancing two opposite needs. On the one hand, we want to include as many companies as possible to gain statistical power. On the other hand, we want to drop companies which are different in nature from those which receive venture financing, as their inclusion would add noise.

We strike a balance by defining our sample as the set of all companies that satisfy (for

[4] VentureXpert has been used in many studies on venture capital (e.g., Gompers et al. (2006), Hochberg, Ljungqvist, and Li (2007), and Sørensen (2006)).

[5] Grid Thoma provided us with patent data matched to individual companies. Information on PATSTAT is available at the URL: $http://europa.eu.int/estatref/info/sdds/en/pat/pat-epo-nat-sm.htm$. Notice that EPO data refer to patent applications as opposed to patents granted, as in the case of USPTO data.

any CIS wave in which they took part) at least one of the following two restrictions: (i) they introduced an innovation, (ii) they performed some innovation activity (i.e., they used some innovation input). This means that we include all the firms which have introduced an innovation in the CIS wave years, but also those which have used innovation inputs without introducing an innovation, on the grounds that—due to the relatively short period covered by a CIS wave—they are likely to do so in a subsequent year.

We also drop all observations in two NACE 2-digit industries in which we do not have any venture-backed companies (Oil&Energy and Metals), and companies with more than 415,529 euros of turnover (equal to one standard deviation above the average value for venture-backed companies).

These restrictions bring our control sample from 23,677 to 7,808 companies. In other words, we eliminate about two thirds of the companies in the CIS which would be unlikely control units.

2.3 Dataset construction

Building our dataset involved two major steps: aggregating information from different CIS waves for each company, and merging the information from the CIS, VentureXpert and PATSTAT databases.

2.3.1 Aggregating information across CIS waves

Not all companies present in the CIS participate in each survey wave. In fact, 57% of the companies take part in only one wave, 28% takes part in two waves, and only 15% in all three waves, as shown in Table 1. It follows that aggregation is only necessary for less than half of the sample.

When there is a need for aggregation of information, we consider that companies may undertake different innovation activities over time. It is important to notice that the timing of the CIS waves is somewhat artificial. Consider a company which starts doing intramural R&D in December 2000 and buys a patent in January 2001; these two activities would fall in different CIS waves, but are clearly closer than if they had taken place at two distant dates within the same CIS wave (say February 1998 and November 2000). Since we do not know the exact timing of each activity, we consider the company actively engaged in an R&D activity if it is ever active across the CIS waves it takes part in. With this approach we are able to exploit the richness of our data, which in almost half of the cases extends over more than one CIS wave. We argue that this allows us to obtain a better picture of companies' innovation strategies than a purely cross-sectional dataset.

Since we want to study how venture capital shapes innovation strategies, for venture-backed companies we need to take into account the timing of the funding. Therefore, we consider CIS information only *after* a company's first venture funding so as to evaluate the impact of venture capital on innovation strategies. Unfortunately, we typically do not have information on innovation strategies both before and after the arrival of the venture capital, which prevents us to use a potentially useful identification strategy.[6] However, in our robustness tests, we analyze the ten venture-backed companies for which we have both pre- and post-funding innovation data.

Finally, we aggregate patent information. Patent data are collected at the level of each single application. We aggregate the patent applications made to the EPO by each company taking into account the year of application. For each company we then compute the applications in the two years before the first CIS-wave it took part into. For venture-backed companies we compute the patent applications during the time period in the two years before funding. Based on the patent applications falling in these sets, we build our measures of patent quality.

2.3.2 Merging information from different sources

The second major step in building the database consisted of merging the relevant information coming from each of the three sources. In other words, we need to match the information relative to each company so as to ensure that its innovation strategy, venture financing, and patenting data are correctly assigned to it. This is achieved by exploiting the fact that each Dutch company is assigned a unique ID number by the Dutch Chamber of Commerce. Crucially, this number is used by CBS to identify companies.

As VentureXpert does not contain this information, we identified the Chamber of Commerce data manually on the Chamber of Commerce website, using an algorithm based on the company name, city, address, and sector. The website of the Chamber of Commerce makes such information publicly available. By joining the Chamber of Commerce ID of CIS respondents with that of the venture-backed companies, CBS could provide us with a precise identification of which CIS companies are venture backed. Our sample contains 110 such unique companies. The sample was then anonymized by CBS by substituting the Chamber of Commerce IDs with random ones.

Finally, identification of patent applicants was also obtained using the Dutch Chamber of Commerce ID. For the patent data we received we applied the same algorithm used for companies found in VentureXpert and obtained the Chamber of Commerce ID number

[6] The lack of a panel dimension prevents us to use firm fixed effects, which would be the optimal solution to this problem.

from its website. In this way we were able to precisely assign patent data to each company.

2.4 Variables

In this section we describe all the variables we use in the empirical analysis. Table 2 provides formal definitions and reports the CIS questions from which innovation activities and strategies were obtained. In order to avoid measurement error, we make an effort to use only objective measures from the Survey. Table 3 provides descriptive statistics for all dependent and independent variables.

