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The Equity Gap and Knowledge-based Firms

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Abstract

The equity gap, the difference between the amount of (risk) capital that would be invested under conditions of well-informed and competitive markets and the amount of capital actually invested, covers both startups and ventures moving beyond startup to the establishment and early growth phase. We provide estimates for the size of the equity gap for firms facing later stage financing issues, the second equity gap. This 'second' equity gap relates to a second so-called 'valley of death' in financing the growth phase, and is particularly pertinent for knowledge-intensive (KI) firms. We utilize a unique panel database covering the population of limited companies, which includes 2,852 VC backed companies and 4,048 deals. Using propensity scoring methods and multivariate models determining investment demand we screen the corporate population for potential VC investments and estimate the size of the equity gap in total and the KI firms that face, potentially, the second equity gap as a subset of our total estimates.

Keywords: equity gap; venture capital; knowledge intensive firms

JEL Codes: G32

Introduction

There is a long-standing and contentious debate about the funding gap or valley of death in funding private entrepreneurial ventures. The 'Valley of Death' literature identifies a funding gap during the stages in the innovation process beyond basic research to the formulation of a business plan for the commercialization of products and services (e.g. Auerswald & Branscomb, 2003; Beard et al., 2009; Frank et al, 1996; Wessner, 2005). Much of the extant theoretical literature on funding gaps focuses on credit markets and debt finance (DeMeza & Webb, 1987; Stiglitz & Weiss, 1981), but more recent attention has also highlighted the gap in provision of equity finance (Cosh et al., 2009; Cressy, 2012; Cumming & Johan, 2013; Lopez de Silanes et al., 2015).

Building on recognition of its presence, we estimate the size of the equity gap for which there is little systematic quantitative evidence using data from the UK corporate sector. The equity gap concerns the difference between the amount of (risk) capital that would be invested under conditions of well-informed and competitive markets and the amount of capital actually invested. It is an outcome of market failure arising from informational asymmetry issues when entrepreneurs have more knowledge than potential investors, when customer-bases, markets and technology are new and when potential investees have no or little credible track record (Busenitz et al., 2005). These problems are likely to be heightened in knowledge intensive firms which require greater sunk cost investment and are likely to take longer to generate revenue after product/service development since their customer bases and offerings are more complex and/or client specific and assets are intangible. The challenges are exacerbated in rapidly changing environments, such as web-based technology, apps, etc.

These factors combine to make risk assessment, viability and revenue projection problematic for venture capital investors (VC) that are reluctant to invest, thus increasing the equity gap. Valuing firms with innovative but complex business models, intangible assets (and hence low collateral value) and where founder/directors have a wide range of technical and business expertise is challenging. Enterprises successful in acquiring equity investors are able to overcome informational asymmetries by demonstrating, communicating and signaling desirable attributes to outside investors. Equity gaps tend to be persistent in comparison to the transitory rationing of loan finance due to disequilibrium in credit markets related to changing demand (excess demand) and supply conditions (reduced supply) (Atanasova &

Wilson 2004). The scale of the equity gap is clearly worsened by recession, as in recent periods, when the supply of VC investment fell alongside a severe decline in bank lending (Fraser, 2012).

Few papers have rigorously directly estimated the size of the equity gap (see Cressy, 2002, 2012 for reviews). Lopez de Silanes et al., (2015) estimate the finance gaps of SME's in an empirical study of five European countries (Germany, France, Netherlands, Poland and Romania). The authors estimate demand and supply for both loans and equity finance for all SME's using a combination of aggregate publically available data on SME finance and SME survey data. The authors report estimates of equity gaps ranging from around 1 to 13% of GDP in the selected countries, some three to five times larger than estimates for the US economy. However, the authors do not investigate subsamples based on industry, technology, age, size etc. Cosh, Cumming and Hughes (2009) and Lockett, Murray and Wright (2002) show that SMEs and high tech firms face financing constraints in accessing equity capital. Harding and Cowling (2006), on the basis of GEM data and a survey of industry experts, find evidence of an equity gap in the UK in the £150,000 to £1.5million range in the period 2001-3.

Some studies are sanguine about the existence of an equity gap, pointing to the substantial extent of venture capital investment at lower value ranges suggesting that the problem essentially lies in poor quality demand (Library House/UBS, 2006). Other studies have debated whether the equity gap is spatially related (Aslesen & Langeland, 2003; Fritsch & Kilder, 2007; Mueller et al., 2012) in that both funders and investees may be regionally or locally clustered. Governmental funding initiatives have tended to address this equity gap for seed and start-up stage ventures requiring funding for the development of proof of concept and prototypes (Cumming & Johan, 2013; Cumming, Colombo, & Vismara, 2016). However, these sources oftentimes provide little opportunity for the follow-on funding needed for these firms to grow beyond start-up.

Practitioners and policy-makers are therefore beginning to recognize the existence of a second valley of death (e.g. Sadler, 2016) which gives rise to a second equity gap involving somewhat older and larger firms beyond the initial startup revenue generation phase. Interview evidence from fund managers and business owners, for example, suggests that the equity gap in the UK is positioned well beyond the £2m investment level for early stage high tech ventures with long lead times to market and high set-up costs and as much as £10m some seven years ago (Baldock & North, 2012; SQW Consulting, 2009; Rowlands, 2009). There is evidence of an increase in the funding of growth stage deals in the above £10m investment category, but investment in the later venture stage between these two categories has declined (British Business Bank, 2014; BVCA, 2014). Clarysse et al. (2007) conclude from their study of spin-offs from universities that the availability of suitable funding sources is now more of a problem at the stage beyond start-up where the venture begins to need significant levels of funds to realize growth potential beyond initial revenue generation.

While this gap between initial funding provision and the venture becoming viable through generating significant revenues is recognized, there is an absence of systematic assessment of the size of this gap. This is an important omission both from a research perspective as well as for policy. For policy instruments, such as tax incentives (Litan & Robb, 2012), to be designed to encourage VCs to invest in these firms in order to address the gap it is important to have a clear understanding of the scope of the problem. In this paper, therefore, we seek in addition to estimate the size of this second valley of death equity gap for KI firms moving beyond the start-up to the growth phase. In doing so we outline a methodology for screening the corporate sector that may have utility for policy makers and practitioners.

Using data for the UK corporate sector, we construct a novel dataset covering the period 2004-2014 comprising 12.2 million 'active' company-years to which we match data on all known VC backed deals from proprietary databases[1]. In total we have data on 2,258 individual VC backed enterprises over the period covering 4048 individual investments. In addition to compiling a panel of financial and non-financial company characteristics we match firms to manufacturing and service technology or knowledge intensity, using NACE codes[2]. We construct variables from 'event' filing and director and shareholder records that capture relational capital, expertise and resource-combination 'signals' that differentiate target VC investees from other companies. Thus we profile the financial and non-financial characteristics of VC backed enterprises in the period before investments. For the corporate population we construct variables capturing director and board characteristics and ownership

[1] NESTA and Zephyr

[2] NACE is the acronym for "Nomenclature statistique des activités économiques dans la Communauté européenne", the European statistical classification of economic activities

structure. Foreign owned firms, subsidiaries, listed companies and companies that are part of a group can be identified and eliminated as potential VC targets. Analysis of shareholder records facilitates the identification of companies that have received equity finance during the time period so that these can be eliminated from the VC target sample. A proprietary database[3] of all private equity backed firms is used to profile PE targets as distinctive from VC targets. We use a combination of matching techniques and multivariate propensity score modeling and derive the equity gap from estimating the total potential demand and subtracting the known supply of venture capital.

Our study, therefore, contributes by providing novel in-depth quantitative evidence on the size of a second equity gap or valley of death for KI firms that have been neglected by prior research. Our findings emphasize the importance of looking beyond the first equity gap for very early stage firms. The method explores the potential of screening the corporate population for VC targets a technique that may have utility both for practitioners and policy makers.

The structure of the paper is as follows. We first review the relevant literature concerning equity gaps. We discuss the distinctive characteristics of firms that seek equity finance. We then outline the empirical strategy we adopt and provide estimates of the size of the gap.

Equity gap: Start up and Later Stage

Venture capital finances companies where the investments involve new technological combinations and innovations and/or lack the tangible assets that secure traditional investment. The valuation of such businesses by VC firms poses major challenges as classic valuation techniques are of little use (Manigart et al., 2000). Over-valuation of start-up ventures having raised initial venture capital is associated with them being unable to raise significant further venture capital (Clarysse et al., 2007). As informational asymmetries may persist, resulting in valuation challenges, viable businesses at the later venture stage may face an equity funding gap. Murray and Lott (1995) highlight the second equity gap for technology-based firms who are successful in raising early stage finance to get them to initial revenue generation but are unable to gain follow-on finance because of the difficulties that VC have in assessing the time these firms require to achieve commercially viability. In order

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both to reduce and offset informational asymmetries VCs engage in screening activities in selecting their portfolio of investments relating to assessment of asset intangibility, collateral assets, the nature and complexity of customer bases, whether an initial revenue generating but loss-making early stage venture is potentially viable, and quality of the entrepreneurial and management expertise (Busenitz et al., 2005; Knockaert et al., 2010). In what follows we extend beyond traditional arguments relating how these factors may contribute to the early stage valley of death funding gap to consider the conditions leading to a second valley of death funding gap for businesses at the later venture stage. Figure 1 provides a schema outlining the typical financing stages of a new venture and the potential equity gaps, ‘valleys of death’, as the firms develops. Clearly individual firms will follow different growth paths and the dotted line (actual) in Figure 1 may, in fact, flatten, decline or even grow but against a widening gap with potential growth unless equity funding is obtained. The funding requirements traced for VC backed and other firms in Figure 1 aggregate to an overall equity gap that extends across the VC investment stages.

Asset intangibility.

Knowledge-based ventures typically take time to build the value of the knowledge base (Clarysse, Bruneel & Wright, 2011; Teece, 1986). During this period, the value of intangible, rather than tangible, assets may be increased ahead of substantial future revenue generation.

Knowledge-based companies often have to undertake specific investment in intangible assets such as know-how for particular customer relationships. In new markets, such firms may need to reposition themselves to develop a successful business model consistent with market demand (Lerner, 2002), requiring different intangible assets and customer relationships to be built. VC investors may be reluctant to invest further absent reliable information regarding the attractiveness of the most appropriate market that the firm needs to shift to and the ability of entrepreneurs to adapt. In such circumstances, knowledge-based firms may need to run the existing and new business model side-by-side for a transitional period. As such they are likely to require significant injections of equity funding but this may not be forthcoming. Hence the presence of greater intangible assets is likely to increase the equity funding-gap.

Collateral.

Lack of cash flow and relatively low levels of assets to provide collateral likely mean firms are under-capitalized and unable to take on debt (Wilson & Altanlar, 2013a, b). These problems are likely worse for knowledge intensive firms with higher levels of intangible assets. These firms are more likely to have to provide collateral to creditors through floating charges on assets. Charges on company assets provide evidence that the firm successfully underwent the screening process by a lending institution. A company with charges on assets signals creditworthiness and commitment (by providing collateral) but may be an unattractive proposition for additional debt finance. The absence of sufficient collateral is likely to increase the equity funding-gap.

