

VCT Skill and Deal Structure vs. Luck: What Drives the Success of VCT-Backed Firms

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September 10, 2023

Abstract

In this study, we document the importance of Venture Capital Trust (VCT) funding to small, young and risky firms' in the U.K. At a minimum, the VCT scheme is important given that it increases the supply of capital to small, young, and risky firms. Using this as a starting point, we ask whether VCT skills and the funding deal structure or luck determines the success of VCT-backed firms. Beyond the increased supply of capital to small, young and risky firms, do VCT skills and the funding deal structure determine the success of VCT-backed firms? With the aid of a Deep Neural Network Binary Classification model, a Deep Neural Network Regression model, and several attribution algorithms, we quantify the relative importance of VCT skills and the funding deal structure for the success of VCT-backed firms. We find that VCT skills and the funding deal structure are significant determinants of the success of VCT-backed firms. Specifically, prior high financial performance is the most important VCT skill determinant of the success of VC-backed firms, contributing an average of 13% to the success of VCT-backed firms.

Keywords: Venture Capital Trust, Deep Neural Network, Hand-Collected Data, Feature Importance.

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1 Introduction

The Venture Capital Trust (VCT) Scheme is designed to support U.K. based, young, private companies. As stated in Her Majesty’s Revenue and Customs (HMRC) (2016) internal manual “The VCT scheme encourages indirect investment by individuals, through a VCT, a corporate vehicle similar to an investment trust, into small, high-risk companies or social enterprises, to help them grow and develop.”¹ Crucially, the VCT scheme creates value for the U.K. economy. Classic pecking order theory implies that outside equity is the least preferred source of financing for firms. However, due to a lack of cashflows, firms might prioritise external equity as a source of financing. But, especially for start-ups, they face significant equity financing constraints as a result of capital market frictions such as information asymmetry, which inspires the need for a governmental policy intervention such as the VCT scheme. The VCT scheme, which broadens the range of financing instruments available to start-ups and increases the supply of capital to them as well, meets their demand for external equity financing, and allows for the U.K. economy to extract economic rents from entrepreneurship. As to whether VCTs skilfully deploy this increased supply of capital, Kaplan and Schoar (2005) uncover sizeable persistence and heterogeneity in VC success and attribute both results to VC skill and heterogeneity in VC skill. However, Sørensen (2007) finds that endogenous selection bias is twice as important as VC skill for explaining the observed heterogeneity in VC success.²

We find that VCTs are skilled along several dimensions, and these skills, in addition to the funding deal structure, are significant determinants of the success of VCT-backed firms. Our goal is to develop a numerical algorithm that would allow for the quantification of the relative importance of each measure of VCT skill and the funding deal structure for the success of VCT-backed firms, whilst alleviating the obvious endogenous selection bias inherent in our study. We find that being backed by a VCT with high prior financial performance is the most important VCT skill determinant of the success of VCT-backed firms, contributing an average of 13% to the success of VCT-backed firms. High prior performing VCs have been shown to positively impact the per-

¹VCTs are akin to VCs but also similar to private equity investment trusts which invest in unquoted companies. However and unlike VCTs, the companies private equity trusts invest in tend to be quite big, established businesses.

²Although the Kaplan and Schoar (2005) and Sørensen (2007) studies concern VCs, the analysis is still relevant considering VCTs are akin to VCs

formance of VC-backed firms. Sorensen (2007) shows that when a firm receives backing from a VC with prior success, it acts as a credible signal of unobserved firm characteristics to financial markets, and thus positively affects firm value. Nahata (2008) further reiterates how the prior success of a VC captures the VCs screening and monitoring expertise. In a VC (as opposed to VCT) context, several studies have shown that VC added services as embodied in their skills, are value generating. Kaplan and Schoar (2005) uncover sizeable persistence and heterogeneity in VC success and attribute both results to VC skill and heterogeneity in VC skill. Particularly, heterogeneity and persistence persists if new VCs cannot compete effectively with established VCs. Sørensen (2007) also finds that VC skill is an important determinant of VC success. Although, Sørensen (2007) also finds that endogeneity is twice as important as skill for explaining the observed heterogeneity in VC success. In a similar vein, Ewens, Gorbenko and Korteweg (2022) confirm the first-order importance of VC pre-investment skills (deal sourcing) for the success of VC-backed firms. They employ a dynamic search-and-matching model to deal with endogenous selection and study the impact of VC contract terms on VC-backed firm value. They find that VCs add value to their firms.

In a causal study like ours, as with the aforementioned studies as well, endogenous selection as opposed to VCT skill could drive the match between VCTs and VCT-backed firms. The following conjecture draws on the conjecture in Sorensen (2007). Consider entrepreneurial firms with high potential who also understand that VCT skills are a source of value-added for them. In this conjecture, these high potential entrepreneurial firms will seek to match with the most skilled VCTs. In turn, highly skilled VCTs will enjoy access to a proprietary deal flow of high potential entrepreneurial firms. Indeed, Sorensen (2007) reiterates how VCs consider access to proprietary deal flow as a distinct competitive advantage. Thus, and as discussed in Sørensen (2007), the resultant endogenous selection bias implies that VCT skills are not the sole determinant of the ex-post success of these VCT-backed firms (high potential entrepreneurial firms). Instead, these VCT-backed firms with backing from highly skilled VCTs are intrinsically better than VCT-backed firms with backing from lesser skilled VCTs. To further illustrate based on the illustration in Sorensen (2007), let us consider a standard regression model. Here, VCT skills are endogenous when selection bias causes highly skilled VCTs to invest in firms that are superior along several dimensions - unobserved in the data. VCT-backed firms with superior unobserved

features i.e. a dedicated management team, as reflected in the error term, will match with skilled VCTs. Thus, the error term is positively correlated with VCT skills, and the estimated coefficient is positively biased, relative to the actual impact of VCT skills on the success of VCT-backed firms. Clearly, the ability of the most skilled VCTs to determine the success of the firms they back and the desire of intrinsically better firms to match with the most skilled VCTs are not mutually exclusive (Sorensen (2007)). Our challenge is thus to estimate the importance of VCT skills for determining the success of VCT-backed firms, whilst controlling for endogenous selection bias.

A popular approach to dealing with endogenous selection bias is to estimate a model with instrumental variables as a source of exogenous variation. However, for any instrumental variable to be valid, it must be correlated with the skill of VCTs but independent of the success of VCT-backed firms. Clearly, such instrumental variables are difficult to find. We also know that the two-stage-least-squares (2SLS) - which is a popular estimation approach that uses instrumental variables - makes strong assumptions on the causal model. For instance, the 2SLS will specify a linear relationship between various measures of VCT skills and the success of VCT-backed firms. However, as we will show in a later section, the relationship is non-linear. Also, in a study of 1309 instrumental variables regressions in thirty papers published by the journals of the American Economic Association, Young (2022) employs Monte Carlo simulations and the bootstrap to show that instrumental variable methods yield estimates that seldom outperform estimates produced by biased ordinary least squares. Another popular approach employs structural models to deal with endogenous selection bias. Nonetheless, these structural approaches are computationally intensive which necessitates the adoption of numerous simplifying assumptions to allow for model tractability (Sørensen, 2007, p. 2728).

We deal with the lack of valid instruments, assumptions of linear relationships in the 2SLS, and limitations of structural models, by developing a Deep Neural Network framework, adopting several attribution algorithms, and hand-collecting VCT data to estimate and quantify the relative importance of VCT skills and the funding deal structure for the success of VCT-backed firms. The Deep Neural Network is a flexible model that adopts a data-adaptive self-learning approach to modelling the relationship between VCT skills, the funding deal structure and the success of VCT-backed firms. It is also referred to as Deep Learning, which means that the

model employs interconnected nodes and non-linear mathematical functions, in a multi-layered structure, to continuously learn and capture complex (non-linear) mappings between VCT skills, the funding deal structure and the success of VCT-backed firms. It does not suffer from the the “curse of dimensionality” problem that structural models suffer from, neither does it require the simplifying assumptions that structural models require. Nonetheless, it is widely acknowledged that the lack of interpretability of the output of Deep Neural Network models detracts from its tractability and superior performance. This is where the attribution algorithm comes in. The attribution algorithm enables us extract from the estimates of our Deep Neural Network model, the actual causal effect of each measure of VCT skill and the funding deal structure on the success of VCT-backed firms. Formally, attribution algorithms are algorithms that capture the effect of an independent variable on the output of a model (Sundararajan, Taly and Yan, 2017), which is an inherently causal task. Now, although this combination of a Neural Network and attribution algorithm allows us to sidestep in a data driven manner - the endogenous selection bias issue described earlier, we conduct a robustness check to ensure and demonstrate that our approach does indeed alleviate the endogenous selection bias issue. This robustness check draws on the work of Sørensen (2007), who finds that VC-backed firms with backing from highly experienced VCs are more successful, but that a large proportion of the success is attributable to endogenous selection bias. To that end, we exclude from the analysis, observations for the most experienced VCTs and the firms they backed, and still find that VCT skills and the funding deal structure are important determinants of the success of VCT-backed firms.

Analysing the VCT scheme is all the more important given that it creates value for the U.K. economy, particularly through the increased the supply of capital for small, young and risky firms in the U.K. In excess of £9 billion has been raised by circa 200 VCTs since inception of the scheme in 1995. These monies have had a positive measurable impact: Iweze (2020) shows that the scheme led to an aggregate increase of 41% in the investment of VCT-backed firms between 2003-2018. The Association of Investment Companies (AIC) report how the VCT scheme is associated with an average increase of 51 new employees per VCT-backed firm, post-VCT funding.³ Media reports also enunciate the importance of VCT-backing for VCT-backed firms. For instance, when Convertr Media received £3 million in Series A funding from Albion Ventures in

³Details on this statistic are available at: <https://www.theaic.co.uk/system/files/search-hidden-file/AICVCTDeliveringGrowthOct15.pdf>

2016, and as part of the funding deal, welcomed a partner from Albion Ventures to their board, they highlighted the importance of Albion Ventures expertise to their operations, stating “With a history of working with other tech specialists including , Albion Ventures will bring a depth of knowledge and experience to our operation and this funding will enable us to build on and expand our offering to a wider international market”.

Given the importance of VCTs to VCT-backed firms, the U.K. economy, their positive measurable impact and substantial cost to the taxpayer,⁴ as reported in Iweze (2020), our research question on whether VCT skill or luck determines the success of VCT-backed firms is even more pertinent. An ever growing financial economics literature has and continues to study VCs and their skills at: pre-investment screening, deal-selection, deal contracting and post-investment monitoring and advising. Along the post-investment dimension, Lerner (1995) shows that VCs are influential in the structuring of the boards of directors of the firms they back. Also, Amorn-siripanitch, Gompers and Xuan (2019) find that VCs aid in hiring outside managers and directors for their firms, with these VC-backed firms also likely to exit via relationship-based acquisitions. We also have survey evidence of post-investment value-added documented in Gompers, Gornall, Kaplan and Strebulaev (2020), where VCs enumerate the post-investment services they provide to their firms, ranging from strategic guidance, connecting them with investors and customers, operational guidance, to hiring employees and board members. As highlighted earlier, these VC skills have also been shown to be value generating. Gompers, Gornall, Kaplan and Strebulaev (2020) find that pre-investment skills are more important for VC returns relative to post-investment skills. However, they go a step further in that, in their survey, they make the distinction between deal sourcing and deal selection, with deal selection being the most important value-generating service VCs provide their firms. Sørensen (2007) finds that firms funded by highly experienced VCs are likely to go public. This result stems from the direct impact of the highly experienced VCs and sorting, which leads experienced VCs to invest in better firms. Sorting creates an endogenous selection problem. The study resolves this problem with the aid of a two-sided matching structural model to separately identify and estimate direct impact and sorting. The study finds that both effects are significant and sorting is twice as crucial for explaining the heterogeneity in exit rates across VCs. Similarly, Nanda, Samila, and Sorenson (2020)

⁴For instance, Iweze (2020) details how the VCT scheme cost taxpayers a conservative £201 million in subsidy expenditure in the 2017/2018 fiscal year.

show a reverse relationship between pre-investment skills and VC performance. They analyse VC performance correlations and find that subsequent exits via IPOs are 8% higher than previous IPOs. They conclude that the reason for the subsequent increased exit performance is that the initial successful exit performance improves access to deal-flow (deal sourcing). Regarding deal structure and firm success, Hochberg, Ljungvist, and Lu (2007) find that VC-backed firms that were financed by a syndicate of VCs have a higher likelihood of surviving to subsequent funding rounds, and highly networked VCs produce higher performance as measured by their exit (via IPO and trade sale) ratio.

Two important studies on VC performance are the Achleitner, Engel, and Reiner (2013) and Calder-Wang and Gompers (2021) study. In the former, they analyse how market factors affect VC returns. They employ a proprietary dataset on VC investments to study how market-related volatility impacts VC returns. They find that demand related factors (increase in entrepreneurial activity) initially results in higher returns. They also find that over-funding or over-reaction to the supply of VC funding destroys VC returns. In the latter study, they study whether diversity leads to improved performance of VC-backed firms. They find that when VC partners have female children, there is an increased likelihood that the VC will employ female partners. Additionally, the increased gender diversity improves overall VC performance. In summary, both studies show that VCs have an impact on the market value of VC-backed firms. The latter study especially shows how VC diversity can positively impact the success of VC-backed firms.

In this study, we quantify the relative importance of VCT skills and the funding deal structure for VCT-backed firms success. To begin, we thoroughly analyse the VCT funding of VCT-backed firms from multiple angles. In our empirical tests, we analyse the interplay between the characteristics of VCT-backed firms, the funding deal structure, and the skills of VCTs. We then quantify the relative importance of each measure of VCT skill and the funding deal structure in determining the success of VCT-backed firms. We begin with a simple univariate analysis, where we uncover an enduring relationship between VCTs and VCT-backed firms. In the aggregate, VCTs hold between 19% to 31% equity stake in VCT-backed firms, 56% of VCT-backed firms received multiple VCT funding rounds, and of those, 48% received multiple funding rounds by their original VCT-backers. We find that 44% of VCT-backed firms are successful compared to 56% unsuccessful. Pertinently, the archetypal VCT-backer of successful VCT-backed firms is

remarkably more skilled along several dimensions - relative to the the archetypal VCT-backer of unsuccessful VCT-backed firms. Also, the observed financing deal structure is different for successful relative to unsuccessful VCT-backed firms. These differences are consistent with the prior literature's assertion that VCs are skilled along several pre and post investment dimensions, and these skills are value generating. With our Deep Neural Networks (binary classification and regression models) and attribution algorithms, we are able to measure and rank the relative importance of each measure of VCT skill and the funding deal structure for the success of VCT-backed firms.

Given our finding that being backed by a VCT with high prior financial performance is the most important VCT skill determinant of the success of VCT-backed firms, contributing an average of 13% to the success of VCT-backed firms. This contributes to the Sorensen (2007) finding wherein they show that when a firm receives backing from a VC with prior success, it acts as a credible signal of unobserved firm characteristics to financial markets, and thus positively affects firm value. It also contributes to the Nahata (2008) finding where they show that the prior success of a VC captures the VCs screening and monitoring expertise. To the best of our knowledge, our study is the first to formally quantify the relative importance of various measures of VCT skill and the funding deal structure for the success of VCT-backed firms. Our finding that VCT skills impact the success of VCT-backed firms is also relatable to the Iliev and Lowry (2020) result which shows that VCs are skilled at solving the information asymmetry problem that constrains new IPO firms from accessing growth capital. We also contribute to the literature on the role of VCTs and the VCT scheme. We fill in some of the gaps in our understanding of what VCTs do. Iweze (2020) showed the importance of the VCT Scheme to the U.K. economy albeit at a substantial cost to the U.K. tax payers in the form of tax rebates enjoyed by VCT investors. Our result further justifies this cost in the sense that VCTs play an important role in the success of VCT-backed firms, through the pre and post investment skills they bring to bear on these firms, which in turn has wider implications for entrepreneurship in and growth of the U.K. economy. The outline of our paper is as follows. In Section 2, we discuss the VCT data hand-collection process and present the VCT hand-collected data. We also present the descriptive statistics. Sections 3 and 4 introduces our machine learning approach, presents and discusses our results. Section 5 summarises and concludes.

2 Data and Descriptive Statistics: VCT Skill and Deal Structure

From the Companies House Database, we downloaded and manually read through VCT annual report between the periods 2014 to 2020. From these reports, we collated details on VCTs and the firms that received VCT funding (VCT-backed firms). We thereafter collected financial data on these VCT-backed firms from the FAME database. We lost approximately 13% of our hand-collected data due to a combination of non-reporting of valuations by some VCTs for some of their VCT-backed firms, and the lack of financial data for some VCT-backed firms on the FAME database. Our final sample consists of 3,629 VCT-backed firms backed by 44 VCTs, spanning the period 2014-2020. Although the VCT scheme was introduced in 1995, we began our analysis in 2015 (this reduced our sample to 1,953 VCT-backed firms) because of the structural changes, or if you will, VCT policy changes, introduced by the U.K. government in July 2015 to bring the VCT scheme in line with the European Union's risk capital guidelines. These policy changes - extensively covered in Iweze (2020) and summarised below - caused a structural break in the VCT investment landscape such that the pre-2015 period is structurally different from the post-2015 period. We illustrate below with a few key policies of the VCT scheme, at the start of the scheme in 1995 vs. 2020.

