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Venture Capital as a Driver of Labor Market Performance

An Examination of its Impact on Employment and Labor Costs

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Abstract

Venture capital has been widely recognized to have the potential to promote an economy's growth and competitive position through driving innovation, productivity and job creation, both in certain regions and in countries as a whole. In light of Europe's urgent problems of persistent unemployment and lack of competitiveness, we aim to further investigate how venture capital affects employment and labor costs at an industry level, circumventing potential biases from firm level studies while allowing for more differentiation than research conducted at a country level. We examine the impact of venture capital investments on employment and labor costs across 21 industries in the EU-15 countries between 1995 and 2009. Employing multiple OLS and GLS regression specifications, we find that venture capital raises employment as well as labor costs in receiving industries. This suggests that venture capital has the potential to attract and develop a highly skilled and competitive labor force and may be a driver of employment in entire industries. However, the problem of reverse causality must be borne in mind.

Keywords: Venture Capital, Financing, Employment, Labor costs

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1 Introduction

It has become widely acknowledged that venture capital has the potential to promote an economy's growth and competitive position through driving innovation, productivity and job creation, both in certain regions and in countries as a whole. Venture capital (VC) is a type of private equity investment focused on start-up companies, backing teams of high-potential companies with funding as well as strategic and operational expertise to launch new products and grow their businesses.

VC is often claimed to create high-skilled employment in new and innovative areas where other sources of financing are hard to access (EVCA, 2013). The high and persistent unemployment in Europe today has further shifted the attention to the VC industry as a driver of job creation, and the VC industry has thus become an important pillar in promoting growth in Europe. In addition, the current lack of competitiveness of European companies calls for the continuing development of a highly skilled and productive labor force to attract investment that is increasingly allocated on an international basis to the most competitive companies (Cherif and Gazdar, 2011).

Previous research consistently finds a positive relationship between VC and different indicators of labor market performance. Studies have for example shown that employees in VC-backed firms enjoy higher wages (Samila and Sorenson, 2011; Puri and Zarutskie, 2012). In terms of job creation, a number of researchers have tried to understand the relationship between employment growth and VC funding from a macroeconomic perspective (Wasmer and Weil, 2000; Belke et al., 2003; 2004), and find that VC has a positive effect on employment. Others, composing the larger share of previous research, have instead utilized firm level data to disentangle the relationship between VC and employment (Davila et al., 2003; Chemmanur et al., 2011; Puri and Zarutskie, 2012).

Although significant progress has been made in VC research, there are potential weaknesses as well as shortcomings in the previous literature. We hope to circumvent these problems by applying an approach that, to our knowledge, has not been used before in this area of research. Specifically, this thesis aims to contribute to the growing body of VC research by examining how VC affects aggregate employment and labor costs at an industry level. The industry level analysis adds insight to those of previous literature, which have mainly been based on firm level studies. Furthermore, by employing an industry level analysis we can account for much variation, which is lost at an aggregate country or regional level.

First, we hypothesize that VC has the potential to grow entire industries in terms of employment in line with its recently argued instrumental role in creating high-tech, high-growth industries such as information technology and semiconductor industries (IHS Global Insight, 2009). Our hypothesis is further motivated by the argument that innovations and patent filings driven by VC (Kortum and Lerner, 2000) are likely industry-specific and hence spill over to companies within the same industry, drawing on theories developed by Romer (1986). Therefore, the effects of VC activity should be evident in entire industries where it is present. This can be compared to the view of Samila and Sorenson (2011), who argue that VC instead drives development in certain regions. Second, by examining the relation between VC and labor costs, we aim to test the claimed ability of VC to attract and develop a high-skilled labor force, which contributes to an economy's competitiveness.

In order to address these two questions, we examine the impact of VC on employment and labor costs across 21 industries in the EU-15 countries between 1995 and 2009. Employing multiple OLS and GLS regression specifications, we find evidence supporting our hypotheses that VC has a positive and significant impact on both the level and growth of aggregate employment and labor costs, consistent with previous research. Our findings together propose that well-functioning VC markets can contribute significantly to producing superior employment performance at an industry level and that VC may be a potential driver of employment in entire industries.

In particular, our findings suggest that a doubling of VC investments over four years results in an increase of 0.2 to 7.5 percent in the level of employment. The results also suggest that the presence of VC investments has a positive impact on the growth rate of employment. On average, an industry receiving VC funding in the preceding four years grows faster by 0.5 percentage points annually than industries receiving no VC funding. During our sample period, the average employment growth across industries is 0.04 percent annually. We also find that the growth of employment is positively associated with higher levels of VC activity. A doubling of the supply of VC investments over the preceding four years implies an increase of annual employment growth of roughly 0.1 percentage points. At least part of this higher employment performance is probably due to the fact that VC allows necessary capital to reach young companies in early stages.

However, the results are sensitive to the inclusion of combined industry-year fixed effects suggesting that there are some unobservable factor(s) driving both employment growth and VC activity at an industry level. We suggest that VC may work through different channels and indirectly affect employment growth through its causing of factors driving employment, such as patenting and productivity in entire industries. We further suggest that the effect of VC on employment growth is non-linear and decreasing, implying that the marginal effect of VC investments is greater when the supply of VC is still relatively scarce within an industry.

Labor costs are found to grow faster by 0.65 percentage points annually in industries receiving VC funding than in industries receiving no VC funding, compared to an average growth rate of labor costs of 1.29 percent annually across the sample. Furthermore, a doubling in VC activity results in a 0.3 to 7.3 percent higher level and 0.16 percentage points faster annual growth rate of labor costs. This suggests that VC has the potential to attract and develop a highly skilled and competitive labor force. However, as the conducted Granger causality test provides inconclusive results in light of the reverse causality issues when studying the effect of VC on the growth of labor costs, we are cautious in arguing for causality in terms of VC and labor costs. The positive relation between labor costs and VC potentially illustrates the fact that VC firms are attracted to industries requiring high-skilled labor such as high-tech and service industries.

We further suggest that VC might work more efficiently in the "new economy" industries, here defined as the service sector. When allowing for the distinction between service and manufacturing industries in our regressions, we find a positive and significant impact of VC on both employment and labor cost growth. The effect of VC however loses its significance in manufacturing industries suggesting that the effect of VC found in the full sample is most likely attributable to the service industries.

We recognize the potential of reverse causality issues. However, we argue that this does not undermine the importance of VC for employment performance by much. Even though VC firms may choose to invest in industries with good growth potential, it is partially the capital that VC contributes that facilitates this growth.

In summary, our results support the notion that the presence of VC benefits not only companies backed by VC, but also the entire industries to which they belong. While previous research has examined these spillover effects of VC on a country and regional level our findings suggest that these are also present in industries, which is an important contribution to current research.

The remainder of the thesis is outlined as follows: in section two, we present a brief background of VC development and employment in Europe. In section three, we summarize the current state of literature. In section four, we present the data. For the purpose of this thesis, yearly structural data as well as VC activity data from the EU-15 countries at an industry level during the time period of 1995-2009 has been used. The dataset contains information about the yearly number of employees per industry, labor costs and records of VC transactions. In the fifth section, we formulate a number of regressions to test our hypotheses. We present the results from these regressions in the sixth section and discuss potential problems in our findings. Thereafter, we analyze the implications of the results in section seven. Our results support the existence of a significant effect of VC on employment and labor costs. The eighth section concludes the paper and gives suggestions for future research.

2 Background

VC is of U.S. origin, and the U.S. has by far the largest VC industry in the world. The European VC industry began to develop first in the early 1990s. In its early years, the level of European funds raised and invested was relatively trivial and it reached a low point in 1993 as a result of Europe struggling with recession and its lingering aftermath. In the latter half of the decade however, VC activity in Europe increased thanks to the astonishing returns of the dotcom era (Boquist and Dawson, 2004), with investments amounting to roughly a quarter of the U.S. level in 1999 (Hege et al., 2008). Additionally, a series of legal and regulatory changes took place in the 1990s, which further stimulated the European VC industry (EVCA, 2010). However, the VC industry was badly tarnished by the following burst of the dotcom bubble in the early 2000s when many VC firms were forced to write off large proportions of their investments. The industry has since continued to lag far behind its U.S. counterpart despite the fact that European governments have made the development of the VC industry a key policy priority for over twenty years (Hege et al., 2008).

The European market is not only fragmented but the funding gap, compared to the U.S., remains high. According to a White Paper Report published by the European Private Equity and Venture Capital Association (EVCA, 2010), VC in Europe accounts for about EUR 5 billion to EUR 6 billion on a year average, which is tiny compared to most other asset classes. A striking difference between the European and U.S. VC industry is that although the European industry invests much less than the U.S., it supports nearly twice as many companies. Hence, the average amount invested by company is much smaller in Europe (Bottazzi and Da Rin, 2002).

Even though the gap with the U.S. VC industry is far from closing, the European VC industry is certainly expanding and there are signs of a brightening future for the European VC market. Despite huge losses for the VC industry during the economic downturn of the early 2000s, VC-backed firms outperformed other private sector firms and allegedly contributed significantly to Europe’s growth (EVCA, 2013). The European VC funds have also managed to recover after the most recent financial crisis of 2008-2009 and available funding is increasing. Beyond the VC market’s strength in surviving severe downturns, the European VC market is also argued to have gained experience and competitiveness on the global markets (EVCA, 2012). However, this view is not shared by all. For instance, Hege et al. (2008) suggest that the U.S. venture capitalists are more sophisticated than their European peers, which can explain much of the significant differences in performance between the U.S. and European VC industry.

While the dotcom bubble resulted in a painful crash, the technology boom spurred new ambition and entrepreneurship in Europe. Hubs and clusters, featuring new start-ups and top class academic institutions, developed across Europe. New talent adds to the overall talent portfolio for the entrepreneurial business in Europe, which is growing in both quantity and quality (EVCA, 2013). In addition, advocates of VC claim that it can create opportunities for all segments of the workforce, which many economists point out as critical for the future health and growth of the economy, by building companies from scratch (ECVA, 2012).

The start-up and build-up of prosperous businesses is a main source of Europe's job creation today. Yet, according to EVCA (2012) the European Union (EU) is failing to capitalize fully on this entrepreneurial potential. On the bright side however, European governments have started to realize the importance of entrepreneurial activity as a driver of economic and employment growth and have therefore tried to create an environment in which entrepreneurship can flourish. A cornerstone in achieving this is believed to be a better-quality VC market as the lack of supply of capital to innovative small and medium-sized enterprises (SMEs) is hampering European growth (EVCA, 2012). Recent estimates point out that bank finance is a pressing concern for around a fifth of all SMEs in Europe (EVCA, 2013). Young companies have little or no collateral to secure bank loans at the high risks associated with early-staged financing, which poses a problem for businesses active on the European bank-based market.[1]

[1] A report by the European Private Equity and Venture Capital Association states that about 29 percent of European SMEs claim that a lack of funding prevents them from reaching their main objective of growing their business. In fact, 75 percent of Europeans surveyed consider it difficult to start their own business due to the lack of available financial support (EVCA, 2013).

3 Theoretical Approach and Previous Research

Several researchers have tried to answer the important question where growth is coming from. While some argue that large enterprises are the engine for job creation and growth (Harrison, 1994; 1995), others have come to the conclusion that new firm start-ups are the main contributors to economic development and employment growth. These previous findings will be summarized below, followed by an overview of the current understanding on how VC fits into the picture.

3.1 Employment Growth and Competitiveness

For a long time, economists have made an effort to explain economic progress with the help of the Solow (1956) model, where labor and capital are key determinants of production and hence growth. Three decades later, Romer (1986) criticized the Solow model for omitting one seemingly very important variable – knowledge. As it is endogenously determined through spillover effects and externalities, knowledge is of particular importance. Audretsch and Keilbach (2004) take the critique one step further by suggesting that in order to make the neoclassical production function more accurate, entrepreneurship capital should be added to the model as an additional key explanatory factor for economic growth. In this spirit, several studies have been conducted with the purpose of pinpointing the contribution of entrepreneurs to economic growth. Looking at employment data from the U.S. private sector, over the period 1991-1996, newly started firms accounted for 26.3 percent of the average employment, while older firms contributed with only 17.7 percent, which was offset by employment losses from shrinking firms as well as companies that went out of business. This suggests that new start-ups might be more important for the overall economy than was previously known (Acs and Armington, 2004). Others (Sternberg, 1996; Ettlinger and Tufford, 1996) confirm that successful new start-up companies may fuel economic growth and job creation.

Fritsch and Mueller (2004) argue that while small firms may drive economic development in some growth regimes, large firms are more suited as engine for economic growth in others. Despite the fact that both standardized and entrepreneurial regimes may boost growth, Fritsch and Mueller find that a high start-up rate leads to a higher employment growth rate in the long run.

Another field of research elaborates on the early theories of Romer (1986) and Lucas (1988), which emphasize the role of intellectual property and human capital spillovers in driving economic growth. Glaeser (2000) argues that as the global economy is endogenously growing and if markets are competitive, then intellectual spillovers are a critical feature of economic development. This view is further supported by Green (2012), who argues that skills and knowledge help to support high levels of economic performance, but are not yet widely recognized as an important element. Economies are argued to become more competitive, stimulate innovation and provide better paid jobs by ensuring that skills are utilized effectively. Furthermore, the economy is becoming increasingly knowledge-driven. Brown et al. (2003) imply that the competitive advantage of nations have come to depend on the knowledge, skills and enterprise of the workforce and that those with degree-level education will play an even more important role for the economic welfare in the future.

3.2 The Link between VC, Employment and Labor Costs

Despite the seemingly positive impact of entrepreneurship and a high-skilled workforce on the overall economy, starting a business or increasing the workforce in an existing business may be prevented if financial funds are insufficient. Hence, VC can be expected to stimulate economic growth by easing the binding financial constraint and making sure that good ideas will be provided with funding (Keuschnigg, 2004).