Complex customer bases.

These problems are also exacerbated for knowledge-intensive firms where revenue generation takes longer and customer bases are more complex, necessitating greater sunk cost investment in the sales process and relationship management before cash flows are generated (Dass, Kale & Nanda, 2014). Complexity likely increases the challenges for investors in assessing how the venture creates a competitive advantage. Knowledge-intensive firms in sectors with such complexities are likely to experience information asymmetries between entrepreneurs and equity investors that are challenging to overcome and hence increase the equity funding gap.

Financial performance

Given the challenges noted above, knowledge intensive firms may continue to be loss-making for long periods after start up. VC investors put structural safeguards in place to protect against escalation of commitment (Guler, 2007) and devote their limited attention capacity to investments expected to be viable (Cumming & Dai, 2011). As a result, under-performing ventures are only likely to be maintained in a portfolio where there are expectations of subsequent improved performance (Li & Chi, 2013; Wright & Robbie, 1998). Hence, we do not expect that loss-making and under-performing ventures per se will increase the equity funding-gap for later stage investments.

Signaling of human capital.

Firms able to communicate to outside investors attributes of the entrepreneurial and management team such as commitment, entrepreneurial experience, knowledge and management industry and technical know-how, and relational capital increase their likelihood of accessing finance (Mueller, et al., 2012). As such, firms seeking equity investment are likely to compile larger initial boards aimed at capturing and signaling to potential investors these range of skills, business experience and evidence of networks. Hence, signals that the venture has credible expertise in the entrepreneurial and management team will reduce the size of the equity funding-gap.

Profiling targets for VC investment

Building on the issues outlined above we explore available firm level characteristics that might be used to screen out firms that potentially have a demand for venture capital from the population. We draw on the literature that has employed empirical methods to profile VC backed firms and which has been used to construct control samples of firms that are similar in dimensions to VC firms but remain unfinanced by VC firms. Much of the relevant literature in this area employs empirical methods to match a control sample (untreated group) to the characteristics of VC invested firms (treatment group). These studies adopt various methods of propensity score modeling along with rule-based techniques to identify these VC targets (untreated group).

The relevant literature lacks consensus about the best structure (the number of controls to treated subjects) of the matching process. Methods and variables employed depend very much on the datasets used and the aims of the matching process. The typical options are pair matching, constant matching, variable matching and full matching (Guo & Fraser, 2010). We follow previous studies and experiment with different approaches to come up with matching criteria and a matching approach. We adopt a strategy that works best for the dataset at hand and then undertake a range of robustness tests to validate the chosen approach.

Our model specification utilizes the variables identified above as influencing VC decisions or used signals by firms that seek to attract equity investment. Clearly a balance has to be struck between identifying as many VC targets in the population as possible but at the same time ensuring that the matches are as similar as possible in variable dimensions to the treated group. Thus providing reliable estimates of the demand for equity finance requires that firms are identified in the population that are similar for relevant dimensions in every aspect to VC backed firms except for the fact that they have not been financed. We are, of course, interested in exploring the effect of key variables that might influence a VC funds decision to invest and examine its impact on the size of the equity gap.

Empirical strategy

Investigating the potential size of the equity gap is necessarily exploratory and cannot be arrived at with precision. Our analysis, however, is novel in that we have data on the whole population of limited companies in the UK which enables us to estimate the potential equity gap by identifying all firms in the population that have the characteristics desirable for venture capital investors but nonetheless remain unfinanced. Estimating the potential demand for equity finance within this subpopulation provides an initial estimate of the potential unsatisfied demand for equity finance i.e. the equity gap. Having established the potential target population we then estimate the VC investment amounts required for each target company and aggregate for the population and industry sub-sectors, and of particular interest are knowledge intensive firms. After deriving an estimate of total potential demand, we explore subsamples within this population and explore how this equity gap changes when filtered by some specific firm level characteristics.

Of course only a proportion of firms identified may want equity investors and not all of them, after due diligence and detailed investigation, would be attractive as VC targets. Our database is necessarily limited in the range of variables available for profiling VC firms and identifying potential targets. The firm level information that drives venture capitalists decision-making is likely detailed and complex and our variables will certainly not capture the full range of the covariates on which VC's will make their final choices. These are aspects not typically observable to outsiders and also not amenable to use by policymakers. Policymakers seeking to develop equity gap support will therefore need to base such support on publicly available information. Practitioners may benefit from systematic screening models that identify opportunities that they may otherwise have missed and provide a pool of potential investees for further investigation. On this basis, from our analysis of known VC backed firms we are able to provide a multivariate profile that is then further refined using proxy variables that signal that a firm is in the market for equity finance. These variables relate to financing choices and director or board characteristics. We argue that firms seeking venture capital have some distinctive characteristics that, for convenience, we refer to as 'signaling' variables, outlined below.

We adopt a range of exploratory analyses of data using a combination of descriptive and econometric methods to exploit the unique features of our database. Initially we undertake some descriptive analysis of the known VC backed firms as a subpopulation of the firm level database. We identify the industry sector of each firm and the year of the VC investment. The VC firms are compared across the range of variables to the control sample of non-VC firms. We follow previous and related studies by adopting propensity score modeling along with rule based techniques to identify VC targets (Rosenbaum & Rubin, 1983). Since the goal of this study is not to estimate treatment effects but to identify untreated subjects (those which did not receive the venture capital funding) that are similar to the treated ones (those which were funded by VC), we proceed in two steps. These two steps are first the estimation of probability scores, using multivariate logit, based on the group receiving the treatment and matching to the population based on the estimated probability scores. In the second stage the estimated probability scores are used to match treated subjects with untreated ones. The main goal is not to obtain a balanced sample consisting of two groups, treated and control, unlike in PSM applications where an outcome variable is modeled. We use the propensity score model to identify 'individually similar companies' based on the range of covariates and probability score. We do not control for the number of matched companies per one treated company. Our goal is to identify as many investable companies as possible in order to gauge total potential VC demand. For instance one invested company (treated) may have only a few matches (treatment) whereas another invested company may have many similar matches within the population. This necessarily introduces different distributions of covariates compared to matched samples and therefore covariates will not balance on average between the two main subsamples. This implies that the companies from both groups should have a similar likelihood of being assigned to treatment, in our case the likelihood of receiving the VC funding. Hence the treated and untreated groups should overlap as much as possible. It is important to note that the quality of the matching depends on the quality of the covariates used for calculation of propensity scores.

The companies identified at this stage are potentially those facing an equity gap in general. In order to refine our estimates of the equity gap to identify the potential size of the second equity gap within our overall estimate we construct a propensity score model using firms that we know have received at least one round of VC funding. We detail the method and present the results below.

Data and variable construction

We combine a number of unique and relevant data sources. The core database is the population of limited companies constructed from the filings of all limited companies to Companies House over the period 2004-2014 analysis. Using a definition of 'active company' real total assets over £10k – and taking into account the target population of the study – real total assets less than £20m – the panel amounts to around 12.2 million company-year observations for the purposes of the initial analysis.

Corporate population database

The data fields include statutory accounts (abridged or full accounts) inclusive of financial performance information, from which we construct financial ratios); non- financial information (age, size, industry and technology classification, auditors, audit qualifications, changes in auditor, parent-subsidiary structure, foreign ownership, firm location); other documents filed (insolvency events, creditor charges on assets, changes in board or shareholders). The location of each company is identified by registered and trading address postcode. The postcode data can be matched to various levels of geography including NUTS regions and UK output area classifications. The data set was constructed from bulk supply of data from credit reference agencies (ICC Credit to 2010 and Creditsafe, 2011-2014). Data fields are analyzed and checked against other proprietary data sources for which we have access (e.g. FAME, Datastream). Separate but related databases include details of shareholders and director records and histories from which variables relating to ownership and board characteristics are constructed and matched to company-years in the population database.

Table 1 below compares the number of all companies submitting accounts covering financial year-ends during 2004-2014 with the number of active companies used in the analysis that have submitted at least one set of accounts and have a real total assets value between £10k and £20m.

Table 1 HERE

The core database (2004-2014) includes data on all entry and exits during the time period and (unlike commercially available databases[4]) is not affected by survival bias. Firms that exit via insolvency are tracked until their last filed accounts. Other exits via voluntary closure and dissolution are tracked and flagged. The database includes data on financial performance and constructed financial ratios for each firm over the time period. The accounting data is processed to provide information on the liquidity, profitability, leverage, asset composition, growth and efficiency of firms[5]. The financial structure, debt/equity can be identified for all firms. Firms that have obtained some loan finance may have a 'charge on assets' i.e. creditors use a fixed or floating asset charges as collateral on the loan and is typical when the loan is deemed risky and/or the firm has intangible assets. We identify all firms that have a charge on assets as an indicator that they have been able to raise some debt finance.

NACE codes can be used to identify knowledge intensive sectors. The sub-classification based on two-digit NACE codes[6] was performed using the Eurostat indicators on High-tech industry and Knowledge-intensive services. The classification used by the Eurostat and the European Commission is similar to the older classification used by OECD**.** Further sub-sector classifications based on government listed 'priority areas' are included: Life Science, ICT, Creative and Media; Energy and Environment and Advanced Manufacturing. Data on R&D, Patents and skill level of employees is not available in the database. Other proxies (e.g. asset tangibility, codes of known VC backed enterprises) will be used to examine the knowledge intensive sub-sample of companies. Age of company is calculated from incorporation date and account date. Trends in the age and sector, regional composition of companies can be calculated. From location data (postcode) it is possible to identify geographical clusters of knowledge intensive companies and/or VC backed companies. The data is constructed into a firm-level panel with company registration number as the company identifier and accounting data arranged in date order of submitted annual accounts. We restrict most analysis to the period 2004-2013 since filings for account year-ends in 2014 were not complete.

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[4] Commercial credit reference databases are geared to providing current information on the corporate sector. Consequently they often delete the complete record of a company from the database once the company has been dissolved either as a result of insolvency or voluntarily. Thus creating a data set with survival bias.

[5] Smaller companies typically do not report profit and loss information. They are required to file only abridged accounts inclusive of balance sheet data including P&L reserve (i.e. 'modified balance sheets'). Around 40% of the sample provides data on both balance sheet and profit and loss fields

[6] source http://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an3.pdf

As company law in the UK requires firms to submit an 'annual return' we are able to include details on ownership and board characteristics that we match to each company-year in the database. We developed algorithms to search shareholder records (text strings) for evidence of 'external shareholders' that are organisations rather than individuals so as to identify venture capital companies, LLP and VC trusts. Business Angel syndicates can also be identified from shareholder records along with other equity finance providers such as private equity and investment companies. Thus we identify the changes in share capital of individual firms over the time period of interest and identify firms that have received some external investment from external investors. This data is used to eliminate companies from those identified as targets in the matched sample given that they will have already had equity funding. Thus firms with evidence of external equity investors can then be excluded from the equity gap estimates.