- 1995: No age restrictions on a potential VCT-backed firm.
2020: The maximum age for a potential VCT-backed firm is 7 years old (10 years old for knowledge-intensive firms) since its first commercial sale.
- 1995: VCTs could purchase existing shares i.e. Management Buyouts were permitted.
2020: VCTs can only invest to fund growth: VCT investment cannot be used to finance acquisitions or to buy existing shares. Companies must be able to satisfy HMRC's "risk to capital" condition ⁵.

⁵The "risk to capital" condition requires a potential VCT-backed firm, at the time of investment, to be an en-

- 1995: No limit to the amount of VCT funding a VCT-backed firm can receive.
2020: VCT-backed firms are subject to an overall lifetime limit on VCT funding of £12 million (£15 million for knowledge-intensive firms).
- 1995: 70% of funds-raised by a VCT must be invested in Qualifying Investments (QI) by the third year, post-fundraise.
2020: Non-qualifying investments can no longer be made, except for certain exemptions in managing the Company's short-term liquidity. A minimum of 80% of funds raised must be invested in QIs: 30% of cash raised must be invested in QIs⁶ within the first accounting period following fundraising.

2.1 Data on VCTs and VCT-Backed Firms

The data hand collection entailed reading through the half-year and annual reports filed by each VCT, and SHO filings⁷ by VCT-backed firms between the periods 2014-2020. From the reports, we extracted details on fundraising activity during the year, a breakdown on the uses of funds: what firms were invested in during the year, how the funding deal was structured (mix of equity and debt or equity only), and the equity percentage received by the VCT. We also extracted details such as the current valuation of VCT-backed firms, acquisitions and disposals during the year, and financial statement line items such as: Gains/Losses on Investment, Net Asset Value, Total Value to Paid-In (See Appendix for a description of all variables). Our complete dataset contains 4,178 VCT-backed firms, hand-collected from VCT annual reports between 2014-2020. Next, we obtained the annual financial statements of these VCT-backed firms from the FAME database. By nature of the regulations guiding the VCT Scheme, almost every firm that receives VCT funding is a small firm⁸. And because the disclosure rules for small firms are less stringent (relative to

entrepreneurial firm with the objective to grow and develop, and VCT investment in the firm must carry with it, a genuine risk of loss of capital. Further details on the risk to capital conditions are available at: <https://www.gov.uk/hmrc-internal-manuals/venture-capital-schemes-manual/vcm8530>

⁶QI is an entrepreneurial company with the objective to grow, develop and which has a genuine risk of loss of capital.

⁷Paper forms used by limited companies to notify Companies House of a change to their share capital.

⁸The Companies House Accounting Guidance (2021) defines a small company as one with a maximum annual turnover of £10.2 million, maximum total assets of £5.1 million and an average number of em-

medium or large firms), their coverage on the FAME database is spotty, with empty entries in numerous financial statement line items. As a consequence, we omitted firms without financial information on the FAME database. This, in addition to the non-reporting of valuation by some VCTs for some of their VCT-backed firms, reduced our hand-collected data by 13%, from 4,178 to 3,629 VCT-funded firms. Of the 3,629 VCT-funded firms, 98% are classed as SMEs on the FAME database. The remainder 2% comprises short-term equity investments that do not meet the QI criteria but are used by VCTs for short-term liquidity management. We also excluded from the analysis, numerous financial statement line items (i.e. CAPX, Revenue, Profits, R&D etc.) that could potentially serve as control variables. This is because of the aforementioned disclosure rules for small firms, which results in more than two-thirds of VCT-backed firms not reporting numbers for these line items. Finally, by starting our analysis in 2015, for the earlier detailed reasons, our analysis employs 1,953 VCT-backed firms, backed by 44 VCTs.

In Figure 1, we plot the annual aggregate funding of First-Time vs. Post-First-Time VCT-backed firms. Each year, the majority of VCT GBP investment (between 76% and 83%) goes to firms that had received VCT funding in previous years (red line). At first glance, this observation is puzzling given that the VCT scheme regulations preclude VCTs from funding firms older than 7 years (10 years for knowledge intensive firms), thus impacting a VCT's ability to multiple-fund its firms before the age restriction "bites". However, VCTs mitigate this concern by shortening the Average Time Between Successive VCT Funding Rounds (ATBFR) to 13 months (see Table 1.) whereas from the Crunchbase (2018) study, we know that the Average Time Between Successive VC funding rounds (ATBFR) is 24 months.⁹

2.2 Measuring Success of VCT-Backed Firms

We measure the success of a VCT-backed firm or if you will, a VCT investment, as an equity investment with an unrealised Internal Rate of Return (IRR) greater than or equal to 5%, which is an approximation of the average hurdle IRR at and above which VCTs earn a performance incentive fee (see Table 7 in Appendix). VCT investment managers earn a performance incentive

employees below 50. Further details can be found at: <https://www.gov.uk/government/publications/life-of-a-company-annual-requirements/life-of-a-company-part-1-accounts>)

⁹The ATBFR for VC is publicly available: <https://news.crunchbase.com/news/the-time-between-vc-rounds-is-shrinking/>

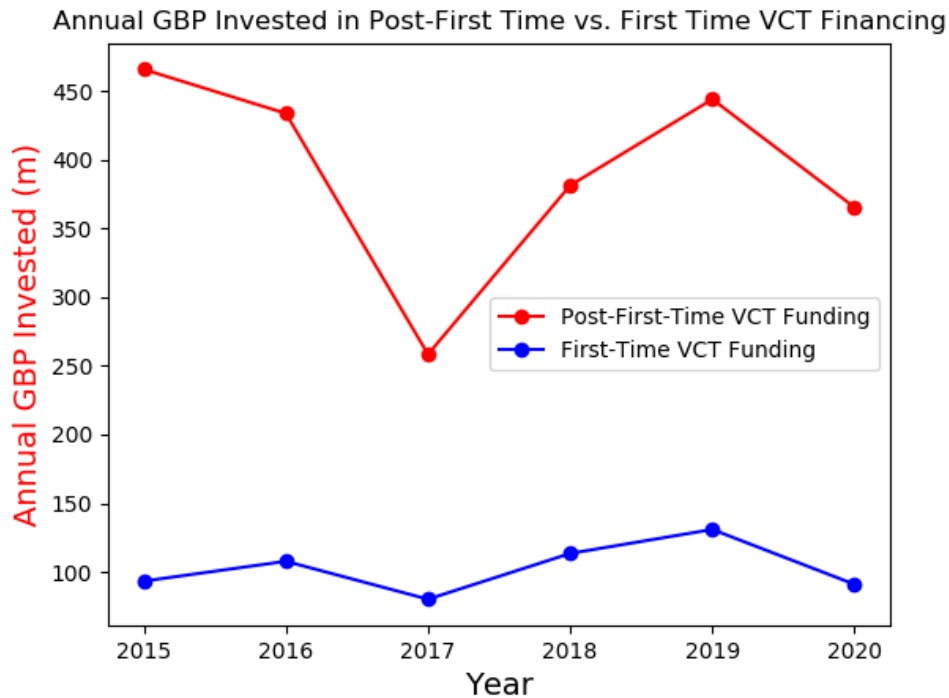


Figure 1: Annual GBP Invested in Post-First-Time vs. First-Time VCT Financing

fee which is supposed to align their interest with their shareholders interests. The aggregate VCT investment managers performance incentive fee is triggered if the VCTs total returns (change in NAV plus dividends paid over an accounting period) exceeds a hurdle rate of 5% (see Table 7 in Appendix). If the VCT investment manager achieves this 5% performance hurdle rate, they earn a performance incentive fee of between 10-20% of the excess of total returns over the 5% hurdle rate. However, if the VCT investment manager fails to meet the 5% performance hurdle rate in an accounting period, the deficit is carried forward to subsequent accounting periods and must be cleared before a performance incentive fee becomes due.

2.3 Descriptive Statistics: VCTs and VCT-Backed Firms

In Table 1., we present descriptive statistics for the 1,953 VCT-backed firms and for the subsets of 851 successful VCT-backed firms compared to the 1,102 unsuccessful VCT-backed firms, where the success of a VCT-backed firm is as defined in the previous section. Our descriptive statistics cover the funding deal structure, our measure of VCT-backed firm success, independent variables

that proxy for VCT skill, and financial variables, with the financial variables measured in the fiscal year of each VCT-backed firm's most recent valuation. For each VCT-backed firm, the variables that proxy for the skill of each of its VCT backers are measured in the fiscal year prior to the first time the VCT-backed firm received VCT funding from the VCT whose skill we are measuring. In column (1), we report means for the 1,953 VCT-backed firms. In column (2), we report means for the 851 successful VCT-backed firms subset and in column (3), we report means for the 1,102 unsuccessful VCT-backed firms subset. In the final column, statistical significance of the differences between subset means at the 1%, 5%, and 10% levels are represented by ***, **, and * respectively.

Successful VCT-backed firms are more likely to have been backed by VCTs in the Top 5. We see from Table 1., that a greater number of Top 5 VCTs backed successful relative to unsuccessful VCT-backed firms. The Top 5 ranking is based on the second measure of VC reputation in the Nahata (2008) study, which is a VC's share of aggregate investment in the VC industry. Nahata (2008) motivates this measure by observing how a higher share of aggregate investment implies a higher share of funds committed by LPs who invest in a VC based on the VC's reputation. Additionally, the Nahata (2008) study further motivates this measure by noting that the Hsu (2004) study implies reputable VCs have a larger investment opportunity set and are likelier to have a higher share of aggregate investment. For each VCT, we calculate its annual Top 5 ranking based on its market share, which is the GBP valuation of all the firms it backed as a fraction of the GBP valuation of all VCT-backed firms in the VCT funding ecosystem. Top 5 VCTs are VCTs that rank in the highest quintile of VCT market share. To wit, we also see in Table 1., that VCTs with specialisation in funding the FTSE-Industry (FTSE-Industry Experience/Total Experience (%) of all First-Time VCT Backers) of its firms, overwhelmingly funded successful relative to unsuccessful VCT-backed firms. We also see in Table 1., that relative to unsuccessful VCT-backed firms, the VCT backers of successful VCT-backed firms have more experience in funding the FTSE-Industry (Log(FTSE-Industry Experience Count of all First-Time VCT Backers)) of its firms. To construct this variable, which is the numerator in the above specialisation variable, we follow Gompers, Kovner, and Lerner (2009) in computing a VCT's experience cumulatively ¹⁰. For instance, consider a software firm (FTSE-Industry is Technology) backed by Unicorn AIM

¹⁰The specialisation variable is also cumulated. Please see Appendix for a description of all variables.

VCT for the first time in 2020. The FTSE-Industry funding experience of Unicorn AIM VCT in 2020 is the total number of funding rounds it has participated in, in the Technology FTSE-Industry, prior to funding the software firm. The difference between this experience variable and the previously mentioned specialisation variable is that the specialisation variable is calculated using the experience variable as the numerator, and the total count of all investments made by the VCT in all industries as the denominator.

Next, we see that VCTs with High Prior Performance overwhelmingly backed successful relative to unsuccessful VCT-backed firms, where we measure a VCT's performance as the annual return on its portfolio of assets. VCTs with high prior performance are those VCTs that rank in the highest quartile of performance among the universe of VCTs in existence at the time. To reiterate, High Prior Performance, as with the other variables that proxy for VCT skill, is measured for each VCT-backed firm. So, # First-Time VCTs with High Prior Performance is the number of VCTs that backed a firm (where we only consider the first time a VCT backed a firm) where said VCT's prior performance ranked in the highest quartile of VCT performance among all VCTs. Analogously, we measure # First-Time VCTs with Low Prior performance as the number of VCTs that backed a firm where said VCT's prior performance, the first time it backed the firm, ranked in the lowest quartile of VCT performance among all VCTs. We see that VCTs with Low Prior Performance overwhelmingly backed unsuccessful relative to successful VCT-backed firms. These results are robust to the use of an alternative measure of VCT performance. This alternative measure of performance - also segmented into quartiles - is Total Value to Paid-In capital (TVPI). TVPI is the current value of outstanding investments plus the cumulative value of all distributions to date divided by the total amount of capital paid into the VCT to date.

From the descriptive statistics in Table 1., we also see that relative to unsuccessful VCT-backed firms, successful VCT-backed firms were backed by a greater number of young VCTs. For each VCT-backed firm, this binary measure of VCT skill is defined as the number of young VCTs that financed the firm, where young is defined as 15 years old¹¹ or younger at the time of the funding. This finding is surprising because of the Gompers (1996) finding of young VCs and the underpricing of their IPOs.

We will soon employ multivariate approaches to test the strength of these successful vs. unsuc-

¹¹The results are robust to setting the threshold for young at 12 and 8 years old respectively.

successful VCT-backed firms differences. Nonetheless, we have thus far seen that our measures of VCT skill reinforces a success-driven-by-skill hypothesis (except for the young VCT measure). To wit, unsuccessful VCT-backed firms were mostly backed by less skilled VCTs. We now turn to the funding deal structure. We observe that relative to unsuccessful VCT-backed firms, successful VCT-backed firms received more VCT funding, were held for shorter periods, and underwent an equal number of VCT funding rounds but with a greater length of time between funding rounds (ATBFR measured in years). In summary, the funding deal structure tells us that, relative to unsuccessful VCT-backed firms, VCTs invest more money in successful VCT-backed firms, they do this over an equal number of funding rounds, and the duration between funding rounds for successful VCT-backed firms is closer to the average duration seen in the wider VC industry. Additionally, the majority (62%) of successful VCT-backed firms received multiple funding rounds (MFR), as seen in Table 1., whereas for unsuccessful VCT-backed firms, the minority (42%) received multiple funding rounds.¹² This also reinforces a success-driven-by-funding deal structure hypothesis. As discussed in Ewens, Nanda, and Rhodes-Kropf (2018), some VCs are moving toward a “spray and pray” strategy whereby they invest smaller amounts in an increased number of startups and spend less time managing and monitoring each one of them - until they startup realises some success. A single funding round indicates a lack of long-term relationship between VCT and VCT-backed firm or a lack of intermediate success by the VCT-backed firm, or both, with a single funding round VCT-backed firm losing out on the benefits of its VCT’s skill. This statistic also provides suggestive evidence consistent with the Information-Asymmetry Hypothesis in Iliev and Lowry (2020): the benefits of receiving multiple funding rounds from existing VCT (VC in their case) backers are greatest among VCT-backed firms with positive NPV projects but high information asymmetry. To wit, skilled VCTs are equipped to overcome such financing friction. As with the previously discussed statistics, these differences also provide suggestive evidence in support of the funding deal structure as a key determinant of the success of VCT-backed firms.

Thus far, we have discussed how VCT backers of successful VCT-backed firms are more skilled along several dimensions relative to the VCT backers of unsuccessful VCT-backed firms. We

¹²We measure the MFR variable at the firm instead of the trust level. i.e. Downing One VCT Plc, Downing Two VCT Plc, Downing Three VCT Plc, Downing Four VCT Plc, Chrysalis VCT Plc, and Draper Espirit VCT Plc are all managed/administered by and therefore grouped as Downing LLP.

have also seen a clear delineation between the deal structure for successful vs. unsuccessful VCT-backed firms. We now firmly turn our attention to the VCT-backed firms themselves. Relative to unsuccessful VCT-backed firms and from Table 1., we observe that the archetypal successful VCT-backed firm is of equal size (Total Assets), older (VCT-Backed Firm Age), has more cash-to-assets and lower debt-to-assets. In upcoming sections, and with the aid of supervised machine learning techniques, we quantify the relative importance of VCT skills and the funding deal structure for the success of VCT-backed firms. But first, we present a primer on our machine learning approach.

Table 1: Descriptive Statistics

Our sample consists of 1,953 VCT-backed firms between 2015 and 2020, defined as U.K. firms that received funding from VCTs within the time period. We require all firms to have FAME data. Independent variables for VCT skill are measured in the fiscal year prior to the first time a VCT funded a firm and financial variables are calculated at the fiscal year end of each VCT-backed firm's most recent valuation. In Panel A, column (1) presents means for the 1,953 VCT-backed firms in our sample. In Column (2), we report means for the 851 successful VCT-backed firms subset and in column (3), we report means for the 1,102 unsuccessful VCT-backed firms subset, though missing FAME data means some of the financial variables are based on fewer observations. In the final column, statistical significance of the differences between sub-sample means at the 1%, 5%, and 10% levels are represented by ***, **, and * respectively. Variables are described in the Appendix. In Panel B, we present descriptive statistics on the 44 VCTs in our sample for the sample period 2015-2020, where each column reports mean values for each year of our sample period.