For quite some time, both politicians and academics have argued that VC-backed firms outperform comparable firms with no VC funding in terms of growth, investment, innovation and job creation. However, instead of empirical evidence these statements were based on intuition regarding these companies' results and the impact of these on the economy (Alemany and Marti, 2005). Recently, as VC has become more important the interest in the field has been growing, which has led to significant progress in VC research. The improved availability of data is probably another reason for the growing number of published papers.

Overall, previous research consistently finds a positive relationship between VC and different indicators of economic growth. In particular, it suggests that well-functioning and highly developed VC markets can contribute much more significantly to producing superior labor market performance than what bank financing or internal financing in large established firms can accomplish. The ability to select good projects and to deal with existing information asymmetries compared to other investors is the comparative advantage of venture capitalists (Amit et al. 1998). The high information asymmetry (Petersen and Rajan, 1995) and uncertainty (Hannan and Freeman, 1989) usually limits a start-up's access to traditional sources of financing. VC firms have the required capabilities to deal with these factors and additionally, they also contribute to the management of start-ups (Davila et al. 2003). Thus, venture capitalists are more than just financiers; they also carry out monitoring and give business advice to new firms. Both of these are important activities that banks are generally unable to perform.

In terms of job creation, a number of researchers have tried to understand the relationship between employment growth and VC utilizing firm level data. Puri and Zarutskie (2012), using U.S. Census data from 1981 to 2005, find that over the 25 year sample period as few as 0.11 percent of new companies received VC. Yet, these companies accounted for 4 percent to 5.5 percent of employment. Additionally, they show that VC-backed companies experience a faster growth both before and after the receipt of VC funding. This gives rise to the question in which direction the relationship between VC and employment performance goes. Davila et al. (2003) attempt to answer this important question by examining whether VC leads to growth or whether growth signals the need for venture finance. Their results suggest that start-ups may postpone growth due to the lack of financing indicating that financing plays an important role in promoting growth rather than the other way around.

In addition to the effect on the number of employees, Puri and Zarutskie (2012) also examine differences in payroll expenditures and show that after receiving financing, VC-backed firms increase their payroll expenditures gradually compared to firms receiving no VC financing.

A major weakness with studies like Puri and Zarutskie's (2012) is that they focus on company-wide employment of VC-backed firms, which potentially gives rise to biases in the results, as pointed out by several researchers. Engel (2002) claims that matching VC-backed firms with ones that have never received VC, based on a few important firm characteristics, which in turn might have an influence on the probability of receiving VC financing and the tendency to grow in the first place, will potentially result in biased estimates of the venture capital impact. Biased samples of very narrow scope, such as the ones including only top performers, as well as inaccurate control groups, which fail to reflect the characteristics of the VC-backed firms, are other problems pointed out by Alemany and Marti (2005).

Another potential flaw when employing firm level data is how employment gains and losses are accounted for. Selling off a division or other business unit is generally counted as an employment loss, even if the sold business unit continues to run without a change in the number of employees, but only under a new ownership. Similarly, when a new division or business unit is acquired, at the firm level it looks like an employment gain, even if the number of employees is unchanged at the business unit itself (Davis et al., 2013).

Moreover, Samila and Sorenson (2011) bring forward some potential biases occurring when extrapolating firm level results to more aggregate levels. They argue that firm level studies potentially underestimate the aggregate economic value of VC. Expectation and spinoff effects suggest that VC may encourage the founding of even more companies than it funds directly and, hence firm level studies focusing on VC-backed companies might fail to incorporate such effects. On the other hand, extrapolating firm level results to a more aggregate level might in some cases overestimate the economic value of VC. New jobs in VC-backed companies might simply be a substitute for jobs in already established firms.

Some researchers have tried to understand the relationship between employment growth and VC from a macroeconomic perspective. Wasmer and Weil (2000) find evidence of the impact of an increase in VC on employment at a country level, but only in the long run, suggesting that there is a "time-to-recruit period" between VC investment and the increase in employment. Belke et al. (2003; 2004) take this research one step further by considering the stage of development of the investments computed, also at a country level. VC can significantly affect the labor market performance; nevertheless the results are stronger for total VC as opposed to early-stage VC, confirming Wasmer and Weil's assumption of a time-to-recruit effect. Samila and Sorenson (2011), using a panel of U.S. metropolitan areas from 1993 to 2002, argue that an increase in the local supply of VC positively affects the number of firms, employment and aggregate income. Their research suggest, in line with Puri and Zarutskie (2012) that VC firms invest heavily in employment via larger numbers, as well as via higher wages after investing in a firm.

These studies, trying to disentangle the effects of VC on the economy as a whole, are conducted at a country or regional level, which allows them to circumvent some of the potential pitfalls from firm level studies discussed previously. However, aggregating the data to a higher unit level also has its potential problems. Samila and Sorenson (2011) themselves point to issues with choosing the analysis unit. Choosing a large unit such as a country level analysis would on the one hand enable them to capture the fully aggregated effects of VC, but on the other hand reduce the statistical power of the tests. A country level approach also misses some potentially important insights into how VC works in different industries or sectors of the economy. For instance, VC might be of less help in preserving or creating jobs in declining industries, whereas VC might contribute significantly to employment growth in new industries. Much of this variation might be lost when aggregating on a country level as an economy has a variety of industries present, while on an industry level these trends can be captured with the help of industry-year fixed effects.

According to Belke et al. (2004), dealing with the rapid and radical process of structural change, such as the ongoing move away from the manufacturing sector to the service sector, but also to new areas, such as biotechnology, information and internet technology, the media or computers, is the major challenge for the advanced economies. Furthermore, Bechter et al. (2012) argue that the sector is the most relevant level for the definition of labor markets in Western Europe and that in comparative industrial relations studies, attention to the national level has often come at the expense of neglecting the sector. In sum, the current scope of previous research inquires for studies conducted at an industry level.

4 Empirical Data

4.1 Introduction to the Dataset

4.1.1 Data Sources

This study draws on two main databases. First, information on VC transactions is derived from the CapitalIQ database. Second, structural data on industry activity and performance is derived from the Structural Analysis Database (STAN) compiled by the Organization for Economic Cooperation and Development (OECD). We limit our analysis to the EU-15[2] countries, since the countries being part of the EU have several similar characteristics in many aspects, which eases comparison among them. Moreover, the EU-15 countries have been part of the EU during the entire time span, 1995-2009, considered in our analysis.

Data on VC transactions announced from January 1991[3] to December 2009 is compiled from the CapitalIQ database. The CapitalIQ database specializes in tracking private equity deals on a worldwide basis. It has become a competitor to the ThomsonOne database for data on buyouts but it also contains information about VC deals; see Bernstein et al. (2010) for more detailed information. We construct a sample consisting of all private placement transactions labeled as "Venture Capital" where the target company is located in one of the EU-15 countries. We exclude transactions that were announced but not yet completed and limit our sample to transactions involving a financial sponsor, i.e. a private equity or VC firm. The deal sizes of the transactions are obtained in historical USD. Industries in the CapitalIQ database are classified according to the Global Industry Classification Standard (GICS).

The STAN database provides industry data across OECD member countries compiled from national statistics offices. Industries are classified according to the International Standard Classification of All Economic Activities (ISIC) Revision 3. Employment data is drawn from the STAN Industry Database (Rev. 3, 2008) for industrial analysis, which provides information on industrial performance at a relatively detailed level across countries. Employment data is expressed in number of persons or jobs. The methodology used for constructing the employment measure in

[2] EU-15 includes the following countries: Austria, Belgium, Denmark, Finland, France, Greece, Germany, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, and United Kingdom.
[3] In our main analysis we employ data from 1991-2009. However, we compile data from 1989 used for robustness tests regarding the definition of VC industries, see below the definition of a VC industry.

the STAN database differs across nations.[4] However, as we are concerned with differences across time, we should be able to reduce the effects of national discrepancies in this measure. Other industry data, such as productivity and labor costs, are expressed in national currency at current prices, i.e. in Euros for EMU countries, see Table A1. The STAN database also provides classification schemes into service and manufacturing industries, which we employ in our analysis.[5]

We collect additional data not included in our two main databases. Exchange rate data is derived from OECD National Accounts Statistics, which collects exchange rates from the International Monetary Fund. Deflators are obtained from OECD International Development Statistics. The deflators include effects of exchange rate changes, and are therefore only applicable after converting figures to USD.

4.1.2 Construction of Sample

We match STAN industry data with data on VC transactions from the CapitalIQ database in a few steps. Where possible, we use the existing mapping between GICS to SIC codes provided in the CapitalIQ database. However, matches are only provided for the most detailed levels of the GICS codes. For the majority of observations, where matches are not provided we map GICS codes to four-digit SIC codes, which are then converted to ISIC codes. Cases, in which we are unable to determine with certainty the appropriate industry match, are dropped. Furthermore, transactions lacking an industry classification in the CapitalIQ database are also dropped from the sample, leaving us with 13,074 VC transactions with an ISIC classification during the years 1989 to 2009. Next, we group ISIC sub-industries into broader industry categories. The grouping into broader industry categories minimizes the subjectivity associated with classifying firms into narrower industry classifications. Lastly, we collapse the data on a yearly basis summing up the number and volume of VC transactions each year, which occur in the same industry and country. This leaves

[4] For most countries, headline total employment by activity tables are based on headcounts. However, number of jobs is used by some (e.g. UK), while others use some notion of full-time equivalence (e.g. Italy). Also, while many countries use 12-month averages for annual employment data, some countries use mid-year estimates (employment for a particular day, week or month each year).

[5] This scheme classifies 6 out of 21 (approximately 30 percent of the sample) industries as service industries: “Community, social and personal services”, “Financial intermediation”, “Hotels and restaurants”, “Internet, software and business services”, “Transport, storage and communications” and “Wholesale and retail trade – repairs”.

us with a sample of 4,725 country-industry-year observations during the years 1995 to 2009.[6]

Information on deal size is only provided for roughly 50 percent of the transactions in the CapitalIQ database why we impute missing deal sizes by constructing fitted values from a regression of deal size on fixed effects for country, announcement year and target industry. We generate aggregate country-industry-year measures of VC deal volume by summing deal volumes before and after imputing missing deal volumes. All data denominated in currency is converted and normalized to 2009 USD.

4.1.3 Questioning the Reliability of the Data

One issue with using data compiled from different databases is the uncertainty about the accuracy of the data. STAN relies on the correct reporting of the variables of interest from various countries, making it possible for mistakes to occur.

Another source of potential errors in our data is the fact that we had to classify the VC transactions that took place at firm level into different industries. The aggregation of data from firm to industry level occurred in several steps, increasing the risk for mistakes. Moreover, since the classification was done manually, it can partially be considered relatively subjective. A majority of the firms included in our sample, engage in more than one activity, sometimes even in activities belonging to totally different industries, which made it necessary to make a subjective judgment, which of the firm's activities should be considered as the main activity, deciding the industry thereafter. However, any industry classification is somewhat arbitrary, and we believe that our ISIC classification scheme captures businesses that have similarities in terms of technology and management.

Another possible error in our data regards the fact that firms might change the industry in which they operate over time. As the industry classification is a static variable where only the latest quote is available it does not capture such changes. In this thesis, we assume that firms receiving VC funding are stable with regard to industry classification and that industry reclassifications are rare and hence have negligible effects on the results.

[6] The sample consists of 15 countries, 21 industries and 15 years which totals to 4,725 observations.

Our data source did not allow for an inclusion of self-employed in our employment measure. As pointed out by Fölster (2000), self-employment might become a viable option in times of low employment and a high VC activity might just enhance the chance of success and profitability of this alternative even more. Thus, not including self-employed in the employment measure may in fact result in a downward bias, underestimating the effect of VC on the number of employees.[7]

Nevertheless, we consider the potential biases to be small enough to avoid causing any major problems with our results. Granted, the results must be interpreted with caution due to the potential underlying biases in the data, but they are still useful when trying to understand how the level of VC activity can affect an industry's labor market performance and its growth.

4.1.4 Critical Measures

Before describing the data we define some variables critical to our analysis of VC activity. First, we divide the sample depending on the presence of VC activity. For each country, industry and year, we construct a measure of VC activity as the presence of VC deals in terms of the number of transactions undertaken in that country and industry during the previous four years, i.e. an observation is a *VC industry* if it had at least one VC investment in one of those four preceding years. More specifically, the variable *VC industry* is constructed as a dummy variable taking on the value of one indicating VC activity in the previous four years, and taking on the value of zero indicating no VC activity in the previous four years. This definition of VC activity does not depend on imputed deal volumes since it only depends on the presence of VC deals. The time span used for the construction of *VC industry* is motivated by a typical VC investment period of three to five years[8] in Europe (EVCA, 2010). We construct this measure for the years 1995 to 2009 using data on VC transactions from 1991.

[7] The inclusion of self-employed workers is mixed in previous research. Samila and Sorenson (2011) exclude self-employed workers in their aggregate regional level study, whereas Puri and Zarutskie (2012), conducting a firm level study, include firms whose only employees are their owners as long as the owners pay themselves some level of wage.
[8] The typical VC fund has a contractual limited life of seven to ten years. The main part of the capital is drawn during the investment period, typically three to five years. After that, there is a divestment period where existing and successful portfolio companies are further supported with some follow-on funding provided to extract the maximum value through exits. The manager's efforts during the divestment period are concentrated on realizing or selling the investment (EVCA, 2010).

We further construct variables depending on the volume of VC activity. For each country, industry and year, we construct $\sum_{t-4}^{t-1}$ *VC volume* as the sum of VC deal volume over the four previous years (corresponding to the definition of *VC industry*). Hence, for each country-industry-year observation we measure the sum of VC activity over the previous four years. This measure is later used in our regression to examine how the amount of VC investments affects the employment and labor cost level and growth. Defining the level of VC activity in this manner, as a sum of the previous four years, enables us to account for the activity taken place over the past recent years instead of an industry's current VC activity. This way, the problem of reverse causality is reduced.

For an intuitive description of our dataset, we also construct variables to capture whether the industry is a high or low VC industry. We define the variables *VC High* and *VC Low* for each year. We use the median of $\sum_{t-4}^{t-1}$ *VC volume* across all countries and industries for each year as a threshold. Observations above the threshold are defined as *VC High*, whereas those observations below are defined as *VC Low* (conditional on having a non-zero level of VC investment).