Our database on individual company directors (over 60 million records) includes for each director the recorded date of birth (age), director name and title (gender), appointment date (and resignation date), tenure with a given company directorship (tenure) can be calculated, nationality of each director and geographic location of the directorship (company address, postcode). Company directors have a unique identification number that can be used to identify their involvement with all current and previous directorships. We measure director experience by the number of years since their first appointment (for each company-year). Organisations, trusts and other companies (non-individuals) can be registered as 'the director'. We identify companies that have an institution as one of the registered directors. In order to classify directorships by ethnic and cultural group we adopt two approaches. The first uses nationality as per director record at Companies House. However, recorded nationality may not reflect the ethnic origin of individual directors particularly those who have been naturalized or those born in the UK of immigrant parents. Of course directors recording a non-UK nationality may be associated with foreign owned companies or their subsidiaries in the UK. These directors may not be resident or permanent residents of the UK. We are able to identify both foreign companies and UK subsidiaries of foreign parents in the database. The second, more comprehensive, approach involves an analysis of the directors given and family name. The latter approach uses the 'Onomap' coding algorithms. Onomap is a name-classification system and ethnicity-coding (cultural-ethnic-linguistic) tool developed at University College London (Mateos et al., 2011)[7].

From this database we identify board size and characteristics at the start of each financial year. These characteristics measure experience and diversity (age, gender, nationality, ethnicity) of the board for each company year. Thus each individual director is matched to a directorship (limited company) and board characteristic variables are created. As directors may have multiple directorships, we calculate the number of directorships that each director on the board of a company has. For each firm we can identify if there are directors with a common surname (e.g. family members). Our constructed variables for use in the analysis are: board size (number of current directors), indicator of 'common surnames' on the board, the average age, tenure and experience of directors (and variation within a company, coefficient of variation), the proportion of directors that are female, foreign nationals on the board, directors of ethnic origin, and are directors that are institutions rather than individuals. We calculate the number and average number of multiple directorships for each board.

Companies that seek venture capital may have characteristics that provide a credible signal to the investors about otherwise unobservable viability of the business, especially in its early stage. From the data-base we construct variables that relate to age diversity on the board; board size; multiple directorships, the presence of institutional directors and creditor charges on assets. As noted earlier, a company with charges on assets signals to VCs its creditworthiness and commitment and indicates that the firm has attracted some debt finance in its early stages. Higher board diversity represented by a coefficient of variation for age may show the willingness of the company to incorporate various perspectives into the decision-making process. Despite the possible cognitive conflict arising from age dissimilarity (Goergen et al., 2015), having age diversity and a range of perceptions and skill on the board may be useful in dealing with heterogeneous customer bases or negotiating

[7] Ethnicity measures used in this study are based on twelve geographical origin zones, where this origin is taken as a proxy for 'roots'. These are: British Isles; South Asia; Central Europe; East Asia; Southern Europe; Eastern Europe; Middle East; Northern Europe; Rest of World; Africa Central; Asia; Americas. A more detailed set of 68 CEL 'subgroups' within these broad classifications are available. The software algorithms classify individuals according to most likely 'cultural–ethnic–linguistic' (CEL) characteristics, identified from forenames, surnames and forename–surname combinations. The algorithms work by reference to the structural similarities and differences between name families, which reflect underlying cultural, ethnic and linguistic features. Moreover it is apparent that there are 'distinctive naming practices in cultural and ethnic groups are persistent even long after immigration to different social contexts' (Mateos et al., 2011, p. e22943).

conditions with creditors and suppliers. Given that managerial competence or capabilities provide one of the significant decision criteria for VCs (Knockaert et al., 2010) higher directors' age diversity may signal important information about one of its facets. It is in the interest of companies keen on receiving VC funding to take on board directors with necessary contacts and networks, thus bringing extended experience to the team and possibly the positive relationships with the VCs (Hall and Hofer, 1993). As a consequence, the board gets bigger. At the same time, similar to the reasoning in the previous paragraph, it may take more effort for a large board to reach consensus. Moreover, the decisions of larger boards are less extreme and the company performance less volatile (Cheng, 2008). Both characteristics may appeal to VCs. Hence we propose that having a relatively large board may convey a positive signal to VCs about the quality and ambitions of the firm. All else equal, the directors with multiple directorships contribute with experiences and networks and as such, this characteristic may appeal to VCs and at the same time convey the quality and ambitions of the company. Institutional directors are outside directors and according to agency theory this may lead to a better performance (Jensen and Meckling, 1976). Indeed, in certain settings outside directors may contribute to growth (Peng, 2004). Moreover, as the representatives of institutional investors on the company board outside directors improve the quality of financial reporting (Pucheta-Martínez and García-Meca, 2014). A willingness to appoint institutional directors is a further way that a potential VC investee may signal its willingness and readiness to receive VC financing. At the same time, a company with improved performance and financial monitoring may be more attractive for VCs. These variables are included in the propensity score modeling subject to collinearity issues. Thus we expect that the known VC backed companies in our data base will differ with respect to some of these variables compared to non VC.

In addition data on buyout activity and Private Equity investments collected and provided by CMBOR facilitates the identification and profiling of PE backed enterprises within the limited company population. The CMBOR data includes information on: sector, financing structure and financiers, location, transaction date and value enabling trends to be examined from the start of this market in the early 1980s covering approximately 20,000 buyouts. The firms identified as private equity backed are matched to the core limited company database to facilitate sub-population analysis (PE sample) and comparisons with non-private equity backed companies, buyouts and matched companies (PE control sample). The purpose is to exclude these companies from the target VC sample when calculating the equity gap. In analyses not reported in detail here we find that private equity targets tend to be established companies in terms of age and size and are more likely to have a higher proportion of tangible assets. The targets are in stable industry sectors with a lower than average failure rate and are less likely to be diversified (single product). The firms that private equity investors target are generally cash generative, profitable and have high interest coverage ratios on existing debt. The target firms are likely to have borrowed in conventional debt markets. These firms have lower levels of equity and lower than average productivity thus providing opportunities for investors to realise performance improvement, and growth, post investment. There is, therefore, little if any overlap between VC and PE target companies.

Table 2 HERE

VC backed firms subsample

The main subsample of interest is companies that have received VC funding. Our data on VC deals come from two sources. The first dataset originates from NESTA (former National Endowment for Science, Technologies and Art) and covers the period from 1 January 2007 to 21 April 2011. In its original form, it comprised altogether 1,738 deals for 1,277 unique companies. The second dataset was obtained from the Zephyr database (provider Bureau van Dijk) covering the period from 1 January 2005 to 31 December 2014 and containing information about 2,964 deals for 2,088 companies.

The two datasets were merged and after removing duplicates the dataset held information on 4,048 deals for 2,852 unique companies. This dataset was appended with the last financial accounts prior to the deal date. This further reduced the dataset of VC deals because of the non-existence of the corresponding registered number in the main database at our disposition (170) or there were no last accounts filed prior to the deal date simply because the VC investment was start-up investment (697). If there were multiple deals related to the same company and last submitted account date, only the first one was retained and the value of deals were added (180 observations were lost due to this step). After this step, the dataset contains information about 3,001 deals for 2,258 unique companies. Finally, we limited the sample to companies with real total assets between £10k and £20m. The resulting VC sample used for further analysis and calculations comprised 2,487 deals for 1,847 unique companies. Table 3 shows the number of deals completed in individual years in the sample period and Table 4 reports the incidence of VC investments based on the knowledge and technological intensity of industrial sector. The majority of these companies can be deemed as 'knowledge-intensive' manufacturing or service companies (VC sample). The characteristics of these companies in terms of age, financial profile and industry sector is available within the population database and therefore the VC backed enterprises can be analyzed as a distinct subsample of the corporate population. The characteristics of the VC subsample are analyzed using data within one-year period of the company receiving funding i.e. before they received the funding.

Table 3 HERE

Table 4 HERE

Descriptive statistics of the estimation sample

Table 5 reports descriptive statistics of the relevant variables within the whole estimation sample[8]. The basic descriptive statistics (minimum, maximum, standard deviation, median and mean) are calculated both for the sub-sample of non-VC-backed companies and the sub-sample of VC-backed companies. The descriptive statistics for the companies financed by VC relate to the last available company-year observation before the company received the funding. To measure the differences in means between the two sub-samples Cohen's d statistic[9] is shown in the last column.

The greatest differences between the two sub-samples are in terms of P&L account reserve to total assets (average value -0.95 for the VC-backed companies compared to 0.17 for non-VC-backed companies, the difference amounts to 2.07 standard deviation), charges on assets (about 23% of VC-backed firms have charges on assets compared to average of about 4% of non-VC-backed firms, difference of about 0.92 standard deviation), board size (on average nearly six directors for VC-backed companies compared to three directors for non-VC-backed firms), proportion of audited companies (61% of VC-backed firms compared to 27% of non-VC-backed companies), proportion of female directors (only 11% for VC-

[8] Companies with real total assets lower than £10k or higher than £20m were eliminated from the sample (population). This step removed about 40% observations from the main sample (about 8.4 million observations) and 514 observations from the VC sample. Thus the whole sample contains 12,218,367 observations (2,528,048 unique companies) and the sub-sample of VC-backed firms comprises 2,487 observations (1,847 unique firms).
[9] Given the size of the sample t-tests (not surprisingly) showed statistically significant difference among the two sub-samples. Unlike t-tests, Cohen's d statistic shows the difference measured in standard deviation and as such conveys better understanding of the real size of the difference.

backed firms, 32% non-VC-backed firms), growth in total assets (38% for VC-backed firms compared to 10%).

Thus the known VC backed firms have larger initial board sizes and a greater age variation than the control sample and have directors with experience with a greater number of other directorships (multiple directorships). They are more likely to have foreign nationals and a proxy directorship representing an institution. Interestingly they have a significantly lower percentage of female directors. The VC backed firms are more likely to have raised some debt finance and are more likely to have a creditor charge on assets that we can interpret as a signal of commitment.

Table 5 HERE

Empirical Analysis of VC investees and Equity Gap Estimates

Using the combination of exact matching and propensity score matching, we identify firms that have not obtained VC investment but have the identifiable characteristics of venture capital-backed enterprises in order to provide an estimate of the potential total demand for equity funding. These demand estimates are then extrapolated to the matched population of investable companies, by sector, as an equity-gap estimate. The equity gap estimates represent a snapshot of unmet demand amongst the relevant company population at a given time. As such, they do not represent an annual requirement for firms, nor do they represent a lifetime figure of the companies funding needs. Instead they provide an assessment of the typical funding required to overcome the market failure or information asymmetry at which point the firm should have reached a sustainable growth path.