	Panel A: Descriptive Statistics for VCT-Backed Firms			Mean-Difference
	VCT-Backed Firms	(851) Successful VCT-Backed Firms	(1,102) Unsuccessful VCT-Backed Firms	
Unrealised IRR (%)	5.38	32.73	-15.74	0.485***
VCT Skill Measures				
# First-Time VCT Backers in Top 5	0.91	1.13	0.74	0.397***
FTSE-Industry Experience/Total Experience of all First-Time VCT Backers (%)	18.47	21.46	16.17	0.053***
Log(FTSE-Industry Experience Count of all First-Time VCT Backers)	3.98	4.04	3.94	0.097*
# First-Time VCTs with Low Prior Performance	0.75	0.67	0.81	-0.144***
# First-Time VCTs with High Prior Performance	1.10	1.39	0.88	0.508***
# First-Time VCTs that are Young	0.78	0.91	0.68	0.233***
Deal Structure				
# Funding Rounds	2.10	2.09	2.10	-0.0120
Log(Total VCT Funding)	6.78	7.15	6.50	0.649***
ATBFR(Years)	1.11	1.15	1.08	0.066***
Holding Period (Years)	2.12	2.10	2.14	-0.0460

(Continued)

Table 1: *Continued*

Panel A: Descriptive Statistics for VCT-Backed Firms				
	VCT-Backed Firms	Successful (851) VCT-Backed Firms	Unsuccessful (1,102) VCT-Backed Firms	Mean-Difference
VCT Equity Stake in VCT-Backed Firms (annual range: %)	19-31	18 - 32	20 - 30	
Multiple Funding Rounds (%)	55.84	62.03	41.87	-
Multiple Funding Rounds sameVCT (%)	47.67	-	-	-
Control Variables				
VCT-Backed Firm Age	10.95	11.82	10.28	1.539**
Log(Total Assets)	11.17	11.08	11.27	-0.191
Debt-to-Assets	0.47	0.43	0.51	-0.075***
Cash-to-Assets	0.53	0.57	0.49	0.067***

(Continued)

Table 1: *Continued*

Panel B: Descriptive Statistics for VCTs									
	2015	2016	2017	2018	2019	2020			
Net Asset Value (in millions)	57.26	63.96	63.86	87.57	97.51	114.60			
Investment Income / Net Asset Value (%)	3.16	2.87	2.40	2.19	2.18	2.10			
Investment Management Fees / Net Asset Value (%)	2.00	2.26	2.24	1.94	2.09	2.07			
Total Dividend Payout / Net Asset Value (%)	9.22	9.25	9.51	9.00	8.72	7.82			
Total Value (Net Asset Value plus Cumulative Dividends Paid in millions)	63.11	71.37	98.01	95.43	105.36	122.55			
Total Capital Paid in to Date (in millions)	63.83	72.65	86.60	104.03	119.92	142.84			
Total Value to Paid in (TVPI in multiples)	1.66	1.70	1.65	1.74	1.74	1.83			
Fundraising in the Year (in millions)	9.84	13.18	17.44	19.95	22.14	18.54			
Fundraising to Net Asset Value (%)	18.89	18.94	51.21	24.39	21.03	24.83			

3 Primer on Deep Neural Networks and Attribution Algorithms

Deep Neural Networks or Artificial Neural Networks are a series of algorithms that form an important sub-field of Machine Learning. The Deep Neural Network architecture in Figure 2. is composed of interconnected group of nodes called neurons or activation functions, where a neuron or activation function is a differentiable non-linear mathematical function that receives data as input, conducts a transformation on the data, and produces an output, which may be the final output or act as an input for the next neuron.

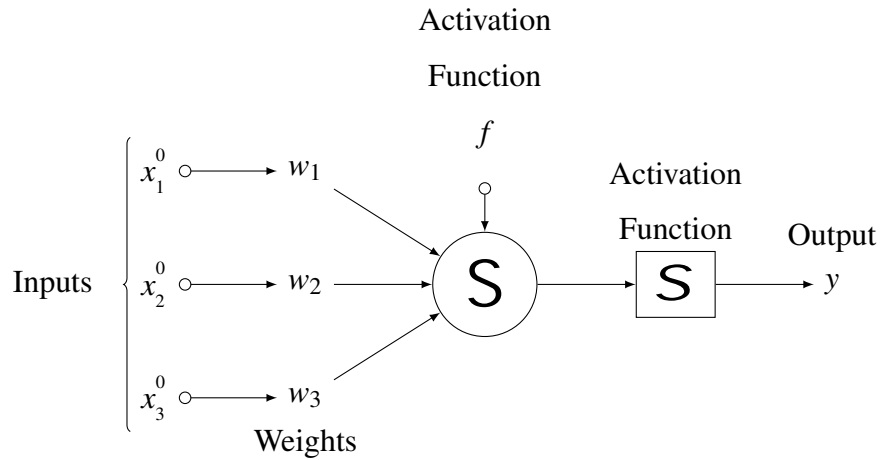


Figure 2: Simple Neural Network Architecture with One Hidden Layer

For illustration purposes, we have kept the Neural Network simple by drawing the architecture with one input layer, one hidden layer (weights and activation function S) and the output layer, whilst ignoring the addition of a bias vector to the neurons in the hidden layer, which together with the weights, are learnable parameters. Of course, the Deep Neural Network Binary Classification model and Deep Neural Network Regression model we build and employ in this study has multiple hidden layers. The x_1^0 are the input data, the w_1 are weight matrices connected to the neurons in the input layer and hidden layer, and are conceptually similar to coefficients in a regression. There are many non-linear activation functions. For instance, the *sigmoid* non-linear activation (which we use in this study) function allows us to uncover non-linear relationships between variables, and is given by:

$$S = \frac{1}{1 + e^{-z}} ,$$

where z is a matrix. For a Deep Neural Network Binary Classification model, the output layer (y) is a binary output that undergoes a *softmax* (S) operation, where *softmax* is a mathematical function that converts a vector of numbers (z) into a vector of probabilities, and is given by:

$$S(z)_i = \frac{e^{z_i}}{\sum_{j=1}^K e^{z_j}} ,$$

where S is *softmax*, $(z)_i$ is an input vector, e^{z_i} is a standard exponential function for the input vector, K is the number of classes in the binary classifier, and e^{z_j} is a standard exponential function for the output vector. In conclusion, we summarise the key steps of our Deep Neural Network in Algorithm 1.

We now elaborate on our Deep Neural Network Binary Classification (DNNBC) model based on the steps in Algorithm 1. To begin, a tensor is a specialised data structure that is similar to a matrix, and is useful for encoding the inputs, outputs, and parameters of a model. Tensors can run on GPUs or other specialised computing hardware to speed up computing. Our DNNBC model has an architecture of 2 hidden layers, the first with 14 hidden units (corresponding to the number of independent variables) and the second with 9 hidden units (this number of hidden units is a fine-tuned hyper-parameter), each with *Sigmoid* non-linearity. The output layer performs a softmax operation and has 2 units, corresponding to the outcome of either successful VCT-funded firm (1) or unsuccessful VCT-funded firm (0). All layers are parameterised i.e. have associated weights and biases that are optimised during training of the DNNBC model. The linear component of both hidden layers applies a linear transformation on the independent variables using its stored weights and biases. The non-linear component employs a *Sigmoid* non-linear activation function to create complex mappings between the independent variables and our [1, 0] outcome variable. The final hidden layer of our DNNBC model returns raw values in $[-\infty, \infty]$, which are then processed by the *softmax* activation function to scale them to values [0, 1] representing the DNNBC model's predicted probability for our [1, 0] outcome variable. In the forward propagation (forward function) part of training the DNNBC model, the DNNBC model predicts whether a VCT-funded firm was successful or unsuccessful. It achieves this by running the independent

Algorithm 1: Deep Neural Network

1. Define the Neural Network that has some learnable parameters

- Define the forward function to compute output tensors from input tensors.
- Define the backward function which receives the gradient of the output tensors WRT some scalar value and computes the gradient of the input tensors WRT that same scalar value.

2. Define a loss function (i.e. Cross-Entropy) and optimizer (i.e. ADAM - Adaptive Moment Estimation)**3. Randomly split the data into separate 70% training and 30% test sets****4. Train the Neural Network on Training Data**

- Backpropagate the error from the loss function.
- Update the weights of the network via ADAM:
 $\text{Weight} = \text{Weight} - \text{Learning Rate} \times \text{gradient}.$

5. Test the Neural Network on the Test Data**6. Deploy the Neural Network on Complete Dataset to make Predictions**

variables through each of its layers. We use the DNNBC model's prediction and a Cross-Entropy (Log-Loss) function to calculate the error (loss), then we backpropagate this error through the DNNBC model. In the backward propagation (backward function) part of training, the DNNBC model adjusts its parameters proportionate to the error in the prediction. It does this by traversing backwards from the prediction, collecting the derivatives of the error with respect to the parameters of the layers - gradients, and optimising the parameters using ADAM optimisation algorithm.¹³ In summary, we train the DNNBC model by looping over our data iterator, feeding

¹³ADAM is a superior type of stochastic gradient descent optimisation algorithm, where stochastic gradient is a stochastic approximation of gradient descent, and gradient descent is an optimisation algorithm that follows the negative gradient of an objective function in order to locate the minimum of the function.

the independent variables to the DNNBC model, and optimising. After training the DNNBC model for 400 epochs (passes) over the training dataset, we apply it on the test data to predict whether each VCT-funded firm in the test data was successful or unsuccessful. We then compare these predictions against the observed success of each VCT-funded firm in the test data, to obtain a test accuracy.

We now turn to elaborating on attribution algorithms and its usefulness. Consider a linear regression model. The coefficients represent the slope between the independent variables and the dependent variable, and we fit a linear model with coefficients to minimize the residual sum of squares between the observed success of VCT-backed firms, and the success predicted by the linear approximation. However, notice that with our DNNBC model, weights are embedded in every hidden layer. They capture the relationships between the neurons in the different layers, and are continuously updated via backward propagation. This means that we don't know exactly which of the weights - hence which of the independent variables - in which of the layers were most important, or how the neurons work together to predict the final classification of successful VCT-funded firm or unsuccessful VCT-funded firm. This is referred to in the Machine Learning literature as the *black box* issue of Deep Neural Networks. Attribution algorithms were developed to resolve this issue. An attribution algorithm helps attribute or measure the contribution of each independent variable to the predictions of a Deep Neural Network - an inherently causal task. We employ three different attribution algorithms to interpret the outputs of our DNNBC model. The first is the Sundararajan, Taly and Yan (2017) *Integrated Gradients* algorithm. Their algorithm builds on the simple axiom that in a Deep Neural Network model, the gradients of the outcome variable with respect to the independent variable is analogous to the coefficients of a linear model. They thus employ the product of the gradient and the value of the independent variable as the foundation for their *Integrated Gradients* attribution algorithm. However, because gradients do not satisfy several axioms that all attribution algorithms should satisfy, they cumulate the gradients. Formally, "*Integrated Gradients* are the path integral of the gradients along the straight line path from the baseline" - defined as the starting point from which gradients are integrated - to the independent variable. (Sundararajan, Taly and Yan., 2017, p. 3). The second is the *Integrated Gradients with Smooth Gradient* algorithm, which approximates smoothing the *Integrated Gradients* method with a Gaussian Kernel.¹⁴ The third is the Shrikumar, Greenside

¹⁴For more details on adding Gaussian noise, please see https://captum.ai/api/_modules/captum/attr/

and Kundaje (2017) *DeepLift* algorithm, which is based on back-propagating the output of a Deep Neural Network model through each layer of the network, down to the independent variables. We also build a Deep Neural Network Regression model for our secondary empirical specification, this model has an architecture that is conceptually similar to the DNNBC model. We use this model to carry out a regression as opposed to a binary classification task. In other words, the outcome variable (VCT success) is now a continuous as opposed to a binary variable. We will elaborate on this model in a later section, but for now we turn to showing the results from our DNNBC model and all three attribution algorithms.

4 Main Result

4.1 Factors that Determine the Success of VCT-Backed Firms: Binary Classification Model

Capital markets phenomena such as financial constraints, asymmetric information and the separation of ownership and control, combined with the remit of the VCT scheme, suggests that (especially with the former two phenomena) VCT investment managers can ease or exacerbate these phenomena by efficiently or inefficiently allocating capital across VCT-backed firms, i.e. invest in viable projects or transfer wealth (asset substitution) from VCT shareholders to themselves by investing in negative NPV projects. We will soon elaborate on the incentives of VCT investment managers to engage in asset substitution, but for now, we note that this agency problem introduced by Jensen and Meckling (1976) has been and continues to be extensively explored in studies such as Bolton, Becht, and Roell (2002), Morck, Wolfenzon, and Yeung (2005), Eisdorfer (2008), and Iliev and Lowry (2020). Given this backdrop, we hypothesise that if the match between a VCT and a potential VCT-backed firm is not animated by capital market phenomena and the ability to resolve them, but by randomness, then in the aggregate, skilled VCTs are just as likely as unskilled (lesser skilled) VCTs to finance ex-post successful VCT-backed firms. With the same being true for skilled VCTs being just as likely as unskilled (lesser skilled) VCTs to finance ex-post unsuccessful VCT-backed firms.

To wit, in this section, we present our main results where we quantify and rank the impact of each

VCT skill and the funding deal structure on the success of VCT-backed firms. Our main results are presented in Table 2., where we provide evidence on the importances, in descending order, of each measure of VCT skill and the funding deal structure for the success of VCT-backed firms. In each column, we report the average attribution scores from a Deep Neural Network we built and trained on our hand-collected and FAME data to carry out a binary classification task (DNNBC model), where the dependent variable is equal to 1 if the VCT-backed firm was a success (unrealised IRR $\geq 5\%$) and 0 otherwise. An attribution score from an attribution algorithm helps assess the contribution of each independent variable to the output of a Deep Neural Network model. Therefore, in each column, the reported attribution score is the average percentage contribution of each measure of VCT skill and the funding deal structure for the success of VCT-backed firms. The average attribution scores in column 1 are from the *Integrated Gradients* attribution algorithm. The second and third columns report the average attribution scores from the same Deep Neural Network Binary Classification (DNNBC) model, but estimated using the *Integrated Gradients with SmoothGrad* and *DeepLift* attribution algorithms respectively.

Our independent variables include measures of VCT skill, funding deal structure, and several control variables. For each VCT-backed firm, we measure the skill of its VCT backer in the fiscal year preceding the first-time said VCT backed the firm. Our reasoning for measuring VCT skill in the fiscal year prior to the first-time it financed a firm as opposed to say the second time or third time is simple. Studies such as Sørensen (2007) and Gompers, Gornall, Kaplan, and Strebulaev (2020) show that deal sourcing and deal selection (VCT pre-investment skills) are the most important for value creation relative to post-investment monitoring and advising (VCT post-investment skills). Also, this approach is less susceptible to the reverse causality problem because measuring VCT skill prior to the first time it finances a firm captures the VCT's skill before its first involvement with the VCT-backed firm, which of course precedes the observed success of the VCT-backed firm.

Our first measure of VCT skill is # First-Time VCTs in Top 5, which as detailed earlier, measures whether a VCT was ranked in the annual Top 5 ranking of all VCTs. This measure derives from studies such as Sahlman (1990) which discusses the skill of top VCs at post-investment value added-on, Sorensen (2007) which discusses the skill of top VCs in deal sourcing and selection, Gompers et al. (2008) which discusses the skill of top VCs at timing their exit from an

investment, and most importantly, the Nahata (2008) study on VC reputation and investment performance. Nahata (2008) suggests that a VC or in our case a VCT's ranking effectively captures its pre-financing deal expertise (deal sourcing and deal selection) and post-financing deal expertise (deal monitoring and advising). The ensuing discussion is going to focus on the *Integrated Gradients* average attribution scores in column 1, but the sign on each independent variable is consistent across all three columns (all three attribution algorithms). From the average attribution score in Table 2., we follow the prior literature in demonstrating that being backed by a VCT ranked in the Top 5 is a significant positive determinant of the success of VCT-backed firms. The average contribution of # First-Time VCTs in Top 5 to the success of a VCT-backed firm is 13% (*Integrated Gradients*), and it is the joint most important VCT skill determinant of the success of VCT-backed firms.

Our second and third measure of VCT skill, Low Prior Performance and High Prior Performance, are motivated by Carpenter (2000), wherein the model in their study centres around a risk averse fund manager compensated with a call option on the assets she controls. They then analyse how the option compensation impacts the manager's risk appetite when she cannot hedge the option position. We are further motivated by Barrot (2017) and Nanda and Rhodes-Kropf (2018) who discuss how VCs sometimes make investment decisions based on factors unrelated to the NPV of an investment, and also by Iliev and Lowry (2020) who discuss the increased incentives of poorly performing VCs to take lottery type gambles and the analogous reduced incentives of high performing VCs to take lottery type gambles. We follow the aforementioned studies in hypothesising that the convexity or option-like nature of a VCT investment manager's total compensation contract can incentivise said VCT investment manager to base investment decisions on her prior performance. From Table 7 in the Appendix, we see that the average VCT investment manager's compensation contract is composed of two parts: an annual 2% management fee pegged to the Net Asset Value at fiscal year-end plus a performance incentive fee also at fiscal year-end. The average performance incentive fee ¹⁵ is a percentage of the excess Total Returns, the excess over a hurdle rate of approximately 5%.

From Table 2., we find that High Prior Performance is the most important and a significant positive determinant of the success of VCT-backed firms, whereas Low Prior Performance is a neg-

¹⁵Colloquially referred to as carried interest

ative determinant of the success of VCT-backed firms. Our finding that High-Prior-Performing VCTs contribute an average of 13% to the success of VCT-backed firms is consistent with the results of corporate finance empirical studies such as Pindyck and Solimano (1993), Episcopos (1995), Caballero and Pindyck (1996), Ghosal and Loungani (1996), Leahy and Whited (1996), Bulan (2005), and Eisdorfer (2008), all of whom reinforce the axiomatically acknowledged existence of an inverse relationship between current investment and risk. High-Prior-Performing VCTs make fewer risky bets. Also, our finding that Low-Prior-Performing VCTs take more risk and as such, in the aggregate, finance unsuccessful VCT-backed firms, is consistent with the results in Carpenter (2000) who show that options that are deep out of the money seemingly incentivises excessive risk taking. Pertinently, as in the Eisdorfer (2008) study, they show that when an investor (VCT in our case) is in financial distress (Low Prior Performance in our case), risk-shifting incentives are added to its real-options consideration in determining its investment-risk assessment. As the upside of risky bets benefit the distressed investor (VCT), an increase in the risk of a project is a potential source of value for the distressed investor (VCT). They thus show how risk has diametrically opposing effects on current investment. On the one hand, the real options consideration act as a depressant of current investment - due to the option-to-delay, whereas, the risk-shifting consideration has a positive effect. This argument is the central thesis of Eisdorfer (2008), where he shows that the risk-shifting effect dominates the real-options effect - and in fact, there is a positive relationship between investment and risk - when the firm is in distress. Crucially, given that high prior performing VCTs are analogous to reputable VCs in Nahata (2008), the finding that high prior financial performance is the most important VCT skill determinant of the success of VCT-backed firms, reinforces the Nahata (2008) findings of reputable VCs adding value to VC-backed firms.