4.2 Data Description

Table A2 shows the distribution of deals across years in our sample. During the early years of the 1990s the VC industry had not yet grown a strong foothold in Europe. VC activity was slow, with low volumes of VC investments taking place. One reason may have been Europe's struggle with the recession and its lingering aftermath. It took until the mid-1990s and the dotcom boom before VC activity took off.

Both the number of VC deals and the amount invested reached its highest level in year 2000, amounting to 1,719 investments at a value of nearly USD 28.1 billion. The second largest annual deal volume can be found in year 2001. The four subsequent years experienced a significant decline in VC activity following the crash of the dotcom bubble in 2000-2001. Furthermore, the average deal size per transaction decreased after the dotcom crash as can be seen in Figure 1. After the initial drop in VC activity, in the aftermath of the crash of the dotcom bubble, there was a steady increase in the VC deals undertaken until year 2009. By that time, the financial crisis seems to have had a significant impact on the VC industry and the decrease in VC activity was felt all over Europe.

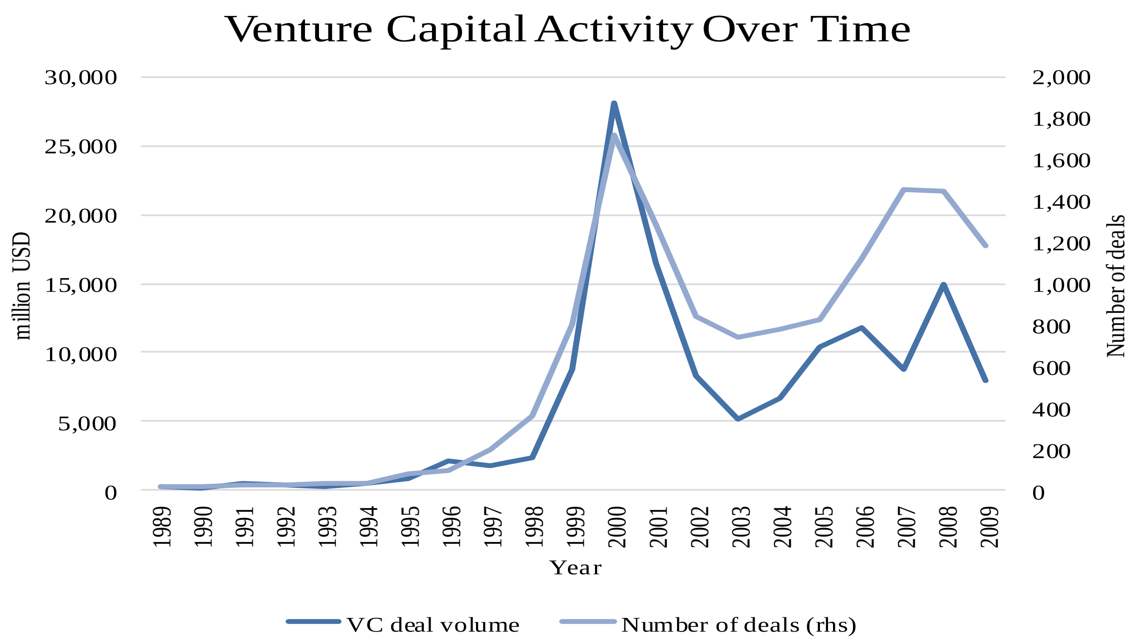

Figure 1: The development of VC activity in terms of deal volume and number of deals during 1989-2009 in EU-15 countries. Both actual and imputed deal volumes are included.

Table A3 and Figure A1 depict the distribution of VC deals across countries. It is of no surprise that the United Kingdom (UK) is by far the leading country with regard to the level of VC activity. UK has an especially well-developed VC market, with VC fund flows around 1 percent of GDP in some years (Oehler et al., 2006). Over the sample period used in our study, 4,440 VC deals took place to a total amount of USD 41 billion in the UK. This corresponds to a 35 percent share of the total deal volume across all countries. France and Germany have had the second highest VC activity, both in terms of deal volume and number of deals. However, the two countries have, and still do, lagged far behind the UK. Other countries with relatively high VC activity, both in terms of deal volume and number of deals are Sweden, Spain, the Netherlands, Italy and Ireland. Greece have had the lowest level of VC activity in terms of deal volume, with only 46 deals to an amount of USD 490 million taking place over the entire period. Luxembourg on the other hand, have had even fewer VC deals taking place, but to an amount of more than ten times higher than the one in Greece. The high observed level of VC deal volume in Luxembourg can be explained by many firms' tendency to domicile in Luxembourg for tax reasons, even though the main part of their operations are elsewhere (Bernstein et al., 2010). For this reason, we exclude Luxembourg from our analysis, which leaves us with 4,410 country-industry-year observations.

Figure 2 below illustrates the VC intensity relative to employment across countries. Ireland, the UK and Netherlands have received a relative large share of VC investment flows in relation to their share of employment across the countries. Although France and Germany received the second highest amount of VC investment flows, the VC intensity relative to employment has been rather low in these countries.

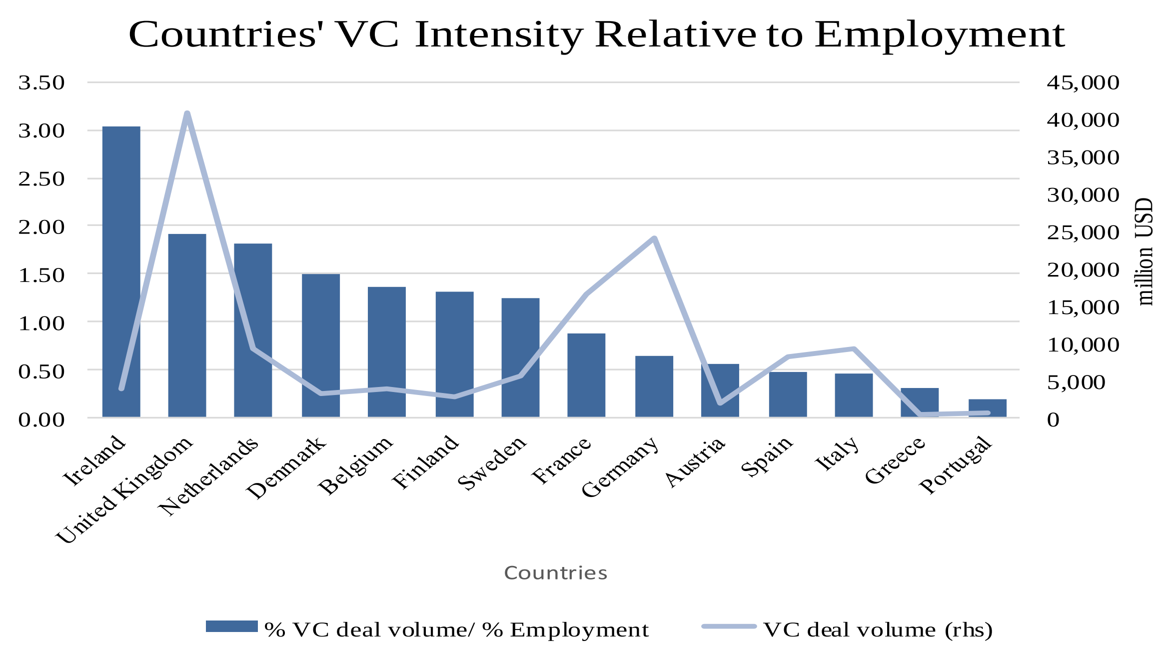

Figure 2: Countries' VC intensity relative to employment. Countries are ordered on the fraction of their share of VC deal volume and share of employment across countries (excl. Luxembourg). Both actual and imputed deal volumes are included.

Table A4 and Figure A2 convey information about the distribution of VC deals across industries. It is evident that VC investments are clustered. In general, industries receiving the most VC investment belong either to the service sector or can be classified as high-technology industries. During the sample period, service industries have attracted roughly two thirds of total VC investments. Industries with the fewest VC deals are manufacturing industries such as "Mining and quarrying", "Wood and products of wood and cork", "Agriculture, hunting, forestry and fishing", and "Other non-metallic mineral products". The industry receiving by far the highest amount of VC investments is the "Internet, software and business activities"[9] industry with a total

[9] This industry is named "Real estate, renting and business activities" in the ISIC Rev. 3 classification scheme. However, real estate and renting activities account for a minor part of VC investments and employment in our sample, whereas the majority consists of internet, software and business services.

of 6,242 deals to a value of nearly USD 48 billion over the entire period. Other large industries in terms of VC investment are the “Financial intermediation”, “Transport, storage and communications” and “Chemical, rubber, plastics and fuel products” industries.

Figure 3 below illustrates the VC intensity relative to employment across industries. In relation to employment, the “Financial intermediation”, “Chemical, rubber, plastic and fuel products” and “Electrical and optical equipment” industries received a high level of VC investments. The high VC intensity of the “Electrical and optical equipment” industry is most likely attributable to the sub-industry of semiconductors, which is included in the aggregated industry classification. The semiconductor industry has experienced a huge inflow of VC capital during recent years. The “Internet, software and business activities” industry received by far the largest amount of VC investments, but also employs a large share of the total labor force.

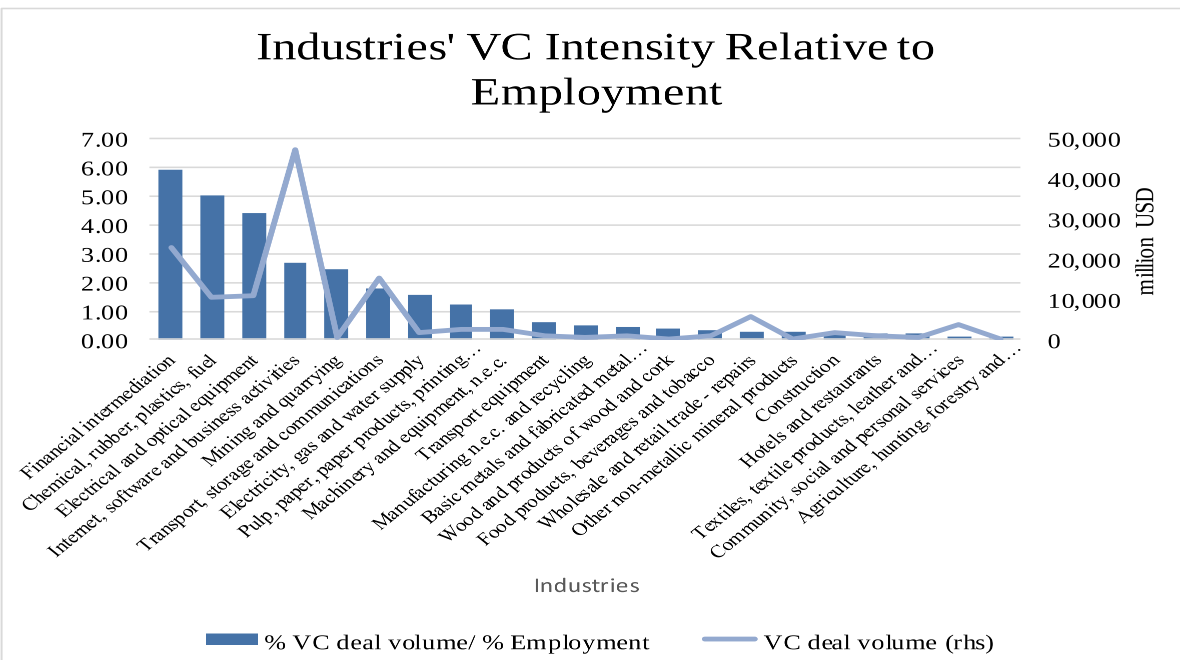

Figure 3: Industries’ VC intensity relative to employment. Industries are ordered on the fraction of their share of VC deal volume and share of employment across industries. Both actual and imputed deal volumes are included.

Table A5 shows the growth rate of industry variables. The average annual employment growth rate for all the industries included in our sample was 0.04 percent, whereas service industries grew on average by 2.04 percent annually and manufacturing industries shrank on average by 0.77 percent on an annual basis. Service industries have outperformed manufacturing industries in terms of labor costs and production as well.

Dividing the industries in recipients of VC funding and non-recipients, we can see that *VC industries* have had an average annual employment growth rate of 0.26 percent while those industries with no VC have had an average annual employment growth rate of -0.20 percent. This suggests that the presence of VC activity might have a positive effect on the employment growth rate. VC industries have also grown more rapidly in terms of labor costs. Interestingly, average annual production growth rate has been higher for industries with no VC activity than for industries receiving VC. Also, manufacturing industries receiving VC have in fact had lower employment and labor costs growth than industries not receiving VC.

When focusing on the *VC industry* subsample, it seems as if the higher the level of VC activity is, the higher is the average annual employment growth rate, see Table A6. The *High VC* industries experienced an average annual growth rate of 0.78 percent, while the *Low VC* industries have had an average annual employment growth rate of -0.27 percent. In general, industries with relatively high VC activity (over 500 deals) have depicted a positive annual employment growth rate, whereas industries with relatively lower VC activity (less than 50 VC deals) have experienced an average negative annual employment growth rate, see Table A7. However, industries have depicted varying trends. The "Internet, software and business activities" industry, which has seen high VC activity, experienced the highest average annual employment growth across industries, whereas the "Chemical, rubber, plastics and fuel products" industry, also with a quite substantial amount of VC activity, depicted a negative average annual employment growth.

Varying correlations between employment and VC activity is also apparent when looking at individual countries. For instance, in the UK and Germany, two of the countries with the highest level of VC activity, employment has shrunk on average by 0.93 percent and 0.99 percent annually respectively, see Table A8.

In summary, in the whole sample VC industries have on average outperformed non-VC industries. However, looking at the service and manufacturing subsamples, VC industries have on average outperformed non-VC industries in the service sector whereas VC industries have in fact underperformed non-VC industries in the manufacturing sector. Additionally, we note that some countries and industries are more attractive to VC funds than others.