Propensity Score Matching

In the analysis that follows the VC subsample is referred to as the 'treated sample' in line with previous literature. Before providing a detailed discussion of the statistical methods and empirical results we first outline the basic logic involved in deriving an estimate of the equity gap. The steps are as follows: 1) using the data on the VC backed enterprises (the treated group) we identify companies from within the population data base that fit the profile of the treated group along dimensions related to size, age sector, financial characteristics, board size and characteristics and other controls. Following several other VC studies reviewed (e.g. Chemmanur et al. 2011; Masulis & Nahata 2011; Tian 2012; Groce et al. 2013; Alperovych et al. 2014; Cumming et al. 2014), this analysis is undertaken using various exploratory methods of matching and propensity score matching. The goal is to identify a control group of companies (which we refer to as the VC target group) that have the characteristics of VC backed enterprises in the period immediately before the investment but have not received equity finance. These are companies considered to be potential targets for VC investment. The control group obviously does not include the known VC backed companies so these companies are not part of the aggregate demand estimates. 2) Of course, within the VC target group (control group) there will be companies that may have received venture capital finance and have not been identified in the treated sample. As noted above we have access to shareholder records for all companies in the population sample and it is possible to identify VC investors from shareholder records. We do not have data on the amounts of investment that these companies have received. However, once we have identified these externally financed (VC invested) companies we can flag them and eliminate them from within the matched group. Interestingly and reassuringly our matching process selected less than 7% of the firms identified as having equity investors providing evidence that our matching process is selecting the appropriate firms. 3) Using the data on the treated sample we identify for each company the total amount of VC investment received. We use two approaches – median based calculation and regression based calculation. The median based approach utilizes the medians of the ratio of actual VC deal to total assets for certain size bands. The regression-based approach utilizes a multivariate model determining the VC amount received for the companies in the treated sample. This constitutes a model of the demand for venture capital based on the target company characteristics pre investment. The model is tested for significance and robustness. The multivariate demand model can now be applied to the VC target group to provide an estimate of the demand for VC investment amongst target companies in the population based on their characteristics. 4) Having estimated a value of VC investment demand for each company in the VC target group we can aggregate the figures in total and by company subsamples within a range of size bands, age bands, industry sectors and other variables of interest. This is regarded as an estimate of the total potential demand for VC finance as a snapshot of the corporate population within a given accounting year. 5) We refine our estimates of the equity gap for a subsample of firms that fulfill stricter selection requirements, based on our signaling variables and refine our estimates. The next stage is to eliminate from the total demand estimates firms that fall outside of these criteria. The revised demand estimate can now be aggregated under selection assumptions.

Description of the matching procedures

As an exploratory exercise we adopted a number of different approaches to matching the characteristics of the treated group with the corporate population database. We performed a range of different types of the matching but only report our final models.

The variables used for the profiling of the VC firms are based on the prior literature and we exploit the unique features of our database. Age of the companies was used in Puri & Zarutskie (2012), Croce et al. (2013) and Cumming et al. (2014). Size in various forms was employed in Chemmanur et al. (2011), Lejpras (2012), Puri & Zarutskie (2012), Alperovych et al. (2014), Tian (2012), Croce et al. (2013) and Cumming et al. (2014). Industry sector was used, as well. Masulis & Nahata (2011) argue that 72% of VC-backed targets belonged to technology intensive industries. Another important predictor of a VC investment appears to be location of a company (Puri & Zarutskie, 2012; Lerner, 1995; Tian, 2012). Profitability was employed in Ivanov and Xie (2010), Tian (2012) and Alperovych et al. (2014). And competition was utilized in Alperovych et al. (2014). In addition we draw on Mueller et al. (2012) and explore variable reflecting the characteristics of the board and management team including board size, experience, relational capital and networks and measures of diversity.

The approach adopted in the study combines rules based matching with propensity score matching, similar to Alperovych et al. (2014). For rule based matching we utilize variables with several categories – age, output classification area, industry sector and financial year-end. The details about these variables and the categories used are outlined in Table 2, above. The propensity score models used the continuous and binary variables as predictors. They were grouped into three groups – company characteristics, macroeconomic and industry sector characteristics and board characteristics as defined in detail above.

In order for a company to be matched to the VC sample it had to fulfill two conditions – it had to be in a stratum[10] defined by a company from treatment group (a company financed by venture capital) and at the same time the absolute value of the difference between the predicted propensity scores of the treated and the control company has to be smaller than a defined caliper. All companies from the control pool that fulfilled these two conditions were flagged as matched companies.

[10] The stratum is determined by age group, output classification area, HTKI industry sector and financial year-end. See Table 2 for the detailed description of the variables.

Propensity Score Matching (PSM): Multivariate Logit Models

We present the results of the multivariate estimation of the PSM models in Table 6. The dependent variable is the indicator of VC investment. The coefficients are generally robust to alternative specifications and the discriminating performance of the models, as measured by area under ROC curve, is strong with values over 0.94. The VC investment is a positive function of size and net worth, asset intangibility and evidence that the firm has utilized some bank borrowing (loans and charges on assets) and trade credit. Firms that receive VC are more likely to have attracted some debt finance and provided collateral (charge on assets) that we suggest is an important signal of credit worthiness and founder commitment. VC backed firms report audited accounts which is important for potential funders' due diligence. They are more likely to be in an important subset of knowledge intensive sectors, high technology manufacturing and knowledge intensive services. The models control for both industry competition (HHI-Turnover and HHI-Total Assets) and industry risk (Industry WOE).

The results provide evidence that VC companies are investing into industry sectors with lower default rates and lower competition. Firms seek equity funding at times of higher real interest rates and lower GDP growth. Here we include some of our additional variables capturing board characteristics. These are board size, age diversity, the presence of foreign nationals, and director experience. There is some collinearity between our measures of board characteristics so we retain other characteristics to explore the sensitivity of equity gap estimates using these firm characteristics. The results show that VC seeks to favor companies with larger boards with more diverse directors' mix. On the other hand, after controlling for other factors, VC-backed companies tend to have lower incidence of foreign directors and less overall experience in their teams but, of course, have recruited some experienced directors. However we note that larger boards in small companies reflect a wider range of skills, knowledge and experience. The age variation of directors in VC backed firms is significantly higher than the control group. Since the third model (3) captures multiple dimensions of VC decision criteria, it was used to estimate the propensity scores.

TABLE 6 HERE

Description of the matching results

We report the results of two matching procedures. They are identical in terms of exact matching and propensity score models but differ in choice of caliper. The value of the caliper recommended in the literature (Rosenbaum and Rubin, 1985; Guo and Fraser, 2010) is one quarter of standard deviation of predicted propensity scores in the sample. This value was used for matching 1. However this value was rather generous given the above-average discriminating performance of the propensity score model and hence a more restrictive value was used for matching 2 – interquartile range of the predicted propensity score within the sample. Thus the control group of companies (potential VC target group) obtained by matching 2 is a subset of that obtained by matching 1.

The overall size of the control pool (the companies to choose from) was 8,318,180 company-year observations for the period 2004 to 2013. We excluded companies that underwent a buyout or were part of a divestment in the past, exited via bankruptcy (administration, creditors voluntary arrangement, liquidation or receivership), are active in specific industrial sectors. At the same we excluded non-independent companies, foreign-owned companies or those that have an indication of having received equity finance before. After the matching was performed, we tabulated the number of matched companies for each treated company and each matching procedure. The number of control companies for each treated company is shown in Table 7. The breakdown of matched companies by year is displayed in Table 8.

TABLE 7 HERE

TABLE 8 HERE

The relatively large caliper used in matching 1 provides a higher total number of matched companies (1,985,322). At the same time, there are not many VC-financed companies for which no match was found (92). On the other hand, the total number of matched companies is smaller for matching 2 (510,702) and the number of unmatched companies is higher (256). We use more the conservative matching 2 in further analyses.

Calculation of the potential gap in financing

To estimate the equity gap we estimate the possible investment for each company from the control group. We use two approaches – median based and regression based. Both approaches derive the value of the VC deal from our VC backed sample. In median-based approach we assume that the value of the VC is proportional to the total assets. Hence we calculate the ratio of the venture capital deal to the total assets for the companies from the treatment group. The basic statistics of the ratios are calculated for four size bands (the thresholds between the bands are those used for distinction between micro, small, medium and large company in UK) and are shown in Table 9. For the initial calculation of potential VC deal the median will be used – thus for each company from the control group the potential investment will be calculated as a product of the median for the respective group and total assets.

TABLE 9 HERE

The regression-based approach takes into account several predictors of VC deal. We estimated a multivariate regression model with VC deal value as dependent variable (natural log). The explanatory variables are the same set as those used in the propensity score model. Table 10 presents the estimation results for various specifications of the venture capital deal model.

TABLE 10 HERE

As expected, the size of a VC deal is a positive function of company size. At the same time, companies with a higher proportion of cash receive more investment and similarly have some experience with loan finance (Charges) and audited accounts (Audited). On the other hand, the features such as higher proportion of intangible assets, higher proportion of profit and loss account reserve, higher bank overdraft and long-term liabilities, or higher net worth lead on average to lower VC investment. From the perspective of macroeconomic environment, a higher net lending growth is associated with lower VC deals, as opposed to GDP growth that contributes positively to the size of VC deals. Industry sector characteristics such as default rates or competition do not seem to play any role here. The board characteristics are important. Board size or incidence of foreign directors are positively related to VC deals, while directors' total experience has a negative sign. In order to keep the model parsimonious and minimize the loss of observations, we use model (4) to calculate the predicted VC deal for each potential VC target company as determined by a matching procedure.

Finally, in order to arrive at an estimate of the equity gap for a given period, we sum up the potential VC deals for all matched companies, or for a relevant subgroup. Thus we report two magnitudes – median total and regression total. At the same time, to convey an idea of an average VC deal we report average VC deal, calculated simply as the total divided by a corresponding number of companies.

Estimates of the Equity Gap

In this section, we present the results from applying the matching 2 criteria with the total and average equity gap calculated using the median and regression approaches.

Superset

Firstly we present the estimates of the overall equity gap that we call the superset. This entails summing up the individual potential VC deals for each matched company. As mentioned above, this group of companies is similar to the VC-backed companies along several dimensions and at the same time excludes the companies that are holding companies, part of a group of companies, subsidiaries or companies with a foreign parent, listed on any markets, or those that received other types of equity finance in the past (as determined by analysis of shareholders' data). At the same time we consider only companies in the size range from £10k to £20m in real total assets.

Table 11 HERE

Table 11 reports the estimates of the overall potential equity gap. The results suggest that there is a sizable equity gap in the UK, annually estimated at values from about £12 billion to nearly £32 billion with average investment from £400k to £540k per company (regression based approach). The number of potential VC targets is in the region of 23,000 to 73,000 annually. Figure 2 plots the equity gap estimates by year and the pattern of investment follows the economic cycle. In Table 12 we provide a breakdown of these figures by including only knowledge intensive companies that provide plausible numbers of companies and equity demand in the region of £2 to £20bn, regression estimates. Again there is a cyclical pattern in line with the recent economic cycle as shown in Figure 3.

Table 12 HERE

Fine Tuning

In this section we outline the adopted strategy for identifying the companies from the selected superset that face, potentially, the second equity gap. We focus only on high-technology or knowledge intensive companies at this stage. To identify the companies in the superset facing the second equity gap we assume that their characteristics are similar to those that we know received a second or subsequent round of VC funding[11.]

To achieve further insights and estimates of the second equity gap we estimate a propensity score model where the dependent variable is the indicator of the second or subsequent round of VC funding and the estimation sample comprises all high-technology or knowledge intensive companies that received at least one round of VC financing. The set of explanatory variables is the same as in the first propensity score model with one difference – the variable Age is added among the predictors. Although this variable was not included in the first propensity score model, it was used for the exact matching.

