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# RESEARCH PAPER NO. 25

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Keywords:
venture capital, governmental venture capital, European Investment Fund, public policy, green technology, cleantech

## ABSTRACT

In this paper we analyze how different types of venture capital investments – private, public and indirect public – affect performance of “cleantech” start-ups in Europe. We hand collected a unique dataset on the institutional setting (public/indirect/private) of almost 15000 investors in Europe, which we combine with portfolio-company and deals data from Preqin to assess performance. Two results stand out: First, public venture capital does not underperform private venture capital in a broad cross-country sample of European deals. This is a novel finding, as it doesn't confirm some previous findings in the literature that government-backed VCs underperform their private counterparts. We also find that there is no significant difference between direct and indirect government support of venture capital for cleantech investments.  Second, GVCs perform well when they specialize in cleantech investments and are well connected within a network of other investors.

# How to support cleantech start-ups? Lessons from European venture capital deals

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**Abstract**

In this paper we analyze how different types of venture capital investments – private, public and indirect public – affect performance of “cleantech” start-ups in Europe. We hand collected a unique dataset on the institutional setting (public/indirect/private) of almost 15000 investors in Europe, which we combine with portfolio-company and deals data from Preqin to assess performance. Two results stand out: First, public venture capital does not underperform private venture capital in a broad cross-country sample of European deals. This is a novel finding, as it doesn't confirm some previous findings in the literature that government-backed VCs underperform their private counterparts. We also find that there is no significant difference between direct and indirect government support of venture capital for cleantech investments. Second, GVCs perform well when they specialize in cleantech investments and are well connected within a network of other investors.

**JEL Codes:** G24, G28, H81, L26, D73

**Keywords:** venture capital, governmental venture capital, European Investment Fund, public policy, green technology, cleantech

## 1. Introduction

The International Energy Agency (IEA, 2022) report highlights the importance of breakthrough innovations in energy generation and storage, industrial production, and carbon capture and sequestration to reduce CO2 emissions by 2050. This kind of disruptive innovation is often backed up by venture capital (Kortum & Lerner, 2000). To stimulate innovation in the cleantech sector, governments worldwide are implementing policies to promote investments in green technologies. The European Union, for example, is investing equity in green technologies through the European Innovation Council and the InvestEU program. However, there is a concentration of venture capital (VC) funds in sectors such as IT and life sciences, with "deep tech" investments, i.e., investments in sectors with a stronger relationship to fundamental science such as cleantech, receiving comparatively less VC funding (Nanda and Dalla Fontana, 2022). This is due to various factors, including the long horizons required for scalability, asset-heavy development, lack of established exit mechanisms, high political and regulatory risks, and the commodity nature of energy, leading to lower margins. This makes the task of promoting investment in this sector particularly challenging. Furthermore, Gaddy et al (2017) show that purely VC-backed cleantech investments fail more often and proposes that broader support from policymakers, corporations, and investors is needed to underpin new innovation pathways for cleantech.

In addition to supply-side issues, a critical difference between cleantech and other types of VC is the public good nature of cleantech VC investments. In other words, the development of clean technologies is associated with a particularly high positive externality, so the problem of reaching a socially optimal level is much more pronounced. Both the financing problems and the particularly high potential positive impact have made the development of cleantech a priority for governments worldwide.

As a result of the above issues, governments are introducing policies that facilitate the development of VC in cleantech, both supply-side and deployment or demand-side policies. As shown by Criscuolo & Menon (2015), deployment policies designed with a long-term perspective of creating a market for environmental technologies, such as price and quantity policies for renewables, such as FITs and tradable certificates, are associated with higher levels of investment compared to more short-term fiscal policies, such as tax incentives and rebates. Cumming et al. (2016) additionally show that media attention stimulates cleantech VC, and government effectiveness can further positively contribute to the positive effect of policies. Several recent reviews have identified further elements of policy towards cleantech financing (Polzin, 2017; Polzin et al 2019; Mazzucato & Semieniuk 2018). It is less clear, however, which types of supply-side policies have the highest chances of success. One highly important policy instrument is public venture capital (government-backed venture capital, GVC). In general, however, most of the available evidence points to the conclusion that government equity investments do not lead to higher exit rates or innovation (see e.g., Köppl-Turyna et al., 2022; Pierrakis and Saridakis, 2017; Da Rin, Hellmann and Puri, 2013).

As described in more detail in the next section, there is considerable empirical evidence that government-backed VCs are less effective than private VCs in positively stimulating firm performance. As Köppl-Turyna et al (2022) show, this may be related to their network characteristics. Due to different incentives compared to private funds, public VC firms are less often involved in outstanding deals as they are not a welcome partner for private firms. As a result, they are less well connected, which is crucial for their performance.

In this paper, we explore whether, due to the specificities of the cleantech market, public VC might, however, be more helpful here than in other sectors. In addition, if most governmental VC in

Europe goes into deep tech, which is much more difficult to exit, due to high public interest, this could have led to a misperception of the effectiveness of GVCs in some previous studies. In such a case, previous results in the literature could have been the result of self-selection of public VC into "difficult" markets and some of the conclusions could have been different.

Thus, the aim of this project is to address several novel research questions regarding the interaction between fund characteristics, such as their public/private ownership or their networks, and the success of cleantech ventures. First, we examine whether GVCs and indirect (or hybrid) public venture capital can contribute to the success of cleantech ventures. Second, we examine whether some fund characteristics that have been found to affect investment performance - such as experience and specialization - play a particular role in the case of cleantech, and whether they interact with the public/private nature of funds. Finally, we examine the interaction between the green focus of funds and their network characteristics, which have been identified as a factor influencing the success of firms. These steps should allow us to answer our main research question: what is the "perfect" fund for financing cleantech investments?

## 2. Related literature

### 2.1. The role of the government and GVC in stimulating cleantech investments

This work is related to some recent research on the development of cleantech VC and its support by government policies, such as van den Heuvel and Popp (2023), who identify the “failure” of cleantech VC and link it to missing demand-side policies while the evidence for supply-side factors is less clear. As for the role of public investment (whereas the focus of the paper is on public grants rather than public VC), Heuvel and Popp (2023) show that when in early stages, public investors provide small-sized grants that help startups prove the viability of their project and attract Series A funding, those funded firms are no likelier to have long-term success than other VC-funded firms. When in later stages, governments provide larger sums aimed at helping startups expand and scale their business, these investments have not fared worse than their private-sector counterparts, and may improve chances for exit if one assumes that public funding goes to startups less likely to attract late round private funding on their own. This latter result stands in certain opposition to some results in the literature for other industries than cleantech, showing that direct governmental venture capital performs consistently worse than private investments (e.g., Köppl-Turyna et al, 2022; Bertoni and Tykova, 2015; Pierrakis and Saridakis, 2017; Grilli and Murtinu, 2014). This suggests that cleantech could profit more from governmental support than other industries.

Some additional light on the mechanism can be shed by looking at the results by Alperovych et al (2020). They find that GVCs that build up industry-specific expertise and those who previously coinvested with PVCs are more likely to successfully bridge equity gaps which highlights the importance of learning processes for GVCs. This feature may be particularly important for new industries, such as cleantech, where there is generally little experience available and, as mentioned above, no established exit mechanisms are present.

Also Arora et al (2022) identify that deep tech start-ups face challenges because they face both technological and commercial challenges. In their model, government venture capital, if only acting as co-investor of projects with positive returns will not have a positive effect on the functioning of the market.

Further instruments for government policies for VC support of cleantech technologies have been analyzed in the literature. Croce and Bianchini (2022) explore whether policies have a differential effect in fostering institutional venture capital (IVC) and governmental venture capital investments. Their findings suggest that IVC investments in cleantech are mainly driven by the level of environmental taxes and market pull mechanisms such as feed-in tariffs and R&D subsidies, whereas GVC investment decisions are driven by a country's commitment to reach environmental targets. Migendt et al (2017) ask how innovation and financial policy influence the supply and demand of equity finance along the financial value chain, with a particular focus on cleantech investments. They conclude that diverse aspects of innovation and financial policies affect equity financing of cleantech. Finally, Doblinger et al (2019) conclude that government can further support cleantech startups by providing them with network resources and forming technology development alliances which in turn serve as a quality signal to private sector investors.

Polzin and Sanders (2020) also discuss the literature on supply side policies (university R&D support, SBIR grants) and deployment policies (feed-in tariffs, regulations and standards) designed with a long-term perspective of creating a market for environmental technologies, and find that these are associated with higher levels of venture capital (Criscuolo and Menon, 2015; Polzin et al., 2018a).

More generally, we also contribute to the literature on the governmental support of the energy transition, as discussed e.g., by Polzin and Sanders (2020), Goldstein et al (2020), Wu et al (2020). These include: the effect of government subsidies towards the adoption of renewable energy (Wu et al, 2020), role of government towards green entrepreneurship (X. Yang et al., 2021), role of influencing factors for clean energy adoption (Malen and Marcus, 2017), or, as mentioned above role of government's environment policies for the supply of green VC (Bianchini and Croce, 2022)

### 2.2. Specialization and industry experience

The second strand of literature to which we contribute is the question of what factors characterizing the venture-capital funds can contribute more to the success of investments, and in particular cleantech investments. In this work, we focus on specialization of funds. We hypothesize that one of the reasons for why cleantech VC was not successful in the past was insufficient specialization of funds. Prominently, Sørensen (2007) found that more experienced VC investors are more successful, as their investee companies are more likely to go public. The more subtle question is whether this is about general experience or rather specific one, related to just one particular industry or type of market. This issue has also been raised by Alperovych et al (2020), who mention the importance of industry-specific experience.

Following Gompers et al (2014) and others, we look at both specialization and industry experience of funds. They argue that the theoretical impact of funds' specialization is far from clear. While Stein (1997) argues that less specialized funds would allocate funding more efficiently, Rajan et al (2000) and Scharfstein and Stein (2000) argue the opposite. Indeed, Gompers et al (2014) find the latter to be the case. Conversely, Buchner et al (2017) argue and provide empirical evidence that diversification of investments is beneficial for performance. The channel that they analyze is the impact of risk: greater diversification reduces fund risk, enabling risk-averse managers to select riskier investments in the first place and, thus, investments with higher expected returns. However, they also find that the overall effect of industry diversification on fund performance depends on which industries managers choose for diversification. When managers diversify primarily into industries in which they lack experience, high industry diversification can even have a negative overall impact on fund performance. In contrast, they find that deviations from past investment stage experience do not significantly affect fund performance, which suggests that past industry experience is more important for fund performance than stage experience (Buchner et al, 2017). Similarly, Hull (2021) finds that the probability of a successful exit is higher when a VC invests in their preferred investment industry and that VCs that invest outside of their preferred industry can partially mitigate this negative effect by co-investing with a VC that prefers to invest in the industry of the investment firm.

All in all, the above literature suggests that both industry focus and experience of VCs should positively affect the investee companies.

### 2.3. The role of networks

The third question is whether specific network properties can affect cleantech investment more so than other types of VC. This is also related to the work by Doblinger et al (2019) who analyze network support of cleantech start-ups by the government. While there is work on syndication and network effects considering general VC investment, this is less so specifically for the case of cleantech startups. There is a fair amount of evidence that syndication of investments affects the performance of companies, as reviewed by Jääskeläinen (2012), among others. Several channels are believed to be responsible for the positive effect of syndication: "four-eyes principle" improving the selection process, overcoming informational asymmetries, diversification for financial risk, improved deal flow, and finally, window dressing in later rounds. Building upon this literature Hochberg et al (2007) argue, that strong network characteristics of VC firms allow them to profit more from the benefits of syndication, and thus be related to more successful portfolios: for example, the number of VCs with which it has a relationship as proxies for the information, deal flow, expertise, contacts, and pools of capital it has access to. They conclude that strong network properties result in more financing rounds and a higher probability of an exit.

Christopulos et al (2022) and Köppl-Turyna et al (2022) show that also in Europe better connected VCs are associated with a better performance of portfolio companies. Christopoulos et al (2022) point also to the fact that network properties of investors are more important for performance in the earlier stages of investments. Köppl-Turyna et al (2022), moreover, show that GVCs are generally worse connected than private VCs, while indirect public (hybrid) funds are better connected. GVCs do not enter the best performing syndicates, likely due to their incentive-incompatible and bureaucratic structures. In the context of this work, the latter factor could be particularly important, as according to the literature cited in Section 2.1. there is a fair amount of consensus that some governmental support is necessary for cleantech start-ups to be successful.

## 3. Theory and hypotheses

The related literature aims to formulate some predictions about the characteristics of funds investing in cleantech ventures and their impact. According to this literature, network properties of funds are crucial for their success. Therefore, it is important to analyze, whether funds investing in cleantech start-ups possess those "successful" properties. We hypothesize that those funds that specialize in cleantech will have different characteristics from the rest of the VC system.

