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THREE ESSAYS ON FINANCING INNOVATION DURING THE CRISIS

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Abstract

The Global Financial Crisis of 2007-2009 has been widely considered as the worst recession period since the Great Depression of the 1930s. Despite the roots of the crisis were entrenched in the U.S. housing bubble, clear signs only appeared when Bear Stearns liquidated two hedge funds that invested in various types of mortgage-backed securities. Following events, starting from the collapse of Lehman Brothers in September 2008, intensely shook the financial sector leading to banking panic, bankruptcy and public bail-outs which rapidly spread globally to the real economy with harsh recessions, private defaults and high unemployment rates. In several European countries, the financial crisis later developed into a proper Sovereign Debt crises which prolonged the recessionary environment and the global uncertainty. While during this period all companies faced a sharp drop in product demand and investments returns, innovative firms may have also particularly suffered from the credit crunch and financial turmoils which affected their ability to receive external financing on risky projects (OECD, 2012). Consequently, the turbulence brought about by the crisis may have modified or hindered the capacities and innovative path of companies, originating severe long-term consequences. So far, literature has only partially analyzed the consequences of the recent crisis on innovative firms. Noteworthy examples include Block and Sandner (2009); Filippetti and Archibugi (2011); Paunov (2012); Block et al. (2012); Archibugi et al. (2013). In particular, Archibugi and Filippetti (2013) gather a significant part of their latest empirical studies on the effects exerted by the recent downturn on the innovation activity of European firms. We contribute to this stream of literature by investigating the impact of the crisis on financing innovation, taking a broad perspective.

The analysis consists of three essays which separately explore the differential effects of economic downturns on heterogeneous samples of both young and newly founded American venture-backed start-ups and relatively mature and established Italian firms. We aim to shed more light on the effect of the crisis on funding availability, venture project selection and innovative performances. The first two essays focus on U.S. start-ups financed by venture capitalists. The third essay examines a larger sample of Italian established businesses, shedding light on their innovative activity and financial profile. However, the choice of the topics is not accidental. On the one hand, U.S. represents the most relevant example of countries where the Global Financial crisis hit harshly, but eventually resulted in a temporary negative shock followed by a

relatively fast recovery. Moreover, it is characterized by the high availability of specialized financial intermediary which invests money raised from institutional investors or wealthy individuals, in promising start-ups characterized by prevalence of intangible assets, years of negative earnings, facing high-risk, but potentially with high-rewards. However, a sudden and enduring decreasing of venture capital finance, due to a financial shock, may have jeopardized a pivotal source of funding in key sectors for growth and economic development. On the other hand, Italy is an interesting alternative scenario. First, it was exposed to a longer double-dip recession with a following sluggish recovery that has not reached yet the pre-crisis levels. In fact, the Italian economy was severely hit first by the Global Financial crisis and later by the public debt crisis, which affected many other southern European countries. Second, unlike U.S., equity markets are underdeveloped and the innovation funding relies mostly on internal resources or bank relationship (Accetturo et al., 2013). Moreover, even the presence of venture capital and other specialized equity investors is still lacking in comparison with U.S. and other European countries (Bronzini et al., 2015).

The first chapter analyzes the effect of the Global Financial Crisis of 2007-2009 on U.S. venture capital market. Venture financing, by targeting enterprises and sectors where information asymmetries are stronger, typically young companies in high-tech industries, has been beneficial in bridging the funding gap for young and innovative firms (Hall and Lerner, 2009). Venture capital market has been historically highly cyclical and volatile as demonstrated by persisting fluctuations in number of investments and amount raised (Lerner, 2003; Metrick and Yasuda, 2010; Cumming and Johan, 2012). The Global Financial Crisis shook this industry, coming as an external shock, which obliged intermediaries to adapt and react to the changing environment. The chapter aims to revisit the existing empirical evidence (Block and Sandner, 2009; Block et al., 2012) by shedding new light on VCs' behavior during a negative business cycle and measuring the effects in number of investments and funding size. By using a multiplicative interaction model which controls for development stage of the venture-backed company, firms' characteristics, sector and regional effects, we test a differential effect during the crisis for each company stage. The empirical results of this study can be summarized as follows. First, descriptive analysis shows how the effect of financial crisis on venture funding depends on company stage at financing. In fact, when the conditional effect is measured, the reduction in number of deals and size of financing appears to be concentrated only on later stages, while VCs increased follow-on investments for seed and early stage companies. Second, there is a *ceteris paribus* effect of boosting the size of investments on early development stages, while reducing their exposure to later stages companies. Third, there is statistically significant evidence that, during the crisis, experienced venture capitalists reallocated their investments towards seed and early stage companies more than new and relatively inexperienced intermediaries. Forth, business angel and government sponsored programs have kept sustaining venture funding during the financial crisis, particularly in first rounds. Lastly, there is not enough evidence in support of any geographical change in VCs' funding allocation during the crisis. Overall, we find clear evidence of a severe funding gap connected with the financial turmoil only for expansion and later stage companies. The study demonstrates that venture capitalists significantly changed investment strategies, boosting the size of investments on early development stages, while reducing their exposure to later stages companies. These results reinforce the hypothesis of stage selective investing in order to postpone IPOs, avoiding the lower valuation during a crisis.