The estimated parameters are used to calculate the predicted probability score for each high-technology or knowledge intensive company in the superset. The companies with the score above a threshold will be flagged as those potentially facing the second equity gap. The sum of the predicted VC deals constitutes the potential second equity gap. The VC deals are predicted again using the median and regression approach, exactly as before. The estimate of the second equity gap is thus a parametric one and the parameter is the cut-off value for the probability score.

[11] The distinction between the companies that received only the first round of VC funding and those that received the second or the subsequent rounds is an objective criterion, and it may not completely capture the differences between the companies in the first and the second equity gap. There may be companies that are identified as receiving only one round of VC funding but may be genuinely in the position of the second equity gap. On the other hand, there may be companies that received several rounds of VC funding but are still in the earlier stages of their lifecycle corresponding to the first equity gap. In order to gain additional insights about the differences between these two types of companies (i.e. those in the first and the second equity gap), we performed cluster analysis of our sample of VC deals. Given the theoretical reasons outlined in the above text we used the set of 'signalling' variables for clustering. The variables are Directors' Age Diversity, Board Size, Multiple Directorships, Non-institutional directors and Charges. The results support the idea that among the companies that received the VC funding there is indeed a specific cluster with higher proportion of all signalling variables. At the same time, companies in this cluster are larger and older, there is a higher proportion of companies that received later stages financing which is why they are similar to companies facing the second equity gap. The results and the technical details of the cluster analysis are not reported but they are available upon request from authors. A possible alternative to our approach would be to flag companies in this cluster and use them to identify the companies in the superset facing the second equity gap.

The estimation results of the second propensity score model are reported in Table 13. We estimated two model specifications – the first with the complete vector of explanatory variables and the second with only those variables that were individually statistically significant. The results confirm that the companies that receive later stages of financing are relatively bigger (positive coefficient for Total Assets and Board Size) and older (positive coefficient for Age) than those that received just the first round. Moreover, on average they have higher accumulated loss (negative coefficient for P&L Account Reserve), higher holdings of cash (positive coefficient for Cash) and more experiences with debt financing (positive coefficient for Charges). The companies receive later stages of VC funding in the periods with lower interest rates (positive coefficient for Real Interest Rate) and the funded companies operate in more concentrated industry sectors (positive coefficient for HHI – Total Assets).

Table 13 HERE

The coefficients from the second model were used to calculate a probability score for each company in the superset. We use the value of 0.3 for the cut-off level[12], i.e. the high-technology or knowledge intensive companies from the superset having the predicted probability score higher than 0.3 are flagged as those potentially facing the second equity gap. Table 14 shows the estimates of the potential equity gap. The magnitude of the estimated second equity gap changes considerably in time, ranging from about 150 million in 2008 to over 1.2 billion in 2013 (regression total). The average predicted VC investment changes, as well, from about 1.4 million in 2009 to over 2.6 million in 2013 (regression average) or £3m-£5m median investment. Figure 14 presents the estimates of regression total and regression average in graphical form.

Table 14 HERE

[12] The choice of parameter at this stage is subjective. Even though there exist criteria for optimal choice of cut-off level based on the comparison of proportion of correctly predicted positive and negative outcomes, such as those outlined in Youden (1950) or Liu (2012), the true optimal cut-off depends on a loss function. The optimal cut-off level based on these criteria is about 0.387 and this cut-off value leads to 1,414 companies flagged as potentially facing the second equity gap. We do not have an objective loss function at hand in this case, however it is usually more costly to miss the positive outcome (false negative). Somewhat smaller value of the cut-off level of 0.3 decreases the more expensive misclassification and at the same time increases the number of flagged companies to 2,859.

Conclusions

Using a novel dataset based on the population of UK private firms we find evidence of an equity gap and particularly in the complex and fast growing knowledge intensive sectors where informational asymmetries and market failure are perhaps more acute. We add to prior literature both by emphasizing the importance of looking beyond the first valley of death (equity gap) for very early stage firms and by adopting a more in-depth quantitative analysis to establish the existence and extent of a possible equity gap. We first estimate the gap based on a superset of companies including all that are selected by our matching methods. The results suggest that there is a sizable equity gap in UK, annually estimated at values from about £12 billion to nearly £32 billion with average investment from £400k to £540k per company. Examination of only knowledge intensive companies (advanced manufacturing and high technology services) provides a plausible number of companies and equity demand in the region of £2bn to £20bn, regression estimates. Further breakdown by sectors[13] deemed 'priority sectors' shows the highest potential demand in the information and communication technology sectors and creative and media sectors with fewer companies identified in advanced manufacturing, energy and life sciences. We identify the subset of firms in the region of the second valley of death (equity gap) which, as expected, are larger and older but with increased accumulated losses. The magnitude of the total second equity gap is £1.5bn in 2013. We find a strong cyclical pattern to our results. We suggest that innovative new and growing ventures may be particularly vulnerable to failure and dissolution during downturns hampering growth and technology spill-overs.

Clearly, these estimates do not provide direct evidence that the companies not currently financed by VC are in search of VC finance or that they are particularly attractive for the VCs. However, what has been lacking so far is a quantitative assessment of the equity gap. The study is perhaps a first step in this direction.

Governments intervene to address financing problems in the SME sector and to address the particular issues facing innovative and high technology new starts and growing ventures facing funding challenges in crossing the valley of death (Litan & Robb, 2012). In the UK the Enterprise Investment Scheme and Venture Capital Trusts are long-standing tax incentives to encourage investment in small and growing businesses introduced in the mid 90's.

[13] This analysis is not reported in the paper but is available from authors upon request.

Amendments to the legislation[14] in 2015 attempted to tailor these schemes to focus investments on a subset of knowledge intensive companies falling within specific size and age bands. Owing to the size of these schemes, EIS and VCT the policy is subject to European Union state-aid approval rules. This requires a rationale for intervention is provided by member states, i.e. there is market failure, along with evidence on the likely size of the funding gap and the characteristics of the firms affected by it. We believe that our approach could provide an important input into these submissions and provide a robust basis for policy interventions. Moreover our methods, used for screening the corporate population, could be a useful tool for VC fund managers seeking to identify potential opportunities prior to more detailed investigation and due diligence. Efficient and consistent screening may help alleviate the funding gap.

Further research might usefully explore the existence and nature of an equity gap for KI firms beyond the start-up phase in other jurisdictions. In other jurisdictions, VC markets and government support programs may be either more or less developed than that studied here. Exploration of these markets would help establish the relative size of any equity gap for these firms as well as to assess the effectiveness of support programs in addressing such a gap. An additional area for further research may be to explore the extent to which herd behavior (Lerner, 2002) and escalation of commitment by VCs (Bragger, et al., 1998) may lead to initial over-funding of unviable deals in certain sectors. This may then be followed by a retreat from these sectors with the result that potential viable deals are not funded, creating a funding gap. More generally, although it was beyond the scope of this study, this leads to a need for further research on whether firms suffering from the second equity gap fail systematically more often than other comparable firms or whether they are able to continue to operate but only as 'zombie' or 'living dead' firms that lack growth. This may be an especially important research and policy issue since as KI firms important questions concern whether the lack of funding means that they are unable to continue to develop the knowledge they need to survive or whether they retreat into less innovative areas.

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"The aim of the amended EIS/VCT scheme is to support the growth of certain SMEs and knowledge-intensive SMEs and mid-caps which due to their early developments stage, would otherwise struggle to have access to finance due to an insufficient track record and/or poor collaterals. For this purpose, tax incentives are provided under the scheme to private individuals (natural persons) investing in qualifying companies (EIS), or in financial intermediaries (VCT), which carry out the eligible investments". European Commission, Brussels, 09.10.2015 C(2015) 6841 final

We have focused on the equity gap relating to VC funding arising from the second valley of death as the increasing amounts of funding involved per firm would appear to be most relevant to traditional formal VC provision. As the entrepreneurial finance market evolves, with the emergence of business angel syndicates and equity crowd funding, future research may be able to examine the extent to which these new funding sources are able to provide a solution to solving the equity gap problem for KI firms beyond the start-up phase.

Finally, as our method is exploratory there is clearly much scope for further research. Over time the predictive accuracy of such approaches could be tested. For example by using random surveys designed to find out whether a company has an interest in equity finance and/or by checking the "holdout false negatives" i.e. identifying, in later periods, firms that received VC finance but were not identified as targets by the PSM method. Of course there are other ways of combining evidence for gauging the economy-wide equity gap that can be investigated. Moreover, it would be informative to analyse the failure/dissolution rate of firms with VC backing compared to the identified VC targets and/or analyse the evolving capital structure of both subsamples. Of course, having identified VC backed firms in the population, it would be informative to track them over time with a view to modelling outcomes such as survival, growth and profitability post investment and in comparison to matched non-invested companies.

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Figure 1 Chart of the first and second equity gap

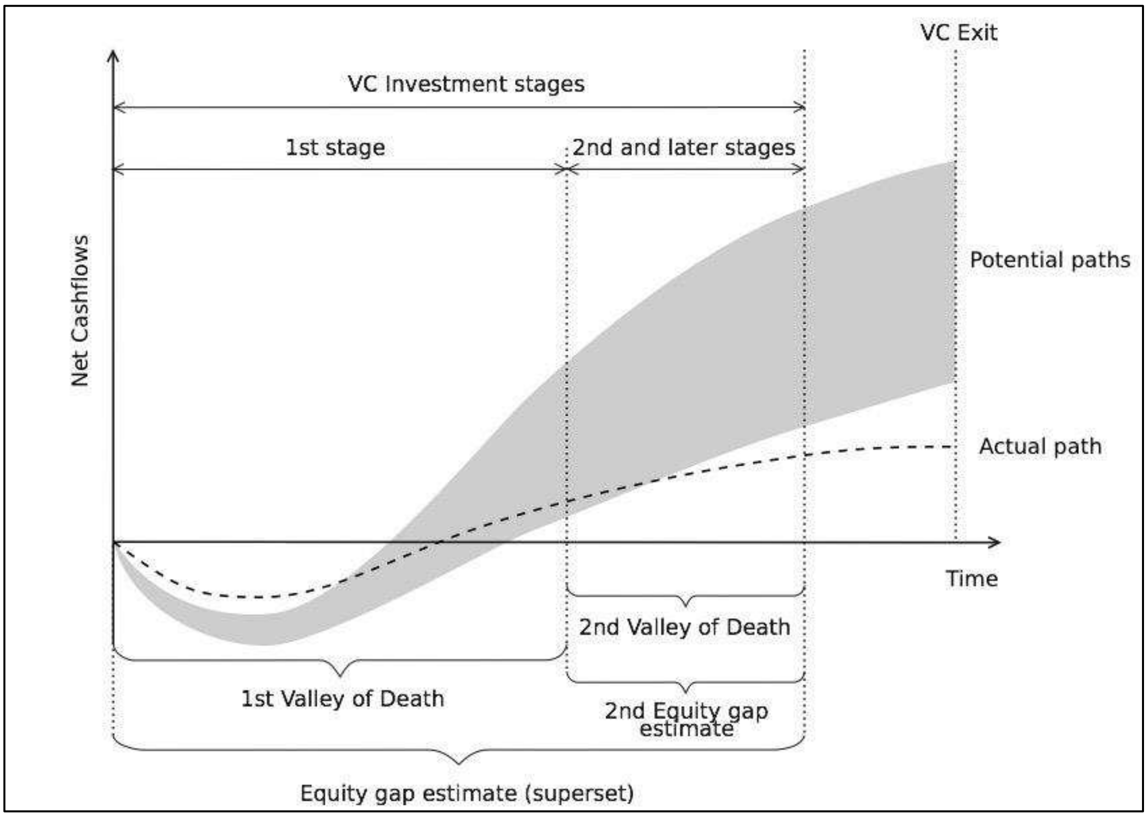

Table 1 Company-year Panel (2004-2014)

	Company-year observations	
Year	All companies	Real Total Assets higher than 10k and less than 20m
2004	1,523,027	931,683
2005	1,634,106	1,002,139
2006	1,746,401	1,038,578
2007	1,833,000	1,061,240
2008	1,882,846	1,118,544
2009	1,920,010	1,147,882
2010	1,983,190	1,168,722
2011	2,078,751	1,220,603
2012	2,210,818	1,287,822
2013	2,356,887	1,361,772
2014	1,506,646	879,382
Total	20,675,682	12,218,367

The table displays the number of company-year observations in the initial estimation sample for each year in estimation period. The second column shows the number of observations for all companies and the third column shows the number of observations only for companies of interest, i.e. those with value of total assets over £10k and less than £20m (in constant prices of 2010).