Although the cleantech market has been around for quite some time, for most of that time only a few deals were done each year. It is only recently that the issue has gained much wider public attention. As a result, we expect the networks of funds investing in cleantech to be less well developed. First, we expect that specialized green funds will not be as central as funds with a broad range of investments. This is a direct consequence of the fact that broad-based funds often invest as co-investors with small tickets with many different partners. Second, the density of green fund networks is expected to be higher simply because there are still few available co-investment partners capable of analyzing and developing deals in industries that require specialized knowledge. Third, for the same reason, the networks of green funds should be more homophilic, i.e., green funds would tend to invest jointly with other green funds.

***Hypothesis 1:*** **VC funds specialized in cleantech start-ups have different network properties than other funds.**

> ***Hypothesis 1a: VC funds specialized in cleantech start-ups have lower centrality and belong to fewer cliques.***
>
> ***Hypothesis 1b: Ego networks of VC funds specialized in cleantech start-ups have higher density.***

***Hypothesis 1c: Ego networks of VC funds specialized in cleantech start-ups contain a high fraction of other green funds.***

We now turn to the second focus of the paper: public VC. In essence, two types of public equity support are being used:

- Public venture capital funds directly investing in companies (henceforth ***direct public VC or GVC***): investment decisions are made by public officials, usually alongside a private co-investor.
- Public funds investing in private VC funds (henceforth ***indirect or hybrid VC or EIF***): Public funding is used only to leverage private investment. Investment decisions are taken by the private actors, but the government sector may influence private funds' actions through guidelines or conditions governing investment criteria or individual deals. Public officials sit on the investment committees of the private funds. One of the most common vehicles for indirect support is the fund-of-funds instrument whereby public funds-of-funds invest in private VC funds. This form of investment became highly important in the last years since the European Investment Fund (EIF) started its fund-of-fund investments.

Direct public funds are characterized by a different investment horizon than private funds, as their performance is typically not evaluated on an annual basis. This means that they can enter longer-term projects and gain experience - and since experience is an important factor in the performance of investee companies, gaining industry experience early on could prove important. They also tend to have better access to complementary instruments, such as grants, which are likely to allow them to successfully leverage more capital, which is particularly important in an "asset-heavy" industry such as cleantech. All this points to the conclusion that direct GVCs may be more successful in cleantech investment than in other industries, where direct state VCs typically underperform private funds. However, this is more likely the case, if they have previous experience in the industry and/or have coinvested with private partners.

On the other hand, indirect VCs have a classic VC model, including a relatively short fund duration. Therefore, the advantage of a direct public VC for cleantech investments is not present for the indirect VC ("*fund-duration effect*"). However, indirect public funding can leverage more capital compared to purely private models, which is a desirable feature for cleantech investments due to their asset-heavy nature ("*leverage effect*"). Given this, we hypothesize an ambiguous effect of indirect VCs. This leads to our Hypotheses 2, 2a and 2b.

***Hypothesis 2:*** **Direct GVCs perform better in the cleantech industry than in other industries.**

***Hypothesis 2a: Direct GVCs perform better if accompanied with higher expertise, focus, and green focus, and/or those who have previously co-invested with private funds.***

***Hypothesis 2b: Due to opposing effects (leverage vs. fund duration), the theoretical effect of***

***indirect government VC is ambiguous.***

The question of specialization brings us to our third hypothesis. Unlike software, cleantech requires specialized knowledge on the part of investors. This is because cleantech is very research- and IP-intensive and has very long time-to-market cycles. Typically, an investor in cleantech must hold the investment for a long time without a positive return. Therefore, these investors need to be very sure that the industry is going to be successful. This also suggests that not only the funds themselves need to be specialized, but the networks of funds investing in cleantech are much more specialized as noticed in Hypotheses 1b and 1c.

***Hypothesis 3:*** **Industry experience and focus are particularly important for cleantech investments.**

The final Hypothesis 4 considers the role of network properties. In general, we hypothesize that the networks of funds investing in cleantech are different, according with Hypothesis 1. The question remains, whether we believe that the ***impact*** of those networks is different than for the case of general VC investments. We indeed believe that this is the case, by similar argumentation as for the case of focus: specific networks, concentrated among the topic of green investments are more capable of pool the necessary knowledge and resources. Networks of investors are characterized by more constant syndicates building (i.e., less variation of partners), and fewer pure co-investors. In this set-up the actual properties of the network – its optimal organization – is crucial for the success.

***Hypothesis 4:*** **Specific network characteristics are particularly important for cleantech investments.**

## 4. Data and methods

### 4.1. Data

We look at data from the Preqin database, which covers all VC deals in Europe from 1988 to the end of November 2022. The total number of companies in the sample across all industries is 24,960 and the number of investors is 18,848. This results in approximately 45,000 deals and 110,000 investor-investee pairs – the basis for the estimates. The first cleantech deal in our database took place in June 1999. We have 1955 unique investors in cleantech, of which 78 are government VCs and 121 have received an Investment from the European Investment Fund (indirect government VCs). These investments went to 963 unique cleantech companies. Following the work of Köppl-Turyna et al (2022), we manually collected data on the status and ownership of all investors in the sample from the websites and other sources (such as registry entries) –- to assess whether funds are primarily public or private. In total, we covered around 5,000 investors in Europe and some US investors investing in Europe. University funds were generally coded as private or public, depending on whether the university was private or public. Regional authorities are coded as public enterprises. Public-private partnerships (PPPs) are coded as either public or private, depending on who has more power or who the private partners are. for example, if a public authority invests with two banks and the website indicates that the fund has a regional policy purpose, we coded it as public.

In addition, to analyze the impact of indirect (hybrid) VC, and in particular the European investment strategy, we combine the data with portfolio investments by the European Investment Fund (EIF), which are collected from the EI''s official sources. While the EIF offers several different products (e.g., equity, debt, and microcredit), we focus on venture capital investments in funds. These investments are part of several European programmes such as the European Fund for Strategic Investments (EFSI) “"Juncker Plan"), EIB Risk Capital Resources (RCR), Joint European Resources for Micro to Medium Enterprises (JEREMIE), Midcap Facility and others. This data has been compiled manually from information published by the European Investment Fund.

We define a cleantech company belonging to one of the following classifications based on the sub-industry classification of Preqin: Biomass, Energy Storage & Batteries, Environmental Services, Green IT, Hydro Power, Pollution Control, Power & Utilities, Power Generation Equipment & Services, Power Plant, Recycling, Renewable Energy, Solar Power, Waste Management, Waste to Energy, Water & Sewer Utilities, Wind Power.

Based on the deal data, we can construct several network characteristics of the funds involved in the deals. We first differentiate between funds according to their overall **green focus**, defined as the share of deals with cleantech companies in the total number of deals. We then look at various aspects of the networks of these funds, as described in the next subsection.

For the questions of portfolio-company performance, we also need to include information on the stages of funding. In general, Preqin provides information on rounds, which can then be logically ordered–- Pre-Seed or Angel, Seed, Series A, Series B and so on, with each being assigned an integer starting with 1 in the Angel round. The ultimate success–- assigned the maximum value of 14–- was one of the following events: Merger, PIPE, Pre-IPO or Secondary Stock Purchase. However, some information is missing or misclassified. In such cases, we used information on the size of the deal or the size of the syndicate. Rounds have been assigned a next round characteristic (e.g., Series A after Seed) if the round is larger than the previous one or the syndicate involved has become larger–- this allows us to exclude cases of “bridge round” financing, which should not be considered a successful next round. Whenever there was no information on a round for some companies, we classified the rounds according to the average values in the sample, year, country, and industry, e.g., a typical Series A in “Renewable Energy” was around 13 million Euros, while in “Internet Services” it was around 8 million Euros. We used different definitions in the robustness estimations to rule out the influence of coding. We define a successful exit as a case where either an IPO, a merger or a trade sale took place. Following Gompers et al. (2008) and Gompers et al. (2009), we also include information on other firm and investor characteristics in the analysis: the size of the investment syndicate, the size of the deal, the total known funding of the firm, the age of the firm at the time of the deal (in years), the *industry expertise* of the investors measured by the *number* of previous deals in the same industry, and the *focus* of the investors measured by the *percentage* of deals in the current industry as a share of all deals. We also measure the overall *specialization* of the funds using the Herfindahl-Hirschman index for each company, i.e., the sum of the squares of the percentage of investments in each industry: the higher the value, the more specialized the fund.

### 4.2. Social network analysis

Network analysis aims to describe the structure of networks by focusing on the relationships that exist among a set of economic actors. A key aim is to identify influential actors. Influence is measured by how "central" an actor's network position is, based on the extent of their involvement in relationships with others (Hochberg et al, 2007). Network analysis formalizes the concept of centrality and develops several measures, which help identify key actors in a network. We use two concepts of centrality: eigenvector centrality and betweenness, to measure different aspects of the central role of investors. Technically, eigenvector centrality scores correspond to the values of the first eigenvector of the graph adjacency matrix. In turn, these scores may be interpreted as arising from a reciprocal process in which the centrality of each actor is proportional to the sum of the centralities of those actors to whom he or she is connected. In general, vertices with high eigenvector centralities are those that are connected to many other vertices, which, in turn, are connected to many others (and so on). VCs that have ties to many other VCs may be in advantageous positions. As they have many ties, they are less dependent on any single VC for information or deal flow. In addition, they may have access to a wider range of expertise, contacts, and pools of capital (Hochberg et al, 2007). In the VC context, eigenvector centrality shows not only that a particular investor has many co-investors but that he/she has many important co-investors (i.e., co-investors with multiple syndicated partners), who themselves play a key role in a network.

On the other hand, betweenness attributes influence actors on whom many others must rely on to make connections within a network. This is roughly defined as the number of shortest paths (geodesics) going through a vertex. Vertices with high betweenness may have considerable influence within a network because of their control over information that passes between other vertices. They are also the ones whose removal from the network will most disrupt communications between other vertices, because they lie on the largest number of paths taken by messages. Betweenness measures the degree to which a VC firm may connect or bring together other VCs with complementary skills or investment opportunities that would otherwise lack a direct relationship. It also measures the degree to which a particular VC can control the information flow among other active VCs in a market. Both measures should be associated with a higher success rate of a funds.

Further, we use the concept of "clique'' to identify the existence of closed and cohesive groups of investors, who tend to invest together. The concept of a clique is a complete sub-graph, which means that in a clique, each member has direct ties with each other member or node. In many cases this definition would be too restrictive. Therefore, we decided to use the concept of a 2-clique instead (Luse, 1950). The 2-clique is the maximal complete sub-graph with a path length of one or two edges. The path distance of two can be exemplified by the “friend of a friend” connection in social relationships. Again, belonging to more 2-cliques or to 2-cliques which have better properties, should be associated with more successful funds.

To operationalize how well specific funds are connected we use three measures related to 2-cliques, to which they belong. First, we measure the number of 2-cliques, a particular funds is a member. Secondly, we look at the network characteristics of the clique members: whenever the members of my clique are well-connected, this indicates that my importance in the network is increased. That is we assign the funds with the *centrality and betweenness of the best connected member* of the same clique.

We further look at two characteristics of ego networks around the funds: the network densities and the similarity between the funds in each network. First, we construct ego subnetworks of order 1 and order 2 (i.e., with the vertices no further than one or two links from the vertex) around each fund and calculate the network density of these subnetworks. The density of a graph is a measure of how many connections between actors exist compared to how many connections between actors are possible, and it helps to understand how connected the network is. We then compare the densities of networks with higher and lower green focus. In line with our Hypothesis 1b, we expect the networks to be denser, the higher the green focus of a fund. Finally, we analyze how homophilic green funds behave. We look again at the order 1 and order 2 ego-subnetworks and calculate the average green focus of the funds’ investment partners. A high green focus of the partners of green focus funds would imply that funds specializing in cleantech tend to invest jointly with other specialized funds (homophily). This is what we expect to be the case. We will further use those measures to test Hypothesis 4 regarding the impacts of diverse network characteristics of funds on the success of startups.

### 4.3. Regression models

In each regression model, we look at the impact of three main (groups of) variables of interest: first, whether an investment considers a cleantech company as defined above. Second, whether the investor is a public fund (direct GVC and indirect EIF) or a private fund. Third, what characteristics the funds have in terms of the variables defined above, such as expertise and focus, as well as network characteristics (density, homophily, etc.). Finally, these characteristics are interacted with each other to answer the question of what a “perfect” public cleantech investment fund should look like to contribute most to the success of its portfolio companies.

To assess the performance of the analyzed fund characteristics, we will run regressions on the probability of a successful exit of a company. A successful exit event is defined as a company exiting via an IPO, merger, or a trade sale. This is done using panel Probit models with industry and country fixed effects and standard errors clustered at the portfolio-company level.