5 Empirical Approach

We employ Ordinary least squares (OLS) and Generalized least squares (GLS) regressions, in order to test the explanatory power of VC activity on employment (labor cost) levels as well as employment (labor cost) growth in the EU-15 industries. We conjecture that the presence of VC improves employment and labor cost performance in a panel analysis with cross-country-industry data. First, we present regressions with the level of employment (labor costs) as dependent variable, followed by regressions with the growth rate of employment (labor costs) as dependent variable instead. Finally, we allow for differences in the effect of VC on employment (labor costs) depending on whether the industry belongs to the service or manufacturing sector.

5.1 Level Regressions

Our basic model is an OLS regression with the employment level, in natural logarithms, for each country-industry-year observation as dependent variable. The exogenous variable is an indicator, which denotes whether the industry is a VC industry or not. This specification allows us to compare employment levels in industries with VC activity to all other industries with no VC activity across countries at a given time. We include dummy variables for each calendar year to control for macroeconomic factors that might influence the availability of VC, entrepreneurship and economic performance across countries and industries as a whole. Country and industry dummy variables are included to control for time-invariant characteristics of countries and industries that might attract VC and influence entrepreneurship, employment and economic growth as well. Furthermore, the inclusion of country fixed effects controls for potential systematic biases in measurement differences of the variables across countries.[10] In particular, we estimate the following model:

$$\begin{aligned} Employment\ level_{ijt} &= \beta_0 + \beta_1 VC\ industry_{ijt} + \delta_2 C_2 + \cdots + \delta_K C_K + \gamma_2 I_2 + \cdots \\ &+ \gamma_N I_N + \alpha_2 Y_2 + \cdots + \alpha_T Y_T + \varepsilon_{ijt} \end{aligned} \tag{1}$$

where $C, I,$ and Y are here dummy variables for country, industry and year respectively. One assumption when running OLS regressions is that the error term is independently and identically

[10] The methodology used for constructing the employment measure in the STAN database differs across nations, see section 4.1.1 Data Sources.

distributed (Baum, 2006). However, especially when panel data is used this is often violated, resulting in biased standard errors and hence incorrect inference. Therefore, we cluster the standard errors on a country-year level to allow for correlation in the errors within countries across years.

Based on previous literature (Wasmer and Weil, 2000; Samila and Sorenson, 2011; Puri and Zarutskie, 2012), we expect to see a positive coefficient of *VC industry* indicating that the presence of VC activity within an industry will result in a higher level of employment in that industry than in industries with no VC activity.

We elaborate on the first specification by examining how the amount of VC activity impacts employment using the measure of $\sum_{t-4}^{t-1} VC\ volume$ previously described. $\sum_{t-4}^{t-1} VC\ volume$ measures VC activity over the previous four years not including the year for which employment is measured. Hence, no contemporaneous effect is picked up. $\sum_{t-4}^{t-1} VC\ volume$ is transformed to natural logarithm values to facilitate the interpretation of the coefficients. More specifically, the model we estimate now looks as follows:

$$\begin{aligned} Employment\ level_{ijt} \\ &= \beta_0 + \beta_1 \sum_{t-4}^{t-1} VC\ volume_{ijt} + \delta_2 C_2 + \cdots + \delta_K C_K + \gamma_2 I_2 \\ &+ \cdots + \gamma_N I_N + \alpha_2 Y_2 + \cdots + \alpha_T Y_T + \varepsilon_{ijt} \end{aligned} \qquad (2)$$

We expect to see a positive coefficient of $\sum_{t-4}^{t-1} VC\ volume$, consistent with expecting a positive coefficient on the overall measure *VC industry* used in the basic model specification. A positive coefficient of $\sum_{t-4}^{t-1} VC\ volume$ would imply that a higher level of VC activity is associated with higher levels of employment within industries.

Next, we run the model including various combined fixed effects. We incorporate country-year fixed effects in our model in order to capture national differences in time dynamics, such as labor policies. We also run the model with industry-year fixed effects to control for industry differences in time dynamics, such as innovations and technological developments within specific industries. Moreover, industry-year fixed effects also capture industry-year specific incentives to increase employment depending on whether the industry is declining, growing or just shifting from being labor-intensive to more capital-intensive. For instance, the chemicals industry has experienced an employment decline due to its movement to less labor-intensive production (European Community Programme for Employment and Solidarity, 2009). We likewise incorporate country-industry fixed effects to control for industries' size and importance in different countries which would make them more likely target industries for VC investments. Lastly, we include a measure of $\sum_{t-4}^{t-1}$ *VC volume* in squared terms, $\sum_{t-4}^{t-1}$ *VC volume^2,* in order to capture any non-linearity in the model.

One drawback with the models depicted above is their static nature, which makes it impossible to take the dynamics of employment into account. However, it is very likely that the past year's employment level has an effect on this year's employment (Belke et al., 2004). As a consequence, the previous specifications may be dynamically mis-specified, resulting in an omitted variable bias in the static models. In order to account for the dynamic process, we include a lagged variable of the dependent variable in our analysis, $Employment\ level_{t-1}$. We run the regression including the lagged variable once again for our specifications listed above with different measures of VC activity and with country-industry combined fixed effects.

$$\begin{aligned} Employment\ level_{ijt} \\ &= \beta_0 + \beta_1 VC\ industry_{ijt} + \beta_2 Employment\ level_{ijt-1} \\ &+ \delta_2 CountryIndustry_2 + \cdots + \delta_I CountryIndustry_I \\ &+ \gamma_2 Y_2 + \cdots + \gamma_T Y_T + \varepsilon_{ijt} \end{aligned} \tag{3}$$

This setup has the appeal that it models employment levels in a dynamic context. However, including a lagged dependent variable as an explanatory variable brings other problems with it. In some cases, the lagged dependent variable suppresses the effect of the other explanatory variables included in the regression. When serial correlation is present, including a lagged dependent variable in the regression might bias the other coefficients of interest (Achen, 2001). Nevertheless, according to Keele and Kelly (2006), using a lagged dependent variable is superior to other models in case of a dynamic process as long as two conditions are met. First, the dependent variable has to be stationary and second, after employing a lagged dependent variable approach the model residuals should be white noise. These conditions can be tested with help of the Harris-Tzavalis unit root test and the Lagrange Multiplier test.

As we are able to reject the null hypothesis of employment being stationary when running the Lagrange Multiplier test, using an OLS model with a lagged dependent variable is both statistically and theoretically wrong. One possibility to adjust for the non-stationarity of the natural logarithm of employment level, justifying the usage of an OLS model with a lagged variable included, would be to take the first difference of the model. However, first differencing the model means that an analysis of the impact of VC on the employment level as such would not be possible anymore, but just on the change in the employment level. In order to avoid a bias in the estimated coefficients caused by the usage of an inappropriate model and at the same time still focusing on the effect of VC on the employment level instead of just employment growth, we utilize a GLS model, which is better suited for cases like this one. GLS models estimate unbiased coefficients even in the presence of autocorrelation within panels. Hence, dealing with a dynamic process where the dependent variable is non-stationary, GLS outperforms OLS with a lagged dependent variable included (Keele and Kelly, 2006).

The exact same logic and procedure is applied when we study the effect of VC activity on the level of labor costs. Here too, we reject the null hypothesis of labor costs being stationary when running the Lagrange Multiplier test. Hence, we again apply a GLS model to our analysis when the lagged dependent labor cost variable is included in the regression as an explanatory variable.

5.2 Growth Regressions

When testing the explanatory power of VC activity on the growth rate of both employment and labor costs, we again follow a similar approach as above employing multiple OLS regressions. However, we do not employ GLS regressions as the inclusion of lagged dependent variables as an explanatory variable in the regression is not necessary in this setting. In each case, we use the country-industry-year as an observation and the dependent variable is the growth rate along a given dimension (employment or labor costs). This specification allows us to compare growth along a dimension in industries with VC activity to all other industries with no VC activity across countries at a given time.

5.3 Service versus Manufacturing Sector

Recognizing the potentially greater value of VC activity in industries with network effects and economies of scope, as is typical for many “new economy” industries (Metrick and Yasuda, 2010), we repeat the analysis above, but include one new variable in our regression; an interaction term between a *Service* dummy and the $\sum_{t\text{-}4}^{t\text{-}1}$ *VC volume* variable. The extended regression specification takes on the following form:

$$
\begin{aligned}
&Employment\ growth_{ijt} \\
&\quad = \beta_0 + \beta_1 \sum_{t-4}^{t-1} VC\ volume_{ijt} + \beta_2 \sum_{t-4}^{t-1} VC\ volume\ Service_{ijt} \\
&\quad + \ \delta_2 C_2 + \cdots + \delta_K C_K + \gamma_2 I_2 + \cdots + \ \gamma_N I_N + \alpha_2 Y_2 + \cdots + \alpha_T Y_T \\
&\quad + \varepsilon_{ijt}
\end{aligned}
\tag{4}
$$

In the next steps, we include country-year, country-industry and industry-year fixed effects one at a time. The effects of VC activity on labor cost growth are studied in the same manner.

According to OECD (2004), the "new economy" can be described as '[…] aspects or sectors of an economy that are producing or intensely using innovative or new technologies. This relatively new concept applies particularly to industries where people depend more and more on computers, telecommunications and the internet to produce, sell and distribute goods and services'. Specifically, in the Stan Industry Classification, subcategories such as "Pharmaceuticals" and "Aircraft and Spacecraft" are listed as high-technology industries. However, since we have aggregated our data to a higher level, such a distinction between high- and low-technology industries is not possible in our dataset. Instead, we apply the logic that the "new economy" is the result of the shift from a manufacturing-intensive economy to a service-intensive economy and hence differentiate between manufacturing and service industries in our analysis.

Further justification for including a control variable for service industries is supported by Belke et al. (2003), who have recognized the challenge to advanced economies posed by the ongoing move from largely standardized products of the industrial sector to the service sector, as well as by areas of the new economy, such as biotechnology, information and internet technology, computers or the media. Moreover, this shift of the economy to the service sector also imposes some changes in the demand for labor, with the demand for high-quality and skilled labor rising relative to low-quality workers.

6 Results

6.1 Employment

The results in Table 1 indicate that VC investments have a positive impact on the level of employment. Columns 1-6 present OLS estimates of the impact of VC on employment levels, whereas columns 7-9 present GLS regressions with the inclusion of a lagged dependent variable. Changing to a GLS model to account for the dynamic nature of employment levels alters the magnitude of the estimated coefficients significantly downwards. However, the statistical significance is unchanged. For instance, OLS regression coefficients in columns 2-5 suggest that a doubling of VC investments results in a 1.5 to 7.5 percent increase in the level of employment, whereas the GLS regression estimate in column 8 suggests that such an increase would result in a 0.2 percent higher employment level. The obtained results are robust to the inclusion of various combined fixed effects.

In column 6, the coefficient of $\sum_{t-4}^{t-1}$ *VC volume^2* suggests that the relation between VC activity and employment level is non-linear. The positive sign in front of the squared term reveals a convex relationship between the two variables of interest. However, the suggested non-linearity disappears in the GLS regression with the inclusion of a lagged dependent variable, see column 9.

The results obtained are robust to the exclusion of UK, see Tables A11-A13.[11] We further test the robustness of our specification by altering the period in defining VC industries between two to six years, employing VC transaction data back to 1989. Our results remain robust also to these changes, why we have chosen not to disclose these in our thesis.[12]

[11] This robustness check is conducted to see whether the UK drives our results, since the UK is the most advanced country in Europe with regard to VC activity. We employ this robustness test to all the regressions examining the level and growth of both employment and labor costs.

[12] We employ these robustness test regressions including both the level and growth of employment and labor costs.

Table 1: VC Activity and Level of Employment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Employ. Level	Employ. Level	Employ. Level	Employ. level	Employ. level	Employ. Level	Employ. Level	Employ. level	Employ. level
VC industry	0.157***						0.005***		
	(0.022)						(0.002)		
$\sum_{t-4}^{t-1}$ *VC volume*		0.069***	0.075***	0.073***	0.015***	0.035***		0.002***	0.002*
		(0.006)	(0.007)	(0.006)	(0.002)	(0.009)		(0.001)	(0.001)
$\sum_{t-4}^{t-1}$ *VC volume* ^2						0.007***			-0.000
						(0.002)			(0.000)
Employ. Level (t-1)							1.004***	1.003***	1.003***
							(0.001)	(0.001)	(0.001)
Country FE	Yes	Yes	No	Yes	No	Yes	No	No	No
Year FE	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	No	No	Yes	No	No	No
CountryYear FE	No	No	Yes	No	No	No	No	No	No
IndustryYear FE	No	No	No	Yes	No	No	No	No	No
CountryIndustry FE	No	No	No	No	Yes	No	Yes	Yes	Yes
Observations	4178	4178	4178	4178	4178	4178	4084	4084	4084
R-squared	0.939	0.941	0.940	0.940	0.995	0.942	-	-	-

** p<0.1, ** p<0.05, ***p<0.01.*

The table contains OLS regression coefficients (columns 1-6) and GLS regression coefficients (columns 7-9). An observation is a country-industry-year pair. The endogenous variable is the level of employment (as defined by OECD) measured in natural logarithm. The exogenous variables are indicators for positive VC activity over the previous four years at the country-industry level (*VC industry*), indicators for the level of VC activity over the previous four years at the country-industry level measured in natural logarithm ($\sum_{t-4}^{t-1}$ *VC volume*), a squared term of $\sum_{t-4}^{t-1}$ *VC volume* to capture non-linearity ($\sum_{t-4}^{t-1}$ *VC volume* ^2), lags of the dependent variable (*Employment level (t-1)*). The omitted base category is industries with no VC activity over the previous four years. The regressions include country, industry, year, country-year, industry-year and country-industry fixed effects. Standard errors are clustered at the country-year level and presented in parentheses.