Table 2 Definition of variables

Variable	Definition
Variables used for propensity score models and models of deal value	
Total Assets	Total assets deflated to 2010 prices (GDP deflator)
Total Assets (log)	Natural logarithm of total assets deflated to 2010 prices (GDP deflator)
Turnover	Turnover deflated to 2010 prices (GDP deflator), winsorized at 1st and 99th percentile
Turnover (log)	Natural logarithm of turnover deflated to 2010 prices (GDP deflator)
Age	Age of a company in years calculated as the difference between the account date and date of incorporation truncated to the whole number, winsorized from above at 95th percentile
Intangible Assets	Intangible assets to total fixed assets, winsorized at 1st and 99th percentile
P&L Account Reserve	Profit and loss account reserve to total assets, winsorized at 5th and 95th percentile
Cash	Cash to total assets, winsorized at 1st and 99th percentile
Bank Overdraft and LTL	Bank overdraft and long-term liabilities to total assets, winsorized at 5th and 95th percentile
Trade Debtors	Trade debtors to total assets, winsorized at 1st and 99th percentile
Trade Creditors	Trade creditors to total assets, winsorized at 1st and 99th percentile
Net Worth	Net worth to total assets, winsorized at 5th and 95th percentile
Charges	Charges on assets indicator, equals to one if the company has at least one charge on assets, zero otherwise
Audited	Indicator of being audited, equals to one if the company has been audited, zero otherwise
Turnover Growth	Annual growth rate of turnover, winsorized at 5th and 95th percentile
Total Assets Growth	Annual growth rate of total assets, winsorized at 5th and 95th percentile
Board Size	Sum of all directors in board
Common Surname	Proportion of directors with common surname
Directors' Age	Mean of directors' age
Directors' Tenure	Mean of directors' tenure
Directors' Experience	Mean of directors' experience
Female Directors	Percentage of female directors
Foreign Directors	Percentage of directors who are foreign nationals
Ethnic Directors	Percentage of directors from ethnic minorities
Multiple Directorships	Average of directors with multiple directorships
Directors' Age Diversity	Coefficient of variation of directors' age
Non-institutional Directors	Percentage of non-institutional directors
Net Lending Growth	Three months Bank of England net lending growth rate
Real Interest Rate	Bank of England interest rate minus inflation, i.e. year-to-year growth rate of consumer price index
GDP Growth	Year-to-year real GDP growth rate
Industry WOE	Industry weight of evidence
HHI – Total Assets	Hirschman-Herfindahl index - total assets
HHI – Turnover	Hirschman-Herfindahl index - turnover
HTKI company	Indicator of HTKI company, equals to one if the company operates in industry sector belonging to high-tech manufacturing industry or knowledge-intensive services (based on Eurostat indicators), zero otherwise
Variables used for exact matching	
Age group	Age of a company in years calculated as the difference between the account date and date of incorporation truncated to the whole number; 15 groups – the first 13 categories correspond to the actual age from 0 to 12, the 14th group is for age from 13 to 15 years and the 15th group for the age category over 16 years
Output Area Classification	Top-tier output area classification based on 2001Census; 7 groups
HTKI Industry	Aggregation of manufacturing and services based Industry sector based on Eurostat indicators; 7 groups – high-tech manufacturing, knowledge-based services, high-tech manufacturing, medium high-tech manufacturing, medium low-tech manufacturing, low-tech manufacturing, less knowledge-intensive services and others
Year	Year of the financial accounts' end

Notes:
The sources of the variables are as follows: Net Lending Growth and Real Interest rate – Bank of England; GDP growth and GDP deflator – Federal Reserve Bank of St. Louise; HTKI company, HTKI industry – indicators generated using the Eurostat categorization of companies on the basis of two-digit NACE codes; Output Area Classification – Office of National Statistics, matched by postcode; all other variables come either directly or are calculated using the data provided by credit reference agencies ICC Credit and Creditsafe,

Table 3 Breakdown of VC deals according to year of deal completion and round

Year of VC deal completion	1st round	2nd or subsequent round	Total
2005	165	4	169
2006	129	16	145
2007	229	139	368
2008	203	149	352
2009	138	157	295
2010	195	162	357
2011	117	86	203
2012	151	57	208
2013	121	43	164
2014	166	60	226
Total	1,614	873	2,487

The table shows the number of venture capital deals in the VC sample broken down by the year of VC deal. The unit of analysis is VC deal. The frequencies are further broken down according to the round of investment. The second column displays the number of deals receiving the first round of investment and the third column shows the number of deals receiving the second or subsequent round. The last column shows total number of deals obtained in given year.

Table 4 Breakdown of VC deals according to the technology sector

Sector	1st round	2nd or subsequent round	Total
High-technology	62	40	102
Knowledge-intensive services	982	587	1,569
Less knowledge-intensive services	338	129	467
Low technology	74	32	106
Medium-high-technology	43	24	67
Medium-low-technology	59	41	100
Other	56	20	76
Total	1,614	873	2,487

The table shows the number of venture capital deals in the VC sample broken down by the industrial sector classified according to technological and knowledge intensity. The adopted Eurostat classification is based on NACE rev. 2 at two-digit level (which corresponds to SIC 2007). The unit of analysis is VC deal. The frequencies are further broken down according to the round of investment. The second column displays the number of deals receiving the first round of investment and the third column shows the number of deals receiving the second or subsequent round. The last column shows total number of deals for given sector.

Table 5 Descriptive statistics

	Non-VC deals						VC deals						
	N	Minimum	Maximum	St. dev.	Median	Mean	N	Minimum	Maximum	St. dev.	Median	Mean	Cohen's d
Total Assets	12,215,880	10,000	19,999,518	1,997,648	102,119	713,015	2,487	10,082	19,983,809	3,435,868	585,354	2,026,237	-0.641
Age	12,215,852	0.00	23.00	7.23	6.00	8.51	2,487	0.00	23.00	4.50	3.00	4.61	0.54
Intangible Assets	9,949,574	0.00	1.00	0.26	0.00	0.10	2,296	0.00	1.00	0.38	0.00	0.25	-0.572
P&L Account Reserve	12,215,880	-1.76	0.87	0.54	0.19	0.17	2,487	-1.76	0.87	0.81	-1.09	-0.95	2.072
Cash	12,215,880	0.00	1.00	0.33	0.16	0.30	2,487	0.00	1.00	0.32	0.33	0.39	-0.263
Bank Overdraft and LTL	12,215,880	0.00	0.74	0.22	0.00	0.11	2,487	0.00	0.74	0.29	0.01	0.21	-0.463
Trade Debtors	12,215,880	0.00	1.00	0.29	0.15	0.26	2,487	0.00	1.00	0.25	0.15	0.23	0.103
Trade Creditors	12,215,880	0.00	1.00	0.41	0.96	0.66	2,487	0.00	1.00	0.39	0.47	0.52	0.357
Net Worth	12,215,880	-1.95	1.00	0.58	0.25	0.21	2,487	-1.95	1.00	0.94	0.10	-0.18	0.667
Charges	12,215,880	0.00	1.00	0.21	0.00	0.04	2,487	0.00	1.00	0.42	0.00	0.23	-0.917
Audited	12,215,880	0.00	1.00	0.45	0.00	0.27	2,487	0.00	1.00	0.49	1.00	0.61	-0.753
Total Assets Growth	9,699,733	-0.46	1.12	0.38	0.01	0.10	1,838	-0.46	1.12	0.60	0.28	0.38	-0.741
Board Size	11,217,335	1.00	918.00	2.62	2.00	2.92	2,387	1.00	89.00	3.49	5.00	5.71	-1.064
Common Surname	11,217,335	0.00	102.00	1.43	1.00	0.79	2,387	0.00	75.00	2.05	0.00	0.85	-0.048
Directors' Age	11,083,069	16.00	80.00	9.84	48.50	48.76	2,382	19.00	74.00	7.11	46.67	45.95	0.285
Directors' Tenure	11,124,806	1.00	60.00	4.67	4.60	5.90	2,374	1.00	18.33	1.98	2.00	2.56	0.715
Directors' Experience	11,031,347	0.00	144.00	5.39	7.00	8.02	2,370	0.00	20.50	3.43	5.75	6.09	0.357
Female Directors	11,217,335	0.00	100.00	28.50	33.33	32.48	2,387	0.00	100.00	17.76	0.00	11.17	0.748
Foreign Directors	11,217,335	0.00	100.00	20.44	0.00	6.79	2,387	0.00	100.00	22.84	0.00	14.58	-0.381
Ethnic Directors	11,217,335	0.00	100.00	25.16	0.00	7.86	2,387	0.00	100.00	13.19	0.00	4.30	0.142
Multiple Directorships	11,217,335	0.00	267.11	5.26	0.00	1.03	2,387	0.00	33.17	2.15	1.17	1.44	-0.077
Directors' Age Diversity	11,217,335	0.00	91.85	12.37	5.11	10.14	2,387	0.00	61.97	9.51	15.87	16.06	-0.479
Non-institutional Directors	11,217,335	0.00	100.00	13.48	100.00	96.61	2,387	16.67	100.00	11.06	100.00	95.31	0.096
Industry WOE	11,336,580	-1.31	1.79	0.48	0.06	0.03	2,410	-1.24	1.79	0.38	0.12	0.13	-0.215
HHI – Total assets	11,336,580	18.88	10000.00	838.17	215.18	458.27	2,410	19.22	5445.62	1511.64	256.59	923.88	-0.555
HHI – Turnover	11,336,578	29.76	10000.00	255.78	137.81	223.09	2,410	29.76	3641.32	313.62	158.81	281.99	-0.23
HTKI company	12,215,880	0.00	1.00	0.48	0.00	0.35	2,487	0.00	1.00	0.47	1.00	0.67	-0.665

The table shows the descriptive statistics for the relevant variables used in the study. The more detailed definition of the variables is in Table 2. The sample is limited to companies with real total assets in the range from £10k to £20m. The first subsample comprises the companies that are not backed by venture capital and the second subsample contains VC deals. The descriptive statistics for the companies financed by VC relate to the last available company-year observation before the company received the funding. For each subsample the following quantities are indicated – number of non-missing observations, minimum, maximum, standard deviation, median and mean (in this order). In the last column, Cohen's d-statistic for the difference in means is shown.