2.5 Dependent variables

Our first set of dependent variables is given by the innovation activities within a company. These are the basic constituents of innovation strategies and consist of individual innovation processes. We take them from the responses to the CIS. There are two main innovation activities. One is *Make*, which is engaging directly in R&D within the firm ('intramural,' or 'in-house' R&D). The other is *Buy*, which consists of buying innovation activities performed by other companies or research institutes. *Buy*, in turn, may consist of either of two components. One is *Buy–R&D,* the purchase of extramural R&D activities; the other is *Buy–Know-How,* the purchase of external know-how (patents, inventions, or other disembodied knowledge). We also consider in the analysis that a company may acquire know-how 'embodied' in advanced machinery and equipment (*Buy–Machinery*). We include this variable because it provides interesting information about companies' indirect acquisition of external know-how. However, following Cassiman and Veugelers (2006) we cautiously choose not to include this variable in the construction of innovation strategies because it is not clear whether this activity refers to technology acquisition or just to the purchase of means of production.

Our second set of dependent variables is given by a company's innovation strategies. These consists of four mutually exclusive categories defined by the combinations of the two innovation activities, *Make* and *Buy.* The baseline category is *No–Make–No–Buy*, and corresponds to companies which never engage in innovation activities. *Make–Only* and *Buy–Only* are the strategies of companies which engage in *only* one of these two activities in the sample period. Finally, *Make–and–Buy* is the strategy of combining the internal and external knowledge acquisition, and corresponds to the build-up of absorptive capacity.

An additional variable of interest is whether a firm engages in in-house R&D continuously or not. We define *Permanent–R&D* as a dummy which identifies companies that perform in-house R&D continuously during the period covered by the CIS.

2.6 Independent variables

Our set of independent variables is computed at the company level and is obtained from the Community Innovation Survey, VentureXpert, and the PATSTAT database of the EPO.

The explanatory variable which is the focus of this study is *VC*, an indicator variable for whether the company has received venture financing before participating in a CIS wave.

We then consider the importance of alternative finance for innovative companies, which are often credit constrained. Innovative companies are particularly likely to be credit rationed due to the riskiness of their activity, the lack of track record, or the presence of large agency costs (see Carpenter and Petersen (2002), Hall (2002), and Himmelberg and Petersen (1994)). In this context, the availability of public funds can be an important source of financing (Hall and van Reenen (2000)). *Public–Funds* is a dummy variable equal to 1 if the company received public funds, at either the national or the European level. We obtain this information from the CIS. We want to stress that it is important to control for the availability of public funds to each company to account for a potentially different role of public and private finance, and also to take into consideration the possible correlation of venture financing with the receipt of public funds.

Since we do not have information on the pre-funding levels of innovation, it is important that we control for how innovative a company was before the arrival of the venture firm. For this, we use a standard measure of innovation output, patents. Notice that the patent data we have is particularly suited for this purpose, since it contains the entire universe of patent applications filed with the EPO, which provide a set of better applications than those filed at the purely national level (see Hall, Thoma, and Torrisi (2007)). Our main patent measure (*L(Patent–Citations)*) is a measure of patent quality widely used in the literature (see Kortum and Lerner (2002)), the number of 3-year forward citations received by a company's patent applications filed with the EPO before the year of its first venture financing (if venture-backed), or before the first CIS wave it has responded to (if non venture-backed). This measure was introduced by Trajtenberg (1990), who found a strong relationship between the number of patent citations received and the economic importance of a patent.

Company age is an important variable in determining corporate strategy and the ability to reach out to external resource providers (Hsu (2006)). We measure company age (*L(Company–Age)*), which we obtain from the Business Register database of CBS, at the time of its first venture financing (if venture-backed), or at end of the first CIS wave it has responded to (if non venture-backed). Firm size is another factor widely used in the literature to capture a company's ability to mobilize resources. We use *L(Sales)*, the company's turnover in the last year of the first CIS wave it took part in (whether or not the company is venture-backed). For all three continuos variables—patent citations, age, and size—we use log transformations to account for possible non-linearities of their effects, as well as to account for the possible presence of outliers.

Previous studies show that R&D orientation affects innovation activities (e.g., Colombo and Garrone (1996), Röller, Tombak, and Siebert (1997)). We control for this with the industry a company operates in. For our main analysis we aggregate this information into a dummy variables which naturally lends itself to interpretation. We define as *High–Tech* the following NACE 2-digit industries: Chemicals, Pharmaceuticals, Electronics, Computer Services, and R&D Services. We obtain the necessary information from the CIS. In the robustness section we replace *High–Tech* with industry fixed effects.

3 Results

3.1 Univariate analysis

We start our analysis with some non-parametric tests of the difference in means (or frequency, for dummy variables), between venture-backed and non ventured-backed companies, for both dependent and independent variables.

Table 3 reports our results. In the first panel we focus on innovation activities. Venture-backed companies present higher frequencies of all innovation activities (both *Make* and *Buy*), and also permanent in-house R&D. The only exception is the acquisition of machinery, but—as we argued in Section 2.5—this category is likely to be associated more to production that to innovation.

We then analyze innovation strategies. Interestingly, venture-backed companies show a significantly higher frequency of the *Make–and–Buy* strategy, while they present a significantly lower frequency for the *Buy–Only* and the *No–Make–No–Buy* strategies, and no differential effect for *Make–Only*. This is indicative of a role of venture capital in pushing the portfolio companies towards building absorptive capacity, a result we are going to examine more thoroughly in the next section.

With respect to the control variables, venture-backed companies have a higher probability of receiving public funds than non-venture backed. This could be due to the certification role of venture funding in facilitating the access to public funds. However another possible explanation is that venture capital may have a preference for companies that are receiving public subsidies that may further alleviate financial constraints.