Table 2 indicates that VC also has a positive impact on the growth rate of employment. The average VC industry grows faster in terms of employment than the average non-VC industry. The coefficient of *VC industry* in column 1 suggests that the employment in the average VC industry grows at an annual rate that is 0.50 percentage points higher than for a non-VC industry. This can be compared to an average annual employment growth rate of 0.04 percent during the same period across the entire sample, reported in table A5.

The estimate in Table 2 column 2 suggests that the growth of employment is also positively associated with higher levels of VC activity. For instance, a doubling of the supply of VC investments over the previous four years implies an increase of annual employment growth of 0.1 percentage points.

The negative sign of $\sum_{t-4}^{t-1}$ *VC volume^2* in column 3 implies that the relationship is non-linear and that there are negative returns to VC in terms of employment growth after a certain amount of VC investments over four years is reached. This turning point is reached at an amount of USD 100 million (normalized to 2009).[13] The average sum of deal volumes over four years across all country-industry-year observations in our sample is USD 118 million (normalized to 2009).[14] However, the employment growth of industries receiving VC financing is predicted to be above the employment growth of industries not receiving any VC until the volume of VC reaches slightly more than USD 12 billion (normalized to 2009) over four years, which is by far exceeding any level observed in our sample.[15]

The significance level of the estimates differs however depending on the inclusion of various combined fixed effects, see columns 4-9. The results are most sensitive to the inclusion of combined industry-year fixed effects, see columns 6-7. Also, the non-linearity between VC and employment seems to be important to account for when including country-industry fixed effects.

[13] The turning point is calculated with help of the coefficients in Table 2 column 3 as follows:
$\frac{0.232}{x} - \frac{0.05\ln(x)}{x} = 0, x \approx$ USD 100 million (normalized to 2009).
[14] However, the median sum of deal volume over four years is only USD 33 million (normalized to 2009).
[15] The “Internet, software and business services” industry, which has received the most VC during the sample period, has received USD 900 million (normalized to 2009) over four years on average over time and across countries.

Table 2: VC Activity and Employment Growth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Employ. growth	Employ. growth	Employ. growth	Employ. growth	Employ. growth	Employ. growth	Employ. growth	Employ. growth	Employ. Growth
VC industry	0.504***								
	(0.148)								
$\sum_{t-4}^{t-1}$ *VC volume*		0.103**	0.232***	0.126**	0.210***	0.081	0.097	0.042	0.248***
		(0.049)	(0.077)	(0.049)	(0.079)	(0.057)	(0.074)	(0.053)	(0.090)
$\sum_{t-4}^{t-1}$ *VC volume* ^2			-0.025**		-0.016		-0.003		-0.041***
			(0.012)		(0.014)		(0.013)		(0.014)
Country FE	Yes	Yes	Yes	No	No	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	No	No	No	No	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	No	No	No	No
CountryYear FE	No	No	No	Yes	Yes	No	No	No	No
IndustryYear FE	No	No	No	No	No	Yes	Yes	No	No
CountryIndustry FE	No	No	No	No	No	No	No	Yes	Yes
Observations	4,084	4,084	4,084	4,084	4,084	4,084	4,084	4,084	4,084
R-squared	0.317	0.317	0.317	0.392	0.392	0.366	0.366	0.342	0.343

* $p<0.1$, ** $p<0.05$, *** $p<0.01$.

The table contains OLS regression coefficients. An observation is a country-industry-year pair. The endogenous variable is the growth rate of employment (as defined by OECD) measured in percentage. The exogenous variables are indicators for positive VC activity over the previous four years at the country-industry level (*VC industry*), indicators for the level of VC activity over the previous four years at the country-industry level measured in natural logarithm ($\sum_{t-4}^{t-1}$ *VC volume*) and a squared term of $\sum_{t-4}^{t-1}$ *VC volume* to capture non-linearity ($\sum_{t-4}^{t-1}$ *VC volume* ^2) The omitted base category is industries with no VC activity over the previous four years. The regressions include country, industry, year, country-year, industry-year and country-industry fixed effects. Standard errors are clustered at the country-year level and presented in parentheses.

Table A9 reports the additional effect of VC on the growth of employment when occurring in a service industry. The coefficient of the interaction term between $\sum_{t-4}^{t-1}$ *VC volume* and *Service* in column 1 suggests that a doubling in VC activity over four years leads to an additional 0.18 percentage points higher annual employment growth in that industry if it is classified as a service industry. However, when including the interaction variable between $\sum_{t-4}^{t-1}$ *VC volume* and *Service*, the coefficient on $\sum_{t-4}^{t-1}$ *VC volume* alone loses its significance. The results remain positively significant and robust to the inclusion of various combined fixed effects. Worth noting is that in contrast to the estimates obtained for the full sample, the effect of VC on employment growth in service industries, i.e. “new economies”, remains significant even when controlling for combined industry-year fixed effects, see column 3.

6.2 Labor Costs

Table 3 reports our regression results for the level of labor costs. The results indicate that VC investments have a positive impact on the level of labor costs. Columns 1-6 present OLS estimates of the impact of VC on labor cost levels, whereas columns 7-9 present GLS regressions with the inclusion of a lagged dependent variable. Changing to a GLS model to account for the dynamic nature of labor cost levels alters the magnitude of the estimated coefficients significantly downwards. However, the statistical significance is unchanged. For instance, the OLS coefficients in column 2-5 suggest that a doubling in VC activity results in a 1.4 to 7.3 percent higher level of labor costs whereas the GLS coefficient in column 8 estimates this effect to be a 0.3 percent increase instead.

As for employment levels, the coefficient of $\sum_{t-4}^{t-1}$ *VC volume^2* in column 6 suggests that the relation between VC activity and labor cost levels is non-linear. Again, the positive sign in front of the squared term implies a convex relationship between the two key variables. However, the suggested non-linearity disappears in the GLS regression with the inclusion of a lagged dependent variable, see column 9.

Table 3: VC Activity and Level of Labor Costs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Labor cost level	Labor cost Level	Labor cost level	Labor cost level	Labor cost level	Labor cost level	Labor cost level	Labor cost level	Labor cost level
VC industry	0.147***						0.009***		
	(0.023)						(0.002)		
$\sum_{t-4}^{t-1}$ *VC volume*		0.064***	0.073***	0.065***	0.014***	0.038***		0.003***	0.003**
		(0.006)	(0.007)	(0.006)	(0.002)	(0.010)		(0.001)	(0.001)
$\sum_{t-4}^{t-1}$ *VC volume* ^2						0.005***			0.000
						(0.001)			(0.000)
Labor cost (t-1)							1.001***	0.999***	0.999***
							(0.001)	(0.001)	(0.001)
Country FE	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Year FE	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	No	No	No	No	No	No
CountryYear FE	No	No	No	Yes	No	No	No	No	No
IndustryYear FE	No	No	No	No	Yes	No	No	No	No
CountryIndustry FE	No	No	No	No	No	Yes	Yes	Yes	Yes
Observations	4,230	4,230	4,230	4,230	4,230	4,230	4,215	4,215	4,215
R-squared	0.936	0.937	0.936	0.936	0.994	0.938	-	-	-

** p<0.1, ** p<0.05, ***p<0.01.*

The table contains OLS regression coefficients (columns 1-6) and GLS regression coefficients (columns 7-9). An observation is a country-industry-year pair. The endogenous variable is the level of labor costs (as defined by OECD) measured in natural logarithm. The exogenous variables are indicators for positive VC activity over the previous four years at the country-industry level (*VC industry*), indicators for the level of VC activity over the previous four years at the country-industry level measured in natural logarithm ($\sum_{t-4}^{t-1}$ *VC volume*), a squared term of $\sum_{t-4}^{t-1}$ *VC volume* to capture non-linearity ($\sum_{t-4}^{t-1}$ *VC volume* ^2), lags of the dependent variable (*Labor cost (t-1)*). The omitted base category is industries with no VC activity over the previous four years. The regressions include country, industry, year, country-year, industry-year and country-industry fixed effects. Standard errors are clustered at the country-year level and presented in parentheses.

The results in Table 4 indicate that VC also has a positive impact on the growth rate of labor costs. The average VC industry grows faster in terms of labor costs than the average non-VC industry. The coefficient of *VC industry* in column 4 suggests that the labor costs in the average VC industry grow at an annual rate that is 0.65 percentage points higher than for a non-VC industry. Table A5 reports an average growth rate of labor costs of 1.29 percent during the time period.

Like for the growth of employment, estimates in Table 4 in column 4 suggest that the growth of labor costs is positively associated with higher levels of VC activity. A doubling of the supply of VC investments over the previous four years implies an increase of annual labor cost growth by 0.16 percentage points.

As the coefficient of $\sum_{t-4}^{t-1} VC\ volume^{\wedge}2$ in column 3 is statistically insignificant, the result suggests no non-linear relationship between VC activity and labor cost growth. Overall, the significance level of the estimates differs depending on the inclusion of different combined fixed effects, see columns 4-9. The regression coefficients are most sensitive to the inclusion of $\sum_{t-4}^{t-1} VC\ volume^{\wedge}2$ in combination with different combined fixed effects, see columns 5 and 7. A non-linear relationship between VC activity and labor costs seems to be present only when incorporating combined country-industry fixed effects in the regression, see column 9.

Table 4: VC Activity and Labor Cost Growth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Labor cost growth	Labor cost growth	Labor cost growth	Labor cost growth	Labor cost growth	Labor cost growth	Labor cost growth	Labor cost growth	Labor cost growth
VC industry	0.652***								
	(0.186)								
$\sum_{t-4}^{t-1}$ *VC volume*		0.160***	0.261***	0.144**	0.244***	0.170***	0.070	0.109*	0.339***
		(0.055)	(0.094)	(0.057)	(0.092)	(0.059)	(0.090)	(0.057)	(0.110)
$\sum_{t-4}^{t-1}$ *VC volume* ^2			-0.019		-0.019		0.021		-0.046**
			(0.016)		(0.016)		(0.017)		(0.019)
Country FE	Yes	Yes	Yes	No	No	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	No	No	No	No	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	No	No	No	No
CountryYear FE	No	No	No	Yes	Yes	No	No	No	No
IndustryYear FE	No	No	No	No	No	Yes	Yes	No	No
CountryIndustry FE	No	No	No	No	No	No	No	Yes	Yes
Observations	4,215	4,215	4,215	4,215	4,215	4,215	4,215	4,215	4,215
R-squared	0.296	0.296	0.296	0.360	0.360	0.357	0.357	0.318	0.319

* *p<0.1, ** p<0.05, ***p<0.01.*

The table contains OLS regression coefficients. An observation is a country-industry-year pair. The endogenous variable is the growth rate of labor costs (as defined by OECD) measured in percentage. The exogenous variables are indicators for positive VC activity over the previous four years at the country-industry level (*VC industry*), indicators for the level of VC activity over the previous four years at the country-industry level measured in natural logarithm ($\sum_{t-4}^{t-1}$ *VC volume*) and a squared term of $\sum_{t-4}^{t-1}$ *VC volume* to capture non-linearity ($\sum_{t-4}^{t-1}$ *VC volume* ^2) The omitted base category is industries with no VC activity over the previous four years. The regressions include country, industry, year, country-year, industry-year and country-industry fixed effects. Standard errors are clustered at the country-year level and presented in parentheses.

Table A10 reports the additional effect of VC on the growth of labor costs when occurring in a service industry. The coefficient of the interaction term between $\sum_{t-4}^{t-1} VC\ volume$ and *Service* in column 1 suggests that a doubling in VC activity over four years leads to an additional 0.12 percentage points higher annual labor cost growth in that industry if it is classified as a service industry. The additional effect of VC activity on labor cost growth within service industries is positively significant and robust to the inclusion of several combined fixed effects. However, with the inclusion of combined country-industry fixed effects it loses its significance. As for employment growth, the inclusion of the interaction variable between $\sum_{t-4}^{t-1} VC\ volume$ and *service industry* decreases the significance of the $\sum_{t-4}^{t-1} VC\ volume$ variable. However, with the inclusion of combined country-industry fixed effects it remains significantly positive on a five percent level.

6.3 Issues with the Results

Despite the high significance of the VC activity variables (*VC industry* and $\sum_{t-4}^{t-1} VC\ volume$) in the majority of our regression specifications, there are other potential sources for the greater level of employment (labor costs) and higher employment (labor cost) growth rate, which were not controlled for in our model. One alternative explanation for the observed results, which has been put forward by several researchers (Belke et al., 2003; Kanniainen and Keuschnigg, 2005; Dessí and Yin, 2012), is a potential endogeneity problem, caused by the fact that VC funds actually choose to invest in industries that depict a higher growth from the beginning or that there are other omitted factors that influence both VC activity and employment performance. The latter problem is mitigated by the inclusion of fixed effects in our regressions, but as far as we know, academics have not yet come to a final conclusion on the direction of the relation between VC and employment performance. In previous papers, this issue has most of the time been addressed by employing an instrumental variable approach.

Samila and Sorenson (2010; 2011) have used endowment returns as an instrument to address the potential endogeneity problem when studying the effect of VC on employment. In the U.S., endowments have been a major contributor to the development of the VC industry. Typically, they invest in innovations from their own university, making it easier for them to identify investments with a chance for success. Contrarily, in Europe the VC industry is more reliant on funds from government agencies (Kelly, 2011), making it unlikely for endowment returns to be a good fit as a strong instrument in a European setting.

Others (Popov and Roosenboom, 2012; González-Uribe, 2013; Popov, 2013) have used variations in pension reforms as an instrument for the supply of VC. In the context of labor market performance, the validity of this instrument is based on the logic that the size of pension funds is correlated with risk capital investment, while the institutional investors' demand for alternative assets should not be dependent on entrepreneurship. However, we look at employment in general not specifically at the number of entrepreneurs and as Tuladhar (2007) has found evidence of a negative relation between the unemployment rate and the size of pension funds, we argue that pension funds are not a valid instrument in our case. Moreover, pension reforms may very well vary across nations, but the pension reforms across industries within one country face the same pension reforms, which would make it impossible for us to conduct an analysis at an industry level.