In all specifications, we include control variables that affect the probability of additional rounds and successful exits. These include the age of the firm at the time of the deal (measured in years since incorporation), the size of the deal (in EUR million), the total funding of the firm (in EUR million), the size of the investment syndicate, and the stage of each deal. Regarding the stage: this variable does certainly affect the time to exit, and thus our dependent variable. However, due to some missing information in the dataset, addition of this variable results in a significant loss of observations of about one-fourth of the overall sample, which moreover, likely is not random, as the Stage is typically reported for larger and older companies. Thus, in each case, we look at the results with and without including this variable.

# 5. Results

## 5.1. Network characteristics of green vs non-green funds[1]

As mentioned above, we define *green focus* of a fund as a fraction of its investments in cleantech companies to a total number of investments - it can, thus, vary between 0 and 1. On average, the funds in the sample have very few green investments. To assess the distribution more in detail, Table 1 presents the average green focus of funds in the sample divided in 20 groups according to increasing fraction of green investments in their portfolio.

***Table 1: Average green focus of funds in 20 groups***

| Ventile | Mean | SD |
|---|---|---|
| 12 | 0.000 | 0.000 |
| 13 | 0.003 | 0.001 |
| 14 | 0.006 | 0.001 |
| 15 | 0.009 | 0.001 |
| 16 | 0.013 | 0.001 |
| 17 | 0.021 | 0.004 |
| 18 | 0.039 | 0.006 |
| 19 | 0.088 | 0.030 |
| 20 | 0.447 | 0.268 |

[1] In the main text we focus on the characteristics of the whole sample. For descriptions and visualizations for individual countries, please refer to the online appendix involving interactive visualisations which can be found here: https://sites.google.com/view/networks-in-cleantech/home

As can be observed, the bottom 12 ventiles, i.e., 60% of funds have no green investments whatsoever. Above that in the first group, which has a positive fraction of green investments it accounts for merely 0.3 percent of deals. It raises to about 8.8 per cent in the 19th ventile and almost 45 percent in the top 5% of the "greenest" funds. This classification into twenty groups will now serve to compare some network characteristics of funds in several dimensions.[2]

First, we look at the eigenvector centrality of funds, to assess how central their role in the network of investors is. Then we look at several properties of the 2-cliques to which they belong. We first assess the overall number of 2-cliques, to which each fund belongs, again to measure their importance in the network of the investors. Then we look at the actual properties of those 2-cliques. Belonging to many cliques does not yet imply that those cliques are *important* in the network. To assess this, we assign a characteristic of the most important member of each clique: either measured by centrality or by betweenness. The interpretation is as follows: the higher the number, the more central the most important member of the 2-clique is. This allows us to analyze whether green-investing funds have important co-investors in the network within their closed cliques.

As can be observed, funds which invest nothing in cleantech tend to have the lowest centrality and belong to the lowest number of cliques (Figure 1). However, for those companies, which have a positive fraction of investments in green companies, the relationship between both centrality and the number of cliques, to which they belong is negative. The highest centrality and the highest number of cliques are achieved at the 12th to 14th ventiles. This relationship also holds, if we control for the overall size of the funds measured as the overall number or volume of deals ever completed (Table 2), allowing to control for how well established the fund is.

[2] We present the figures for the whole sample here. For individual countries, please refer to the online appendix.

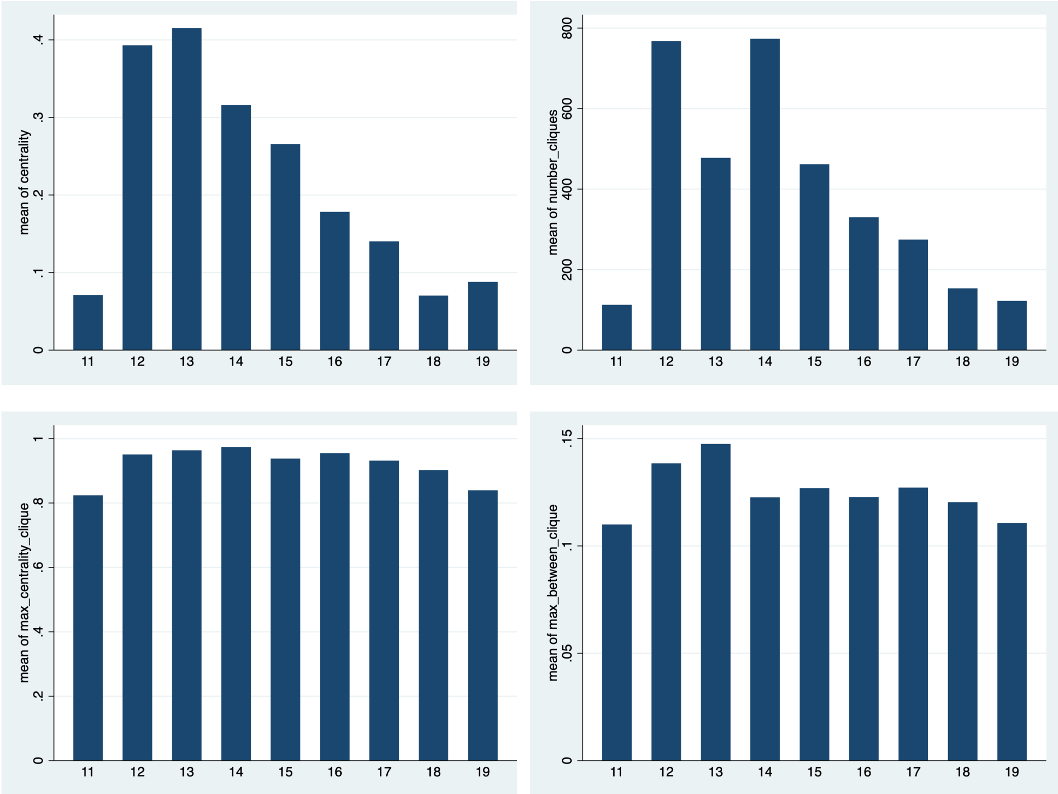



***Figure 1: Network characteristics of funds according to green focus***

***Table 2: Relationship between centrality and number of cliques and green focus (conditional on green focus being positive)***

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | **Centrality** | **Number of Cliques** | **Betweeness of Clique** | **Centrality of Clique** |
| Green Focus | -0.11** | -264.60* | -0.02*** | -0.19*** |
| | (-2.50) | (-1.80) | (-4.55) | (-5.27) |
| Volume of Deals | -0.00 | 0.01 | 0.00 | 0.00 |
| | (-0.58) | (0.86) | (0.33) | (1.07) |
| Number of Deals | 0.00*** | 1.17*** | 0.00 | 0.00 |
| | (6.49) | (9.70) | (0.92) | (0.11) |
| Constant | 0.65*** | -112.65*** | 0.01*** | 0.51*** |
| | (4.87) | (-3.58) | (31.90) | (191.71) |
| Observations | 39915 | 28386 | 28331 | 28331 |

p<0.1 *, p<0,05**, p<0,01***; Linear regressions; Not reported: 51 country dummies; t-Statistics in parentheses; standard errors clustered at the country level.

Hypotheses 1b and 1c can be tested by looking at the properties of the ego networks around each fund in the sample. These relationships for the order-1 and order-2 networks are presented in Figure 2.

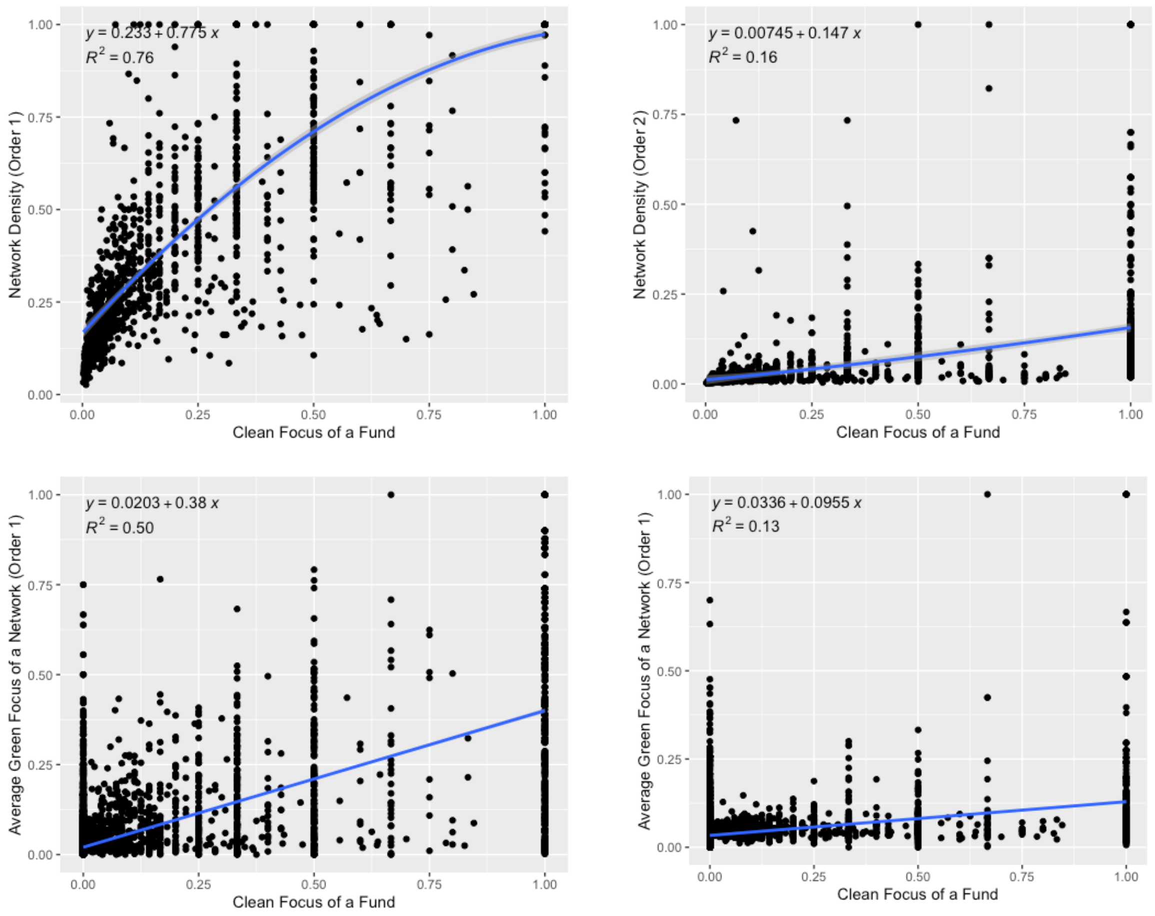



***Figure 2: Density and homophily of ego-networks***

The upper panel shows the relationship between the network density of a ego subnetwork (of order 1 to the left and of order 2 to the right) and the green focus of each fund. In particular, for the order-1 network a visible strong positive correlation between the density and the green focus can be established with a linear $R^2$ at 0.76. While weaker at 0.16 $R^2$ a positive relationship can also be found for the order-2 subgraph. In the lower panel correlations between each fund's green focus and an average green focus (excluding itself) of their ego networks are shown. For the order-1 networks, a strong positive correlation is visible with $R^2$ at 0.5. For the order-2 network there is a weak positive correlation. It is, however, in both cases nor surprising that the order-2 networks show weaker characteristics. These results suggest that Hypotheses 1b and 1c can be confirmed: funds investing primarily in cleantech startups have tight relationships with other funds in the sector. What follows, their networks are much denser than in the case of the funds without cleantech focus.

## 5.2. Effects of funds on cleantech start-ups

### 5.2.1. Performance of cleantech start-ups

The next question, which we want to answer, is whether cleantech startups perform worse than other companies in the sample – which would be in line with the previous literature. In Table 3, we present some descriptive statistics regarding firms and deals from the cleantech vs. non-cleantech sectors.

Cleantech companies receive on average 1.96 rounds of financing compared to a slightly lower value of 1.86 for other sectors. They also receive financing for slightly later stages. Governmental VC is invested in about 14% of Cleantech firms, compared to 11% of non-cleantech sectors. A major difference can be seen regarding the EIF investments: 21% of firms in non-cleantech sectors received an investment from a fund with an EIF involvement, compared to only 13.8 % of cleantech firms – which is surprising given the environmental focus of the European Union programmes but could be either a result of the fact that cleantech strartups are on average younger or the fact that (as shown e.g., by Köppl-Turyna et al, 2022), or the fact that the EIF invests more often in large, well-known and well-connected funds, which are typically generalist. The average size of deals is much higher in the cleantech sector, as is the total funding. This is to be expected as the capital requirements are typically much higher. The average size of the investment syndicate is, perhaps surprisingly, slightly lower in cleantech deals at 3.9 as compared to 4.6 in other sectors. In this case, this is a result of smaller networks of investors in cleantech, with, as discussed above typically involve less "pure" co-investors. There is a significant difference between the expertise of funds between cleantech and other industries: on average more than 14 deals have been conducted within the same industry in other industries, compared to only about 4.7 in cleantech - showing that this area of investing only has been around for a shorter time and much more know-how still needs to be built up. Finally, Cleantech companies are significantly less likely to be successfully exited – the unconditional probability is at 15 % compared to 25 % in the non-cleantech sectors.