Table 2: Comparing VCT Skill and Deal Structure Importances Across Multiple Attribution Algorithms: Firm Level Deep Neural Network: Binary Classification Model: Binary Dependent Variable is the Unrealised IRR

Our sample consists of 1,953 VCT-backed firms between 2015 and 2020 as defined in Table 1. We employ various attribution algorithms to interpret the results from our Deep Neural Network Binary Classification model, where the binary dependent variable is equal to 1 if the VCT-backed firm is successful. In column 1, we report the average attribution score from the *Integrated Gradients* algorithm. In columns 2 and 3, we report the average attributions scores from the *Integrated Gradients with SmoothGrad* and *DeepLift* algorithms respectively. Control variables are also included with all variables defined in the Appendix.

	Integrated Gradients	Integrated Gradients w/SmoothGrad	DeepLift
VCT Skill Measures			
# First-Time VCTs with High Prior Performance	0.13	0.10	0.11
# First-Time VCTs in Top 5	0.13	0.07	0.06
FTSE-Industry Experience / Total Experience of all First-Time VCT Backers (%)	0.09	0.23	0.06
# First-Time VCTs with Low Prior Performance	-0.02	-0.03	-0.00
# First-Time VCTs that are Young	-0.01	-0.01	-0.05
Log(FTSE-Industry Experience Count of all First-Time VCT Backers)	0.00	0.00	0.00
Deal Structure			
ATBFR(Years)	0.18	0.15	0.09
Holding Period (Years)	-0.11	-0.11	-0.05
Log(Total VCT Funding)	0.01	0.00	0.04
# Funding Rounds	0.01	0.01	0.04

(Continued)

Table 2: *Continued*

	Integrated	Integrated	Integrated
	Gradients	Gradients w/SmoothGrad	DeepLift
Control Variables			
VCT-backed Firm Age	0.09	0.10	0.11
Log(Total Assets)	0.05	0.05	0.03
Cash-to-Assets	0.05	0.04	0.02
Debt-to-Assets	-0.01	-0.09	0.04
Training Accuracy	0.71	0.71	0.71
Test Accuracy	0.67	0.67	0.67

Our next measure of skill is the age of a VCT: “young VCT”, where, as earlier discussed, a young VCT is one that is less than 15 years old at the time of funding a firm for the first time. The measure is inspired by studies such as Lee and Wahal (2004), Tian and Wang (2014), and Iliev and Lowry (2020), but primarily derives from Gompers (1996) wherein the study samples 433 IPOs, then develops and tests the hypothesis that young VCs exit (IPO) earlier, relative to older VCs. Their behaviour is motivated by their need to signal reputation, or “Grandstand” and thus successfully fundraise in the future. Also, younger VCs back younger firms and hold smaller equity stakes, all of which results in more underpricing when these firms go public - relative to firms backed by older VCs. In line with these studies, we find (presented in Table 2.) that being backed by a young VCT is a negative determinant of the success of VCT-backed firms, contributing an average of -1% to the success of VCT-backed firms. To the extent that innovation is synonymous with success (as defined in this study), our results are also consistent with that of Tian and Wang (2014) who show that being backed by a younger VC is related to lower innovation in the VC-backed firm.

The penultimate VCT skill measure (FTSE-Industry Experience/Total Experience of all First-Time VCT Backers) captures a VCT’s specialisation in funding the FTSE-Industry of its firms and our final VCT skill measure (FTSE-Industry Experience Count of all First-Time VCT Backers) captures the sheer number of deals a VCT undertook in the FTSE-Industry of the firms it backed and thus the VCT’s experience within the industry of the firms it backed. These variables are motivated by a growing body of work on VC experience and specialisation. Studies such as: Sørensen (2008) show how the VC investment decision is based on the tradeoff between specialisation, which allows them learn from past investments, and generalisation, which provides the option value of future learning. Gompers, Kovner, and Lerner (2009) analyse the relationship between specialisation at the individual and firm level at a VC and VC success. They find that the lower levels of success experienced by generalist VCs are due to poor selection of investments within industries and inefficient allocation of capital across industries.¹⁶ Racculia (2014) shows that being financed by a specialist VC as opposed to a generalist VC results in a stronger IPO. This is due to the ability of said specialist VC to select firms with potentially innovative or disruptive technology. Our results in Table 2., show that VCT funding specialisation is a signif-

¹⁶Their results also suggest that specialisation at the individual VC investment manager level is more important than specialisation at the VC organisational level

ificant positive determinant of the success of VCT-backed firms, contributing an average of 9% to the success of VCT-backed firms, whereas funding experience is an insignificant but positive determinant of the success of VCT-backed firms, contributing an average of 0% to the success of VCT-backed firms. Our results are also in line with the results in the earlier mentioned Gompers, Kovner, and Lerner (2009) study, wherein they show that VCs with more specialisation often outperform less-specialised VCs.

Turning now to the deal structure, we see from Table 2., that the ATBFR (Years) is a significant positive determinant of the success of VCT-backed firms. Now we recall that the ATBFR for VC-backed firms as shown in the crunchbase (2018) study is 24 months whilst we showed in Table 1., that for VCT-backed firms (regardless of success) it is approximately 13 months. From this, we conjecture that the positive relationship between the ATBFR and the success of VCT-backed firms speaks to VCTs and their desire to structure financing rounds as close to the average of 24 months that we see in the larger VC ecosystem. We also know from Sahlman (1990) that staggered funding is a key control mechanism employed by VCs, where they show that VCs increase the ATBFR as the firm becomes better established. Indeed, Gompers (1995) asserts that the ATBFR should be inversely correlated with expected agency costs. We also see in Table 2., that the Total VCT funding of VCT-backed firms is a positive determinant of the success of VCT-backed firms, and is in line with the findings in Gompers (1995). The more successful a VCT-backed firm is, the more money a VCT invests in the VCT-backed firm. But, we can also relate this result to and analyse it in tandem with the ATBFR result. VCTs shorten the ATBFR or intensify their monitoring as VCT-backed firms realise less and less success, but they do not increase the amount of funding they provide to these unsuccessful VCT-backed firms simply because they are not realising intermediate success. In other words, and to use a colloquialism, VCTs do not “throw good money after bad”. The number of funding rounds (# Funding Rounds) is a positive determinant of the success of VCT-backed firms, and is inconsistent with our finding of a positive relationship between the ATBFR and the success of VCT-backed firms. Indeed, this finding goes against the discussion in Gompers (1995), which in our case implies that VCTs who exit via non-IPO routes, would do so quickly (stage their investments over fewer funding rounds), the more success a VCT-backed firm realises. Nonetheless, the sign on the deal structure variables are mostly in line with Sahlman (1990) and Gompers (1995). VCTs invest

more money, over an industry standard or increasing length of time, in successful VCT-backed firms. That they invest these monies over more funding rounds, is an inconsistent finding that we will further investigate in the next subsection. We also include the VCT holding period of VCT-backed firms, which is a significant negative determinant of the success of VCT-backed firms, and affirms the results in Gompers (1995), wherein investors (VCTs) cash in on their successes quickly - if they plan to exit via a non-IPO route - which in the case of VCTs is almost exclusively true due to the rules and regulations guiding the VCT scheme, which in turn dictates the type of firms VCTs can and cannot invest in, how long they can hold an investment, among other concomitant restrictions.¹⁷ With regards the controls, we include firm level variables such as VCT-backed firm financials and age.

In Table 3., we present results from a robustness-check exercise, in further consideration of the selection bias issue raised in Sørensen (2007), where he shows a connection between experienced VCs and selection bias, wherein the most experienced VCs tend to invest in better firms. To that end, we restrict our sample to the subset of VCT-backed firms backed by VCTs not in the top quartile of experience at funding any FTSE-Industry. Succinctly put, we exclude from our sample, VCTs in the top quartile of experience at funding firms - regardless of FTSE-Industry. Although the order of importance of the attribution scores on each measure of VCT skill and deal structure is slightly changed, the sign remains unchanged as shown in Table 3. We also see that VCTs with High Prior Performance and VCTs in the Top 5 remain among the most important of VCT skill measures for determining the success of VCT-backed firms, especially VCTs with High Prior Performance, which contributes an average of 34% to the success of VCT-backed firms.

¹⁷See Iweze (2020) for details.

Table 3: Does VCT Skill and Deal Structure Still Determine the Success of VCT-Backed Firms When We Exclude Experienced VCTs from the Analysis? Comparing VCT Skill and Deal Structure Importances Across Multiple Attribution Algorithms: Binary Classification Model: Binary Dependent Variable is the Unrealised IRR

Our sample consists of 844 VCT-backed firms between 2015 and 2020 as defined in Table 1, but excludes the data for VCTs in the top quartile of experience at funding firms in any FTSE-Industry. We employ various attribution algorithms to interpret the results from our Deep Neural Network Binary Classification model, where the binary dependent variable is equal to 1 if the VCT-backed firm is successful. In column 1, we report the average attribution score from the *Integrated Gradients* algorithm. In columns 2 and 3, we report the average attributions scores from the *Integrated Gradients with SmoothGrad* and *DeepLift* algorithms respectively. Control variables are also included with all variables defined in the Appendix.

	Integrated Gradients	Integrated Gradients w/SmoothGrad	DeepLift
VCT Skill Measures			
# First-Time VCTs with High Prior Performance	0.34	0.22	0.28
# First-Time VCTs that are Young	-0.25	-0.11	-0.11
# First-Time VCTs in Top 5	0.14	0.11	0.14
FTSE-Industry Experience/Total Experience of all First-Time VCT Backers (in percentages)	0.08	0.03	0.06
# First-Time VCTs with Low Prior Performance	-0.06	-0.05	-0.04
Log(FTSE-Industry Experience Count of all First-Time VCT Backers)	0.05	0.01	0.00
Deal Structure			
ATBFR(Years)	0.40	0.26	0.26
Log(Total VCT Funding)	0.25	0.12	0.19
Holding Period (Years)	0.15	0.11	0.08
# Funding Rounds	-0.02	0.05	-0.00

(Continued)

Table 3: *Continued*

	Integrated	Integrated	Integrated
	Gradients	Gradients w/SmoothGrad	DeepLift
Control Variables			
VCT-backed Firm Age	-0.35	-0.19	-0.22
Log(Total Assets)	0.30	0.15	0.19
Cash-to-Assets	-0.11	-0.14	-0.10
Debt-to-Assets	-0.04	-0.00	0.02
Training Accuracy	0.75	0.75	0.75
Test Accuracy	0.66	0.66	0.66

4.2 Factors that Determine the Success of VCT-Backed Firms: Regression Model

For completeness and given that we have thus far employed the unrealised IRR, in a binary form, as our dependent variable, we employ another empirical specification, this time using the unrealised IRR in its continuous form, as the dependent variable. For this empirical specification, we build another Deep Neural Network (DNN) and train it on our hand-collected and FAME data, but this time, to carry out a regression task. This Deep Neural Network Regression (DNNR) model is conceptually similar to our Deep Neural Network Binary Classification (DNNBC) model but with an architecture more suited to a regression task.¹⁸ The DNNR model is a four layer neural network with the non-linear component of each layer containing rectified linear activation function (ReLU).¹⁹ We interpret the results of our DNNR model with the three different attribution algorithms described in Section 3 and report the results (mean attribution scores) in Table 4. We find further support for VCT skills and funding deal structure as determinants of the success of VCT-backed firms.

The sign on the mean attribution scores are largely consistent with that in Table 2. There is a slight re-ordering in terms of the ranked importance of each VCT skill measure relative to the results in Table 2. VCT skill: # First-Time VCTs in Top 5, is now the least important VCT skill determinant of the success of VCT-backed firms, whereas in Table 2., Log(FTSE-Industry Experience Count of all First-Time VCT Backers) was the least important VCT skill determinant of the success of VCT-backed firms. # First-Time VCTs with High Prior Performance is still the most important VCT skill determinant of the success of VCT-backed firms, contributing an average of 13% to the success of VCT-backed firms. Also, we see that VCT funding specialisation (FTSE-Industry Experience/Total Experience of all First-Time VCT Backers (%)) is still a top three VCT skill determinant of the success of VCT-backed firms, with an average contribution of 6% to the success of VCT-backed firms.

Turning to the deal structure, we see that the Holding Period (Years) and the number of funding

¹⁸The chosen hyper-parameters are suited to a regression task i.e. the loss function, which is the MSE loss function and the optimizer, Root Mean Squared Propagation (RMSProp), which is an enhanced form of gradient descent that employs a decaying mean of partial gradients in determining the step size for each parameter.

¹⁹ReLU is a non-linear activation function employed in Deep Neural Networks, and is given by: $ReLU(x) = (x)^+ = \max(0, x)$

rounds (# Funding Rounds) are significant and negative determinants of the success of VCT-backed firms. This finding is in line with the assertions in Gompers (1995) and Sahlman (1990) wherein they show that the Holding Period (Years) and the number of funding rounds (# Funding Rounds) are metrics for the intensity with which VCs monitor firms, and is an increasing function of expected agency costs, or in this study, should be a negative determinant of the success of VCT-backed firms. Additionally, this finding also emphasises the usefulness of employing the continuous form of our dependent variable given that we found in the previous section, that the number of funding rounds (# Funding Rounds) is a positive determinant of the success of VCT-backed firms. As detailed in the previous section, VCTs cash in on their successes quicker than they realise losses, or if you will, they hold on to unsuccessful VCT-backed firms for longer than they do successful VCT-backed firms. Cashing-in on investment successes is all the more important given that we know from our hand-collected data that in any given year, VCTs pay out a substantial average range of 8% - 10% of their Net Asset Value in dividends.²⁰ Dividends received from VCTs are tax exempt, which incentivises potential investors to invest in VCTs, and VCTs in turn promote their dividend payout track record when fundraising. Finally, we see in Table 4., that the ATBFR (Years) and Log (Total VCT Funding), are all important determinants of the success of VCT-backed firms, contributing a respective average of 9% and 7%, to the success of VCT-backed firms. In summary, the results from our DNNR model in this section, which employs the continuous form of our dependent variable (unrealised IRR), reaffirms VCTs with High Prior Performance as the most important and a significant positive determinant of the success of VCT-backed firms, contributing an average of 13% to the success of VCT-backed firms. This finding is consistent with Nahata (2008), who finds that reputable VCs add value to VC-backed firms.

²⁰See Table 1.

Table 4: Comparing VCT Skill and Deal Structure Importances Across Multiple Attribution Algorithms: Regression Model: Continuous Dependent Variable is the Unrealised IRR

Our sample consists of 1,953 VCT-backed firms between 2015 and 2020 as defined in Table 1. We employ various attribution algorithms to interpret the results from our Deep Neural Network Regression Model, where the continuous dependent variable is the unrealised IRR, which proxies for the success of VCT-backed firms. In column 1, we report the average attribution score from the *Integrated Gradients* algorithm. In columns 2 and 3, we report the average attributions scores from the *Integrated Gradients with SmoothGrad* and *DeepLift* algorithms respectively. Control variables are also included with all variables defined in the Appendix.

	Integrated	Integrated	
	Gradients	Gradients w/SmoothGrad	DeepLift
VCT Skill Measures			
# First-Time VCTs with High Prior Performance	0.13	0.10	0.09
# First-Time VCTs with Low Prior Performance	-0.09	-0.01	-0.01
FTSE-Industry Experience / Total Experience of all First-Time VCT Backers (%)	0.06	0.11	0.05
Log(FTSE-Industry Experience Count of all First-Time VCT Backers)	0.04	0.03	0.04
# First-Time VCTs that are Young	0.01	0.02	0.03
# First-Time VCTs in Top 5	0.00	0.04	0.03
Deal Structure			
Holding Period (Years)	-0.31	-0.17	-0.18
# Funding Rounds	-0.20	-0.09	-0.07
ATBFR(Years)	0.09	0.03	0.02
Log(Total VCT Funding)	0.07	0.06	0.03

(Continued)

Table 4: *Continued*

	Integrated	Integrated	Integrated
	Gradients	Gradients w/SmoothGrad	DeepLift
Control Variables			
VCT-backed Firm Age	0.18	-0.05	-0.05
Log(Total Assets)	-0.15	-0.21	-0.13
Cash-to-Assets	0.05	0.05	0.04
Debt-to-Assets	-0.06	-0.04	-0.02
RMSE	0.27	0.27	0.27

4.3 Factors that Determine the Success of VCT-Backed Firms: OLS Regression Model

Here, our intention is simple. We employ an OLS linear regression model with fixed effects on FTSE-Industry and standard errors clustered by year of first investment, to conduct further analysis, which in turn serves to emphasise the superior performance of our Deep Neural Network Binary Classification (DNNBC) model and Deep Neural Network Regression (DNNR) model. We start with Table 5., which we will compare against Table 1. (Descriptive Statistics), where we presented average values for both successful and unsuccessful VCT-backed firms, and their differences. To allay the concern that the differences between the average values might derive from FTSE-Industry differences,²¹ we employ two OLS models to conduct our analysis, where the first exclusively employs data on the subsample of successful VCT-backed firms and the second exclusively employs data on the subsample of unsuccessful VCT-backed firms. We present both results in columns 1 and 2, with t-statistics in parentheses, and the Z test for the difference between two regression coefficients in column 3.²² We see that the results are consistent with those in Table 1. # First-Time VCTs in Top 5 is positively correlated to the success of successful VCT-backed firms and negatively correlated to unsuccessful VCT-backed firms, with the coefficient for successful VCT-backed firms significant at the 5% level. This result is consistent with that of # First-Time VCTs in Top 5 in Table 1., where we see that Top 5 VCTs overwhelmingly backed successful relative to unsuccessful VCT-backed firms, with the difference being positive and significant at the 1% level. Again, we see in Table 5., that the difference in the coefficients for VCT funding specialisation (FTSE-Industry Experience/Total Experience of all First-Time VCT Backers (%)) is positive and significant. This result affirms the finding in Table 1. We see a consistent theme with the remaining measures of VCT skill and deal structure, where the coefficients are significant at conventional levels and the differences are in line with the differences

²¹For instance, VCTs or VCT funds that specialise in funding firms in the renewable energy sector might enjoy success not because specialisation is a value-added skill, but due to government programmes like the Feed-in Tariffs scheme introduced by the U.K. government to encourage the production of renewable energy, a scheme that ran between 2010-2019, a period that also saw the establishment of several VCTs and VCT funds specialising in the renewable energy sector, prominent among them - Foresight Solar & Technology VCT Plc in 2010.