Finally venture-backed companies are characterized by a larger number of pre-funding patent citations, and are more likely to operate in high-tech industries. They are also significantly younger and slightly larger. These characteristics suggest that these companies are more innovative than non venture-backed firms.

3.2 Multivariate analysis

We move to the regression stage by first examining the determinants of companies' innovation activities. We base our analysis on probit regressions, report the results in Table 4. Our first finding is that venture finance has a positive and significant effect on the likelihood of undertaking in-house R&D (*Make*). It also has a positive effect on the likelihood of purchasing innovation activities developed outside the company (*Buy*). This effect is only marginally significant, at a 12% confidence level; however the effect on the two components, *Buy–R&D* and *Buy–Know-How*, is statistically significant at conventional levels. Interestingly the receipt of public funding has a positive, and statistically highly significant effect on all innovation activities. The effect of the two sources of finance, private venture capital and public funds, is also sizeable in economic terms. Funding from a venture capitalist increases the likelihood of *Make* by 18%, and the likelihood of *Buy–R&D* and *Buy–Know-How* by 9% and 12%, respectively. Receiving public funding increases the likelihood of *Make* by 36%, and that of *Buy* by 21%. Interestingly, public funding, but not venture funding, also positively affects the likelihood of buying advanced machinery.

There is therefore some indication that public funding helps companies overcome financing constraints and increase their spending across the board, while the effect of venture financing appears to be somewhat more selective. We also find reassuring that venture financing is significant even if we include public funding as a regressor, as this avoids the possibility that the *VC* variable captures the combined effect of these two sources of funds.

The results also for our control variables are also interesting. As expected, companies in high-tech industries tend to make more use of innovation inputs. This effect is quite strong for *Make*, with companies in high-tech industry showing a 20% higher probability to undertake in-house R&D, and weaker and marginally significant (at the 10.5% confidence level, with an economic effect of only 3%) for *Buy*. We also find that bigger companies undertake innovation activities more frequently, and that older companies are less active in innovating than younger ones. Finally, our control for pre-funding patent quality turns out to be highly significant for both *Make* and *Buy*. This control aims at helping the identification of the effect of *VC*, but also brings an interest of its own, as it measures the quality of a company's past innovation efforts. We find that a one standard deviation increase in (logarithm of) the number of pre-funding patent citations results in a 12% increase in the likelihood of *Make* and in a 4% increase in the likelihood of *Buy*.

These results suggest that the direction of venture capital does provide support to the build-up of absorptive capacity. However, as discussed by Cassiman and Veugelers (2006), we need to resort to a different set-up to obtain direct evidence on this. We therefore turn to an examination of the effects of our explanatory variables on innovation strategies, which we have defined as *exclusive* combinations of the two innovation activities. By using a multinomial logit regression, we can then try to identify which factors affect the joint adoption of *Make* and *Buy*, i.e., the accumulation of absorptive capacity. Table 5 reports the results of our multinomial logit, where we leave the *No–Make–No–Buy* strategy as the residual one. The result which stands out is that *VC* indeed affects (positively, and significantly) the *Make–And–Buy* strategy, but not the other two strategies (*Make–Only* and *Buy–Only*), confirming that venture finance does indeed brings portfolio companies to accumulate absorptive capacity. This effect is also economically significant, as venture finance increases the likelihood of *Make–And–Buy* (compared to the baseline case of no innovation activity) by 18%.

An interesting finding comes from the comparison of the effect of private venture funding with that of public funds. While *VC* has a selective effect on alternative combinations of innovation activities, and thus an effect on the innovation strategies of portfolio companies, the availability of public funds simply results in an across-the board increase in innovation activities. In other words, public funds are just money, which does not discriminate across innovation activities. Venture capital, on the contrary, comes with an additional strategic influence. This is a novel and relevant finding which contributes to the debate on the economics of public subsidies to R&D (see Hall and van Reenen (2000) for a discussion). The other explanatory variables are found to have less discriminating effect on innovation strategies than venture capital. Like public funds, also firm size indiscriminately raises the probability to undertake any innovation strategy (relative to none at all). Patent citations, company age, and high-tech industry are associated with a higher likelihood of both *Make–Only* and *Make–And–Buy*, suggesting that younger firms with more past patent citations and which operate in high-tech industries rely more on in-house R&D than on the purchase of externally produce innovation activities.

Finally, we consider whether the presence of venture capital, beyond leading to the build-up of absorptive capacity, also results in companies engaging in R&D in a more continuous way. For this, we exploit a question of the CIS, which asks respondents which have engaged in *Make* activities whether they have done so continuously or occasionally over the three years covered by the Survey. Table 6 reports the results of a probit regression where we look at the determinants of the choice to undertake in-house R&D on a continuous basis. We find that the effect of VC is positive and highly significant, leading to an increase of the likelihood of permanent R&D equal to 13%. We interpret this as further evidence in favor of venture capital having an important strategic impact on portfolio companies.

Overall, our results are largely consistent with previous studies of innovation activities, and point to a different role of private venture capital and public funds for innovative companies. This has clear implications for both strategic management and for public policy. Companies receiving venture finance will receive more than just money, and the contribution of this form of specialized financial intermediation includes an influence on the fundamental choice of innovation activities. Receiving public funds, on the other hand, is mainly a way to alleviate financing constraints. From a policy perspective, we provide a new element for the evaluation of public policies. If venture financing favors the build-up of absorptive capacity and public funds do not, this should be given due consideration in the evaluation of public policy for innovative companies.