*Table 3: Descriptive statistics Cleantech vs Non Cleantech*

| | Not Cleantech | | Cleantech | |
|---|---|---|---|---|
| | **Mean** | SD | **Mean** | SD |
| Number of rounds | **1.863** | 2.426 | **1.961** | 2.187 |
| Stage | **3.434** | 2.108 | **3.606** | 2.104 |
| Age at Deal Time | **5.054** | 6.268 | **5.66** | 7.191 |
| GVC | **.1065** | .3084 | **.1386** | .3456 |
| EIF | **.2151** | .4109 | **.1378** | .3448 |
| Deal Size (in Mio Eur) | **22.56** | 127 | **42.54** | 213.8 |
| Total Funding (in Mio Eur) | **82.27** | 361.5 | **148.4** | 729.2 |
| Syndicate Size | **4.632** | 4.96 | **3.913** | 3.303 |
| Industry Expertise | **14.25** | 27.87 | **4.738** | 12.83 |
| Specialization (HHI) | **.3704** | .2864 | **.3703** | .3122 |
| Focus | **.3781** | .3159 | **.3299** | .3506 |
| Green Focus | **.0190** | .0688 | **.3299** | .3506 |
| Successful Exit | **.2516** | .4339 | **.1494** | .3565 |

Table 4 further presents the probability of a successful exit in cleantech vs. non-cleantech industries divided according to the types of investment: GVCs, EIF-backed VCs and purely private.

*Table 4: Successful exit probability dependent on investment types*

| | EIF | GVC | private |
|---|---|---|---|
| Clean | 0.247 | 0.154 | 0.150 |
| Non-Clean | 0.316 | 0.214 | 0.267 |

As expected, the exit probabilities in cleantech are systematically lower than in non-cleantech, while this is to some extent driven by the fact that this industry is on average younger. For cleantech, the highest probability of exit is associated with a syndicate involving an EIF-backed investment, at 25 percent. Purely private VC-backing averages in over 15 percent exits, comparable with a direct GVC involvement. The averages for the non-cleantech sector are higher, but the pattern is the same, except that private-backing results in successful exits more often compared to GVC involvement. The question we have begun with, can be, thus, partially answered with yes: cleantech investment are on average less successful. Nevertheless, these descriptive statistics do not account for further characteristics, such as e.g., the stage of investment, so that a more nuanced analysis is needed.

### 5.2.2. Governmental VC, Expertise and Specialization in Cleantech

First, we run a set of panel probit regressions for the probability of a successful exit on the overall sample of firms, with the addition of a dummy variable for the identified Cleantech sectors, to get the first impressions about the factors behind the success of startups in the analyzed data. The results are presented in Table 5. It seems that, controlling for further characteristics of deals, despite the initial suspicions, the cleantech companies do not on average have a lower probability of an exit compared to other industries. The question is rather, which of the structural differences between investments in cleantech and other industries is responsible for the lower average probability. Furthermore, in the next steps, we want to focus on the factors for which we have formulated our hypotheses.

Among the fund characteristics, the clear a positive correlation is visible between the success probability and the focus of a fund. This is further confirmed by the negative correlation with the HHI, measuring the (inverse of) the specialization of the funds, supporting our Hypothesis 3. Contrarily, the number of previous deals in the same industry does not have an effect. Neither does the percentage of deals in the broadly defined cleantech sector: the funds investing in cleantech are not less successful than those who do not. As expected, the total funding of the firm and its age correlate positively with the probability of an exit. The size of the syndicate is also important, despite controlling for the funding size. Finally, as reported in the previous literature, exits are less likely if a deal involved a direct governmental VC, and more likely if it involved a fund supported by the European Investment Fund.

***Table 5: Panel Probit regressions for a probability of a successful exit in the general sample***

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Clean | -0.27 | -0.30 | -0.30 | -0.11 | -0.15 | -0.15 |
| | (-1.33) | (-1.51) | (-1.49) | (-0.46) | (-0.63) | (-0.62) |
| Green focus | -0.20 | -0.20 | -0.20 | -0.15 | -0.13 | -0.13 |
| | (-1.54) | (-1.54) | (-1.52) | (-0.96) | (-0.82) | (-0.77) |
| Expertise | -0.00 | $-0.00^{**}$ | -0.00 | 0.00 | -0.00 | 0.00 |
| | (-0.48) | (-2.26) | (-0.77) | (0.50) | (-0.79) | (0.30) |
| Focus | $0.43^{***}$ | $0.49^{***}$ | $0.45^{***}$ | $0.40^{***}$ | $0.46^{***}$ | $0.42^{***}$ |
| | (4.15) | (4.67) | (4.25) | (3.22) | (3.67) | (3.34) |
| Total funding | $0.25^{**}$ | $0.26^{***}$ | $0.26^{**}$ | $0.36^{***}$ | $0.35^{***}$ | $0.34^{***}$ |
| | (2.42) | (2.58) | (2.57) | (3.15) | (3.11) | (3.08) |
| Syndicate Size | $0.04^{***}$ | $0.03^{***}$ | $0.03^{***}$ | $-0.03^{***}$ | $-0.03^{***}$ | $-0.03^{***}$ |
| | (6.94) | (5.99) | (5.72) | (-3.64) | (-3.68) | (-3.74) |
| Age of the firm | $0.02^{***}$ | $0.02^{***}$ | $0.02^{***}$ | $-0.01^{*}$ | $-0.01^{*}$ | $-0.01^{*}$ |
| | (4.84) | (4.68) | (4.74) | (-1.91) | (-1.78) | (-1.78) |
| HHI | $-0.39^{***}$ | $-0.47^{***}$ | $-0.46^{***}$ | $-0.36^{***}$ | $-0.44^{***}$ | $-0.43^{***}$ |
| | (-3.52) | (-4.15) | (-4.03) | (-2.71) | (-3.29) | (-3.20) |
| GVC=1 | $-0.22^{***}$ | | $-0.20^{***}$ | $-0.20^{***}$ | | $-0.18^{***}$ |
| | (-6.43) | | (-5.89) | (-4.40) | | (-4.03) |
| EIF=1 | | $0.12^{***}$ | $0.10^{***}$ | | $0.11^{***}$ | $0.09^{***}$ |
| | | (5.14) | (4.01) | | (3.84) | (3.00) |
| Stage | | | | $0.17^{***}$ | $0.17^{***}$ | $0.17^{***}$ |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | | | (12.48) | (12.19) | (12.19) |
| Constant | -1.31** | -0.63 | -0.59 | -1.03*** | -1.02*** | -1.01*** |
| | (-2.28) | (-0.98) | (-0.92) | (-5.71) | (-5.59) | (-5.54) |
| Observations | 41732 | 40053 | 40053 | 30341 | 29085 | 29085 |

p<0.1 *, p<0,05**, p<0,01***; Panel Probit regressions; Not reported: 51 country dummies and 52 industry dummies ; z-Statistics in parentheses; the number of observations in columns (4) to (6) lower, because, for some observations no information about the stage of investment is provided; standard errors clustered at portfolio-company level.

To provide an answer to our second research question (Hypothesis 2), i.e., whether GVCs perform better in cleantech than in other industries, we still need to compare the marginal effects of GVC- and EIF-backed funds for cleantech vs. non-cleantech companies. We first run regressions which the interactions between cleantech investments on either GVC or a EIF backing (

Table 6). Then, we present the marginal effects of the interaction (Figure 3). A main conclusion can be drawn that both types of governmental VC (direct and indirect) perform better in cleantech investments than in other industries (controlling for other characteristics of the deals and firms). While the impact of direct GVC for non-cleantech is unambiguously negative, it becomes insignificantly different from zero for the subgroup of cleantech investments. Also, for the case of the EIF investments, the point estimator is higher in cleantech, however, due to a high uncertainty of the estimator, we cannot conclude that it is different from the effect on non-cleantech. It needs to be mentioned though that due to low number of observations, the coefficients for the cleantech case are not estimated precisely.

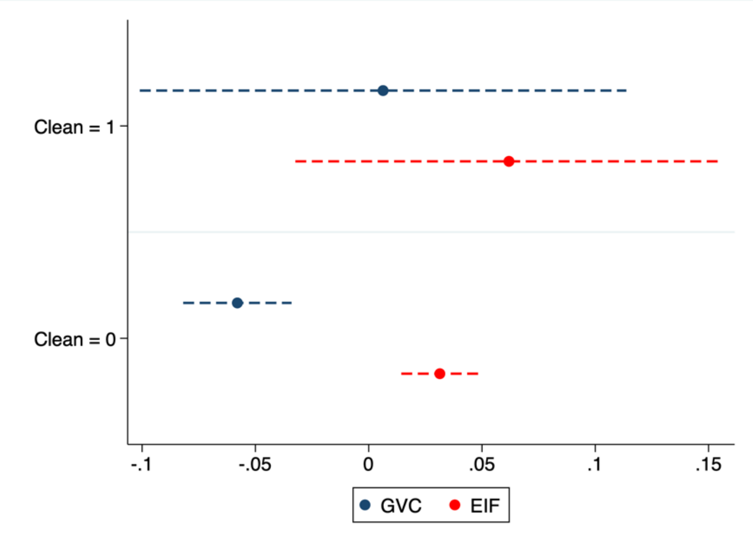



***Figure 3: Marginal effect of GVC and EIF in cleantech and other industries***

To look at Hypothesis 3, Table 7 and Table 8 show further the interactions between cleantech startups, governmental support and two measures of expertise and specialization: the number of previous deals in the same industry (*Expertise*), and the percentage of deals in the same industry to all deals (*Focus*). Several conclusions arise. Neither expertise nor focus have any particular effect on the cleantech industry compared to other industries. Green focus, however, does correlate positively with the probability of an exit by a cleantech startup, controlling for other factors such as the age of the company and the stage of financing. Moreover, inclusion of the interaction between the cleantech and green focus yields the (inverse of) industry specialization (HHI) insignificant, further stressing the role of the focus on the cleantech companies. As for the impact of governmental programs (both direct and indirect) there is only a slightly positive additional effect of an EIF funding for those funds, who either have a very high expertise in the specific sector or a high cleantech focus overall. Conversely, direct public involvement, does not seem to make a particular difference. The latter results are presented in compact form in Figure 4 reporting the marginal effects and in Table 10 in the Appendix.

*Table 6: Regressions with the interaction between cleantech and governmental VC*

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Green Focus | -0.19 | -0.18 | -0.14 | -0.12 |
| | (-1.52) | (-1.40) | (-0.92) | (-0.76) |
| Expertise | -0.00 | -0.00** | 0.00 | -0.00 |
| | (-0.46) | (-2.21) | (0.55) | (-0.77) |
| Focus | 0.43*** | 0.49*** | 0.40*** | 0.46*** |
| | (4.15) | (4.68) | (3.21) | (3.67) |
| Total funding | 0.25** | 0.27*** | 0.36*** | 0.35*** |
| | (2.42) | (2.62) | (3.15) | (3.11) |
| Syndicate Size | 0.04*** | 0.03*** | -0.03*** | -0.03*** |
| | (6.94) | (6.00) | (-3.65) | (-3.67) |
| Age of the firm | 0.02*** | 0.02*** | -0.01* | -0.01* |
| | (4.84) | (4.69) | (-1.91) | (-1.78) |
| HHI | -0.39*** | -0.47*** | -0.36*** | -0.44*** |
| | (-3.52) | (-4.15) | (-2.70) | (-3.29) |
| Clean=1 | -0.28 | -0.36* | -0.14 | -0.19 |
| | (-1.36) | (-1.80) | (-0.55) | (-0.77) |
| GVC=1 | -0.22*** | | -0.21*** | |
| | (-6.38) | | (-4.50) | |
| Clean=1 # GVC=1 | 0.08 | | 0.23 | |
| | (0.49) | | (1.13) | |
| EIF=1 | | 0.12*** | | 0.10*** |
| | | (4.84) | | (3.67) |
| Clean=1 # EIF=1 | | 0.20 | | 0.12 |
| | | (1.42) | | (0.72) |
| Stage | | | 0.17*** | 0.17*** |
| | | | (12.48) | (12.19) |
| Constant | -1.31** | -0.61 | -1.03*** | -1.02*** |
| | (-2.28) | (-0.95) | (-5.71) | (-5.58) |
| Observations | 41732 | 40053 | 30341 | 29085 |

p<0.1 *, p<0,05**, p<0,01***; Panel Probit regressions; Not reported: 51 country dummies and 52 industry dummies ; z-Statistics in parentheses; the number of observations in columns (4) to (6) lower, because, for some observations no information about the stage of investment is provided; standard errors clustered at the portfolio-company level.