²²The Z test is from “Statistical methods for comparing regression coefficients between models” by Clogg, Petkova and Haritou (1995).

in Table 1. Although, the results for VCT funding experience (Log(FTSE-Industry Experience Count of all First-Time VCT Backers)) is not in line with that of Table 1. Nonetheless, we now turn to employing the full sample to test the robustness of these coefficients and their differences. In Table 6., we present our results from analysing the full sample (both successful and unsuccessful VCT-backed firms) using again, an OLS linear regression model with fixed effects on FTSE-Industry and standard errors clustered by year of first investment, with t-statistics in parentheses. The results are inconsistent with the results in Table 2. and Table 4. We see that VCT funding specialisation (FTSE-Industry Experience/Total Experience of all First-Time VCT Backers (%)), which is one of the most important VCT skill determinants of the success of VCT-backed firms across both Table 2. and Table 4., is also a significant and positive determinant of the success of VCT-backed firms. Additionally, # First-Time VCTs in Top 5 is also a significant and positive determinant of the success of VCT-backed firms. For the remainder results, we see that the coefficients are not significant at conventional levels. That we see no statistically significant linear dependence of the mean of the unrealised IRR (dependent variable) on X^{23} emphasises the importance of our DNNBC and DNNR models. These models are built to capture complex mappings (non-linearities) between the unrealised IRR and X, non-linearities we expect to see. Recall, we constructed (as detailed in previous sections) the independent variables that proxy for VCT skill and as such we would expect a non-linear model (DNNBC and DNNR models) to be better at capturing the relationships among these constructed independent variables (VCT skill) and the dependent variable, relative to a linear model. Overall, the results indicate that VCT funding specialisation in the FTSE-Industry of the firm it backs, is crucial for the eventual success of the firm. Additionally, firms that were backed by Top 5 VCTs, are more likely to be successful, where Top 5 VCTs are VCTs that have the most expertise at screening and monitoring their VCT-backed firms. In summary, the insignificance of this OLS result emphasises that the OLS model cannot capture non-linear relationships, whereas our DNNBC and DNNR models are built to capture non-linear relationships.

²³X is all of the independent variables except for # First-Time VCTs in Top 5 and FTSE-Industry Experience/Total Experience of all First-Time VCT Backers (in percentages).

Table 5: Two OLS Models for Both Successful and Unsuccessful VCT-backed Firms with Fixed Effects on FTSE-Industry and Standard Errors Clustered by Year of First Investment: Binary Dependent Variable is the Unrealised IRR

Our sample consists of 1,953 VCT-backed firms between 2015 and 2020 as defined in Table 1., where the binary dependent variable is equal to 1 if the VCT-backed firm is successful and zero otherwise. In columns (1) and (2), we report results from two OLS models with Fixed Effects on FTSE-Industry and standard errors clustered by year of investment. In Column (1), we report coefficients for the OLS model that exclusively employs data on the 851 successful VCT-backed firms subset and in column (2), we report coefficients for the OLS model that exclusively employs data on the 1,102 unsuccessful VCT-backed firms subset. t-statistics are shown in parentheses. Statistical significance of the coefficients at the 1%, 5%, and 10% levels are represented by ***, **, and * respectively. In the final column, the z test for the difference between both regression coefficients are reported. All variables are described in the Appendix.

	(726) Successful VCT-Backed Firms	(1,002) Unsuccessful VCT-Backed Firms	Difference
VCT Skill Measures			
# First-Time VCTs in Top 5	0.0150** (3.80)	-0.0003 (-0.05)	2.12
FTSE-Industry Experience/Total Experience of all First-Time VCT Backers (in percentages)	0.0830* (2.37)	0.0548*** (3.99)	0.76
Log(FTSE-Industry Experience Count of all First-Time VCT Backers)	-0.0100 (-2.01)	0.0000 (1.86)	-2.64
# First-Time VCTs with Low Prior Performance	0.0030 (0.37)	0.0100 (1.38)	-0.54
# First-Time VCTs with High Prior Performance	0.0030 (0.95)	-0.0200*** (-4.24)	4.11
# First-Time VCTs that are Young	-0.0010 (-0.23)	0.0100** (2.72)	-2.22

(Continued)

Table 5: *Continued*

	(726) Successful VCT-Backed Firms	(1,002) Unsuccessful VCT-Backed Firms	Difference
Deal Structure			
# Funding Rounds	-0.0050 (-1.37)	0.0000 (1.07)	-1.65
Log(Total VCT Funding)	-0.0010 (-0.51)	-0.0000** (-2.85)	1.84
ATBFR(Years)	-0.0120 (-0.90)	-0.0300** (-3.84)	1.41
Holding Period (Years)	-0.0080** (-2.70)	-0.0076** (-2.68)	-0.05
Control Variables			
VCT-backed Firm Age	-0.0000* (-2.29)	-0.0000 (-0.18)	-1.18
Log(Total Assets)	0.0010 (0.96)	0.0000 (0.67)	0.04
Debt-to-Assets	-0.0010* (-2.16)	-0.0036 (-1.56)	1.12
Cash-to-Assets	0.0200 (1.43)	0.0100 (0.91)	0.67
Adjusted R ²	0.17	0.20	

Table 6: OLS Model with Fixed Effects on FTSE-Industry and Standard Errors Clustered by Year of First Investment: Continuous Dependent Variable is the Unrealised IRR

Our sample consists of 1,953 VCT-backed firms between 2015 and 2020 as defined in Table 1., where the continuous dependent variable is the unrealised IRR, which proxies for the success of VCT-backed firms. The table contains results from an OLS model with Fixed Effects on FTSE-Industry and standard errors clustered by year of investment. In the Column, we report coefficients for the OLS model. t-statistics are shown in parentheses. Statistical significance of the coefficients at the 1%, 5%, and 10% levels are represented by ***, **, and * respectively. All variables are described in the Appendix.

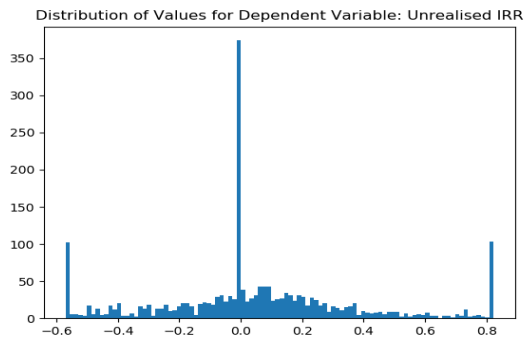
	(1,728) VCT-Backed Firms
VCT Skill Measures	
# First-Time VCTs in Top 5	0.0183** (3.72)
FTSE-Industry Experience/Total Experience of all First-Time VCT Backers (%)	0.2813*** (6.93)
Log(FTSE-Industry Experience Count of all First-Time VCT Backers)	-0.0157 (-1.78)
# First-Time VCTs with Low Prior Performance	0.0053 (0.69)
# First-Time VCTs with High Prior Performance	0.0011 (0.26)
# First-Time VCTs that are Young	0.0033 (0.48)
Deal Structure	
# Funding Rounds	-0.0046 (-1.03)
Log(Total VCT Funding)	0.0020 (1.15)
ATBFR(Years)	0.0163 (1.54)
Holding Period (Years)	-0.0087 (-1.24)
Control Variables	
VCT-backed Firm Age	0.0001 (0.32)
Log(Total Assets)	0.0037 (1.85)
Debt-to-Assets	-0.0033 (-1.23)
Cash-to-Assets	0.0340 (1.25)
Adjusted R ²	0.11

5 Conclusion

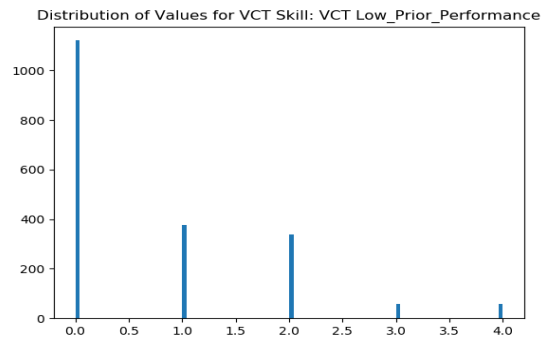
Corporate finance studies have shown that in the aggregate, small, young and risky firms face financial constraints due to various capital market phenomena. These constraints are alleviated by the VCT scheme and its funding of small, young and risky U.K. firms, where we document that in any given year, the average VCT equity stake in a VCT-backed firm is a non-trivial percentage ranging from 19% to 31%. Against this backdrop, we employ several machine learning approaches and hand-collected VCT data to analyse VCTs and their equity investments. We find that VCTs are skilled along several value generating dimensions, and these skills, in addition to the financing deal structure, determine the success of VCT-backed firms. In other words, VCT skill and the funding deal structure are important determinants of the success of VCT-backed firms. Specifically, across all empirical specifications, we find that being backed by VCTs with high prior financial performance, is the most crucial VCT skill determinant of the success of VCT-backed firms, contributing an average of 13% to the success of VCT-backed firms. This result reinforces the findings in Nahata (2008), wherein they show that being backed by VCs with high prior performance (a skill that captures VC screening and monitoring expertise) is a key determinant of the success of VC-backed firms.

Finally, our results offer a road-map to policy makers on future VCT policy changes. Economies all around the world including the U.K. are facing various economic challenges amidst a period of war, food and cost of living crises. These challenges will have an effect on the supply of capital to small, young and risky firms - which are the focus of the VCT scheme. These effects can be mitigated by increasing the VCT funding limit currently set at £15 million and £20 million for firms in non-knowledge and knowledge intensive industries respectively. Based on our results which show that the GBP amount of VCT funding is a significant positive determinant of the success of VCT-backed firms, allowing VCTs the flexibility to intervene and fund their firms beyond the current limits is an approach worth considering.

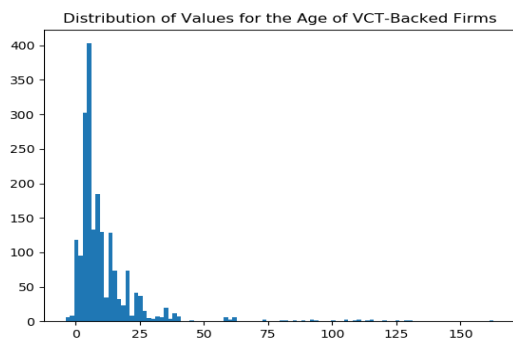
A Distribution of VCT Skill and Deal Structure Variables



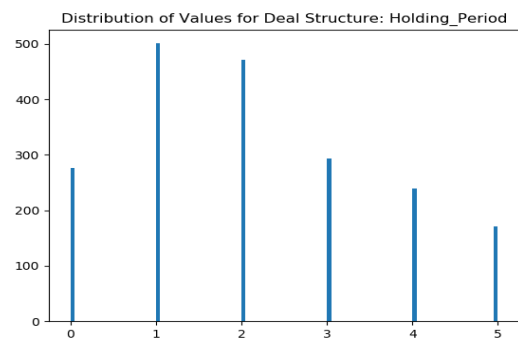
(a) Unrealised IRR



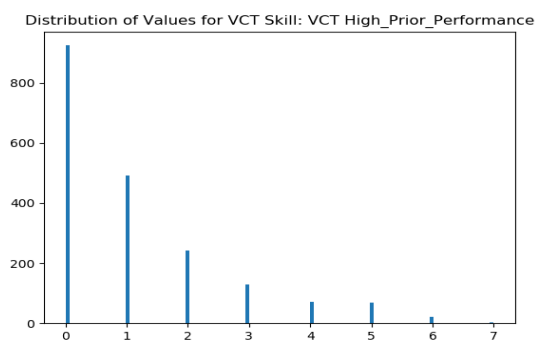
(b) Low Prior Performance



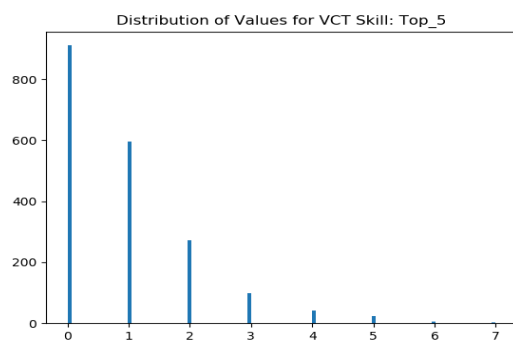
(c) Age of VCT-Backed Firms



(d) Holding Period



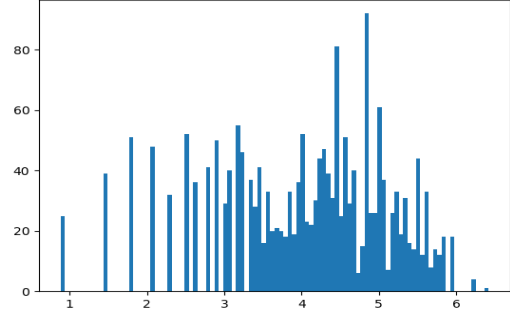
(e) High Prior Performance



(f) Top 5

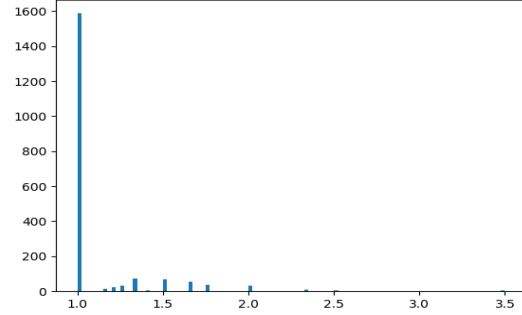
Figure 3: Distribution of VCT Skill and Deal Structure Variables

Distribution of Values for VCT Skill: Log(FTSE_Funding_Experience)



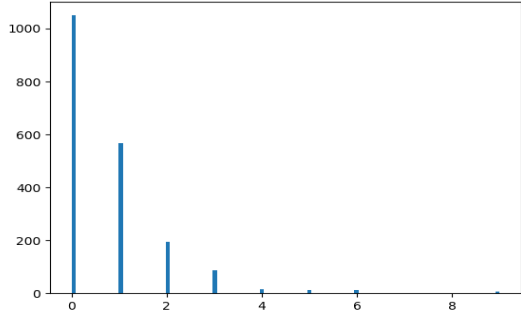
(a) Log(FTSE-Industry Funding Experience)

Distribution of Values for Deal Structure: ATBFR



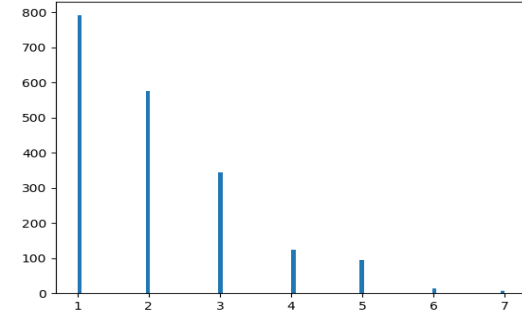
(b) ATBFR(Years)

Distribution of Values for VCT Skill: Young VCT



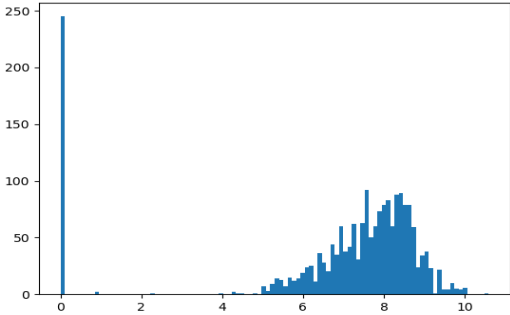
(c) Young VCT

Distribution of Values for Deal Structure: # Funding Rounds



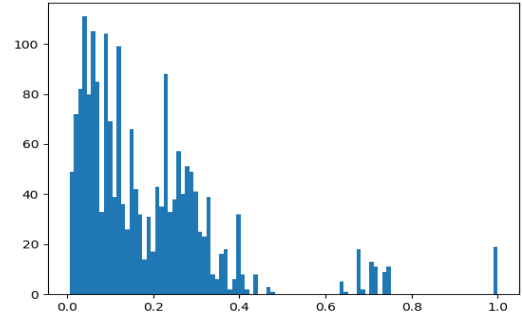
(d) Funding Rounds

Distribution of Values for Deal Structure: Log(Total VCT Funding)



(e) Log(Total VCT Funding)