Engel (2002) and Colombo and Grilli (2005; 2010) used a two-step approach in order to disentangle the treatment and selection effect of VC funding. First, they calculated the likelihood of receiving VC funding employing a selection equation. In the second step, they instrument VC funding with the predicted probability of receiving such finance through the estimation procedure utilized in the first step. However, this approach of dealing with the perceived reverse causality problem may be more appropriate when analyzing the effect of VC at a firm level. In the first step, data on specific firm characteristics are needed in order to compute the probability of obtaining VC finance. To apply this logic to an analysis at an industry level might result in an overestimation of the probability of receiving VC funding. Even though firms in the same industry share certain industry-specific characteristics, which might be more or less attractive to VC funds, there are also huge differences between these firms.

Another method to mitigate the endogeneity problem (see Belke et al., 2004) is the usage of lagged variables as instrument in a first difference model. In such a setting there seems to be a strong correlation between the lagged instrument and the VC variable, suggesting the lagged variables to be a strong instrument. On the other hand, according to Bertoni et al. (2011), in a level model the lagged instruments are only poorly correlated with the VC activity. Lagged instruments in levels hence seem to be a weak instrument, which increases the risk of a serious bias in the results (Wooldridge, 2009).

Many instruments have been tested without succeeding in finding a universally accepted one. Instead of using a mediocre instrument for the supply of VC in an attempt to cope with the potential reverse causality problem, we test whether VC Granger causes the observed employment performance with the help of an OLS regression (see Tables A14 and A15), suggested by Stock & Watson (2007) and Greene (2008). As discussed in Section 5.1, the level of employment and labor costs cannot be considered as stationary, which is one requirement for the Granger causality test. In case of non-stationarity, the test can be conducted using first difference. With this in mind, we limit the application of the Granger causality test to shed light on the relationship between VC and the growth of employment and labor costs.

For the entire sample, the Granger causality test suggests that VC activity actually Granger causes employment growth. In our dataset, employment growth does not seem to Granger cause VC activity on the other hand, giving an indication for the direction of the relationship. Nevertheless, if we would test whether or not VC activity Granger causes employment performance for each panel (country-year), we might end up with different conclusions for different panels (Erdil and Yetkiner, 2004).

When testing whether VC activity Granger causes labor cost growth or not, we fail to reject the null hypothesis at any conventional significance level and thus conclude that VC activity does not Granger cause the growth of labor costs, at least not in our sample. We arrive at the same conclusion when we test whether labor cost growth Granger causes VC activity. Hence, the Granger causality test provides inconclusive results in light of the reverse causality issue when studying the effect of VC on the growth of labor costs. For our purposes however, we consider the Granger causality tests to be satisfying enough to justify our approach and despite the risk for minor biases in our results, we consider them to contribute to current knowledge within the VC field.

7 Discussion and Analysis

Our findings are consistent with the general notion presented in previous research that VC funding has a positive and significant impact on employment performance. To begin with, we find evidence that industries with the presence of VC activity in the preceding four years have on average both a higher level of employment and employment growth rate than industries with no VC activity during the same period. This implies that VC activity can be a potential driver of employment in entire industries.

On a regional level, Samila and Sorenson (2011) argue that the impact of VC activity has decreasing returns to employment growth. Our findings support their conclusion on an industry level as we too find that the elasticity of VC activity to employment is less than one. Furthermore, our results are suggestive of a non-linear relationship between VC activity and employment growth where the effects of VC are negative beyond a certain level. This implies that the marginal effect of VC investments is greater when the supply of VC is still relatively scarce within an industry and as it seems, an unlimited availability of VC investments is not beneficial. Nevertheless, the employment growth in VC industries exceeds the one in non-VC industries in our sample.[16]

Part of this superior employment performance probably stems from the fact that VC firms fill an important niche that allows necessary capital to reach young companies in early stages of the business cycle that involves extraordinary risks. Arguably, this financing cannot be easily substituted by other sources of financing such as banks since young companies allegedly have little or no collateral to secure bank loans and therefore struggle to attract capital (EVCA, 2013). The increased availability of financing to young firms from VC may translate into increased employment through the facilitated start-up of new businesses or the expansion of existing establishments. In addition to mitigating the financing issue stemming from information asymmetry (Petersen and Rajan, 1995) and uncertainty (Hannan and Freeman, 1989), VC firms also carry out other value enhancing activities, such as advising management, which banks are generally unable to perform (Davila et al. 2003). These insights should be of particular importance to the European economy, which is by large a bank-based economy.

[16] The employment growth of industries receiving VC financing is predicted to be above the employment growth of industries not receiving any VC until the volume of VC reaches slightly above USD 12 billion over four years (normalized to 2009), which is far exceeding any reached level in our sample, see Section 6.1.

Our results support the notion that the presence of VC benefits not only companies backed by VC, but also the entire industries to which they belong. Samila and Sorenson (2011) put forward theories of spinoff and expectation effects to explain how VC contributes to additional positive economic impacts in certain regions beyond those accruing to VC-backed companies. In line with their findings, we argue that the effect of VC in companies receiving financing, such as developments or improvements in a specific business area, probably spills over to other companies, which in turn will benefit from it indirectly. These companies are most likely active in the same industry as the ones receiving VC. Hence in contrast to Samila and Sorenson (2011), we argue that not the region, but the industry is more relevant as analysis unit in this case. This reasoning draws on the early economic theories of Romer (1986), who argues that knowledge is endogenously determined through spillover effects and can be considered a public good. For instance, innovations associated with VC (Kortum and Lerner, 2000) are most likely industry-specific and hence benefit companies within the same industry.

Furthermore, VC promotes entrepreneurial activity, which in turn promotes even more start-ups and innovation. Also, the availability of VC in an industry motivates entrepreneurs to adopt high-growth and innovative strategies as they can expect to be supported by VC. In other words, the presence of a well-functioning VC market promotes so called "gazelle" companies even if the companies do not ultimately seek VC financing (EVCA, 2013).

The significance of the estimates of VC activity on employment growth is however sensitive to the inclusion of combined industry-year fixed effects, suggesting that there are some unobservable factors, which drive both the growth of employment and VC activity within industries in the EU-15 countries. Yet, we are not particularly surprised by these findings. Combined industry-year fixed effects capture industry differences in time dynamics, such as innovations and technological developments within specific industries. Kortum and Lerner (2000) show in their research that VC activity causes higher levels of patenting within an industry. This could in turn contribute to higher growth of employment within those industries granted many patents.

Moreover, the opening of Euro.nm[17], coinciding with a surge in VC activity, probably drove employment growth in industries eligible to listing on the exchange. With this in mind, we reason that the insignificance of VC activity on employment growth when incorporating combined industry-year fixed effects in the total sample might be driven by other underlying factors captured in these fixed effects. Nevertheless, VC may in fact work through different channels and indirectly affect employment growth through its causing of factors driving employment, such as patenting and productivity. Despite these findings, we are not immensely concerned about the reliability of our results in this regard, as there is a significant effect of VC when we instead include country-industry and country-year fixed effects.

In addition to VC's effect on employment, our results imply that VC activity may raise the aggregate labor costs in an industry. The motives for investing in higher wages are manifold. First of all, higher wages can attract higher-skilled workers. Green (2012) argues that this is essential for a country to maintaining a competitive business in the increasingly knowledge-based global economy. Furthermore, the competitive advantage obtained through human capital is likely to be enduring and difficult to duplicate. Second, high wages tend to attract more applicants potentially allowing the company to select and hire the most talented workforce. Third, workers have been found to work harder and hence be more productive if wages were higher than might be predicted based on standard demographic and human capital factors (Pfeffer, 1994).

The magnitudes of our results suggest that the effect of VC is found to be larger on the growth of labor costs than on the growth of employment. We find three alternative explanations for these findings, some of which are more plausible. We argue that the most plausible explanation is that VC stimulates the creation of more well-paid jobs, in line with the hypothesis that VC creates and develops a high-skilled labor force. Innovation and technology changes associated with high VC activity (Kortum and Lerner, 1998) raise the demand for highly talented and skilled employees and thus high wages. Alternatively, the greater availability of, and competition for, the labor force from entrepreneurship and small-firm employment exerts an upward pressure on the wages paid by existing employers (Belke et al., 2003). However, we find this explanation less

[17] Euro.nm is a pan-European network of regulated markets dedicated to growth companies. It was formed on March 1, 1996 by the European Association of European Exchanges and members of the network include Euronext Amsterdam, Euronext Paris, Euronext Brussels, Deutsche Börse AG and Borsa Italiana.

plausible as VC tends to predominantly invest in SMEs and hence, their market power is arguably rather weak relative to industry market leaders in terms of wages. A third explanation might be that VC-backed firms invest more in their personnel in terms of training to ultimately gain in productivity and efficiency. However, worth noting is the relatively larger impact of VC on employment growth than labor cost growth compared to their average respective growth rate across industries.

Moreover, our results imply that VC might work more efficiently in terms of achieving higher employment and a more well-paid (potentially high-skilled) labor force in the "new economy" industries. When allowing for this distinction in our regressions, we find a statistically and economically significant higher impact of VC activity on the growth of employment as well as labor costs in service industries. As the effect of VC on both employment and labor cost growth in all cases except for one loses its significance in manufacturing industries, our results suggest that the effects of VC found in the full sample are most likely attributable to the service industries. Taken all together, these findings support those by Metrick and Yasuda (2010) that VC has a greater value in industries with network effects and economies of scope, recognized as "new economy" industries. The magnitude of the impact is slightly higher for employment than for labor costs, in contrast to our findings for the whole sample.

As briefly touched upon earlier, the inclusion of various fixed effects in our regressions is an efficient method to mitigate the endogeneity problem. Different fixed effects can control for industry characteristics such as size, investment opportunities and industry level technology shocks, making the presence of reverse causality less likely. However, it is impossible to control for all the different fixed effects at the same time and thus, we recognize that there still exist possible reverse causality issues in our findings.

Although, our Granger causality test suggested that VC Granger causes employment growth and not the other way around, we cannot entirely rule out the possibility of reverse causality. VC firms might to some extent be attracted to potential high-growth industries rather than causing the high growth themselves. Furthermore, in Western Europe, the sector, or industry, has traditionally been fundamental for the governance of labor markets (Bechter et al., 2012), which in turn adds to the assessment of an industry's attractiveness for VC investments. However, we argue that this does not undermine the importance of VC for employment growth. Even though VC firms may choose to invest in industries with good growth potential, it is partially the capital that VC contributes, which facilitates this growth. For instance, Davila et al. (2003) argue that start-ups may postpone growth due to the lack of financing indicating that financing plays an important role in promoting growth rather than the other way around.

However, in light of the results obtained in the Granger causality test in Table A15, we are cautious in arguing for causality in terms of VC and labor costs. The positive relation between labor costs and VC activity might, and most likely to some extent does, illustrate the fact that VC firms are attracted to industries requiring high-skilled labor such as high-tech and service industries. Yet, we argue that the relationship between VC and labor costs goes in both directions. This suggestion is in line with previous research (Puri and Zarutskie, 2012; Samila and Sorenson, 2011) that VC firms not only invest heavily in employment via large numbers of employees, but also via higher wages.

Nevertheless, our findings support policies aiming to develop the European VC industry as we suggest that well-functioning VC markets can contribute significantly to producing superior employment performance at an industry level. However, it is important to recognize that VC is part of a larger ecosystem. It is not only the supply of VC, which might influence the volume of VC investment. Possibly, the supply of suitable entrepreneurs with innovative ideas and the incentives to disclose those ideas to financiers are other aspects affecting the volume of VC. For instance, policies aiming to implement stronger patent rights could potentially encourage the disclosure of innovative ideas to possible financiers and therefore also the level of VC activity in an industry. Moreover, policies should consider variations in the marginal effects of VC depending on its contextual environment such as in the “new economy” industries.

8 Conclusion

Europe's attempt to cope with its current problem of high persistent unemployment and lacking competitiveness has drawn much attention to the European VC industry's potential ability to create jobs and a high-skilled and competitive labor force. In our thesis, we test how VC affects employment and labor costs at an industry level. Consistent with previous research, our main results support the previously stated hypotheses that VC has a positive impact on both the level and growth of aggregate employment and labor costs.

First, we show that an industry receiving VC funding in the preceding four years has on average a higher employment level and growth than industries with no VC funding. Second, our results suggest that the level of VC activity has a positive and significant effect on employment level and growth but that the effect of VC on employment growth is decreasing and non-linear. Part of this superior employment performance probably stems from the fact that VC enables necessary capital to reach young companies in early stages of the business cycle. Third, we show that both the presence and level of VC activity within an industry has a positive and significant effect on the aggregate labor cost level and growth in that industry. Furthermore, the marginal impact of VC on both employment and labor costs is higher in "new economy" industries. This confirms earlier research suggesting that VC is context-dependent and more efficient in industries with certain network effects.

Given our results, we can conclude that the positive effects of VC accrue not only to companies backed by VC, but also the entire industries to which they belong. These findings support government policies that aim to support and promote the development of the VC industry in Europe. However, care is needed when interpreting our results in light of the potential problem with reverse causality. The relationship between VC activity and labor costs seems to go in both directions, making it hard to pinpoint the casual effect without a valid instrument. Nevertheless, our findings add insight to the relationship between VC and aggregate industry performance, which, to our knowledge, has previously not been researched.

Despite new findings within the area of VC, more research is needed. Future studies should focus on a better understanding of the channels through which context-dependent VC effects work and the underlying mechanisms behind them, drawing on some potential theories that have already been put forward. Also, it would be of interest to study the marginal effect of VC when allowing for a differentiation between high- and low-technology industries both from the manufacturing and service sector. As discussed above, this categorization was not possible in our sample and is therefore left for future research to explore. Another important challenge for future research is finding a valid instrument for VC activity in order to further shed light on the endogeneity problem present in this context.