4 Robustness checks

We undertake several robustness checks. First, we consider that our data reflect strategic choices observed at different points in time, but we treat them as a pure cross-section. We therefore want to explicitly control for the time dimension of the data, and for the fact that we sometimes aggregate them over a different number of CIS waves. To this purpose, we build a set of seven dummies, one for each possible combination of CIS waves (see Table 1). We therefore have dummies identifying whether the value of the dependent variable of a particular observation was built using only CIS–3, only CIS–3.5, only CIS–4, both CIS–3 and CIS–3.5, both CIS3–5 and CIS–4, both CIS–3 and CIS–4, or using all CIS waves. Table 7 reports the results that remain similar to the ones reported in Tables 4 to 6. More precisely, a difference is that there are now no effects of *VC* on any of the *Buy* activities, and that the statistical and economic significance of *VC* in the multinomial logit, while still clearly positive, is slightly reduced. This is not surprising, and is actually comforting, given that several of the CIS wave dummies turn out to be significant, confirming that our robustness check was warranted.

Second, following Cassiman and Veugelers (2006), we include in our main regressions a measure of innovation intensity (defined as the ratio of total expenditures on innovation activities relative to sales). We expect this variable to increase the likelihood of all innovation activities. In fact, we find that innovation intensity increases the likelihood of all innovation activities, except *Make*. More importantly, the effect of VC remains the same as in our main regressions, as reported in Table 8. Both Tables 7 and 8 show a substantial stability of all the estimated coefficients and of their standard errors, confirming that our main model specification is not very sensitive to these additional controls.

We undertake additional robustness exercises.[7] First, we run our regressions adding a company-level measure of reliance on basic R&D. This variable intends to proxy for a company's reliance on more basic types of know-how, and therefore is a likely determinant of the build-up of absorptive capacity (Cassiman and Veugelers (2006)). However, this measure is only available for the CIS–3 and CIS–4 waves, and therefore regressions are run with fewer observations.[8] We find that the addition of reliance on basic R&D—which turns out to positively affects the likelihood of the *Make–And–Buy* strategy—does not change the effect of *VC* found in our main model.

Second, we exploit the additional information present in our patent data, and we build two alternative measures of patent quality. One is the logarithm of the number of the sum of 3-year backward and forward citations a company's patent applications with the EPO. The other is the logarithm of the number of patents granted by non-EPO patent offices to a company's patent applications with the EPO. Both variables are built as *L(Patent–Citations)*, and are widely used in the literature (see Hall, Thoma and Torrisi (2007)). All of our results remain valid, and with these alternative patent quality measures the *Buy* innovation activity, that was marginally significant in our main regressions, becomes insignificant, further stressing the differential effect of venture capital on a company's choice of innovation of activities.[9]

Finally, we replace *High–Tech* with industry dummies. Most of our results are the same, except that *VC* now becomes significant in increasing the likelihood of the *Buy* innovation activity, and loses significance as a determinant of the likelihood of undertaking permanent R&D.

4.1 Accounting for selection biases

It is possible that a company's attitude towards innovation strategies is not only determined by the presence of a venture investor, but also affects the investor's choice to provide finance in the first place. Our sample does not lend itself to the use of a spatial or temporal-based instrument. The Netherlands is a small country, preventing us from

[7] We choose not to report these additional regressions for the sake of brevity, but results are available upon request.

[8] The CIS–3 and CIS–4 include the following question: 'How important to your innovation activities were each of the following sources?' Possible choices are: internal sources, customers, suppliers, competitors, consultants, universities and higher educational institutions, government and public research institutes, conferences, etc. Within each category respondents choose the extent to which the source is important: not used, slightly important, important or very important.

[9] Also a simple count of the number of patent applications filed with the EPO give identical results.

using firm location as an instrument, as used by Baker and Gompers (2004) among others. We cannot use exogenous variation of venture flows either, since most of the financing in our sample takes place after 1997, when a surge in venture funding occurred. A different methodology seems more appealing in our context, namely the use of a 'propensity score' for the receipt of venture financing (Dehejia and Wahba (1999), Rosenbaum and Rubin (1983)).

Propensity score matching employs a predicted probability of group membership[10], e.g., treatment versus control group, based on observed predictors, obtained usually from a logistic regression. The propensity score can then be used for matching the 'treated' units to a suitable set of control units. This methodology therefore allows to correctly estimate the effect of a 'treatment' variable (in our case venture capital) on the relevant dependent variables, provided that the exposure to treatment can be considered to be purely random among observations that have the same value of the propensity score. In other words, the assumption is that selection occurs only on observable characteristics—on which, in fact, the propensity score is calculated. While this is clearly a 'heroic' assumption whose results should be taken with more than a grain of salt, it is often used in empirical studies as a way to test the robustness of regression results and to reduce possible selection biases. The result is the 'average treatment effect,' or ATT, which is the estimated effect on the dependent variables of the variable of interest (, or 'treatment,' VC in our case), which takes into account that assignment to the treatment is caused by different values of the propensity score.

We employ the widely used Kernel method to match on the basis of the propensity score. This method relies on taking each treated unit and matching it with a weighted average of all controls with weights that are inversely proportional to the distance between the propensity scores of the treated and the control units (see Becker and Ichino (2002)).