Table 6 Estimation of propensity score models

Dependent variable:	Indicator of any round of VC financing		
	(1)	(2)	(3)
Total Assets (log)	0.422***	0.426***	0.455***
	(29.59)	(29.18)	(30.35)
Intangible Assets	1.527***	1.477***	1.403***
	(26.43)	(24.68)	(23.10)
P&L Account Reserve	-2.290***	-2.233***	-2.240***
	(-89.54)	(-82.52)	(-78.84)
Cash	2.849***	2.777***	2.686***
	(35.93)	(33.70)	(31.74)
Bank Overdraft and LTL	1.040***	0.995***	1.025***
	(10.13)	(9.66)	(9.75)
Trade Debtors	0.863***	0.913***	0.974***
	(9.13)	(9.56)	(9.98)
Trade Creditors	0.835***	0.800***	0.843***
	(10.70)	(10.23)	(10.41)
Net Worth	0.594***	0.545***	0.558***
	(18.98)	(17.11)	(16.81)
Charges	1.317***	1.322***	1.235***
	(24.06)	(23.87)	(22.23)
Audited	0.501***	0.435***	0.377***
	(8.31)	(7.00)	(5.86)
HTKI company	0.813***	0.816***	0.790***
	(16.69)	(15.97)	(15.14)
Net Lending Growth		0.0108***	0.00782**
		(2.85)	(2.05)
Real Interest Rate		0.0378**	-0.00612
		(2.45)	(-0.40)
GDP Growth		-0.0759***	-0.0620***
		(-8.39)	(-6.88)
Industry WOE		0.196***	0.195***
		(4.06)	(3.82)
HHI – Total Assets		0.000206***	0.000194***
		(11.21)	(10.46)
HHI – Turnover		0.000288***	0.000305***
		(3.33)	(3.45)
Board Size			0.0127***
			(7.35)
Directors' Age Diversity			0.0223***
			(14.88)
Foreign Directors			-0.00504***
			(-5.44)
Directors' Experience			-0.117***
			(-21.44)
Constant	-16.97***	-17.14***	-16.85***
	(-81.12)	(-80.23)	(-77.76)
N	9,951,870	9,228,969	9,034,524
VC deals	2,296	2,232	2,198
AUC	0.942	0.943	0.947

The table reports the estimation results for the propensity score models. In all models the dependent variable is the indicator of any round of VC financing, equal to one if the company received VC financing, zero otherwise. The estimation sample comprised all company-year observations where the value of total assets was over £10k and less than £20m (in constant prices of 2010). The explanatory variables are described in Table 2. The parameters were estimated using logistic regression. z-statistics are in parentheses and the statistical significance of estimated parameters is denoted with stars (*** indicates statistical significance at the 1% level, ** at the 5% level and * at the 10% level). The estimated parameters of model 3 (shaded) were used for calculation of propensity scores.

Table 7 Number of matched companies for each of the VC financed company

Number of matched companies	Matching 1	Matching 2
0 (no company matched)	92	256
1 - 10	39	132
11 - 100	94	212
101 - 1,000	205	267
1,001 - 10,000	527	766
over 10,000	1,241	565
Total	2,198	2,198

The table shows the distribution of VC-backed companies in the sample in terms of the frequencies of matched companies. The second row reports the number of VC-backed companies for which no match was found, the third row presents the number of VC-backed companies for which the number of matched companies lies between 1 and 10, etc.

Table 8 Number of matched companies in individual years

Year of last accounts end	Matching 1	Matching 2
2004	86,554	33,307
2005	127,772	34,609
2006	210,259	67,344
2007	255,399	73,008
2008	219,531	23,047
2009	249,899	46,534
2010	270,744	35,971
2011	187,200	50,030
2012	191,623	70,076
2013	186,341	76,776
Total	1,985,322	510,702

The table reports the number of matched companies for each year and matching strategy.

Table 9 Summary statistics for the ratio of VC investment to total assets

Total Assets	N	Minimum	Maximum	St. dev.	Median	Mean
10k - 312k	685	0.06	2,829.62	144.62	**6.83**	28.18
312k - 3.26m	863	0.01	63.48	5.58	**1.87**	3.55
3.26m - 12.9m	267	0.01	18.24	1.83	**0.94**	1.48
12.9m - 20m	45	0.01	2.22	0.56	**0.38**	0.5

The table reports the descriptive statistics for the ratio of VC investments to total assets for given size-bands. The size-bands considered are shown in the first column and correspond to the real total assets in £. The figures in bold (median for given size-band) are used for median based calculation of potential equity gap.

Table 10 Estimation of VC deals models

Dependent variable:	Natural logarithm of VC deal, any round			
	(1)	(2)	(3)	(4)
Total Assets (log)	0.484***	0.469***	0.463***	0.464***
	(17.31)	(16.27)	(14.45)	(15.29)
Intangible Assets	-0.363***	-0.369***	-0.347***	-0.355***
	(-4.10)	(-4.14)	(-3.86)	(-4.15)
P&L Account Reserve	-0.256***	-0.240***	-0.203***	-0.210***
	(-5.07)	(-4.66)	(-3.79)	(-3.84)
Cash	0.436***	0.457***	0.419***	0.410***
	(3.44)	(3.54)	(3.26)	(3.67)
Bank Overdraft and LTL	-0.653***	-0.672***	-0.653***	-0.678***
	(-4.21)	(-4.32)	(-4.20)	(-5.22)
Trade Debtors	-0.112	-0.0526	0.0461	
	(-0.71)	(-0.33)	(0.29)	
Trade Creditors	0.109	0.0423	0.0515	
	(0.92)	(0.36)	(0.44)	
Net Worth	-0.271***	-0.272***	-0.273***	-0.267***
	(-6.13)	(-6.11)	(-6.16)	(-6.01)
Charges	0.182**	0.177**	0.176**	0.180**
	(2.37)	(2.32)	(2.31)	(2.39)
Audited	0.152*	0.178**	0.178**	0.180**
	(1.95)	(2.12)	(2.12)	(2.20)
HTKI company	-0.00564	0.0329	0.0400	
	(-0.08)	(0.41)	(0.49)	
Net Lending Growth		-0.0217***	-0.0200***	-0.0140***
		(-3.65)	(-3.44)	(-3.29)
Real Interest Rate		0.0450**	0.0302	
		(2.00)	(1.32)	
GDP Growth		0.0338**	0.0377**	0.0343**
		(2.35)	(2.57)	(2.38)
Industry WOE		-0.144	-0.149	
		(-1.42)	(-1.44)	
HHI – Total Assets		0.0000330	0.0000308	
		(1.27)	(1.17)	
HHI – Turnover		0.0000445	0.000113	
		(0.34)	(0.83)	
Board Size			0.0232**	0.0226**
			(2.10)	(2.11)
Directors' Age Diversity			-0.00267	
			(-0.74)	
Foreign Directors			0.00431***	0.00402**
			(2.75)	(2.52)
Directors' Experience			-0.0297**	-0.0310***
			(-2.43)	(-2.61)
Constant	7.262***	7.411***	7.529***	7.625***
	(17.77)	(17.65)	(17.65)	(21.33)
N	1,713	1,664	1,637	1,637
R^2	0.317	0.321	0.342	0.337

The table reports the estimation results of the multivariate regression models of VC deal value. The estimation sample comprised the companies with known values of the VC investments where the value of total assets was over £10k and less than £20m (in constant prices of 2010). In all models the dependent variable is the natural logarithm of the first round of VC deals. The explanatory variables are described in Table 2. The parameters were estimated using ordinary least square method. t-statistics are in parentheses and the statistical significance of estimated parameters is denoted with stars (*** indicates statistical significance at the 1% level, ** at the 5% level and * at the 10% level). The last model (shaded) includes only predictors that are statistically significant and its parameters were used for prediction of potential VC deal value which was further utilized for estimations of potential equity gap (regression based approach).

Table 11 Potential equity gap - breakdown by year

	Total		Average		
year	Median	Regression	Median	Regression	Frequency
2004	29,550,834,749	18,123,672,578	887,226	544,140	33,307
2005	20,541,124,255	13,018,313,110	593,520	376,154	34,609
2006	63,904,437,876	31,782,601,279	948,926	471,944	67,344
2007	72,871,124,820	31,581,638,986	998,125	432,578	73,008
2008	26,497,101,323	12,031,668,474	1,149,699	522,049	23,047
2009	37,372,253,716	18,660,697,414	803,117	401,012	46,534
2010	27,305,158,002	17,853,076,818	759,088	496,319	35,971
2011	30,506,700,156	20,722,255,650	609,768	414,197	50,030
2012	45,969,421,528	28,391,370,844	655,994	405,151	70,076
2013	48,347,118,155	30,208,756,721	629,717	393,466	76,776

The table shows the estimates of the potential equity gap in UK for companies with real total assets from £10k to £20m in the period from 2004 to 2013. The second and third column give the estimates of total equity gap, i.e. sum of predicted VC deals for individual companies calculated using median and regression approach, respectively. The numbers in the fourth and the fifth columns correspond to the average predicted VC deal per company. The last column shows the number of matched companies for given year of financial year end. All quantities indicated in the table are based on matching 2 and represent the potential equity gap superset, i.e. the maximum potential equity gap – basis for further calculations.