*Table 7: Regressions with the interaction between cleantech and expertise*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Clean=1 | -0.38* | -0.39* | -0.38* | -0.21 | -0.23 | -0.19 |
| | (-1.91) | (-1.96) | (-1.84) | (-0.90) | (-0.94) | (-0.73) |
| Expertise | -0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | (-0.71) | (0.25) | (0.15) | (0.32) | (0.96) | (0.80) |
| Clean=1 # Expertise | 0.00 | 0.00 | -0.00 | 0.00 | 0.00 | -0.01 |
| | (0.84) | (0.94) | (-0.56) | (0.63) | (0.47) | (-0.69) |
| Focus | 0.44*** | 0.43*** | 0.46*** | 0.42*** | 0.40*** | 0.43*** |
| | (4.16) | (4.00) | (4.31) | (3.30) | (3.13) | (3.39) |
| Total funding | 0.26** | 0.26** | 0.26*** | 0.34*** | 0.34*** | 0.34*** |
| | (2.57) | (2.56) | (2.60) | (3.07) | (3.08) | (3.08) |
| Syndicate Size | 0.03*** | 0.03*** | 0.03*** | -0.03*** | -0.03*** | -0.03*** |
| | (5.72) | (5.72) | (5.74) | (-3.75) | (-3.76) | (-3.73) |
| Age of the firm | 0.02*** | 0.02*** | 0.02*** | -0.01* | -0.01* | -0.01* |
| | (4.74) | (4.73) | (4.75) | (-1.79) | (-1.78) | (-1.79) |
| HHI | -0.45*** | -0.43*** | -0.46*** | -0.43*** | -0.40*** | -0.44*** |
| | (-3.99) | (-3.77) | (-4.08) | (-3.17) | (-2.95) | (-3.24) |
| GVC=1 | -0.20*** | -0.19*** | -0.20*** | -0.18*** | -0.17*** | -0.18*** |
| | (-5.91) | (-4.90) | (-5.87) | (-4.05) | (-3.27) | (-4.03) |
| EIF=1 | 0.10*** | 0.09*** | 0.12*** | 0.09*** | 0.08*** | 0.11*** |
| | (4.07) | (3.85) | (4.08) | (3.03) | (2.81) | (3.02) |
| Clean=1 # GVC=1 | | 0.13 | | | 0.21 | |
| | | (0.76) | | | (0.87) | |
| GVC=1 # Expertise | | -0.00 | | | -0.00 | |
| | | (-1.14) | | | (-1.12) | |
| Clean=1 # GVC=1 # Expertise | | -0.01 | | | -0.00 | |
| | | (-0.78) | | | (-0.04) | |
| Clean=1 # EIF=1 | | | 0.11 | | | -0.01 |
| | | | (0.65) | | | (-0.06) |
| EIF=1 # Expertise | | | -0.00* | | | -0.00 |
| | | | (-1.76) | | | (-1.13) |
| Clean=1 # EIF=1 # Expertise | | | 0.01 | | | 0.01 |
| | | | (1.48) | | | (1.56) |
| Stage | | | | 0.17*** | 0.17*** | 0.17*** |
| | | | | (12.20) | (12.22) | (12.19) |
| Constant | -0.57 | -0.59 | -0.56 | -1.01*** | -1.02*** | -1.02*** |
| | (-0.89) | (-0.92) | (-0.88) | (-5.55) | (-5.59) | (-5.57) |
| Observations | 40053 | 40053 | 40053 | 29085 | 29085 | 29085 |

p<0.1 *, p<0,05**, p<0,01***; Panel Probit regressions; Not reported: 51 country dummies and 52 industry dummies ; z-Statistics in parentheses; the number of observations in columns (4) to (6) lower, because, for some observations no information about the stage of investment is provided; standard errors clustered at the portfolio-company level.

***Table 8: Regressions with the interaction between cleantech and focus***

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Clean=1 | -0.37$^{*}$ | -0.36$^{*}$ | -0.44$^{**}$ | -0.23 | -0.23 | -0.27 |
| | (-1.80) | (-1.69) | (-2.15) | (-0.90) | (-0.87) | (-1.08) |
| Focus | 0.44$^{***}$ | 0.40$^{***}$ | 0.51$^{***}$ | 0.41$^{***}$ | 0.39$^{***}$ | 0.49$^{***}$ |
| | (4.09) | (3.79) | (4.66) | (3.23) | (3.08) | (3.70) |
| Clean=1 # Focus | 0.15 | 0.02 | 0.17 | 0.21 | 0.10 | 0.24 |
| | (0.61) | (0.09) | (0.70) | (0.61) | (0.28) | (0.74) |
| Expertise | -0.00 | -0.00 | -0.00 | 0.00 | 0.00 | 0.00 |
| | (-0.69) | (-0.94) | (-0.40) | (0.34) | (0.24) | (0.54) |
| Total funding | 0.26$^{**}$ | 0.26$^{**}$ | 0.26$^{***}$ | 0.34$^{***}$ | 0.34$^{***}$ | 0.34$^{***}$ |
| | (2.55) | (2.58) | (2.59) | (3.07) | (3.07) | (3.07) |
| Syndicate Size | 0.03$^{***}$ | 0.03$^{***}$ | 0.03$^{***}$ | -0.03$^{***}$ | -0.03$^{***}$ | -0.03$^{***}$ |
| | (5.71) | (5.74) | (5.71) | (-3.76) | (-3.77) | (-3.77) |
| Age of the firm | 0.02$^{***}$ | 0.02$^{***}$ | 0.02$^{***}$ | -0.01$^{*}$ | -0.01$^{*}$ | -0.01$^{*}$ |
| | (4.74) | (4.78) | (4.76) | (-1.79) | (-1.78) | (-1.78) |
| HHI | -0.45$^{***}$ | -0.45$^{***}$ | -0.50$^{***}$ | -0.43$^{***}$ | -0.42$^{***}$ | -0.48$^{***}$ |
| | (-4.00) | (-3.98) | (-4.41) | (-3.18) | (-3.15) | (-3.52) |
| GVC=1 | -0.20$^{***}$ | -0.31$^{***}$ | -0.21$^{***}$ | -0.19$^{***}$ | -0.26$^{***}$ | -0.19$^{***}$ |
| | (-5.90) | (-6.48) | (-5.99) | (-4.05) | (-4.13) | (-4.10) |
| EIF=1 | 0.10$^{***}$ | 0.10$^{***}$ | 0.16$^{***}$ | 0.09$^{***}$ | 0.09$^{***}$ | 0.15$^{***}$ |
| | (4.08) | (4.10) | (4.52) | (3.03) | (3.05) | (3.51) |
| Clean=1 # GVC=1 | | -0.00 | | | 0.10 | |
| | | (-0.02) | | | (0.41) | |
| GVC=1 # Focus | | 0.48$^{***}$ | | | 0.32 | |
| | | (3.27) | | | (1.60) | |
| Clean=1 # GVC=1 # Focus | | 0.77 | | | 0.99 | |
| | | (1.20) | | | (1.13) | |
| Clean=1 # EIF=1 | | | 0.15 | | | 0.12 |
| | | | (0.88) | | | (0.61) |
| EIF=1 # Focus | | | -0.29$^{**}$ | | | -0.27$^{**}$ |
| | | | (-2.55) | | | (-2.00) |
| Clean=1 # EIF=1 # Focus | | | 0.49 | | | 0.06 |
| | | | (0.67) | | | (0.07) |
| Stage | | | | 0.17$^{***}$ | 0.17$^{***}$ | 0.17$^{***}$ |
| | | | | (12.20) | (12.20) | (12.19) |
| Constant | -0.56 | -0.55 | -0.51 | -1.01$^{***}$ | -1.00$^{***}$ | -1.02$^{***}$ |
| | (-0.88) | (-0.85) | (-0.81) | (-5.54) | (-5.51) | (-5.58) |
| Observations | 40053 | 40053 | 40053 | 29085 | 29085 | 29085 |

p<0.1 *, p<0,05**, p<0,01***; Panel Probit regressions; Not reported: 51 country dummies and 52 industry dummies ; z-Statistics in parentheses; the number of observations in columns (4) to (6) lower, because, for some observations no information about the stage of investment is provided; standard errors clustered at the portfolio-company level.

The marginal effects of two forms of public VC for the cleantech companies at different levels of expertise and focus (from specifications (5) and (6) in Table 7 and Table 8) are shown in Figure 4.

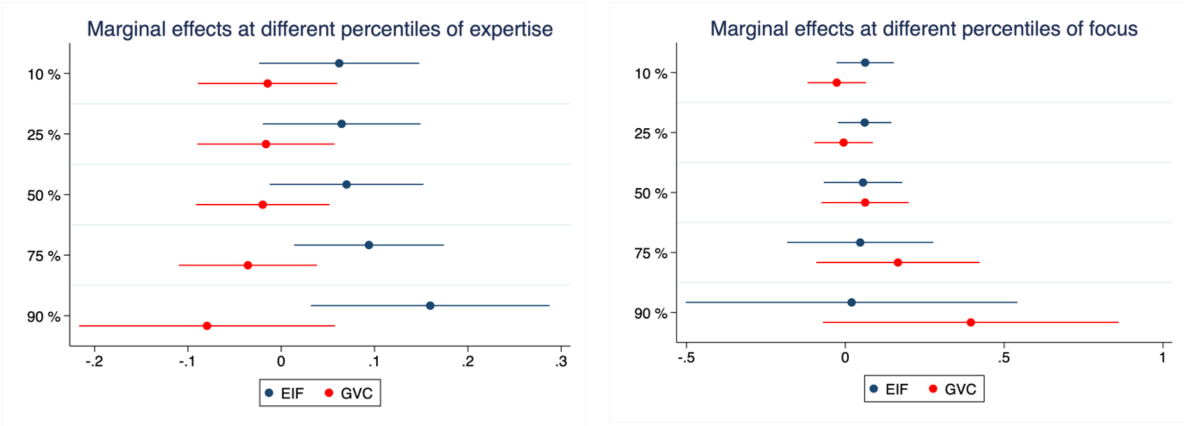



***Figure 4: Marginal effects of GVC and EIF investments in cleantech at different levels of expertise and focus***

Figure 4 presents the marginal effects of GVC and EIF investments for cleantech investments evaluated at different levels of expertise (left panel) and focus (right panel) of funds (from the three-way interaction terms). Different levels of expertise do not affect the success rates of GVC investments – none of the coefficients is significantly different from zero. The coefficient for the EIF investments is positive and significant, but only at the high levels of expertise, i.e., where the number of previous deals in the same industry is high, otherwise it is not different from zero. For the case of focus, we see that GVC investment have the chance of positively affecting cleantech investments, but only when the fund is very strongly specialized. Otherwise, the effect is not different from zero.

Further, we look at the interaction of the public funds with their *clean focus,* that is the fraction of cleantech investments in their overall portfolio. The value is, by definition, the same as focus for the case of cleantech, but different for other industries, so that some conclusions might change (Table 9). The marginal effects for GVC and EIF are presented in Figure 5

*Table 9: Regressions with the interaction between cleantech and clean focus*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Clean=1 | -0.08 | -0.14 | -0.06 | 0.09 | 0.02 | 0.16 |
| | (-0.36) | (-0.58) | (-0.24) | (0.33) | (0.08) | (0.49) |
| log(CleanFocus) | 0.01 | 0.02 | 0.00 | 0.01 | 0.02 | 0.01 |
| | (0.73) | (0.91) | (0.21) | (0.70) | (0.96) | (0.47) |
| Clean=1 # log(CleanFocus) | 0.09 | 0.07 | 0.12* | 0.09 | 0.07 | 0.13 |
| | (1.44) | (1.07) | (1.78) | (1.12) | (0.82) | (1.50) |
| Expertise | -0.00 | -0.00 | -0.00 | 0.00 | 0.00 | 0.00 |
| | (-0.67) | (-0.62) | (-0.66) | (0.20) | (0.32) | (0.19) |
| Total funding | 0.17* | 0.17* | 0.17* | 0.29*** | 0.29*** | 0.29*** |
| | (1.69) | (1.69) | (1.72) | (2.66) | (2.67) | (2.67) |
| Syndicate Size | 0.03*** | 0.03*** | 0.03*** | -0.04*** | -0.04*** | -0.04*** |
| | (4.32) | (4.36) | (4.33) | (-3.60) | (-3.60) | (-3.61) |
| Age of the firm | 0.02*** | 0.02*** | 0.02*** | -0.01 | -0.01 | -0.01 |
| | (3.68) | (3.68) | (3.68) | (-0.83) | (-0.84) | (-0.83) |
| HHI | -0.77*** | -0.78*** | -0.76*** | -0.71*** | -0.74*** | -0.73*** |
| | (-4.51) | (-4.61) | (-4.50) | (-3.44) | (-3.57) | (-3.50) |
| GVC=1 | -0.27*** | -0.41** | -0.26*** | -0.21*** | -0.52** | -0.21*** |
| | (-6.12) | (-2.26) | (-6.10) | (-3.60) | (-2.13) | (-3.59) |
| EIF=1 | 0.10*** | 0.10*** | 0.17 | 0.10** | 0.10** | 0.12 |
| | (3.04) | (3.05) | (1.42) | (2.50) | (2.52) | (0.83) |
| Clean=1 # GVC=1 | | 0.71* | | | 1.24** | |
| | | (1.76) | | | (2.11) | |
| GVC=1 # log(CleanFocus) | | -0.04 | | | -0.10 | |
| | | (-0.76) | | | (-1.25) | |
| Clean=1 # GVC=1 # log(CleanFocus) | | 0.23 | | | 0.38* | |
| | | (1.49) | | | (1.80) | |
| Clean=1 # EIF=1 | | | -0.02 | | | -0.17 |
| | | | (-0.06) | | | (-0.45) |
| EIF=1 # log(CleanFocus) | | | 0.02 | | | 0.01 |
| | | | (0.70) | | | (0.20) |
| Clean=1 # EIF=1 # log(CleanFocus) | | | -0.07 | | | -0.11 |
| | | | (-0.63) | | | (-0.83) |
| Stage | | | | 0.17*** | 0.17*** | 0.17*** |
| | | | | (11.11) | (11.11) | (11.12) |
| Constant | -0.82*** | -0.81*** | -0.85*** | -1.19*** | -1.17*** | -1.20*** |
| | (-4.60) | (-4.52) | (-4.68) | (-5.31) | (-5.20) | (-5.29) |
| Observations | 21280 | 21280 | 21280 | 14909 | 14909 | 14909 |

p<0.1 *, p<0,05**, p<0,01***; Panel Probit regressions; Not reported: 51 country dummies and 52 industry dummies ; z-Statistics in parentheses; the number of observations in columns (4) to (6) lower, because, for some observations no information about the stage of investment is provided; standard errors clustered at the portfolio-company level.