Table 9 reports the ATT and the corresponding t-statistic. We report results based on all the explanatory variables, including the ones we added in the robustness checks (reliance on basic R&D, innovation intensity, and CIS wave effects) in order to increase the number of observables on which the propensity score is calculated, therefore potentially increasing the accuracy of the ATT estimate.

The matching based on the propensity score supports all our previous findings. Specifically, the average treatment effect for all activities is significantly positive, except for the acquisition of machinery. Moreover, in relation to strategies, the average treatment effect is only positive and significant for *Make–And–Buy*, providing support for our conjecture that venture capital plays a key role in the build-up of absorptive capacity. Finally,

[10] The propensity score is defined as the conditional probability of receiving a treatment given pre-treatment characteristics.

propensity score matching also supports the hypothesis that venture capital increases the likelihood of permanent in-house R&D efforts.

We also notice that concerns of selection are less compelling when dealing with strategies, as in our case, than when dealing with outcomes like the venture-backed company's ability to reach IPO status or becoming profitable. In the case of strategies the argument for selection is less compelling, as it is less clear that company characteristics, which lead to a positive selection by a venture firm, should also determine its future strategies. Still, we are aware that our main results should be interpreted with the due caution.

We undertake a last exercise to provide some additional support for a causality effect. There are a few companies, specifically ten, for which we have innovation information before and after the arrival of the venture capitalist.[11] We then look at the distribution of strategies before and after the VC arrival, which we report in Table 10. We notice that after the arrival of the venture capitalist, the company that had chosen the *Buy-Only* strategy does not make any changes. However the two companies that had chosen the *Make-Only* strategy and the firm that employed the *No-Make-No-Buy* strategy changed to the *Make–And–Buy* strategy, bringing the number of companies in this latter category to nine after funding. Though we understand that this result relies on very few observations, and that it could be argued that the venture capitalist anticipated that these companies were moving towards a *Make–And–Buy* strategy, we think that it still provide evidence consistent with a causality effect.

5 Conclusions

In this paper we provide new insights into how venture capital contributes to building successful companies. Building on the literature about the role of absorptive capacity as a source of competitive advantage, we investigate whether venture capital affects the innovation strategies of portfolio companies.

We find that these appear to benefit from expanded financial resources, which increase their innovation effort. More importantly, we find that venture capitalists selectively push portfolio companies towards choosing innovation activities which result in the accumulation of absorptive capacity, and towards more permanent in-house R&D efforts. Venture-backed companies rely more on a Make—and–Buy strategy, rather than on Make–only or

[11] Specifically, these companies have the following characteristics: a) they did not receive any funding before 2001 and, b) they either received VC funding during the years 2001 and 2002, and they participated in CIS–3 (pre-VC funding period) and also in CIS–3.5 and/or CIS–4 (post-VC funding period); or they received VC funding during the years 2003 and 2004, and they participated in CIS–3 and/or CIS–3.5 (pre-VC funding period) and also in CIS–4 (post-VC funding period).

Buy–only strategies.

Interestingly, our results hold after accounting for the availability of public funds. Moreover, we find a clear difference in the role of (private) venture financing and public funding, as the latter relaxes financial constraints but does not provide any additional strategic guidance. This provides novel evidence on the special role of venture funding in driving companies towards successful innovation strategies. From a policy perspective, our results suggests that venture capital may be beneficial not only for individual companies, but may also play an important role in fostering economic growth.

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Table 1
Sample composition by CIS wave

This Table reports the distribution of observations across CIS waves for our whole sample.

	Companies	*Percentage*
CIS 3 only	1,859	*23.8*
CIS 3.5 only	950	*12.2*
CIS 4 only	1,661	*21.3*
CIS 3 and 3.5 only	925	*11.8*
CIS 3 and 4 only	447	*5.7*
CIS 3.5 and 4 only	798	*10.2*
CIS 3, 3.5, and 4	1,168	*15.0*
Total	7,808	*100.0*

Table 2
Variable Definitions

This Table provides formal definitions for all dependent and independent variables.

Innovation Variables

Variable	Description	CIS Survey question
	Innovation Activities	
Make	Dummy variable equal to 1 if the company has engaged in intramural R&D in any CIS wave it took part in; 0 otherwise.	Did your enteprise engage in intramural R&D ('creative work undertaken within your enterprise to increase the stock of knowledge and its use to devise new and improved products and processes')?
Buy	Dummy equal to 1 if the company purchased extramural R&D or know-how in any CIS wave it took part in; 0 otherwise.	
Buy–R&D	Dummy equal to 1 if the company purchased extramural R&D in any CIS wave it took part in; 0 otherwise.	Same activities as above but performed by other companies or research organizations and purchased by your company.
Buy–Know-How	Dummy equal to 1 if the company purchased know-how (patents, inventions, or other disembodied knowledge)in any CIS wave it took part in; 0 otherwise.	Purchase or licensing of patents or non-patented inventions, know-how and other types of knowledge from other enterprises or organizations.
Buy–Machinery	Dummy equal to 1 if the company purchased advanced machinery, equipment or software in any CIS wave it took part in; 0 otherwise.	Acquisition of advanced machinery, equipment and computer hardware or software to produce new products or services.
	Innovation Strategies	
Make–Only	Dummy equal to 1 if the company engaged only in *Make* activities in all CIS wave it took part in; 0 otherwise.	
Buy–Only	Dummy equal to 1 if the company engaged only in *Buy* activities in all CIS wave it took part in; 0 otherwise.	
Make–And–Buy	Dummy equal to 1 if the company if the company engaged in both *Make* and *Buy* activities in some CIS wave it took part in; 0 otherwise.	
No–Make–No–Buy	Dummy equal to 1 if the company did not engage in either *Make* nor *Buy* activities in any CIS wave it took part in; 0 otherwise.	
	Permanent R&D	
Permanent–R&D	Dummy equal to 1 if the company engaged in intramural R&D in a continuous way throughout the three years of any CIS wave it took part in; 0 otherwise.	Did your firm perform in-house R&D continuously or occasionally during the years covered by the CIS?