Distribution of Values for VCT Skill: FTSEFunding/TotalFunding Experience



(f) FTSE-Industry Funding Specialisation

Figure 4: Distribution of VCT Skill and Deal Structure Variables

B Distribution of VCT Skill and Deal Structure Variables for Successful vs. Unsuccessful VCT-Backed Firms

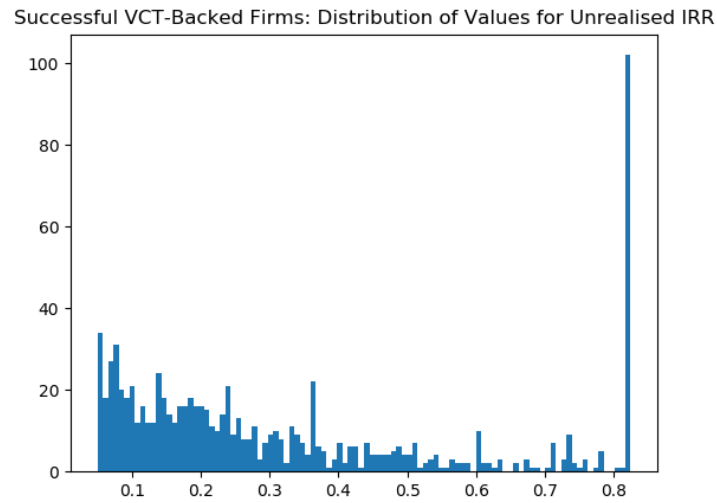


Figure 5: Successful VCT-Backed Firms: Unrealised IRR

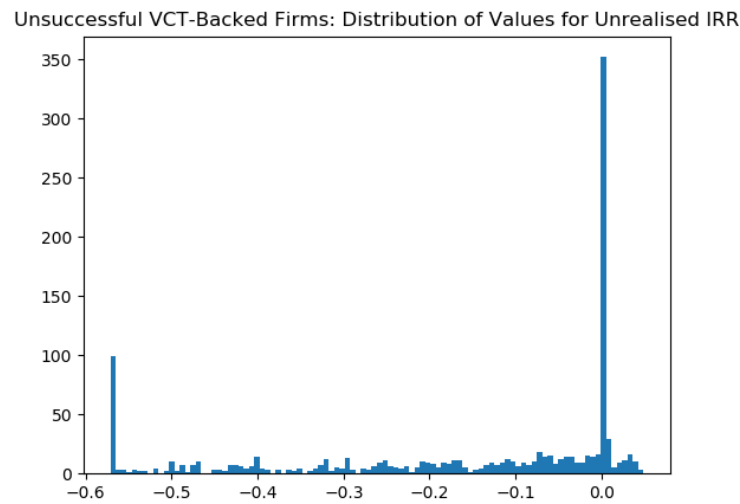


Figure 6: Unsuccessful VCT-Backed Firms: Unrealised IRR

Successful VCT-Backed Firms: Distribution for Low_Prior_Performance

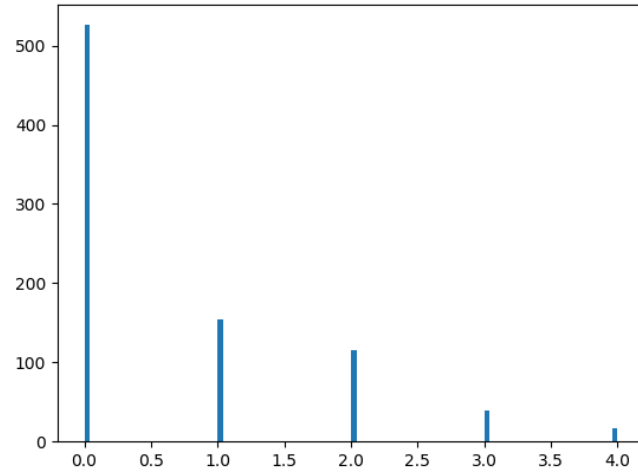


Figure 7: Successful VCT-Backed Firms: Low Prior Performance

Unsuccessful VCT-Backed Firms: Distribution for Low_Prior_Performance

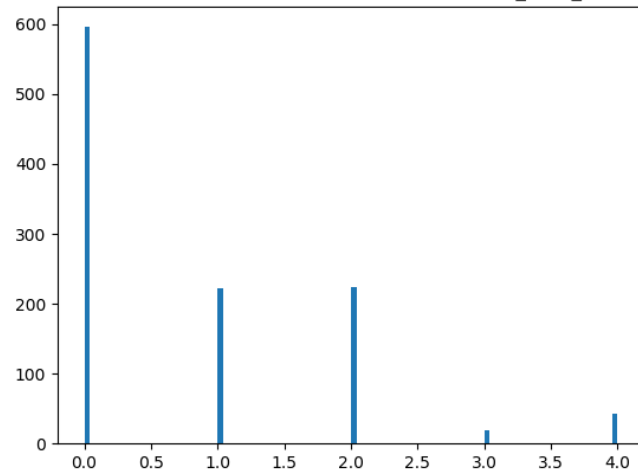


Figure 8: Unsuccessful VCT-Backed Firms: Low Prior Performance

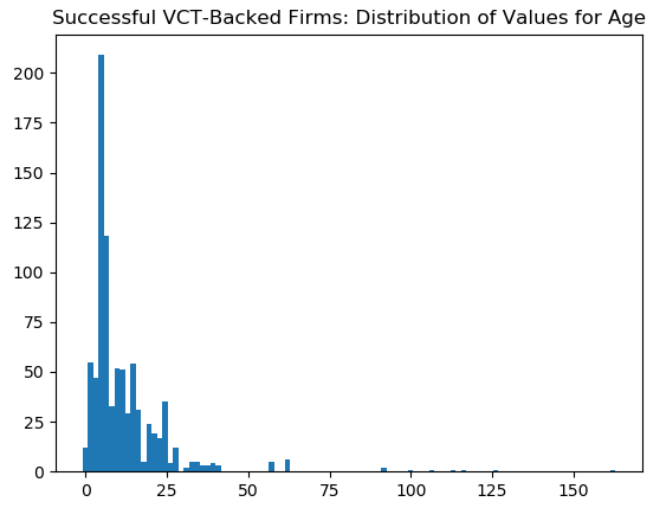


Figure 9: Successful VCT-Backed Firms: Investee Age

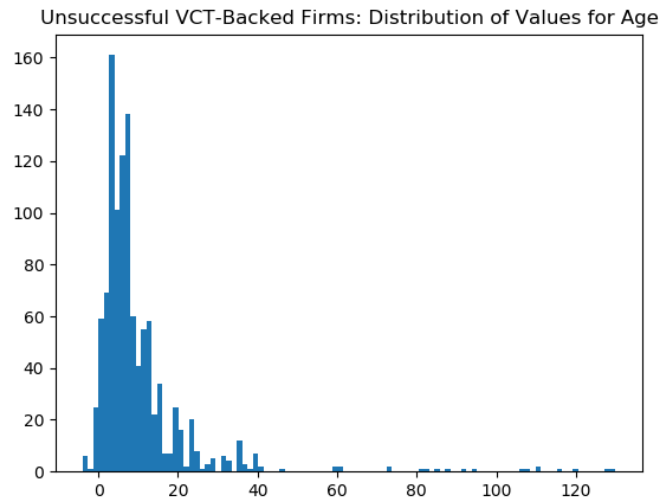


Figure 10: Unsuccessful VCT-Backed Firms: Investee Age

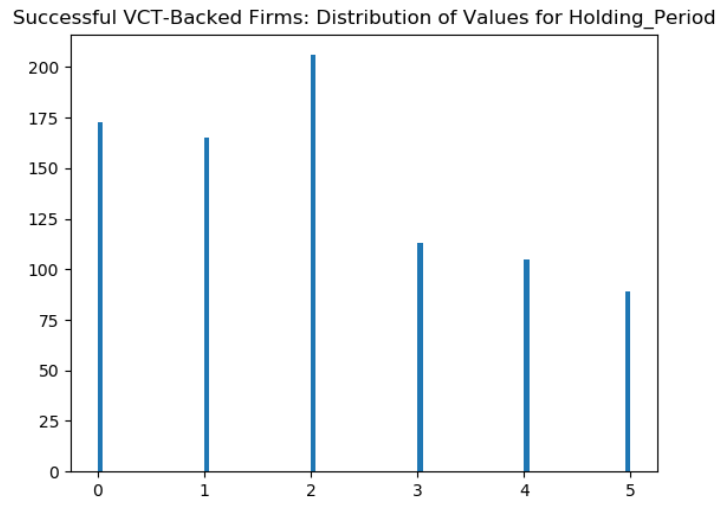


Figure 11: Successful VCT-Backed Firms: Holding Period (Years)

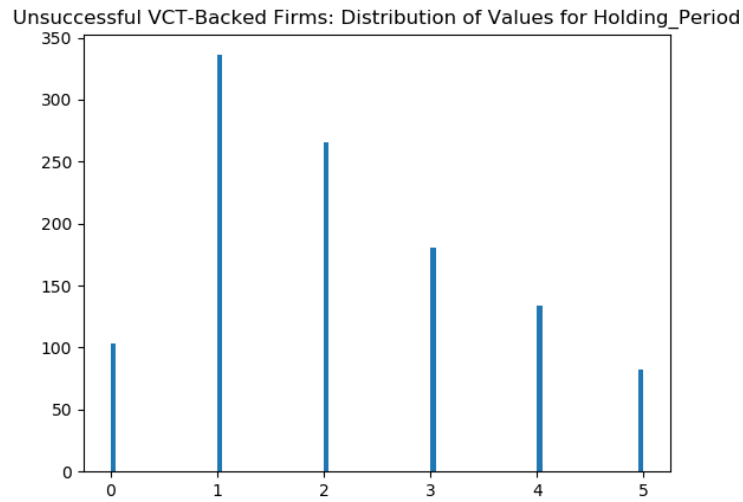


Figure 12: Unsuccessful VCT-Backed Firms: Holding Period (Years)

Successful VCT-Backed Firms: Distribution for High_Prior_Performance

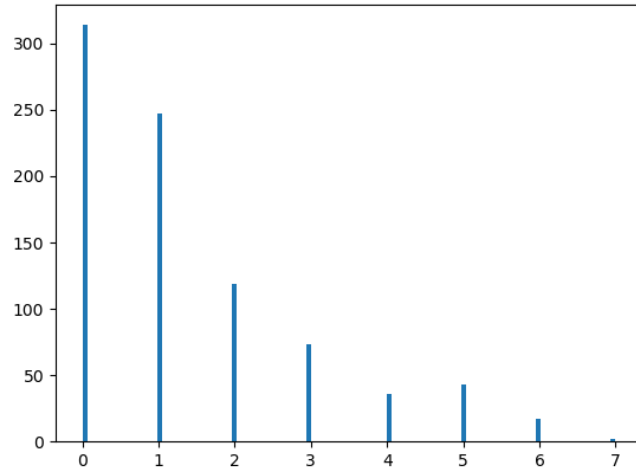


Figure 13: Successful VCT-Backed Firms: High Prior Performance

Unsuccessful VCT-Backed Firms: Distribution for High_Prior_Performance

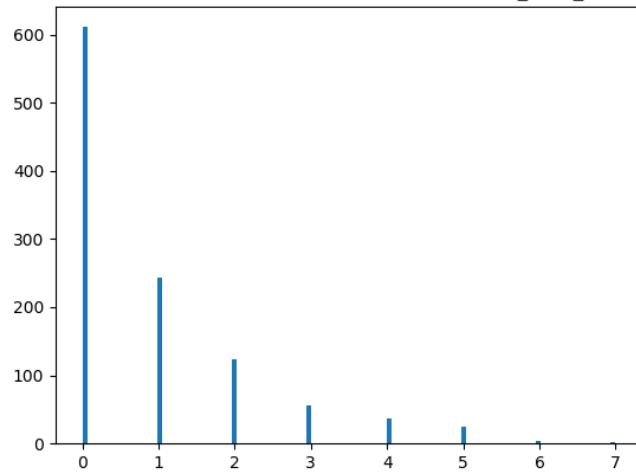


Figure 14: Unsuccessful VCT-Backed Firms: High Prior Performance

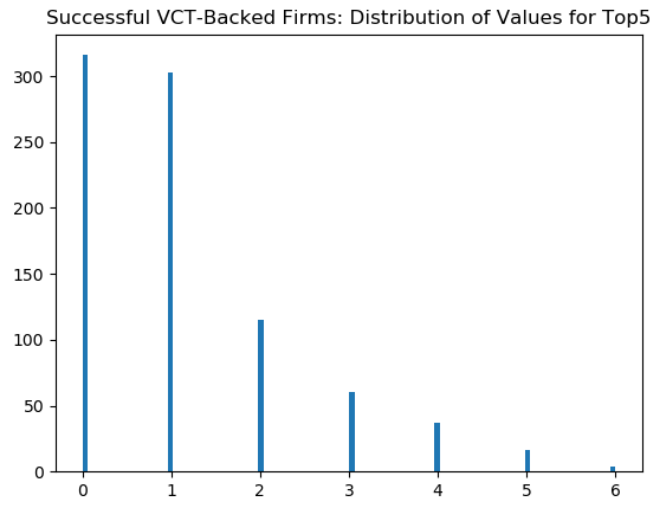


Figure 15: Successful VCT-Backed Firms: Top 5

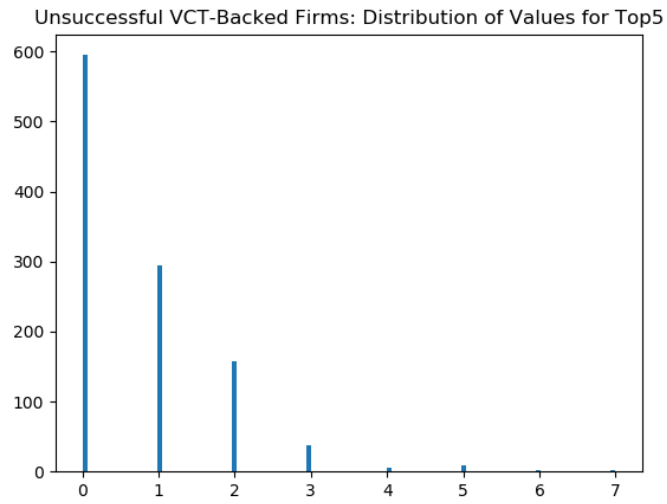


Figure 16: Unsuccessful VCT-Backed Firms: Top 5

Successful VCT-Backed Firms: Distribution of Values for Log(Experience)

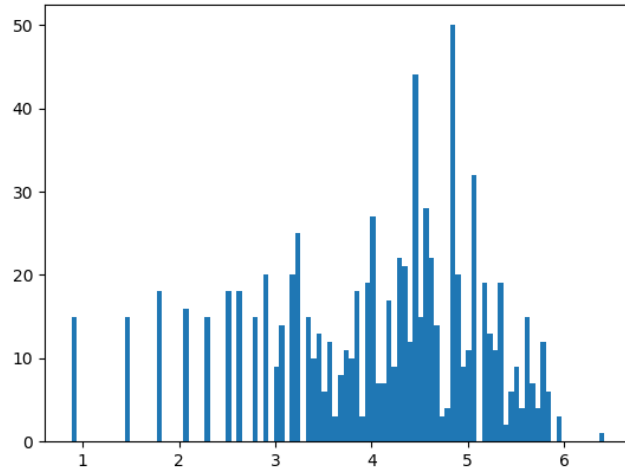


Figure 17: Successful VCT-Backed Firms: Log(FTSE Funding Experience)

Unsuccessful VCT-Backed Firms: Distribution of Values for Log(Experience)

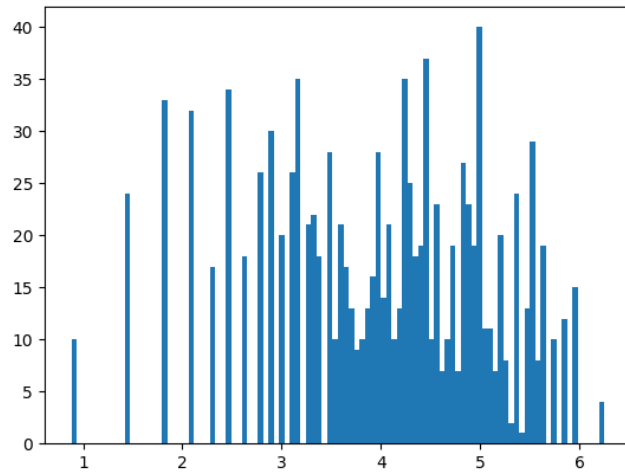


Figure 18: Unsuccessful VCT-Backed Firms: Log(FTSE Funding Experience)

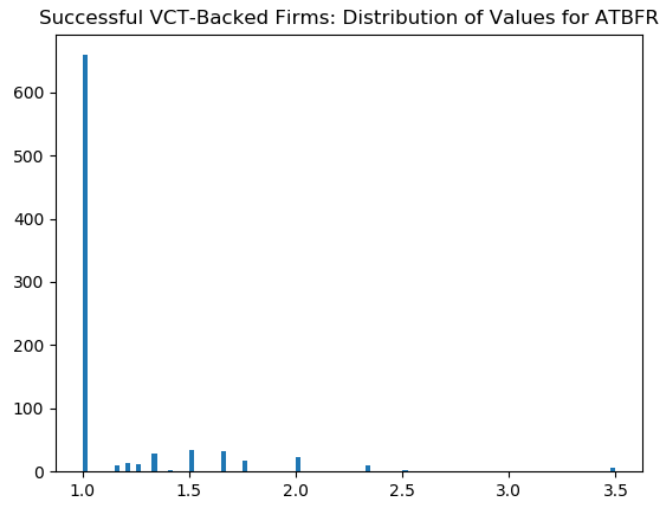


Figure 19: Successful VCT-Backed Firms: ATBFR(Years)