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Appendix

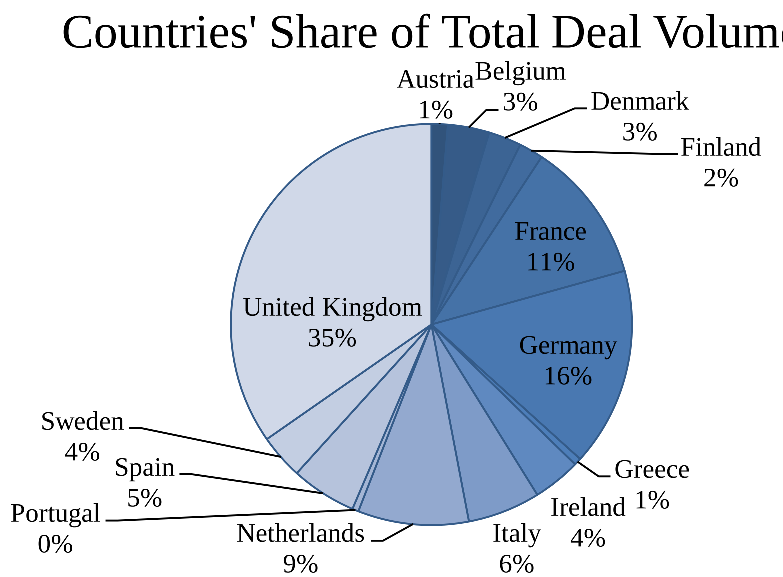

Figure A1: Countries’ share of the total VC deal volume during 1995-2009 in EU-15 countries (excl. Luxembourg).

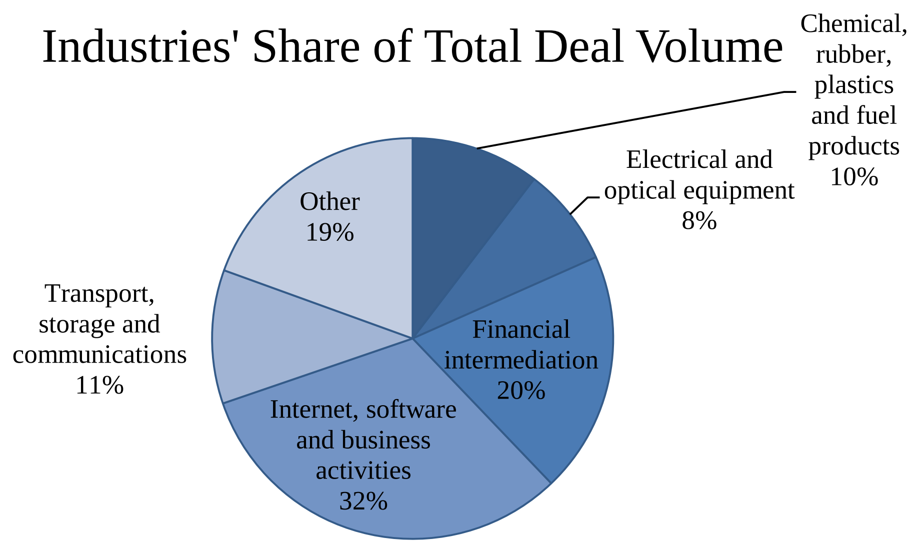

Figure A2: Industries’ share of the total VC deal volume during 1995-2009 in EU-15 countries (excl. Luxembourg).

Table A1: Description of OECD Variables

Variable	Description
Production (gross output)	Production represents the value of goods and/or services produced in a year, whether sold or stocked in current prices
Labor costs	Comprises of wages and salaries of employees paid by producers as well as supplements such as contributions to social security, private pensions, health insurance, life insurance and similar schemes.
Number of employees	Number of employees excluding the self-employed and unpaid family workers
Exchange rate	Exchanges rates are collected from the IMF publication “International Financial Statistics” and refer to IMF series “rf”: year average national currency per U.S. dollars.
Deflator	The deflators include the effect of exchange rate changes, and are therefore only applicable to US dollar figures.

Source: OECD STAN database, OECD National Accounts Statistics, OECD International Development Statistics

Table A2: Distribution of Deals and Deal Volume by Year

Year	Observations	VC industries	Deals	Deal volume	Imputed deal volume
1989	n/a	n/a	18	133	284
1990	n/a	n/a	14	88	158
1991	n/a	n/a	23	125	519
1992	n/a	n/a	29	119	349
1993	n/a	n/a	34	91	243
1994	n/a	n/a	37	268	500
1995	315	58	79	381	870
1996	315	80	94	1,173	2,100
1997	315	87	200	868	1,816
1998	315	101	357	1,215	2,366
1999	315	131	801	5,391	8,815
2000	315	155	1,719	18,775	28,108
2001	315	178	1,284	11,233	16,443
2002	315	194	838	5,567	8,253
2003	315	197	743	3,500	5,210
2004	315	193	778	4,927	6,675
2005	315	184	825	7,768	10,396
2006	315	179	1,117	7,856	11,842
2007	315	197	1,455	5,599	8,816
2008	315	209	1,450	9,522	14,982
2009	315	217	1,179	4,915	7,978
Total	4,725	2,360	13,074	89,513	136,725

Observation is the number of country-industry-year observations per year. *VC industries* is the number of observations classified as a VC industry, i.e. if it had at least one VC deal in the previous four years. *Deals* is the number of deals, *Deal volume* is total size of the deals (normalized to 2009 USD millions). *Imputed deal volume* includes the imputed deal volumes when there is missing information on deal size.

Table A3: Distribution of Deals and Deal Volume by Country

Country	Observations	VC industries	Deals	Deal volume	Imputed deal volume
Austria	315	107	184	1,032	1,886
Belgium	315	167	300	2,785	3,930
Denmark	315	115	366	2,157	3,258
Finland	315	165	401	1,034	2,758
France	315	232	2,447	13,689	16,513
Germany	315	215	1,936	11,171	24,104
Greece	315	89	46	168	488
Ireland	315	128	393	3,371	3,829
Italy	315	166	288	5,316	9,240
Netherlands	315	186	548	3,765	9,213
Portugal	315	88	93	603	730
Spain	315	217	678	6,259	8,157
Sweden	315	162	767	3,813	5,538
United Kingdom	315	283	4,440	31,100	40,871
Total	4,410	2,320	12,887	86,262	130,516

The sample consists of 4, 410 country-industry-year observations of EU-15 countries (excl. Luxembourg) between 1995 and 2009**.** *Observation* is the number of country-industry-year observations per year. *VC industries* is the number of observations classified as *VC industry*, i.e. if it had at least one VC deal in the previous four years. *Deals* is the number of deals. *Deal volume* is total size of the deals in million (normalized to 2009 USD). *Imputed deal volume* includes the imputed deal volumes when there is missing information on deal size.

Table A4: Distribution of Deals and Deal Volume by Industry

Industry	Obs.	VC industries	Deals	Deal volume	Imputed deal volume
Agriculture, hunting, forestry and fishing	210	56	29	105	168
Basic metals and fabricated metal products	210	119	147	437	924
Chemical, rubber, plastics and fuel products	210	167	860	7,634	10,481
Community, social and personal services	210	123	271	2,396	3,840
Construction	210	87	117	1,040	1,856
Electrical and optical equipment	210	170	1,768	7,225	10,830
Electricity, gas and water supply	210	73	81	1,079	1,739
Financial intermediation	210	142	531	13,995	22,811
Food products, beverages and tobacco	210	125	170	409	800
Hotels and restaurants	210	80	127	699	1,016
Internet, software and business activities	210	195	6,242	31,836	47,173
Machinery and equipment, n.e.c.	210	146	507	1,638	2,610
Manufacturing n.e.c. and recycling	210	82	101	348	562
Mining and quarrying	210	26	22	296	599
Other non-metallic mineral products	210	60	32	151	269
Pulp, paper, paper products, printing and publishing	210	120	330	1,776	2,457
Textiles, textile products, leather and footwear	210	85	80	314	429
Transport equipment	210	81	84	470	777
Transport, storage and communications	210	166	638	10,755	15,394
Wholesale and retail trade - repairs	210	174	726	3,552	5,612
Wood and products of wood and cork	210	43	24	106	170
Total	4,410	2,320	12,887	86,262	130,516

The sample consists of 4, 410 country-industry-year observations of EU-15 (excl. Luxembourg) countries between 1995 and 2009. Observation *(Obs.)* is the number of industry observations across countries over the time period. *VC industries* is the number of observations classified as a VC industry, i.e. if it had at least one VC deal in the previous four years. *Deals* is the number of deals. Deal volume is total size of the deals in million (normalized to 2009 USD). *Imputed deal volume* includes the imputed deal volumes when there is missing information on deal size.

Table A5: Industry Variables

	All industries			VC industries			Non-VC industries		
	Obs.	Average growth	Std. Dev	Obs.	Average growth	Std. Dev	Obs.	Average growth	Std. Dev
Total sample									
Number of employees	4,084	0.04%	4.46%	2,183	0.26%	4.26%	1,901	-0.20%	4.66%
Labor costs	4,215	1.29%	5.33%	2,194	1.44%	5.01%	2,021	1.11%	5.66%
Production	4,050	2.16%	7.74%	2,105	2.11%	7.06%	1,945	2.22%	8.42%
Service industries									
Number of employees	1,184	2.04%	3.11%	836	2.15%	3.23%	348	1.77%	2.78%
Labour costs	1,213	3.27%	4.71%	839	3.32%	4.53%	374	3.13%	5.10%
Production	1,140	3.37%	4.74%	794	3.36%	5.00%	346	3.41%	4.08%
Manufacturing industries									
Number of employees	2,900	-0.77%	4.66%	1,347	-0.92%	4.39%	1,553	-0.64%	4.88%
Labor costs	3,002	0.49%	5.36%	1,355	0.28%	4.94%	1,647	0.66%	5.68%
Production	2,910	1.69%	8.59%	1,311	1.36%	7.96%	1,599	1.97%	9.07%

The sample consists of 4, 410 country-industry-year observations of EU-15 countries (excl. Luxembourg) between 1995 and 2009. *VC industries* is the number of observations classified as a VC industry, i.e. if it had at least one VC deal in the previous four years.

Table A6: Industry Variables *High VC* versus *Low VC*

	High VC industries			Low VC industries		
	Obs.	Average growth	Std. Dev	Obs.	Average growth	Std. Dev
Number of employees	1 100	0.78%	3.82%	1 083	-0.27%	4.61%
Labor costs	1 101	1.95%	4.66%	1 093	0.93%	5.30%
Production (gross output)	1 047	2.69%	6.68%	1 058	1.54%	7.37%

The sample consists of 4, 410 country-industry-year observations of EU-15 (excl. Luxembourg) countries between 1995 and 2009. Industries are classified as *High VC industries* or *Low VC industries* according to their total imputed yearly deal volume divided by total production (both normalized to 2009 USD).

Table A7: Employment Growth and Industries' Share of Employment and VC Deals

Industry	Average employment growth	Average Labor cost growth	Share of total employment	Share of total deals	Share of total deal volume	Share of total deal volume/share of total employment
Agriculture, hunting, forestry and fishing	0.02%	0.86%	1.84%	0.29%	0.15%	0.08
Basic metals and fabricated metal products	0.25%	1.45%	2.63%	1.37%	1.16%	0.43
Chemical, rubber, plastics and fuel products	-0.18%	1.19%	2.03%	7.92%	10.36%	5.05
Community, social and personal services	1.66%	3.03%	32.51%	2.27%	3.03%	0.09
Construction	1.55%	2.91%	6.59%	0.96%	1.60%	0.24
Electrical and optical equipment	-0.33%	1.23%	1.98%	13.22%	7.99%	4.40
Electricity, gas and water supply	-0.87%	0.62%	0.73%	0.46%	1.02%	1.54
Financial intermediation	0.59%	2.29%	3.30%	4.83%	19.51%	5.91
Food products, beverages and tobacco	-0.55%	0.34%	2.26%	1.71%	0.73%	0.32
Hotels and restaurants	2.78%	3.57%	4.42%	1.22%	0.96%	0.22
Internet, software and business activities	4.66%	6.12%	11.77%	44.29%	31.89%	2.69
Machinery and equipment, n.e.c.	0.05%	1.29%	2.02%	4.74%	2.14%	1.07
Manufacturing n.e.c. and recycling	-1.19%	0.24%	1.03%	0.89%	0.51%	0.48
Mining and quarrying	-1.41%	-0.27%	0.22%	0.17%	0.50%	2.46
Other non-metallic mineral products	-0.99%	0.31%	0.83%	0.27%	0.22%	0.26
Pulp, paper, paper products, printing and publishing	-1.33%	-0.02%	1.53%	2.92%	1.80%	1.20
Textiles, textile products, leather and footwear	-5.50%	-4.01%	1.52%	0.74%	0.26%	0.19
Transport equipment	-0.40%	0.62%	1.72%	0.59%	0.99%	0.63
Transport, storage and communications	0.85%	1.86%	5.98%	5.15%	10.78%	1.80
Wholesale and retail trade – repairs	1.73%	2.72%	14.55%	5.73%	4.19%	0.29
Wood and products of wood and cork	-0.78%	0.40%	0.51%	0.24%	0.22%	0.40
Total	0.04%	1.29%	4.76%	4.76%	4.76%	1.42

The sample consists of 4, 410 country-industry-year observations of EU-15 (excl. Luxembourg) countries between 1995 and 2009**.** *Average employment growth* is the average yearly growth in employment for each industry. *Average labor cost growth* is the average yearly growth in labor costs for each industry. *Share of total employment* is industry's share of total employment during the sample period. *Share of total deals* is the industry's share of total number of deals during the sample period. *Share of total deal volume* is the industry's share of total deal volume during the sample (using imputed deal volumes normalized to 2009 USD).