Control Variables

Variable	Description
VC	Dummy equal to 1 if the company received venture finance; 0 otherwise.
Public–Funds	Dummy equal to 1 if the company received public funds (tax credits, grants, subsidized loans, loan guarantees), from national or European agencies, in any CIS wave it took part in; 0 otherwise.
L(Patent–Citations)	the number of 3-year forward citations received by all patent applications of a company filed with the EPO before the year of its first venture financing (if venture-backed), or before the first CIS survey it has responded to (if non venture-backed).
L(Company–Age)	Logarithm of 1 plus the age of the company at the time of its first venture financing (if venture-backed), or at end of the first CIS survey it has responded to (if non venture-backed).
L(Sales)	Logarithm of 1 plus the company's turnover in the last year of the first CIS wave it took part in.
High–Tech	Dummy equal to 1 if the company operates in one of the following NACE 2-digit industries: Chemicals, Pharmaceuticals, Electronics, Computer Services, and R&D Services; 0 otherwise.

Table 3
Samples Comparison

This Table reports mean values (frequencies for dummy variables) and standard deviations for all dependent and independent variables, for both the sample of venture-backed and control sample of non venture-backed companies. Variables are defined in Table 2. We also report the p-value of a two-tailed test of difference in means.

	Venture–backed		Non venture-backed		
	Mean	St.Dev.	Mean	St.Dev.	*p-value*
Innovation Activities					
Make	0.802	0.400	0.612	0.487	*0.000*
Permanent R&D	0.808	0.397	0.684	0.465	*0.008*
Buy	0.615	0.489	0.443	0.497	*0.001*
Buy–R&D	0.549	0.500	0.344	0.475	*0.000*
Buy–Know–How	0.352	0.480	0.250	0.433	*0.048*
Buy–Machinery	0.438	0.501	0.587	0.492	*0.362*
Innovation Strategies					
Make–Only	0.220	0.416	0.258	0.437	*0.382*
Buy–Only	0.033	0.179	0.089	0.285	*0.004*
Make–And–Buy	0.582	0.496	0.354	0.478	*0.000*
No–Make–No–Buy	0.165	0.373	0.299	0.458	*0.001*
Control Variables					
VC	1.000		0.000		–
Public–Funds	0.657	0.468	0.329	0.470	*0.000*
L(Patent–Citations)	0.121	0.425	0.026	0.216	*0.036*
L(Company–Age)	1.933	1.290	2.563	0.963	*0.000*
L(Sales)	9.893	2.246	9.232	1.800	*0.006*
High–Tech	0.417	0.496	0.159	0.366	*0.000*
Number of observations	*91*		*7,717*		

Table 4
Innovation Activities

This Table reports results of probit regressions. The dependent variables are innovation activities. Variables are defined in Table 2. For each independent variable, we report the estimated coefficient and the z-score (in parenthesis) computed using (Huber-White) heteroskedasticity-robust standard errors. Values significant at the 1%, 5% and 10% level are identified by ***, **, *.

	Make	Buy	Buy–R&D	Buy–Know-How	Buy–Machinery
VC	0.595**	0.261	0.313*	0.262*	0.064
	(2.43)	*(1.54)*	*(1.85)*	*(1.65)*	*(0.41)*
Public–Funds	1.108***	0.535***	0.654***	0.206***	0.226***
	(26.03)	*(15.41)*	*(18.62)*	*(5.64)*	*(6.45)*
L(Patent–Citations)	0.807***	0.248***	0.327***	0.093	–0.056
	(3.38)	*(2.98)*	*(3.74)*	*(1.37)*	*(–0.83)*
L(Sales)	0.075***	0.118***	0.141***	0.068***	0.048***
	(7.51)	*(11.86)*	*(13.34)*	*(6.49)*	*(5.36)*
L(Age)	–0.074***	–0.037**	–0.915	–0.038**	0.003
	(–4.13)	*(–2.22)*	*(–0.89)*	*(–2.21)*	*(0.17)*
High–Tech	0.620***	0.073	0.084*	–0.035	–0.135***
	(11.49)	*(1.62)*	*(1.83)*	*(–0.74)*	*(–3.08)*
Constant	–0.604***	–1.327***	–1.909***	–1.267***	–0.248**
	(–6.00)	*(–13.31)*	*(–17.76)*	*(–11.94)*	*(–2.72)*
Observations	*6,531*	*6,531*	*6,531*	*6,531*	*6,531*
Pseudo R^2	*0.15*	*0.06*	*0.09*	*0.01*	*0.01*
Model p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*

Table 5
Innovation Strategies

This Table reports results of a multinomial logit regression. The categorical dependent variables are the four innovation strategies, with No–Make–No–Buy being the residual category. Variables are defined in Table 2. For each independent variable, we report the estimated coefficient and the z-score (in parenthesis) computed using (Huber-White) heteroskedasticity-robust standard errors. Values significant at the 1%, 5% and 10% level are identified by ***, **, *.