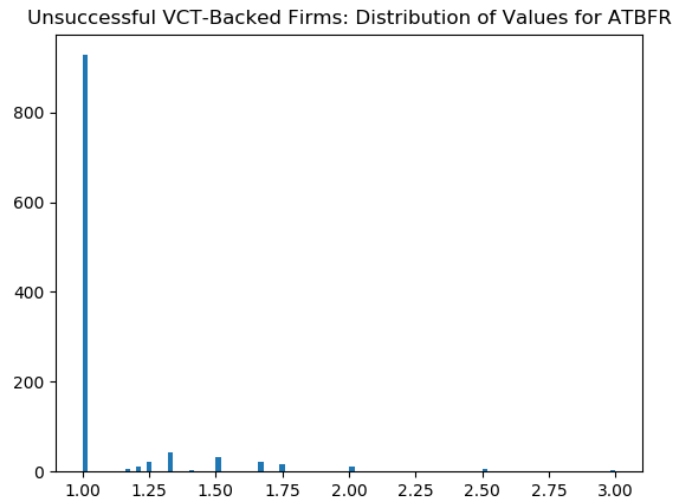


Figure 20: Unsuccessful VCT-Backed Firms: ATBFR(Years)

Successful VCT-Backed Firms: Distribution of Values for Young VCT

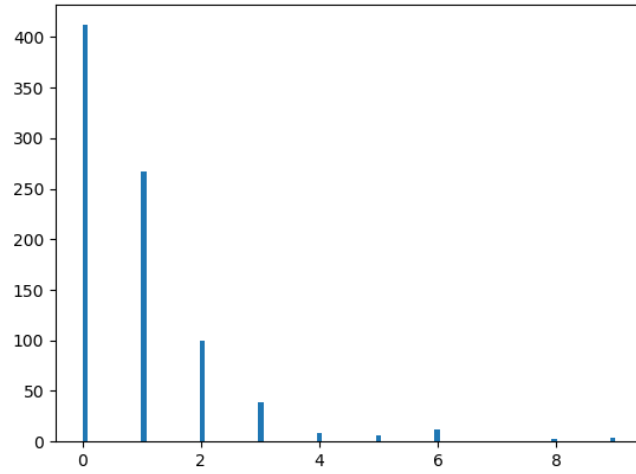


Figure 21: Successful VCT-Backed Firms: Young VCT

Unsuccessful VCT-Backed Firms: Distribution of Values for Young VCT

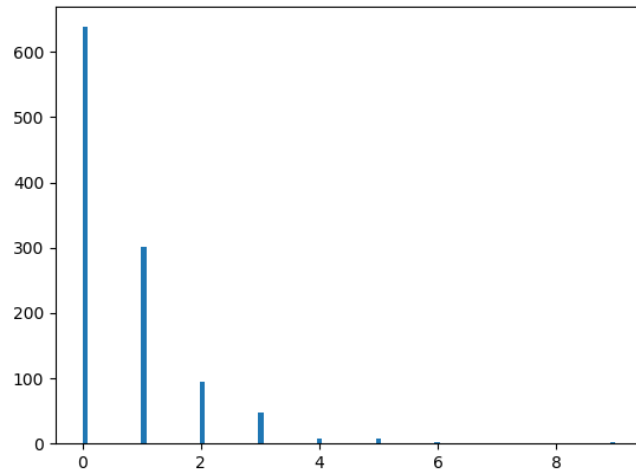


Figure 22: Unsuccessful VCT-Backed Firms: Young VCT

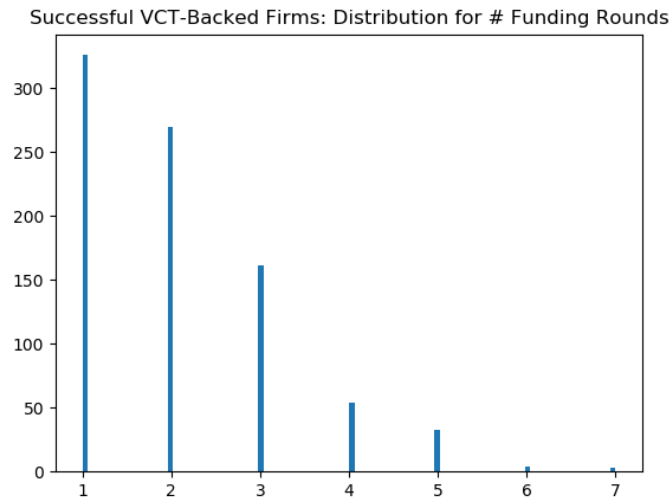


Figure 23: Successful VCT-Backed Firms: # Funding Rounds

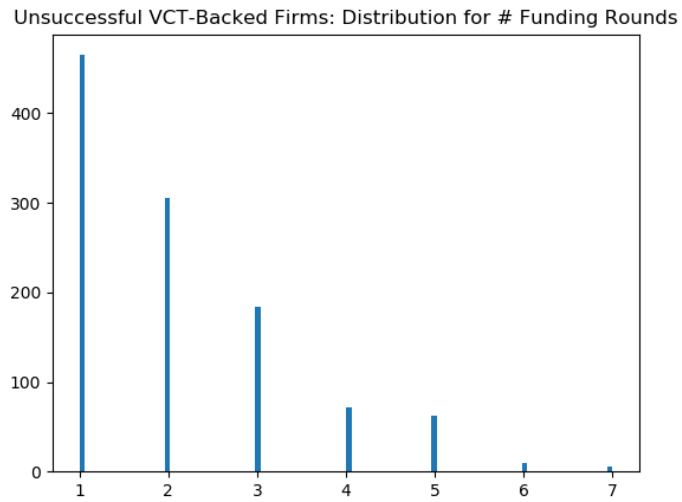


Figure 24: Unsuccessful VCT-Backed Firms: # Funding Rounds

Successful VCT-Backed Firms: Distribution for Log(Total VCT Funding)

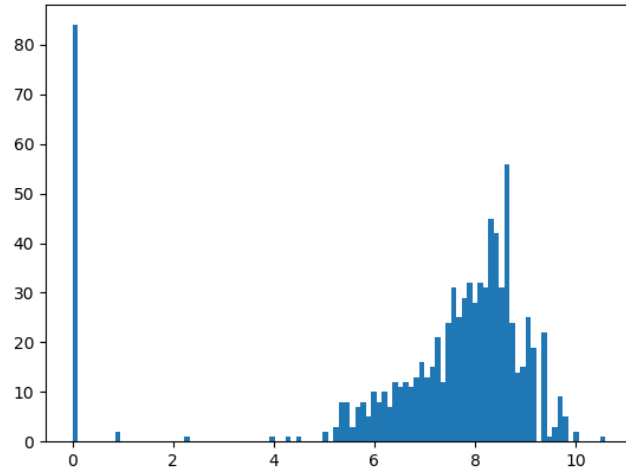


Figure 25: Successful VCT-Backed Firms: Log(Total VCT Funding)

Unsuccessful VCT-Backed Firms: Distribution for Log(Total VCT Funding)

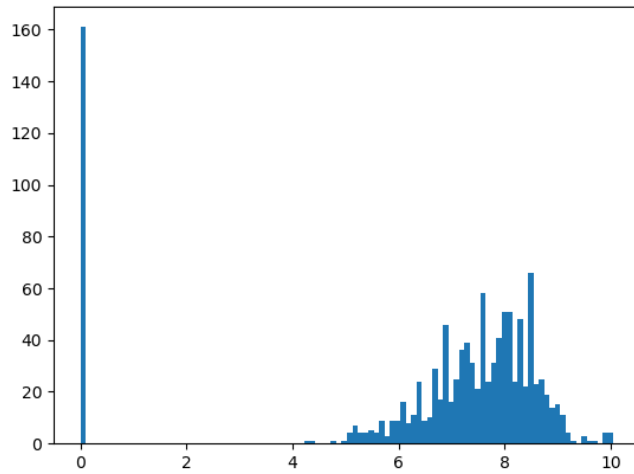


Figure 26: Unsuccessful VCT-Backed Firms: Log(Total VCT Funding)

Successful VCT-Backed Firms: Distribution of Values for Specialisation

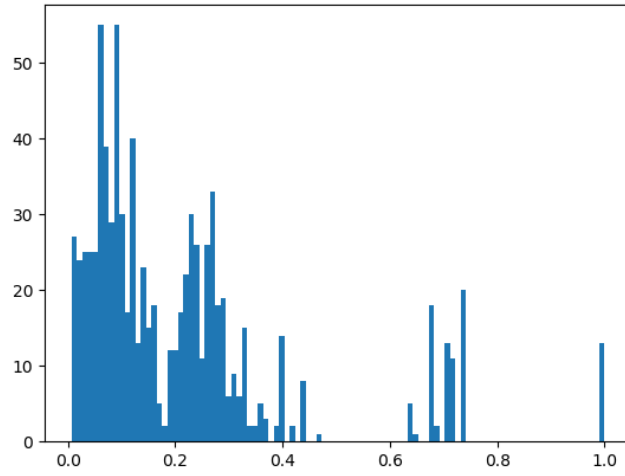


Figure 27: Successful VCT-Backed Firms: FTSE-Industry Funding Specialisation

Unsuccessful VCT-Backed Firms: Distribution of Values for Specialisation

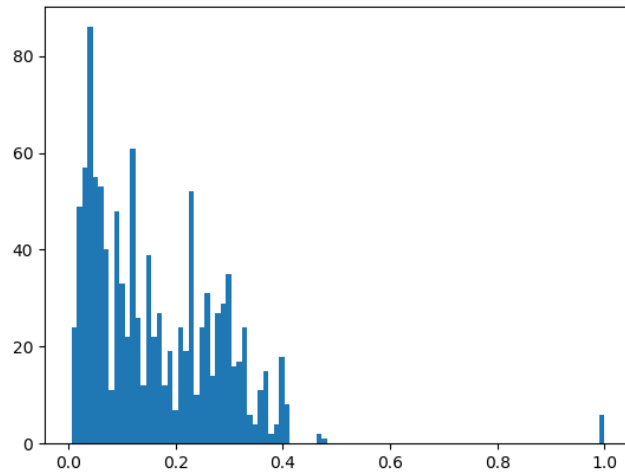


Figure 28: Unsuccessful VCT-Backed Firms: FTSE-Industry Funding Specialisation

C Distribution of Financial Data for VCT-Backed Firms

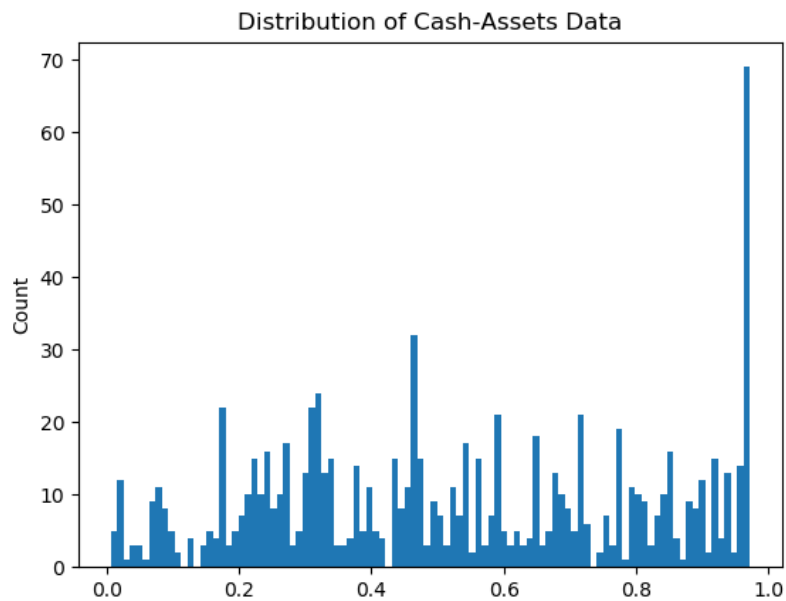


Figure 29: Cash-Assets

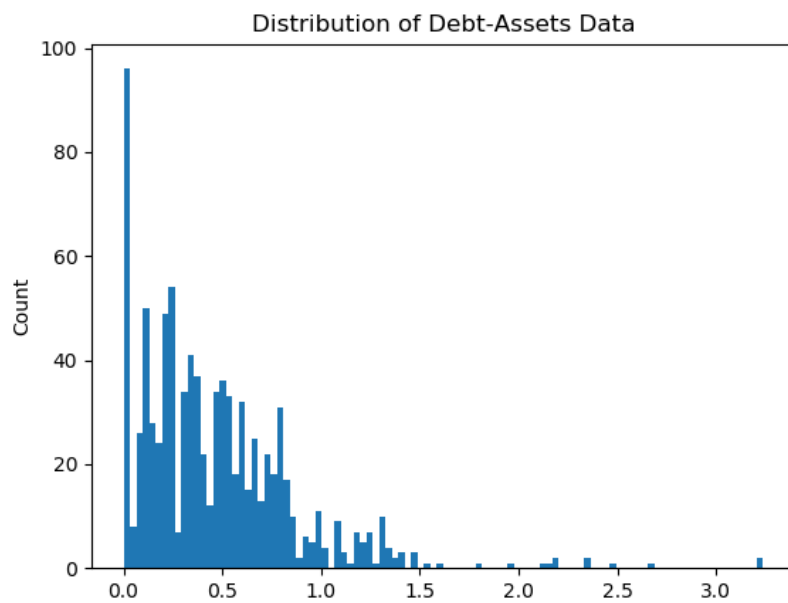


Figure 30: Absolute Value of Debt-Assets

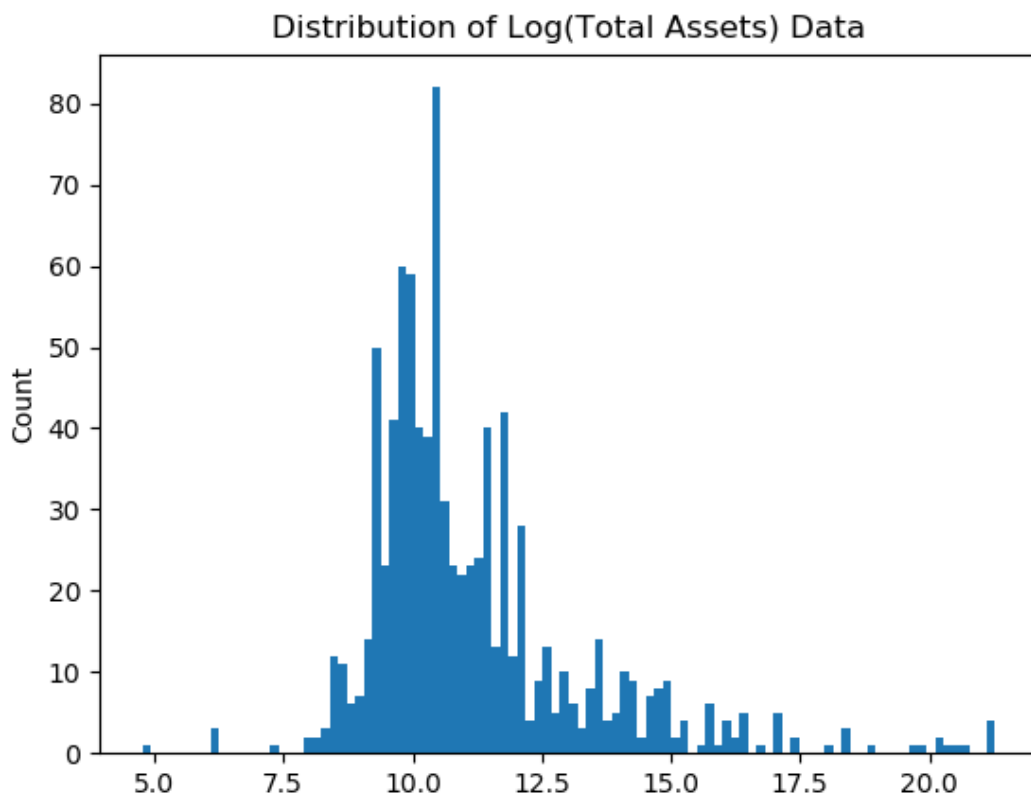


Figure 31: Log(Total Assets)

D Distribution of Financial Data for Successful vs. Unsuccessful VCT-Backed Firms