Table A8: Employment Growth and Countries' Share of Employment and VC Deals

Country	Average employee growth	Average labor cost growth	Share of total employment	Share of total deals	Share of total deal volume	Share of total deal volume/share of total employment
Austria	-0.13%	0.90%	2.41%	1.23%	1.31%	0.56
Belgium	-0.35%	0.57%	2.51%	2.76%	3.34%	1.36
Denmark	-0.30%	0.83%	1.82%	2.95%	2.66%	1.50
Finland	0.36%	2.18%	1.48%	3.07%	1.95%	1.32
France	-0.16%	0.76%	13.59%	17.81%	11.42%	0.87
Germany	-0.99%	-0.23%	24.75%	13.77%	16.01%	0.65
Greece	0.79%	3.03%	2.00%	0.70%	0.58%	0.31
Ireland	-0.21%	3.22%	0.88%	3.57%	3.86%	3.04
Italy	0.39%	0.17%	12.78%	2.08%	5.86%	0.47
Netherlands	-0.06%	0.86%	5.05%	4.80%	8.93%	1.81
Portugal	0.47%	1.74%	2.21%	0.60%	0.51%	0.19
Spain	1.66%	1.07%	10.60%	4.35%	5.27%	0.47
Sweden	0.07%	1.88%	2.95%	5.39%	3.61%	1.25
United Kingdom	-0.93%	0.98%	16.97%	36.92%	34.68%	1.91
Total	0.04%	1.29%	7.14%	7.14%	7.14%	1.11

The sample consists of 4, 410 country-industry-year observations of EU-15 countries between 1995 and 2009. *Average employment growth* is the average yearly growth in employment for each country. *Average labor cost growth* is the average yearly growth in labor costs for each industry. *Share of total employment* is the country's share of total employment during the sample period. *Share of total deals* is the country's share of total number of deals during the sample period. *Share of total deal volume* is the country's share of total deal volume during the sample (using imputed deal volumes normalized to 2009 USD).

Table A9: VC Activity and Employment Growth in Service and Manufacturing Industries

	(1)	(2)	(3)	(4)
	Employ. growth	Employ. growth	Employ. growth	Employ. growth
$\sum_{t-4}^{t-1}$ *VC volume*	0.018	0.052	0.025	-0.043
	(0.065)	(0.062)	(0.070)	(0.082)
$\sum_{t-4}^{t-1}$ *VC volume* Service*	0.184**	0.159**	0.140**	0.187**
	(0.072)	(0.071)	(0.067)	(0.095)
Country FE	Yes	No	Yes	No
Year FE	Yes	No	No	Yes
Industry FE	Yes	Yes	No	No
CountryYear FE	No	Yes	No	No
IndustryYear FE	No	No	Yes	No
CountryIndustry FE	No	No	No	Yes
Observations	4,084	4,084	4,084	4,084
R-squared	0.326	0.393	0.417	0.392

** p<0.1, ** p<0.05, ***p<0.01.*

The table contains OLS regression coefficients. An observation is a country-industry-year pair. The endogenous variable is the level or growth rate of employment (as defined by OECD) measured in natural logarithm and percentage, respectively. The exogenous variables are indicators for the level of VC activity over the previous four years at the country-industry level measured in natural logarithm ($\sum_{t-4}^{t-1}$ *VC volume*) and an interaction term between $\sum_{t-4}^{t-1}$ *VC volume* and a service industry dummy variable ($\sum_{t-4}^{t-1}$ *VC volume* *Service). The omitted base category is industries with no VC activity over the previous four years and being classified as a manufacturing industry. The regressions include country, industry, year, country-year, industry-year fixed effects and country-industry fixed effects. Standard errors are clustered at the country-year level and presented in parentheses.

Table A10: VC Activity and Labor Costs in Service and Manufacturing Industries

	(1) Labor cost growth	(2) Labor cost growth	(3) Labor cost growth	(4) Labor cost growth
$\sum_{t-4}^{t-1}$ *VC volume*	0.105	0.085	0.132**	0.057
	(0.068)	(0.069)	(0.067)	(0.081)
$\sum_{t-4}^{t-1}$ *VC volume* Service*	0.119**	0.125**	0.097**	0.113
	(0.077)	(0.078)	(0.083)	(0.098)
Country FE	Yes	No	Yes	No
Year FE	Yes	No	No	Yes
Industry FE	Yes	Yes	No	No
CountryYear FE	No	Yes	No	No
IndustryYear FE	No	No	Yes	No
CountryIndustry FE	No	No	No	Yes
Observations	4,215	4,215	4,215	4,215
R-squared	0.304	0.360	0.407	0.368

** p<0.1, ** p<0.05, ***p<0.01.*

The table contains OLS regression coefficients. An observation is a country-industry-year pair. The endogenous variable is the level or growth rate of employment (as defined by OECD) measured in natural logarithm and percentage, respectively. The exogenous variables are indicators for the level of VC activity over the previous four years at the country-industry level measured in natural logarithm ($\sum_{t-4}^{t-1}$ *VC volume*) and an interaction term between $\sum_{t-4}^{t-1}$ *VC volume* and a service industry dummy variable ($\sum_{t-4}^{t-1}$ *VC volume* *Service). The omitted base category is industries with no VC activity over the previous four years and being classified as a manufacturing industry. The regressions include country, industry, year, country-year, industry-year fixed effects and country-industry fixed effects. Standard errors are clustered at the country-year level and presented in parentheses.

Table A11: VC Activity and Level of Employment Excluding UK

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Employ. Level	Employ. level	Employ. level	Employ. level	Employ. level	Employ. level	Employ. Level	Employ. level	Employ. Level
VC industry	0.176***						0.007***		
	(0.022)						(0.002)		
$\sum_{t-4}^{t-1}$ *VC volume*		0.068***	0.073***	0.071***	0.016***	0.050***		0.002***	0.002*
		(0.006)	(0.007)	(0.006)	(0.002)	(0.010)		(0.001)	(0.001)
$\sum_{t-4}^{t-1}$ *VC volume* ^2						0.004**			-0.000
						(0.002)			(0.000)
Employ. Level (t-1)							1.004***	1.004***	1.004***
							(0.001)	(0.001)	(0.001)
Country FE	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Year FE	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	No	No	No	No	No	No
CountryYear FE	No	No	No	Yes	No	No	No	No	No
IndustryYear FE	No	No	No	No	Yes	No	No	No	No
CountryIndustry FE	No	No	No	No	No	Yes	Yes	Yes	Yes
Observations	3,884	3,884	3,884	3,884	3,884	3,884	3,790	3,790	3,790
R-squared	0.937	0.938	0.937	0.937	0.995	0.938	-	-	-

** p<0.1, ** p<0.05, ***p<0.01.*

The table contains OLS regression coefficients (columns 1-6) and GLS regression coefficients (columns 7-9). An observation is a country-industry-year pair. The endogenous variable is the level of employment (as defined by OECD) measured in natural logarithm. The exogenous variables are indicators for positive VC activity over the previous four years at the country-industry level (*VC industry*), indicators for the level of VC activity over the previous four years at the country-industry level measured in natural logarithm ($\sum_{t-4}^{t-1}$ *VC volume*), a squared term of $\sum_{t-4}^{t-1}$ *VC volume* to capture non-linearity ($\sum_{t-4}^{t-1}$ *VC volume* ^2), lags of the dependent variable (*Employment level (t-1)*). The omitted base category is industries with no VC activity over the previous four years. The regressions include country, industry, year, country-year, industry-year and country-industry fixed effects. Standard errors are clustered at the country-year level and presented in parentheses.

Table A12: VC Activity and Level of Labor Costs Excluding UK

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Labor cost level	Labor cost level	Labor cost level	Labor cost level	Labor cost level	Labor cost level	Labor cost level	Labor cost level	Labor cost level
VC industry	0.165***						0.010***		
	(0.023)						(0.002)		
$\sum_{t-4}^{t-1}$ *VC volume*		0.064***	0.074***	0.066***	0.014***	0.050***		0.003***	0.004**
		(0.006)	(0.007)	(0.006)	(0.002)	(0.011)		(0.001)	(0.001)
$\sum_{t-4}^{t-1}$ *VC volume* ^2						0.003*			0.000
						(0.002)			(0.000)
Labor cost (t-1)							1.000***	0.999***	0.999***
							(0.001)	(0.001)	(0.001)
Country FE	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Year FE	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	No	No	No	No	No	No
CountryYear FE	No	No	No	Yes	No	No	No	No	No
IndustryYear FE	No	No	No	No	Yes	No	No	No	No
CountryIndustry FE	No	No	No	No	No	Yes	Yes	Yes	Yes
Observations	3,954	3,954	3,954	3,954	3,954	3,954	3,939	3,939	3,939
R-squared	0.933	0.935	0.933	0.933	0.993	0.935	-	-	-

** $p<0.1$, ** $p<0.05$, ***$p<0.01$.*

The table contains OLS regression coefficients (columns 1-6) and GLS regression coefficients (columns 7-9). An observation is a country-industry-year pair. The endogenous variable is the level of labor cost (as defined by OECD) measured in natural logarithm. The exogenous variables are indicators for positive VC activity over the previous four years at the country-industry level (*VC industry*), indicators for the level of VC activity over the previous four years at the country-industry level measured in natural logarithm ($\sum_{t-4}^{t-1}$ *VC volume*), a squared term of $\sum_{t-4}^{t-1}$ *VC volume* to capture non-linearity ($\sum_{t-4}^{t-1}$ *VC volume* ^2), lags of the dependent variable (*Labor cost (t-1)*). The omitted base category is industries with no VC activity over the previous four years. The regressions include country, industry, year, country-year, industry-year and country-industry fixed effects. Standard errors are clustered at the country-year level and presented in parentheses.

Table A13: VC Activity and Employment and Labor Cost Growth Excluding UK

	(1)	(2)	(3)	(4)	(5)	(6)
	Employ. growth	Employ. growth	Employ. growth	Labor cost growth	Labor cost growth	Labor cost growth
VC industry	0.523***			0.654***		
	(0.151)			(0.189)		
$\sum_{t-4}^{t-1}$ *VC volume*		0.107**	0.241***		0.150***	0.282***
		(0.050)	(0.084)		(0.057)	(0.101)
$\sum_{t-4}^{t-1}$ *VC volume* ^2			-0.0264**			-0.026
			(0.0134)			(0.017)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
CountryYear FE	No	No	No	No	No	No
IndustryYear FE	No	No	No	No	No	No
CountryIndustry FE	No	No	No	No	No	No
Observations	3,790	3,790	3,790	3,939	3,939	3,939
R-squared	0.312	0.311	0.312	0.296	0.295	0.295

** p<0.1, ** p<0.05, ***p<0.01.*

The table contains OLS regression coefficients. An observation is a country-industry-year pair. The endogenous variable is the growth rate of employment (as defined by OECD) measured in percentage. The exogenous variables are indicators for positive VC activity over the previous four years at the country-industry level (*VC industry*), indicators for the level of VC activity over the previous four years at the country-industry level measured in natural logarithm ($\sum_{t-4}^{t-1}$ *VC volume*) and a squared term of $\sum_{t-4}^{t-1}$ *VC volume* to capture non-linearity ($\sum_{t-4}^{t-1}$ *VC volume* ^2). The omitted base category is industries with no VC activity over the previous four years. The regressions include country, industry, year, country-year, industry-year and country-industry fixed effects. Standard errors are clustered at the country-year level and presented in parentheses.

Table A14: Granger Causality Test - VC and Employment Growth

	(1) Employment growth	(2) VC volume
Dependent variable (t-1)	0.257***	0.230***
	(0.053)	(0.028)
Dependent variable (t-2)	-0.008	0.166***
	(0.041)	(0.027)
Dependent variable (t-3)	0.019	0.003
	(0.040)	(0.025)
Dependent variable (t-4)	0.034	0.091***
	(0.032)	(0.023)
Explanatory variable (t-1)	0.020	0.005
	(0.060)	(0.006)
Explanatory variable (t-2)	0.123**	0.004
	(0.052)	(0.006)
Explanatory variable (t-3)	0.003	0.002
	(0.054)	(0.006)
Explanatory variable (t-4)	-0.120**	0.002
	(0.051)	(0.005)
Country FE	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
Granger causality test	0.055*	0.821
Observations	2,916	2,994
R-squared	0.3899	0.6515

** p<0.1, ** p<0.05, ***p<0.01.*

The table contains OLS regression coefficients of the Granger causality test. An observation is a country-industry-year pair. In the first column, the endogenous variable is the growth of employment, measured in percentages. The exogenous variables are lagged dependent variables (*Employment growth*) and the level of VC investments in the specific year. Each exogenous variable is lagged up to four times. The regressions include industry, country and year fixed effects. Standard errors are clustered at the country-year level and presented in parenthesis. In the second column, the level of *VC volume* is the endogenous variable instead and *Employment growth* the explanatory variable.

Table A15: Granger Causality Test - VC and Labor Cost Growth

	(1) Labor cost growth	(2) VC volume
Dependent variable (t-1)	0.102***	0.226***
	(0.039)	(0.027)
Dependent variable (t-2)	0.070**	0.167***
	(0.02)	(0.027)
Dependent variable (t-3)	-0.004	0.003
	(0.032)	(0.025)
Dependent variable (t-4)	0.011	0.087***
	(0.029)	(0.022)
Explanatory variable (t-1)	0.114*	0.008*
	(0.069)	(0.005)
Explanatory variable (t-2)	0.086	0.003
	(0.076)	(0.005)
Explanatory variable (t-3)	-0.026	0.004
	(0.054)	(0.004)
Explanatory variable (t-4)	-0.062	0.003
	(0.058)	(0.004)
Country FE	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
Granger causality test	0.156	0.151
Observations	3,047	3,119
R-squared	0.3478	0.6485

** p<0.1, ** p<0.05, ***p<0.01.*

The table contains OLS regression coefficients of the Granger causality test. An observation is a country-industry-year pair. In the first column, the endogenous variable is the growth of labor cost, measured in percentages. The exogenous variables are lagged dependent variables (Labor cost growth) and the level of VC investments in the specific year. Each exogenous variable is lagged up to four times. The regressions include industry, country and year fixed effects. Standard errors are clustered at the country-year level and presented in parenthesis. In the second column, the level of *VC volume* is the endogenous variable instead and *Labor cost growth* is the explanatory variable.