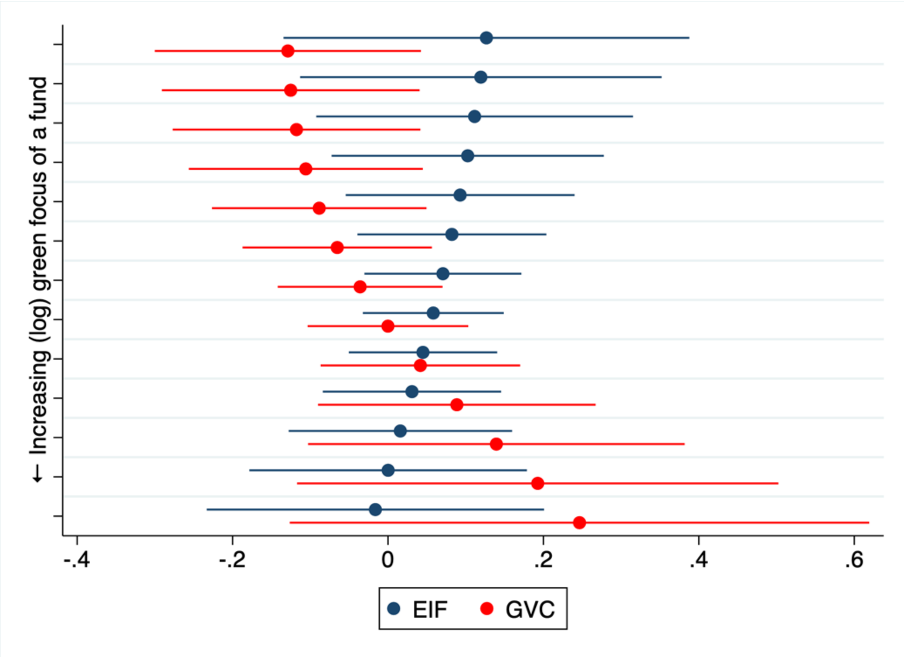
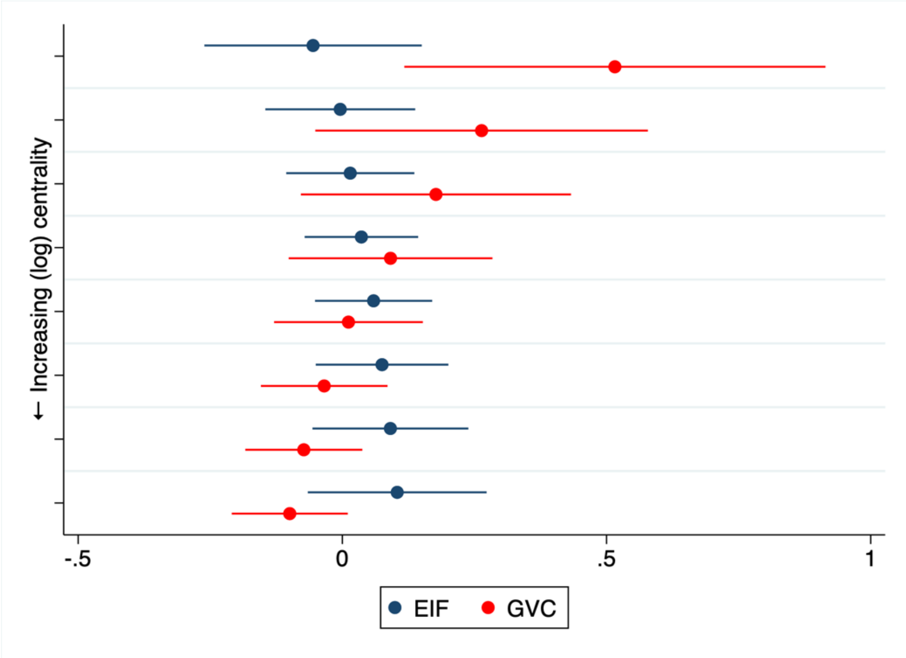



***Figure 5: Marginal effects of GVC and EIF at different levels of clean focus***

The coefficients are similar to Figure 4, but indeed slightly different in magnitude and signs. In particular, the effects of GVC at low levels of clean focus are negative, while not statistically significant.

### 5.2.3. Network characteristics of funds and performance of cleantech startups

Finally, we ask the question whether there is interplay between the fact that green funds have different network characteristics from their non-specialized counterparts, and their success rates – along the argumentation behind Hypothesis 4. For this, we run regressions, in which we take several above-mentioned network measures and their interactions with other characteristics as explanatory variables for the probabilities of successful exits. These are: the centrality of the funds, the betweenness of the funds, the number of cliques to which a fund belongs, and the maximum betweenness within the clique. Further we show the impact of the network density of the order-1 ego networks and their average green focus. The corresponding regression tables are reported in the Appendix, while in the main text we focus on figures presenting the marginal effects. Most measures are presented in log form, to account for the skewness of the respective distributions.



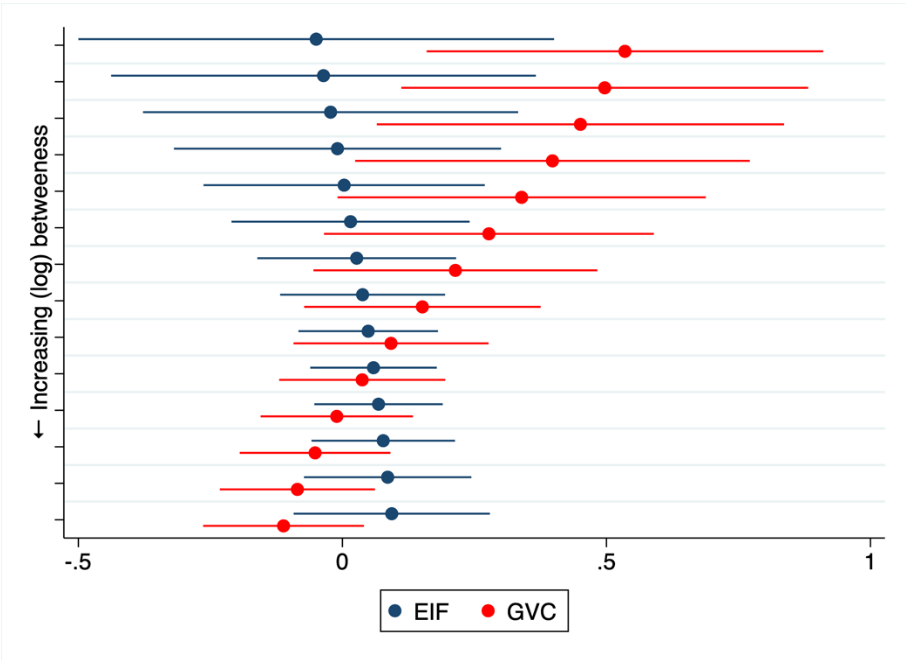




***Figure 6: Marginal effects of GVC and EIF at different levels of centrality (upper panel) and betweeness (lower panel)***

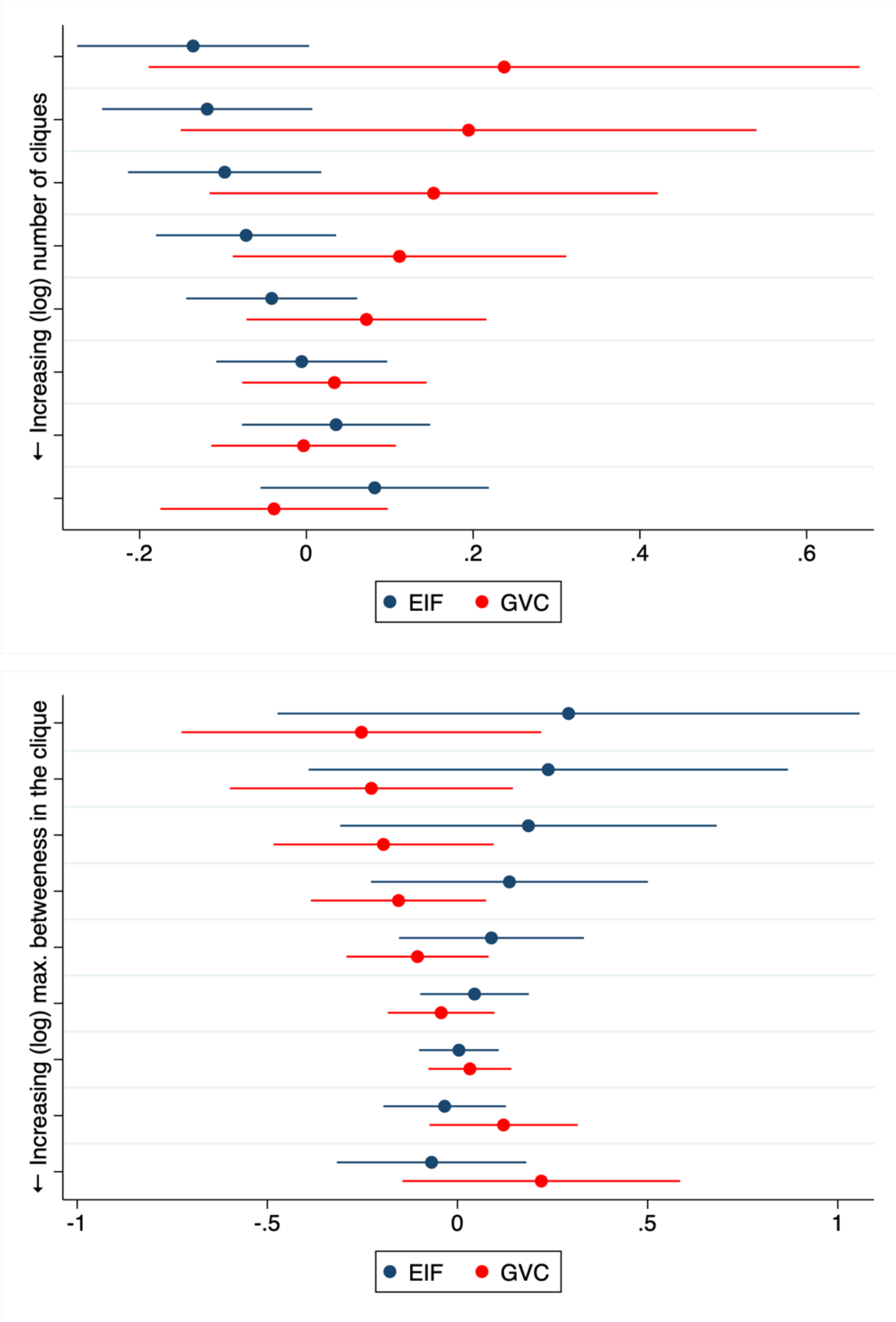



***Figure 7: Marginal effects of GVC and EIF at different levels of the number of cliques (upper panel) and maximal betweeness of the cliques (lower panel)***

Among several ways in which we can measure the network importance of funds, the first three measures (centrality, betweenness and the number of cliques) show very similar patterns (Figure 6, Figure 7: upper panel). At low levels of the network centrality direct public VCs (GVC) performs better and, in fact, despite on average negative contributions, the contribution is positive, even if barely different from zero. At higher levels of centrality, the relationship turns negative. As for the contribution of the EIF, it is generally insignificantly different from zero. Almost the same pattern can be observed for the case of betweenness of the funds. For the case of the number of cliques, the patterns are similar, but not significantly different from zero. A slightly different observation can be made for the case of the maximum centrality within the cliques. In this case, while still statistically insignificant, the probability of a positive impact of a GVC increases with the network measure (Figure 7: lower panel).