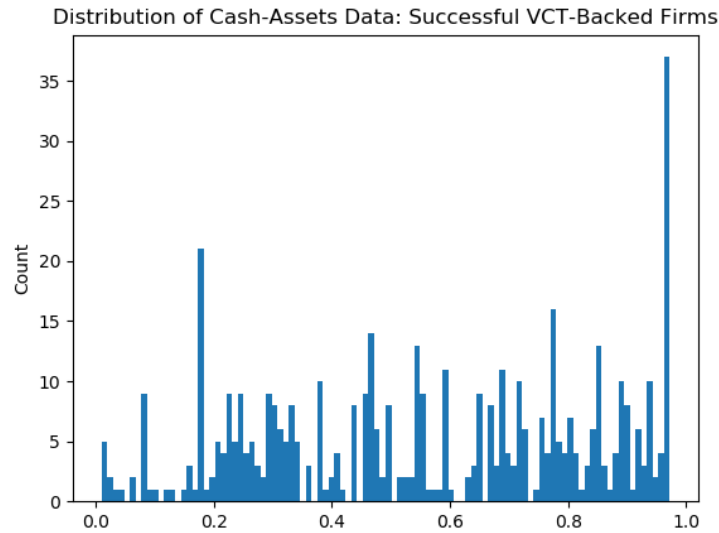


Figure 32: Cash-Assets

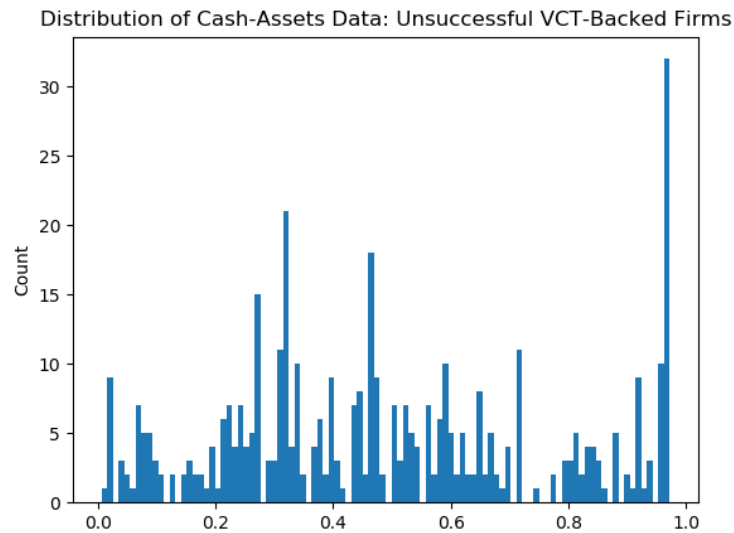


Figure 33: Cash-Assets

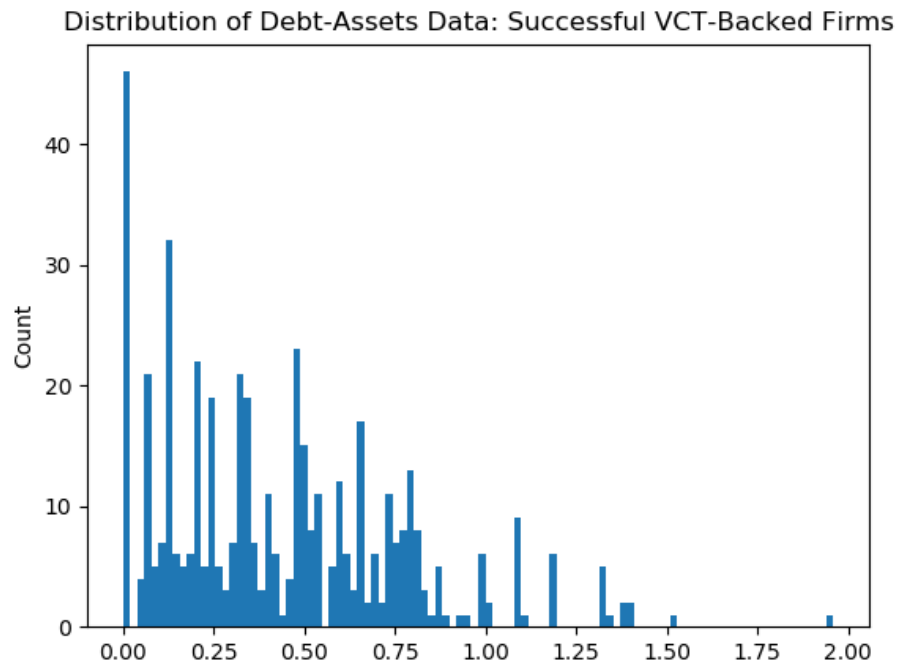


Figure 34: Absolute Value of Debt-Assets

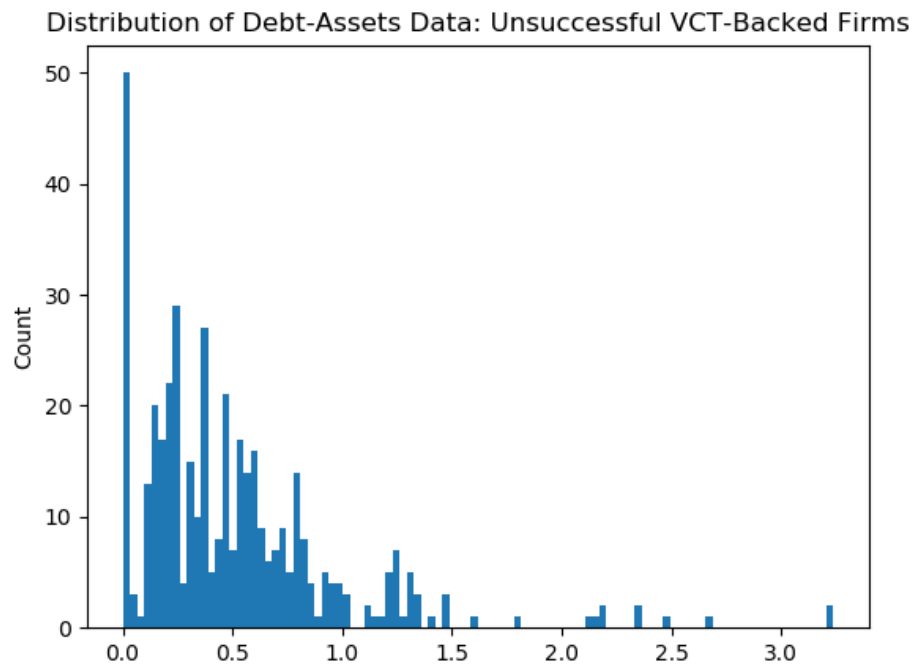


Figure 35: Absolute Value of Debt-Assets

Distribution of Log(Total Assets) Data: Successful VCT-Backed Firms

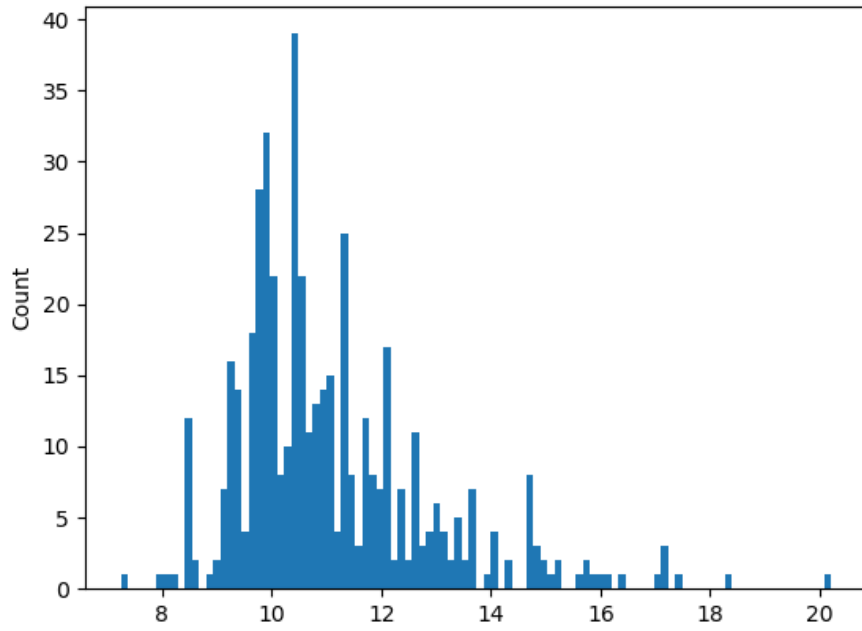


Figure 36: Log(Total Assets)

Distribution of Log(Total Assets) Data: Unsuccessful VCT-Backed Firms

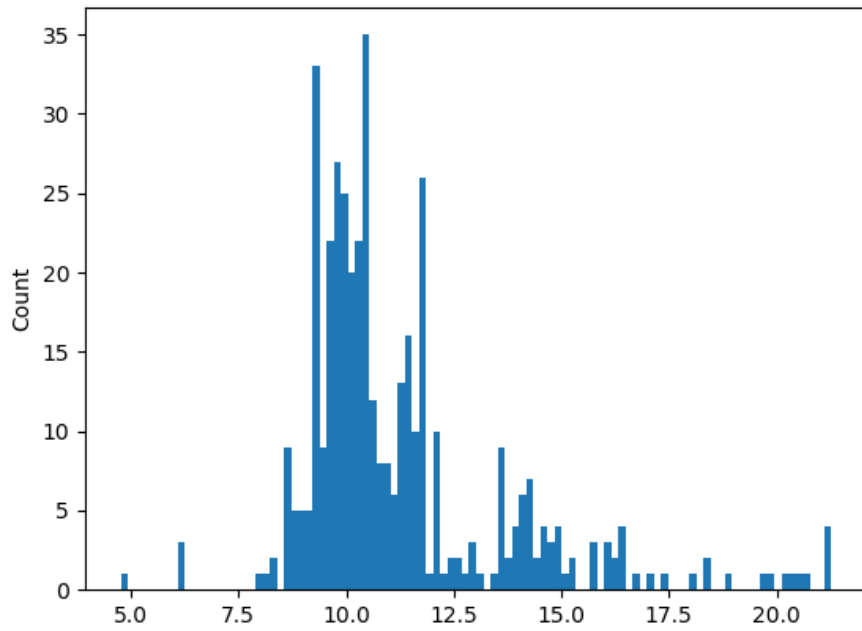


Figure 37: Log(Total Assets)

E Description of Variables

Firm's first-time VCT backer/s skill: Summed across all first-time VCT backers to form one firm level measure; hand-collected data

- #First-Time VCTs in Top 5: A binary variable equal to 1 if the first time a firm was backed by a VCT, said VCT ranked in the Top 5 of all VCTs in the prior fiscal year. Top 5 is defined according to the Nahata (2008) study.
- Log(First-Time VCTs FTSE Industry Experience Count): For a firm, this is the number of times its first time VCT backer funded firms in its FTSE Industry.
- First-Time VCTs FTSE-Industry Experience / Total Experience (%): For a firm, this is the number of times its first time VCT backer funded firms in its FTSE Industry, divided by the total number of times its first time VCT backer funded firms in all FTSE Industries.
- # First-Time VCTs with Low Prior Performance: A binary variable equal to 1 if the first time a firm was backed by a VCT, said VCT ranked in the bottom quartile of VCT performance, in the prior fiscal year. A VCTs performance is measured as the annual return on it's portfolio of assets.
- # First-Time VCTs with High Prior Performance: A binary variable equal to 1 if the first time a firm was backed by a VCT, said VCT ranked in the top quartile of VCT performance, in the prior fiscal year. A VCTs performance is measured as the annual return on it's portfolio of assets.
- # First-Time VCTs that are Young: A binary variable equal to 1 if the first time a firm was backed by a VCT, said VCT was young. For a firm, the age of each of it's VCT backers is calculated as the difference between the year of funding and the VCTs date of incorporation. Young is defined as fifteen years or younger.

VCT Funding Deal Structure

- Log(Total VCT Funding): Total GBP proceeds raised by a firm in all VCT funding rounds from all its VCT backers.

- **ATBFR(Years):** The average time between funding rounds, measured in years for firms with multiple funding rounds, is the average of the difference between a firm's first and second, second and third, third and VCT funding rounds.
- **Holding Period:** For a VCT, the holding period of an investment is the difference between the first time it invested and the fiscal year of the latest valuation of the investment (or the fiscal year it exited the investment).
- **VCT Equity Stake:** Measured on an annual basis, it is the percentage equity stake of an investee, held by its VCT backer.
- **# Funding Rounds:** This is the number of VCT funding rounds a firm underwent per fiscal year (max 1 funding round per fiscal year), from the first VCT funding round to the latest VCT funding round.
- **Multiple Funding Rounds (%):** Measured over the entire fiscal years in our sample, it is the number of investee firms that received multiple VCT funding rounds divided by the total number of investee firms that received VCT funding rounds.

Life Cycle Variable

- **Investee Age:** Measured from its VCT backers perspective as the number of years from the date of incorporation to the fiscal year of its most recent valuation.

FAME Financial Variables (Calculated as of the Fiscal Year-End of the Most Recent Valuation; All Ratios are winsorised at the 0.5% and 95% Levels))

- **Log(Total Assets):** Total assets
- **Debt-to-Assets:** Long term liabilities plus current liabilities divided by total assets.
- **Cash-to-Assets:** Current assets divided by total assets.

Table 7: Comparing each VCT Investment Manager's Management Fee, Performance Incentive Fee and the Hurdle Rate for the Performance Incentive Fee

Column 1 is a list of the 44 VCTs in our sample over the 2014-2020 period. Column 2 reports the latest (2020) management fee for each VCT investment manager. Column 3 reports the latest (2020) hurdle rate before each VCT investment manager's performance incentive fee is triggered. Column 4 is a brief description of the hurdle rate for each VCT investment manager's performance incentive fee. Total returns is calculated as the change in NAV plus Dividends paid - over an accounting period.

VCT Name	Management Fee % of NAV	Hurdle Rate (%) for Performance Incentive Fee	Brief Description: Hurdle Rate for Performance Incentive Fee
1	2	3	4
Albion VCT Plc	1.90	3.5	Total Returns Exceeds RPI Inflation plus 2 percent
Kings Arms Yard VCT Plc	2.0	3.5	Total Returns Exceeds RPI Inflation plus 2 Percent
Albion Enterprise VCT Plc	2.0	3.5	Total Returns Exceeds RPI Inflation plus 2 Percent
Crown Place VCT Plc	1.75	2.75	Total Returns Exceeds Average RBS Base Rate plus 2 Percent
Albion Development VCT Plc	2.25	3.5	Total Returns Exceeds RPI Inflation plus 2 Percent
Albion Technology & General VCT Plc	2.5	3.5	Total Returns Exceeds RPI Inflation plus 2 Percent
Downing One VCT Plc	2.75	5.0	Unrealised and/or Realised IRR of an Investment Exceeds 5 Percent
Downing Two VCT Plc (2019)	2.0	7.0	Dividend Growth of 7 Percent
Downing Three VCT Plc (2019)	2.0	7.0	Dividend Growth of 7 Percent
Downing Four VCT Plc	1.83	7.0	Dividend Growth of 7 Percent
British Smaller Companies VCT 2 Plc	2.0	N/A	-
British Smaller Companies VCT Plc	2.0	5.8	Total Returns Exceeds 5.8 Percent.
Octopus AIM VCT Plc	2.0	N/A	-
Octopus AIM VCT 2 Plc	2.0	N/A	-
Octopus Titan VCT Plc	2.0	N/A	Total Returns is Positive
Octopus Apollo VCT Plc	2.0	0.75	Total Returns Exceeds BOE Base Rate.
Chrysalis VCT Plc	1.65	5.0	Realised IRR of an Investment Exceeds 5 Percent.
Molten Ventures VCT Plc	2.0	3.5	Dividend Growth of 3.5 Percent.
Unicorn AIM VCT Plc	2.0	N/A	-
Northern Venture Trust Plc	2.06	6.0	Total Returns Exceeds 6 Percent
Northern 2 VCT Plc	2.06	6.0	Total Returns Exceeds 6 Percent
Northern 3 VCT Plc	2.06	5.7	Total Returns Exceeds 5.7 Percent

(Continued)

Table 7: *Continued*

VCT Name	Management Fee		Hurdle Rate (%) for		Brief Description:	
	% of NAV	Performance Incentive Fee	Hurdle Rate for Performance Incentive Fee	Hurdle Rate for Performance Incentive Fee		
1	2	3	4	5	6	7
Amati AIM VCT Plc	1.75	N/A	-	-	-	-
Hargreave Hale AIM VCT Plc	1.70	N/A	-	-	-	-
Hargreave Hale AIM VCT 2 Plc	1.50	N/A	-	-	-	-
Mobeus Income & Growth VCT Plc	2.0	6.0	Dividend Growth of 6 Percent			
Mobeus Income & Growth 2 VCT Plc	2.0	8.32	Dividend Growth of 8.32 Percent			
Mobeus Income & Growth 4 VCT Plc	2.0	6.0	Dividend Growth of 6.0 Percent			
The Income & Growth VCT Plc	2.4	6.0	Dividend Growth of 6.0 Percent			
Foresight VCT Plc	2.0	5.5	Realised IRR of an Investment Exceeds 4 Percent plus RPI Inflation.			
Foresight Enterprise VCT Plc	2.0	N/A	High Water Mark			
Foresight Solar & Technology VCT Plc	1.5	5.0	Total Returns Exceeds 5 Percent.			
Calculus VCT Plc	1.75	5.0	Total Returns Exceeds 5 Percent.			
Pembroke VCT Plc	2.0	8.0	Total Returns Exceeds 8 Percent.			
ProVen VCT Plc	2.0	N/A	-			
ProVen Growth & Income VCT Plc	2.0	1.75	Total Returns Exceeds BOE Base Rate plus 1 Percent.			
Maven Income & Growth VCT Plc	1.9	N/A	-			
Maven Income & Growth VCT 3 Plc	2.5	N/A	Total Returns is Positive			
Maven Income & Growth VCT 4 Plc	2.5	N/A	Total Returns is Positive			
Maven Income & Growth VCT 5 Plc	1.675	4.0	Realised IRR of an Investment Exceeds 4 Percent.			
Baronsmead Venture Trust Plc	2.0	4.0	Total Returns Exceeds 4 Percent.			
Baronsmead Second Venture Trust Plc	2.50	8.0	Total Returns Exceeds 8 Percent.			
Gresham House Renewable Energy VCT 1 Plc	1.15	N/A	-			
Gresham House Renewable Energy VCT 2 Plc	1.15	N/A	-			
Number of Observations	44	29	-			
Mean	1.97	5.05	-			
Median	2.0	5.00	-			

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