Figure 2 Charts of potential equity gap - superset

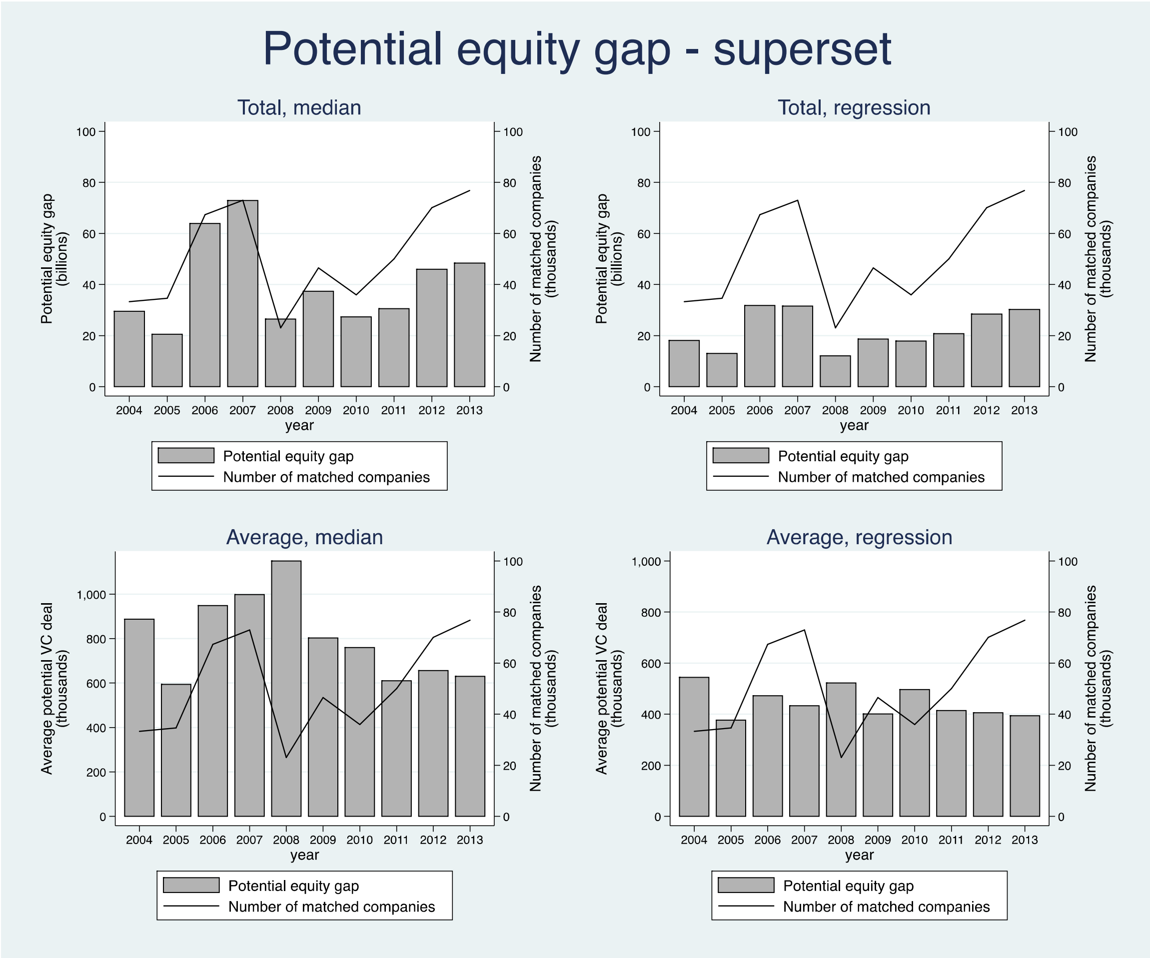

Table 12 Breakdown of potential equity gap and frequencies for high-technology or knowledge intensive companies

	Total		Average		
year	Median	Regression	Median	Regression	Frequency
2004	3,436,479,697	2,987,634,063	574,566	499,521	5,981
2005	7,900,197,712	5,935,465,771	426,600	320,507	18,519
2006	19,165,927,068	10,445,739,802	817,973	445,809	23,431
2007	12,815,253,154	7,119,385,648	819,861	455,466	15,631
2008	4,193,778,870	2,894,298,731	643,316	443,979	6,519
2009	10,782,062,535	5,967,547,584	667,537	369,462	16,152
2010	13,703,867,805	9,531,615,520	691,695	481,103	19,812
2011	18,366,107,447	13,520,819,171	526,687	387,738	34,871
2012	15,600,141,527	10,814,644,030	542,500	376,083	28,756
2013	32,074,333,561	20,705,640,520	582,397	375,967	55,073

The table shows the estimates of the potential equity gap for high-technology or knowledge-intensive companies (HTKI companies) in UK. All calculations are for HTKI companies with real total assets from £10k to £20m in the period from 2004 to 2013. The second and third column give the estimates of total equity gap for HTKI companies, i.e. sum of predicted VC deals for individual companies calculated using median and regression approach, respectively. The numbers in the fourth and the fifth columns correspond to the average predicted VC deal per company. The last column shows the number of matched companies for given year of financial year end for HTKI companies. All quantities indicated in the table are based on matching 2.

Figure 3 Charts of potential equity gap for high-technology or knowledge intensive companies

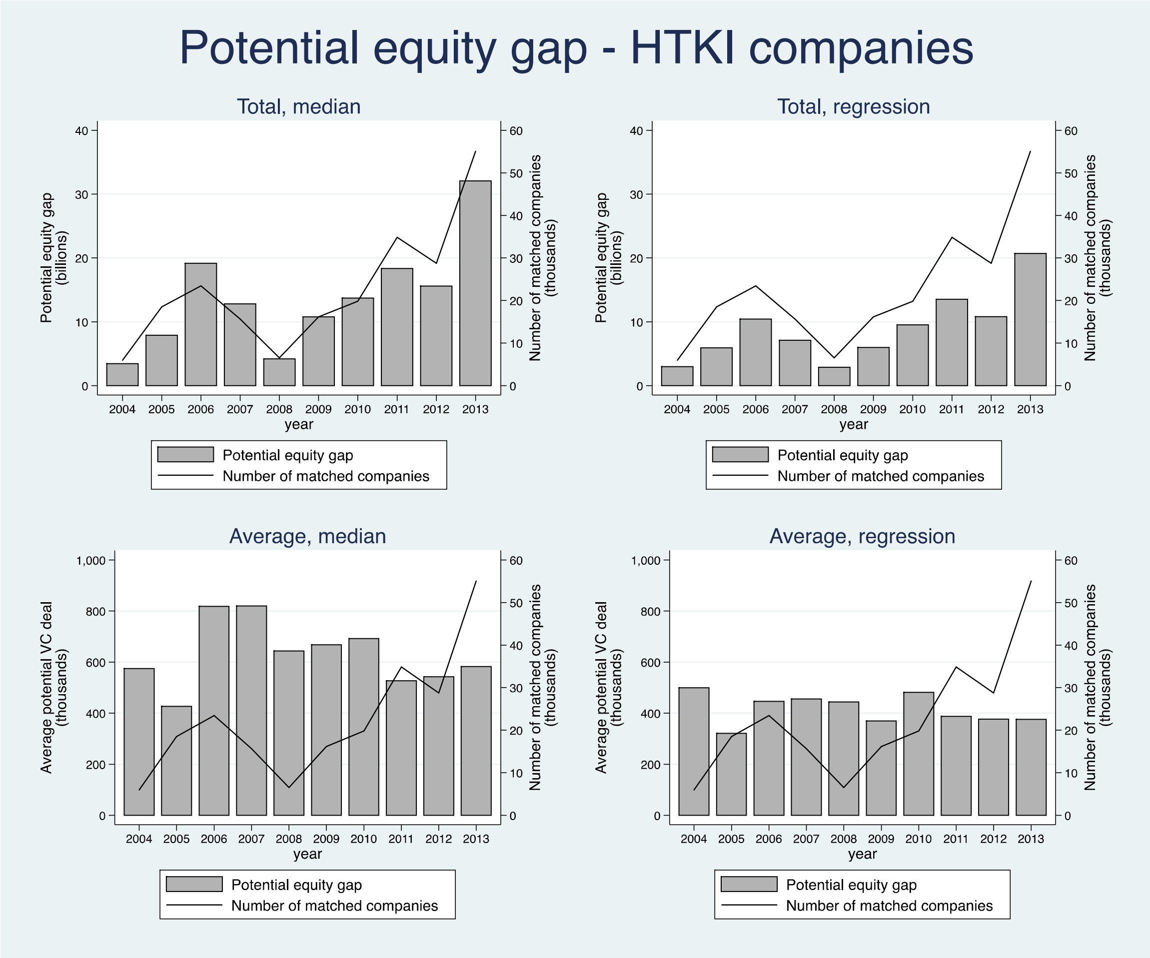

Table 13 Estimation of propensity score models for higher rounds of VC financing

Dependent variable:	Indicator of the second and subsequent round of VC financing	
	(1)	(2)
Total Assets (log)	0.612***	0.567***
	(9.61)	(11.58)
Age	0.0639***	0.0660***
	(3.45)	(4.05)
Intangible Assets	-0.142	
	(-0.73)	
P&L Account Reserve	-1.298***	-1.150***
	(-11.43)	(-11.47)
Cash	1.108***	0.875***
	(4.09)	(4.35)
Bank Overdraft and LTL	0.295	
	(1.00)	
Trade Debtors	0.488	
	(1.44)	
Trade Creditors	0.296	
	(1.29)	
Net Worth	0.104	
	(1.06)	
Charges	0.284*	0.291**
	(1.85)	(2.03)
Audited	0.0388	
	(0.23)	
Net Lending Growth	0.00477	
	(0.38)	
Real Interest Rate	-0.172***	-0.173***
	(-3.35)	(-5.76)
GDP Growth	-0.0457	
	(-1.49)	
Industry WOE	0.119	
	(0.52)	
HHI – Total Assets	0.000240***	0.000117***
	(4.32)	(3.20)
HHI – Turnover	-0.00133***	
	(-3.25)	
Board Size	0.0717**	0.0620**
	(2.54)	(2.51)
Directors' Age Diversity	-0.0151*	
	(-1.82)	
Foreign Directors	-0.00278	
	(-0.80)	
Directors' Experience	-0.0291	
	(-1.28)	
Constant	-10.78***	-10.23***
	(-11.73)	(-14.82)
Observations (all VC deals)	1472	1602
VC deals – higher round	590	617
AUC	0.826	0.816

The table reports the estimation results of the probability models related to the higher rounds of VC financing. In both models the dependent variable is the indicator of the second or subsequent round of VC financing, equal to one if the company received more than one round of VC financing, zero otherwise. The estimation sample comprised the company-year observations for high-technology or knowledge intensive companies that received at least one round of VC funding, with total assets from £10k to £20m (in constant prices of 2010). The explanatory variables are described in Table 2. The parameters were estimated using logistic regression. z-statistics are in parentheses and the statistical significance of estimated parameters is denoted with stars (*** indicates statistical significance at the 1% level, ** at the 5% level and * at the 10% level). The estimated parameters of model 2 (shaded) were used for calculation of probability scores.

Table 14 Potential second equity gap for high-technology or knowledge intensive companies - breakdown by year

	Total		Average		
year	Median	Regression	Median	Regression	Frequency
2006	2,064,460,736	958,199,075	4,104,296	1,904,968	503
2007	1,276,693,015	634,849,595	3,833,913	1,906,455	333
2008	312,183,627	153,683,566	3,902,295	1,921,045	80
2009	1,069,050,539	468,191,992	3,229,760	1,414,477	331
2010	1,842,802,685	986,164,810	2,813,439	1,505,595	655
2011	703,983,988	357,770,704	3,502,408	1,779,954	201
2012	399,219,163	200,743,585	5,252,884	2,641,363	76
2013	2,885,658,186	1,208,597,858	4,243,615	1,777,350	680

The table shows the estimates of the potential second equity gap in UK for high-technology or knowledge intensive companies with real total assets from £10k to £20m in the period from 2006 to 2013. The second and third column give the estimates of total equity gap, i.e. sum of predicted VC deals for individual companies calculated using median and regression approach, respectively. The numbers in the fourth and the fifth columns correspond to the average predicted VC deal per company. The last column shows the number of companies potentially in the situation of the second equity gap in given year. All quantities indicated in the table are based on the potential equity gap superset obtained by matching 2 and represent the parametric estimate of the second equity gap for high-technology or knowledge intensive companies. The parameter was the arbitrarily chosen cut-off point for the probability score of receiving the later stage of VC financing (the value of cut-off point equal to 0.3).

Figure 4 Chart of potential second equity gap for the high-technology or knowledge intensive companies