Finally, as shown in Table 11 and Table 12, the network density seems to fully compensate the negative effects of GVCs in the group of all investments. Evaluated only for cleantech startups, the effects of GVCs are insignificantly different from zero at all levels of network densities and the green focus of the networks.

## 6. Conclusions

Our paper sheds new light on the question of whether public venture capital can be used to stimulate cleantech investment and how this investment should be done to be most effective. Two results stand out: First, public venture capital does not underperform private venture capital in a broad cross-country sample of European deals. This is a novel finding, as it doesn't confirm some previous findings in the literature that government-backed VCs underperform their private counterparts. We also find that there is no significant difference between direct and indirect government support of venture capital for cleantech investments. Second, GVCs perform well when they specialize in cleantech investments and are well connected within a network of other investors.

We can further confirm that funds that primarily invest in cleantech startups have strong network relationships with other funds in the sector. We explain this by the specific nature of sector knowledge and long development cycles in the cleantech industry.

Considering these findings, policymakers should support the cleantech sector through direct or indirect investments in specialized venture capital funds. Excluding broader venture capital-related policy goals, such as promoting private venture capital funds in general, there is little difference between direct and indirect investment in cleantech.

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## Appendix: Additional Tables and Figures

***Table 10: Marginal effects of EIF and GVC at different levels of expertise, focus and green focus for cleantech companies***

| Expertise | EIF | z-stat | GVC | z-stat |
|---|---|---|---|---|
| 10% | .0620 | 1.42 | -.0146 | -0.39 |
| 25% | .0646 | 1.50 | -.0164 | -0.44 |
| 50% | .0699 | 1.66 | -.0199 | -0.55 |
| 75% | .0938 | 2.29 | -.0358 | -0.95 |
| 90% | .1595 | 2.45 | -.0796 | -1.14 |
| Focus | EIF | z-stat | GVC | z-stat |
| 10% | .0624 | 1.36 | -.0278 | -0.58 |
| 25% | .0608 | 1.42 | -.0056 | -0.12 |
| 50% | .0556 | 0.88 | .0622 | 0.89 |
| 75% | .0468 | 0.40 | .1654 | 1.26 |
| 90% | .0196 | 0.07 | .3952 | 1.66 |
| Green Focus | EIF | z-stat | GVC | z-stat |
| 10% | .0635 | 1.22 | -.0418 | -0.80 |
| 25% | .0635 | 1.22 | -.0418 | -0.80 |
| 50% | .0635 | 1.22 | -.0418 | -0.80 |
| 75% | .0630 | 1.34 | -.0268 | -0.54 |
| 90% | .0618 | 1.36 | .0089 | 0.17 |

***Table 11: Interactions with the average green focus of the order-1 ego networks***

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Clean=1 | 0.09 | 0.09 | 0.11 | -0.01 | -0.03 | 0.07 |
| | (0.30) | (0.29) | (0.37) | (-0.02) | (-0.08) | (0.17) |
| log(average greenfocus) | -0.04** | -0.03* | -0.05*** | -0.03 | -0.02 | -0.05** |
| | (-2.43) | (-1.86) | (-3.12) | (-1.39) | (-0.98) | (-2.22) |
| Clean=1 # log(average greenfocus) | 0.16* | 0.17* | 0.18** | 0.06 | 0.07 | 0.09 |
| | (1.86) | (1.96) | (2.05) | (0.56) | (0.61) | (0.82) |
| Expertise | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | (1.02) | (1.18) | (0.97) | (1.44) | (1.64) | (1.38) |
| Total funding | 0.28*** | 0.28*** | 0.28*** | 0.34*** | 0.34*** | 0.34*** |
| | (2.78) | (2.79) | (2.83) | (3.10) | (3.11) | (3.11) |
| Syndicate Size | 0.03*** | 0.03*** | 0.03*** | -0.03*** | -0.03*** | -0.03*** |
| | (5.32) | (5.32) | (5.33) | (-3.79) | (-3.80) | (-3.77) |
| Age of the firm | 0.02*** | 0.02*** | 0.02*** | -0.01* | -0.01* | -0.01* |
| | (4.67) | (4.65) | (4.66) | (-1.70) | (-1.69) | (-1.70) |
| HHI | -0.10 | -0.10 | -0.10* | -0.04 | -0.04 | -0.05 |
| | (-1.60) | (-1.57) | (-1.65) | (-0.51) | (-0.49) | (-0.60) |
| GVC=1 | -0.21*** | -0.58*** | -0.21*** | -0.19*** | -0.69*** | -0.19*** |
| | (-5.85) | (-4.06) | (-5.89) | (-4.05) | (-3.28) | (-4.06) |
| EIF=1 | 0.10*** | 0.10*** | 0.37*** | 0.08*** | 0.08*** | 0.42*** |
| | (3.86) | (3.94) | (3.16) | (2.70) | (2.76) | (2.92) |
| Clean=1 # GVC=1 | | -0.11 | | | 0.76 | |
| | | (-0.19) | | | (0.86) | |
| GVC=1 # log(average greenfocus) | | -0.11*** | | | -0.14** | |
| | | (-2.67) | | | (-2.39) | |
| Clean=1 # GVC=1 # log(average greenfocus) | | -0.12 | | | 0.14 | |
| | | (-0.60) | | | (0.50) | |
| Clean=1 # EIF=1 | | | -0.10 | | | -0.34 |
| | | | (-0.21) | | | (-0.60) |
| EIF=1 # log(average greenfocus) | | | 0.08** | | | 0.09** |
| | | | (2.43) | | | (2.43) |
| Clean=1 # EIF=1 # log(average greenfocus) | | | -0.08 | | | -0.12 |
| | | | (-0.49) | | | (-0.69) |
| Stage | | | | 0.17*** | 0.17*** | 0.17*** |
| | | | | (12.27) | (12.28) | (12.26) |
| Constant | -0.71 | -0.69 | -0.72 | -1.18*** | -1.15*** | -1.25*** |
| | (-1.10) | (-1.07) | (-1.11) | (-5.83) | (-5.68) | (-6.10) |
| Observations | 37952 | 37952 | 37952 | 27526 | 27526 | 27526 |

p<0.1 *, p<0,05**, p<0,01***; Panel Probit regressions; Not reported: 51 country dummies and 52 industry dummies ; z-Statistics in parentheses; the number of observations in columns (4) to (6) lower, because, for some observations no information about the stage of investment is provided; standard errors clustered at the portfolio-company level.

***Table 12: Interactions with the network density of the order-1 ego networks***

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Clean=1 | -0.43* | -0.51** | -0.46* | -0.16 | -0.15 | -0.16 |
| | (-1.85) | (-2.08) | (-1.90) | (-0.51) | (-0.51) | (-0.52) |
| log(network density) | 0.10*** | 0.08*** | 0.09*** | 0.11*** | 0.10*** | 0.10*** |
| | (4.96) | (3.78) | (4.35) | (4.42) | (3.81) | (3.81) |
| Clean=1 # log(network density) | -0.06 | -0.10 | -0.04 | 0.01 | 0.03 | 0.02 |
| | (-0.74) | (-1.08) | (-0.55) | (0.08) | (0.23) | (0.22) |
| Expertise | 0.00*** | 0.00*** | 0.00*** | 0.00*** | 0.00*** | 0.00*** |
| | (3.30) | (3.87) | (3.36) | (3.42) | (3.72) | (3.47) |
| Total funding | 0.26*** | 0.26*** | 0.26*** | 0.34*** | 0.34*** | 0.34*** |
| | (2.58) | (2.65) | (2.62) | (3.12) | (3.12) | (3.13) |
| Syndicate Size | 0.03*** | 0.03*** | 0.03*** | -0.03*** | -0.03*** | -0.03*** |
| | (5.48) | (5.50) | (5.50) | (-3.67) | (-3.69) | (-3.66) |
| Age of the firm | 0.02*** | 0.02*** | 0.02*** | -0.01* | -0.01* | -0.01* |
| | (4.74) | (4.78) | (4.74) | (-1.83) | (-1.83) | (-1.83) |
| HHI | -0.28*** | -0.24*** | -0.26*** | -0.26*** | -0.25*** | -0.25*** |
| | (-3.77) | (-3.31) | (-3.58) | (-2.97) | (-2.74) | (-2.80) |
| GVC=1 | -0.19*** | 0.07 | -0.19*** | -0.16*** | 0.02 | -0.16*** |
| | (-5.18) | (0.88) | (-5.08) | (-3.27) | (0.24) | (-3.23) |
| EIF=1 | 0.13*** | 0.12*** | 0.23*** | 0.12*** | 0.11*** | 0.24** |
| | (5.17) | (4.81) | (2.85) | (3.92) | (3.73) | (2.44) |
| Clean=1 # GVC=1 | | 0.48 | | | 0.33 | |
| | | (1.23) | | | (0.62) | |
| GVC=1 # log(network density) | | 0.12*** | | | 0.09** | |
| | | (3.63) | | | (1.98) | |
| Clean=1 # GVC=1 # log(network density) | | 0.18 | | | 0.00 | |
| | | (1.03) | | | (0.01) | |
| Clean=1 # EIF=1 | | | 0.35 | | | 0.15 |
| | | | (0.92) | | | (0.31) |
| EIF=1 # log(network density) | | | 0.05 | | | 0.06 |
| | | | (1.37) | | | (1.34) |
| Clean=1 # EIF=1 # log(network density) | | | 0.09 | | | 0.02 |
| | | | (0.54) | | | (0.10) |
| Stage | | | | 0.17*** | 0.17*** | 0.17*** |
| | | | | (12.30) | (12.32) | (12.30) |
| Constant | -0.36 | -0.42 | -0.36 | -0.82*** | -0.85*** | -0.84*** |
| | (-0.55) | (-0.64) | (-0.56) | (-4.16) | (-4.28) | (-4.25) |
| Observations | 38486 | 38486 | 38486 | 27877 | 27877 | 27877 |

p<0.1 *, p<0,05**, p<0,01***; Panel Probit regressions; Not reported: 51 country dummies and 52 industry dummies ; z-Statistics in parentheses; the number of observations in columns (4) to (6) lower, because, for some observations no information about the stage of investment is provided; standard errors clustered at the portfolio-company level.

*Table 13: Regressions with the centrality of funds*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Clean=1 | -0.25 | -0.22 | -0.31 | -0.19 | -0.18 | -0.24 |
| | (-1.22) | (-1.07) | (-1.49) | (-0.74) | (-0.69) | (-0.94) |
| (log)centrality | -0.01*** | -0.01** | -0.01*** | -0.00 | -0.00 | -0.00 |
| | (-2.90) | (-2.40) | (-2.91) | (-1.14) | (-0.91) | (-0.98) |
| Clean=1 # (log)centrality | 0.04** | 0.05*** | 0.04** | 0.01 | 0.01 | -0.00 |
| | (2.44) | (3.29) | (2.30) | (0.35) | (0.58) | (-0.18) |
| Expertise | 0.00* | 0.00* | 0.00* | 0.00** | 0.00** | 0.00** |
| | (1.67) | (1.86) | (1.72) | (2.07) | (2.17) | (2.10) |
| Total funding | 0.27*** | 0.27*** | 0.27*** | 0.31*** | 0.31*** | 0.31*** |
| | (2.85) | (2.85) | (2.88) | (2.90) | (2.90) | (2.90) |
| Syndicate Size | 0.03*** | 0.03*** | 0.03*** | -0.03*** | -0.03*** | -0.03*** |
| | (5.84) | (5.88) | (5.84) | (-3.51) | (-3.49) | (-3.51) |
| Age of the firm | 0.02*** | 0.02*** | 0.02*** | -0.01* | -0.01* | -0.01* |
| | (4.55) | (4.57) | (4.55) | (-1.82) | (-1.81) | (-1.82) |
| HHI | -0.04 | -0.04 | -0.04 | -0.01 | -0.01 | -0.01 |
| | (-0.68) | (-0.64) | (-0.67) | (-0.12) | (-0.15) | (-0.08) |
| GVC=1 | -0.22*** | -0.27*** | -0.22*** | -0.20*** | -0.24*** | -0.20*** |
| | (-6.09) | (-6.44) | (-6.08) | (-4.17) | (-4.36) | (-4.17) |
| EIF=1 | 0.08*** | 0.08*** | 0.08** | 0.06** | 0.06** | 0.06 |
| | (3.35) | (3.30) | (2.57) | (2.20) | (2.17) | (1.48) |
| Clean=1 # GVC=1 | | -0.03 | | | -0.46 | |
| | | (-0.14) | | | (-1.54) | |
| GVC=1 # (log)centrality | | -0.02** | | | -0.02 | |
| | | (-2.18) | | | (-1.07) | |
| Clean=1 # GVC=1 # (log)centrality | | -0.02 | | | -0.28*** | |
| | | (-0.74) | | | (-2.71) | |
| Clean=1 # EIF=1 | | | 0.20 | | | 0.39 |
| | | | (1.21) | | | (1.15) |
| EIF=1 # (log)centrality | | | 0.00 | | | -0.00 |
| | | | (0.11) | | | (-0.24) |
| Clean=1 # EIF=1 # (log)centrality | | | 0.00 | | | 0.09 |
| | | | (0.15) | | | (0.97) |
| Stage | | | | 0.17*** | 0.17*** | 0.17*** |
| | | | | (12.46) | (12.46) | (12.47) |
| Constant | -0.47 | -0.56 | -0.46 | -1.11*** | -1.11*** | -1.11*** |
| | (-0.62) | (-0.76) | (-0.60) | (-6.00) | (-5.98) | (-5.99) |
| Observations | 37580 | 37580 | 37580 | 27202 | 27202 | 27202 |

p<0.1 *, p<0,05**, p<0,01***; Panel Probit regressions; Not reported: 51 country dummies and 52 industry dummies ; z-Statistics in parentheses; the number of observations in columns (4) to (6) lower, because, for some observations no information about the stage of investment is provided; standard errors clustered at the portfolio-company level.