	Make–Only	Buy–Only	Make–and–Buy
VC	0.675	–0.532	1.074**
	(1.26)	*(–0.49)*	*(2.13)*
Public–Funds	1.746***	0.422***	2.136***
	(18.56)	*(2.86)*	*(24.03)*
L(Patent–Citations)	1.573***	0.697	1.861***
	(3.40)	*(0.72)*	*(4.08)*
L(Sales)	0.040**	0.122***	0.245***
	(2.05)	*(4.06)*	*(11.43)*
L(Age)	–0.092**	0.015	–0.139***
	(–2.45)	*(0.28)*	*(–3.93)*
High–Tech	0.148***	–0.066	0.987***
	(10.46)	*(0.35)*	*(9.06)*
Constant	–0.877***	–2.489***	–1.446***
	(–4.48)	*(–8.28)*	*(–11.36)*
Observations: 6,531			
Pseudo R^2*: 0.09*			
Model p-value: 0.000			

Table 6

Permanent versus Occational R&D

This Table reports results of a probit regression whose dependent variable is *Permanent–R&D*, defined in Table 2. For each independent variable, we report the estimated coefficient and the z-score (in parenthesis) computed using (Huber-White) heteroskedasticity-robust standard errors. Values significant at the 1%, 5% and 10% level are identified by ***, **, *.

	Permanent–R&D
VC	0.495**
	(1.96)
Public–Funds	0.559***
	(12.41)
L(Patent–Citations)	0.180
	(1.60)
L(Sales)	0.100***
	(8.01)
L(Age)	–0.009
	(–0.42)
High–Tech	0.394***
	(6.65)
Constant	–0.609**
	(–4.82)
Observations	*4,126*
Pseudo R^2	*0.07*
Model p-value	*0.000*

Table 7

Robustness: Accounting for CIS Waves and Time Effects

This Table reports results of probit and multinomial logit regressions, where we add to the main models a set of dummies for each combination of CIS waves, defined in Section 4. The dependent variables are innovation activities and strategies, and the permanent R&D dummy. Variables are defined in Table 2. For each independent variable, we report the estimated coefficient and the z-score (in parenthesis) computed using (Huber-White) heteroskedasticity-robust standard errors. Values significant at the 1%, 5% and 10% level are identified by ***, **, *.

Innovation Activities

	Make	Buy	Buy–R&D	Buy–Know-How	Buy–Machinery
VC	0.532**	0.200	0.263	0.190	–0.047
	(2.20)	*(1.21)*	*(1.60)*	*(1.19)*	*(–0.30)*
Public–Funds	1.099***	0.511***	0.635***	0.172***	0.187***
	(26.65)	*(14.61)*	*(17.94)*	*(4.64)*	*(5.25)*
L(Patent–Citations)	0.737***	0.196**	0.268***	0.069	–0.086
	(3.04)	*(2.43)*	*(3.14)*	*(1.01)*	*(–1.23)*
L(Sales)	0.066***	0.100***	0.123***	0.045***	0.026***
	(6.10)	*(9.58)*	*(10.97)*	*(4.04)*	*(2.69)*
L(Age)	–0.079***	–0.047***	–0.025	–0.049***	–0.005
	(–4.32)	*(–2.79)*	*(–0.42)*	*(–2.80)*	*(–0.33)*
High–Tech	0.720***	0.063	0.067	–0.025	–0.114***
	(11.37)	*(1.39)*	*(1.43)*	*(–0.53)*	*(–2.54)*
CIS–Wave–Dummies	Included	Included	Included	Included	Included
Constant	–0.400***	–0.893***	–1.494***	–0.757***	0.272**
	(–3.09)	*(–7.19)*	*(–11.27)*	*(–5.72)*	*(2.27)*
Observations	*6,531*	*6,531*	*6,531*	*6,531*	*6,531*
Pseudo R^2	*0.16*	*0.08*	*0.10*	*0.03*	*0.04*
Model p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*

Innovation Strategies

	Make–Only	Buy–Only	Make–and–Buy
VC	0.575	–0.679	0.888*
	(1.09)	*(–0.33)*	*(1.81)*
Public–Funds	1.750***	0.411***	2.112***
	(18.52)	*(2.78)*	*(23.26)*
L(Patent–Citations)	1.468***	0.548	1.686***
	(3.24)	*(0.55)*	*(3.78)*
L(Sales)	0.051**	0.121***	0.211***
	(2.42)	*(3.76)*	*(9.23)*
L(Age)	–0.089**	0.011	–0.158***
	(–2.32)	*(0.21)*	*(–4.35)*
High–Tech	1.144***	–0.050	0.972***
	(10.41)	*(0.26)*	*(8.84)*
CIS–Wave–Dummies	Included	Included	Included
Constant	–1.064***	–2.291***	–1.707***
	(–4.14)	*(–5.92)*	*(–6.36)*
Observations	*6,531*	*6,531*	*6,531*
Pseudo R^2	*0.10*	*0.10*	*0.10*
Model p-value	*0.000*	*0.000*	*0.000*

Permanent versus Occasional R&D

	Permanent–R&D
VC	0.452*
	(1.79)
Public–Funds	0.551***
	(12.19)
L(Patent–Citations)	0.186
	(1.73)
L(Sales)	0.073***
	(5.57)
L(Age)	–0.026
	(–1.14)
High–Tech	0.416***
	(6.87)
CIS–Wave–Dummies	Included
Constant	–0.130
	(–0.80)
Observations	*4,126*
Pseudo R^2	*0.08*
Model p-value	*0.000*

Table 8

Robustness: Adding R&D Intensity

This Table reports results of probit and multinomial logit regressions, where we add to the main models the R&D–Intensity variable, defined in Section 4. The dependent variables are innovation activities and strategies, and the permanent R&D dummy. Variables are defined in Table 2. For each independent variable, we report the estimated coefficient and the z-score (in parenthesis) computed using (Huber-White) heteroskedasticity-robust standard errors. Values significant at the 1%, 5% and 10% level are identified by ***, **, *.