***Table 14: Regressions with the betweeness of funds***

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Clean=1 | -0.27 | -0.20 | -0.35 | -0.21 | -0.12 | -0.31 |
| | (-1.16) | (-0.76) | (-1.38) | (-0.68) | (-0.36) | (-0.92) |
| Log(between) | -0.04*** | -0.04*** | -0.04*** | -0.03*** | -0.03*** | -0.04*** |
| | (-7.16) | (-6.26) | (-6.78) | (-4.90) | (-4.46) | (-4.98) |
| Clean=1 # log(between) | 0.01 | 0.02 | 0.00 | -0.01 | 0.00 | -0.02 |
| | (0.32) | (0.70) | (0.12) | (-0.37) | (0.09) | (-0.59) |
| Expertise | 0.00*** | 0.00*** | 0.00*** | 0.00*** | 0.00*** | 0.00*** |
| | (3.32) | (3.74) | (3.35) | (3.15) | (3.37) | (3.15) |
| Total funding | 0.30*** | 0.30*** | 0.30*** | 0.31*** | 0.31*** | 0.31*** |
| | (2.77) | (2.79) | (2.79) | (2.79) | (2.78) | (2.79) |
| Syndicate Size | 0.03*** | 0.03*** | 0.03*** | -0.03*** | -0.03*** | -0.03*** |
| | (4.65) | (4.69) | (4.65) | (-3.63) | (-3.62) | (-3.62) |
| Age of the firm | 0.02*** | 0.02*** | 0.02*** | -0.01* | -0.01* | -0.01* |
| | (4.40) | (4.47) | (4.41) | (-1.71) | (-1.69) | (-1.69) |
| HHI | -0.27*** | -0.25*** | -0.27*** | -0.20** | -0.19** | -0.22** |
| | (-3.59) | (-3.43) | (-3.60) | (-2.24) | (-2.15) | (-2.46) |
| GVC=1 | -0.19*** | -0.42*** | -0.19*** | -0.17*** | -0.35*** | -0.17*** |
| | (-5.16) | (-6.26) | (-5.15) | (-3.49) | (-3.93) | (-3.48) |
| EIF=1 | 0.10*** | 0.10*** | 0.12* | 0.07** | 0.07** | 0.16** |
| | (4.02) | (3.90) | (1.94) | (2.46) | (2.39) | (2.11) |
| Clean=1 # GVC=1 | | -0.37 | | | -0.54 | |
| | | (-1.06) | | | (-0.96) | |
| GVC=1 # log(between) | | -0.05*** | | | -0.04** | |
| | | (-4.04) | | | (-2.33) | |
| Clean=1 # GVC=1 # log(between) | | -0.07 | | | -0.13 | |
| | | (-1.24) | | | (-1.51) | |
| Clean=1 # EIF=1 | | | 0.13 | | | 0.29 |
| | | | (0.37) | | | (0.60) |
| EIF=1 # log(between) | | | 0.00 | | | 0.02 |
| | | | (0.42) | | | (1.30) |
| Clean=1 # EIF=1 # log(between) | | | -0.01 | | | 0.02 |
| | | | (-0.24) | | | (0.32) |
| Stage | | | | 0.17*** | 0.17*** | 0.17*** |
| | | | | (12.32) | (12.31) | (12.31) |
| Constant | -1.12*** | -1.09*** | -1.12*** | -1.29*** | -1.28*** | -1.31*** |
| | (-6.83) | (-6.69) | (-6.83) | (-6.67) | (-6.59) | (-6.75) |
| Observations | 35471 | 35471 | 35471 | 25811 | 25811 | 25811 |

p<0.1 *, p<0,05**, p<0,01***; Panel Probit regressions; Not reported: 51 country dummies and 52 industry dummies ; z-Statistics in parentheses; the number of observations in columns (4) to (6) lower, because, for some observations no information about the stage of investment is provided; standard errors clustered at the portfolio-company level.

***Table 15: Regressions with the number of cliques***

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Clean=1 | -0.66** | -0.75*** | -0.60** | -0.58* | -0.64* | -0.41 |
| | (-2.50) | (-2.73) | (-2.19) | (-1.71) | (-1.81) | (-1.18) |
| Log(cliques) | -0.02* | -0.02 | -0.02* | -0.01 | -0.01 | -0.01 |
| | (-1.84) | (-1.55) | (-1.75) | (-0.95) | (-0.85) | (-0.80) |
| Clean=1 # log(cliques) | 0.04 | 0.06 | 0.02 | 0.05 | 0.05 | 0.01 |
| | (1.01) | (1.30) | (0.43) | (0.85) | (0.90) | (0.21) |
| Expertise | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.51) | (1.08) | (0.52) | (0.69) | (0.96) | (0.68) |
| Total funding | 0.18* | 0.18* | 0.18* | 0.23** | 0.23** | 0.23** |
| | (1.86) | (1.83) | (1.86) | (2.28) | (2.28) | (2.28) |
| Syndicate Size | 0.03*** | 0.03*** | 0.03*** | -0.03*** | -0.03*** | -0.03*** |
| | (4.53) | (4.55) | (4.54) | (-2.65) | (-2.64) | (-2.65) |
| Age of the firm | 0.02*** | 0.02*** | 0.02*** | -0.01* | -0.01* | -0.01* |
| | (3.66) | (3.67) | (3.66) | (-1.74) | (-1.73) | (-1.74) |
| HHI | -0.12* | -0.12* | -0.12* | -0.07 | -0.07 | -0.07 |
| | (-1.66) | (-1.65) | (-1.69) | (-0.83) | (-0.85) | (-0.85) |
| GVC=1 | -0.23*** | -0.02 | -0.23*** | -0.21*** | -0.10 | -0.21*** |
| | (-5.95) | (-0.21) | (-5.93) | (-4.25) | (-0.74) | (-4.23) |
| EIF=1 | 0.06** | 0.06** | 0.05 | 0.02 | 0.02 | 0.03 |
| | (2.13) | (2.08) | (0.73) | (0.65) | (0.61) | (0.43) |
| Clean=1 # GVC=1 | | 0.77 | | | 0.95 | |
| | | (1.60) | | | (1.42) | |
| GVC=1 # log(cliques) | | -0.04** | | | -0.02 | |
| | | (-2.39) | | | (-0.97) | |
| Clean=1 # GVC=1 # log(cliques) | | -0.12 | | | -0.12 | |
| | | (-1.35) | | | (-1.00) | |
| Clean=1 # EIF=1 | | | -0.25 | | | -0.87** |
| | | | (-0.74) | | | (-2.04) |
| EIF=1 # log(cliques) | | | 0.00 | | | -0.00 |
| | | | (0.11) | | | (-0.18) |
| Clean=1 # EIF=1 # log(cliques) | | | 0.07 | | | 0.17** |
| | | | (1.29) | | | (2.42) |
| Stage | | | | 0.17*** | 0.17*** | 0.17*** |
| | | | | (10.33) | (10.32) | (10.33) |
| Constant | -1.18** | -1.19** | -1.18** | -0.98** | -0.98** | -0.98** |
| | (-2.48) | (-2.50) | (-2.47) | (-2.14) | (-2.14) | (-2.14) |
| Observations | 26810 | 26810 | 26810 | 19781 | 19781 | 19781 |

p<0.1 *, p<0,05**, p<0,01***; Panel Probit regressions; Not reported: 51 country dummies and 52 industry dummies ; z-Statistics in parentheses; the number of observations in columns (4) to (6) lower, because, for some observations no information about the stage of investment is provided; standard errors clustered at the portfolio-company level.

## *Table 16: Regressions with the maximal betweeness in the clique*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Clean=1 | -0.46 | -0.52 | -0.49 | -0.36 | -0.61 | -0.29 |
| | (-1.33) | (-1.60) | (-1.07) | (-0.48) | (-0.85) | (-0.33) |
| log(between cliques) | 0.00 | 0.00 | 0.02 | -0.01 | -0.01 | 0.01 |
| | (0.08) | (0.11) | (0.52) | (-0.33) | (-0.33) | (0.22) |
| Clean=1 # log(between cliques) | 0.01 | -0.01 | 0.01 | 0.00 | -0.09 | 0.05 |
| | (0.05) | (-0.09) | (0.08) | (0.01) | (-0.31) | (0.12) |
| Expertise | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.18) | (0.35) | (0.21) | (0.64) | (0.67) | (0.64) |
| Total funding | 0.17* | 0.17* | 0.17* | 0.23** | 0.23** | 0.23** |
| | (1.75) | (1.75) | (1.79) | (2.27) | (2.26) | (2.28) |
| Syndicate Size | 0.03*** | 0.03*** | 0.03*** | -0.03*** | -0.03*** | -0.03*** |
| | (4.46) | (4.46) | (4.46) | (-2.65) | (-2.64) | (-2.64) |
| Age of the firm | 0.02*** | 0.02*** | 0.02*** | -0.01* | -0.01* | -0.01* |
| | (3.63) | (3.67) | (3.63) | (-1.74) | (-1.75) | (-1.75) |
| HHI | -0.04 | -0.04 | -0.03 | -0.01 | -0.02 | -0.02 |
| | (-0.56) | (-0.55) | (-0.54) | (-0.20) | (-0.25) | (-0.20) |
| GVC=1 | -0.24*** | -0.41** | -0.24*** | -0.21*** | -0.03 | -0.22*** |
| | (-6.20) | (-2.56) | (-6.22) | (-4.30) | (-0.14) | (-4.35) |
| EIF=1 | 0.05* | 0.05* | -0.07 | 0.01 | 0.01 | -0.16 |
| | (1.73) | (1.71) | (-0.78) | (0.40) | (0.38) | (-1.50) |
| Clean=1 # GVC=1 | | 0.50 | | | 1.44 | |
| | | (0.58) | | | (1.38) | |
| GVC=1 # log(between cliques) | | -0.08 | | | 0.10 | |
| | | (-1.05) | | | (0.86) | |
| Clean=1 # GVC=1 # log(between cliques) | | 0.14 | | | 0.54 | |
| | | (0.34) | | | (1.05) | |
| Clean=1 # EIF=1 | | | 0.15 | | | -0.47 |
| | | | (0.32) | | | (-0.47) |
| EIF=1 # log(between cliques) | | | -0.05 | | | -0.08* |
| | | | (-1.31) | | | (-1.68) |
| Clean=1 # EIF=1 # log(between cliques) | | | -0.01 | | | -0.25 |
| | | | (-0.04) | | | (-0.52) |
| Stage | | | | 0.17*** | 0.17*** | 0.17*** |
| | | | | (10.27) | (10.27) | (10.27) |
| Constant | -1.16** | -1.16** | -1.12** | -0.94** | -0.94** | -0.88* |
| | (-2.33) | (-2.34) | (-2.25) | (-1.97) | (-1.97) | (-1.84) |
| Observations | 26472 | 26472 | 26472 | 19558 | 19558 | 19558 |

p<0.1 *, p<0,05**, p<0,01***; Panel Probit regressions; Not reported: 51 country dummies and 52 industry dummies ; z-Statistics in parentheses; the number of observations in columns (4) to (6) lower, because, for some observations no information about the stage of investment is provided; standard errors clustered at the portfolio-company level.