Innovation Activities

	Make	Buy	Buy–R&D	Buy–Know-How	Buy–Machinery
VC	0.582**	0.270	0.313*	0.267*	0.078
	(2.36)	*(1.58)*	*(1.84)*	*(1.67)*	*(0.49)*
Public–Funds	1.104***	0.532***	0.652***	0.202***	0.225***
	(26.89)	*(15.32)*	*(18.52)*	*(5.51)*	*(6.39)*
L(Patent–Citations)	0.809***	0.246***	0.325***	0.091	–0.058
	(3.39)	*(2.95)*	*(3.71)*	*(1.35)*	*(–.86)*
L(Sales)	0.079***	0.123***	0.147***	0.073***	0.051***
	(7.64)	*(12.19)*	*(13.81)*	*(6.83)*	*(5.50)*
L(Age)	–0.073***	–0.036**	–0.014	–0.037**	0.002
	(–4.08)	*(–2.16)*	*(–0.84)*	*(–2.15)*	*(0.14)*
High–Tech	0.618***	0.072	0.085*	–0.038	–0.136***
	(11.45)	*(1.60)*	*(1.84)*	*(–0.80)*	*(–3.09)*
R&D–Intensity	0.012	0.006*	0.008**	0.005	0.005
	(1.02)	*(1.86)*	*(2.43)*	*(1.72)*	*(1.34)*
Constant	–0.641***	–1.375***	–1.972***	–0.316***	–0.272**
	(–6.18)	*(–13.49)*	*(–18.14)*	*(–12.19)*	*(–2.90)*
Observations	*6,518*	*6,518*	*6,518*	*6,518*	*6,518*
Pseudo R^2	*0.15*	*0.06*	*0.09*	*0.02*	*0.01*
Model p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*

Innovation Strategies

	Make–Only	Buy–Only	Make–and–Buy
VC	0.600	–0.578	1.020**
	(1.10)	*(–0.53)*	*(2.00)*
Public–Funds	1.732***	0.410***	2.117***
	(18.10)	*(2.77)*	*(23.48)*
L(Patent–Citations)	1.570***	0.693	1.855***
	(3.39)	*(0.69)*	*(4.05)*
L(Sales)	0.048**	0.131***	0.261***
	(2.04)	*(4.01)*	*(10.72)*
L(Age)	–0.087**	0.021	–0.133***
	(–2.29)	*(0.39)*	*(–3.70)*
High–Tech	1.139***	–0.058	0.976***
	(10.33)	*(0.31)*	*(8.91)*
R&D–Intensity	0.176	0.176	0.183
	(0.49)	*(0.49)*	*(0.51)*
Constant	–0.976***	–2.602***	–2.632***
	(–3.90)	*(–7.73)*	*(–10.25)*
Observations	*6,518*	*6,518*	*6,518*
Pseudo R^2	*0.09*	*0.09*	*0.09*
Model p-value	*0.000*	*0.000*	*0.000*

Permanent versus Occasional R&D

	Permanent–R&D
VC	0.437*
	(1.72)
Public–Funds	0.553***
	(12.23)
L(Patent–Citations)	0.167
	(1.48)
L(Sales)	0.110***
	(8.47)
L(Age)	–0.002
	(–0.11)
High–Tech	0.389***
	(6.57)
R&D–Intensity	0.059***
	(1.61)
Constant	–0.740***
	(–5.52)
Observations	*4,117*
Pseudo R^2	*0.07*
Model p-value	*0.000*

Table 9
Propensity score

This Table reports results of propensity score matching for all our dependent variables, which are defined in Table 2. For each independent variable, we report the number of treated and control unites which are matched using the Kernel method, the resulting Average Treatment Effect (ATT), and its t-statistic. Values significant at the 1%, 5% and 10% level are identified by ***, **, *.

	Number of Treated	Number of Controls	Average Treatement Effect	t-statistics
Make	64	5,041	0.227***	4.73
Buy	64	5,041	0.183***	3.21
Buy–R&D	64	5,041	0.217***	3.39
Buy–Know-How	64	5,041	0.135*	1.96
Buy–Machinery	64	5,041	0.019	0.28
Make–Only	64	5,041	0.016	0.32
Buy–Only	64	5,041	–0.126***	–3.42
Make–And–Buy	64	5,041	0.211***	3.23
Permanent–R&D	64	5,041	0.182***	4.23

Table 10
Pre-Post Analysis

This Table reports the distribution of innovation strategies for those observations for which we have information both before and after the arrival of venture financing. Variables are defined in Table 2

	Before VC	After VC
No–Make–No–Buy	1	0
Make–Only	2	0
Buy–*Only*	1	1
Make–And–Buy	6	9
Total	10	10