The second chapter stems from the above mentioned findings to study the innovative outcomes of US venture-backed start-ups in the 2000s. We develop a novel longitudinal dataset which tracks down patenting behavior of 10,119 US venture-backed start-ups companies and use cohort analysis on the financing cohorts 2001-2010. We examine whether the cohorts of companies selected and financed for the first time during financial crises are persistently less innovative than those financed over ordinary periods. The evidence confirms the existence of a generational effect in the companies selected during the Global Financial Crisis which display a persisting lower innovative potential. The empirical model identifies the alleged cohort effect on "recessionary startups", disentangling it from cyclical trends, the development stage, industry and region fixed effects, quantity of funds and other relevant factors. Results confirm a significant reduction of available funding coupled with a negative generational effect in the companies selected during the Global Financial Crisis which display a persisting lower innovative potential (about 30%), as measured by the number of issued patents over time. This evidence is robust to the inclusion of terms which take into account the age-related component, yearly fluctuations, together with other confounding factors. Additionally, the generational effect identified during the GFC is not evenly distributed across industries, but it concentrates in sectors like healthcare, industrial/energy and media and entertainment. We explained this finding with degree to which formalized innovation, as accounted by patents, is an entry requirement to compete in each market. In order to find confirmation of the view of cohort effect as the result of venture capital selection of safer but less innovative projects, the paper tests the correlation of this selection with lower probability to fail and also a lower valuation at exit. Evidence confirms the previous hypothesis. Similar effects are not identified during the previous market turmoil of 2002-2003, when venture capital markets were severely hit by the Dot-com bubble burst. This study highlights the differential consequences for innovation of external shocks which highly increase uncertainty (the Global Financial Crisis) as opposed to traditional boom-and-bust phases (the Dot-com bubble) that reduce funding availability without changing innovative capabilities of financed start-ups.

Lastly, the third chapter examines the innovative activity of a large sample of Italian non-financial companies during the double-dip recession. We aim to shed further light on the innovative performance of Italian firms between 2008-2012. By using a large dataset of 162,959 Italian non-financial enterprises, we analyze the financial characteristics of companies together with their patenting behavior. We compare the financial structure of innovative and non-innovative firms correlating it with the ability to achieve a sustained patenting over the years. One of the main contribution of this paper is represented by the overcoming of the classical dichotomy innovators vs. non-innovators, to adopt an enhanced categorization in four innovative classes (non-innovators, occasional, medium and great innovators), based on their degree of patenting between 2008-2012. Consequently, we will use the between-group differences measured on a large set of financial ratios to define each specific financial profile. The evidence shows that more than 80% of innovation is concentrated in the manufacturing sector. Among innovators, the majority engages in occasional innovation, while very few (mostly large) firms maintain a persistent level of high inventive capacity. Firms in the sample have slightly increased average patenting during the crisis with respect to the previous five years. The empirical analysis finds that Italian innovators are on average relatively large, mature and established. Their higher cash-flow and lower indebtedness clearly signal that they fund their activities mostly with internal resources. Moreover, they grow faster than non innovators, even during a recessionary period. The global picture that emerges is largely consistent with the hierarchical view of pecking-order theory. As we move from non-innovators to great innovators the use of cash flow to fund operations increases, while leverage decreases. However, the direction of causality is not addressed in this study. On the whole, Italian innovation shows both bright and dark sides. On the one hand, the majority of Italian innovators represent a coherent unit of good performers, endowed with a long-term vision, skills and means to pursue innovation and even to overcome adversities, such as the 2008-2012 recession. On the other hand, their number is extremely limited with respect to the Italian productive system. They are mainly concentrated in the manufacturing sector and definitely not sufficient to reverse the poor performance of the Italian economy in the last two decades. In order to start a significant catching up with the majority of European countries, a positive change both in extensive and intensive margin is required. Italy needs both the entry of new innovators and a significant increase in patenting performance among the persistent innovators.

Overall, the conclusions of this work are in line with large part of the literature which highlights the differential impacts of the crisis across countries, industries and types of firm. However, a thorough understanding of the long-run effects of the crisis on heterogeneous innovative firms requires more time and reliable data. Therefore, this may represent a key topic for future micro level research.

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DOTTORATO IN ECONOMIA
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Chapter 1

How did U.S. venture capital react to the crisis? Revisiting evidence

Abstract

We employ a large dataset of venture capital investments to analyze the effect of the Global Financial Crisis of 2007-2009 on U.S. venture financing. By using a multiplicative interaction model which controls for this effect conditional on development stage of the venture-backed company, we conclude that VCs changed investment strategies, boosting the size of investments on early development stages, while reducing their exposure to later stages companies. Investments directed to startups at the beginning of venture cycle generally increase in dollar amount and number of deals or do not significantly change respect to the previous period. However, there is clear evidence of severe funding gap (ranging from 20% to 30%) for companies at later stages, in both first and later rounds. There is significant evidence which shows that most of this response is connected to the behavior of experienced venture capitalists. Collectively, the results reinforce the hypothesis of stage selective investing in order to postpone IPOs, avoiding the lower valuation during a crisis.

JEL Codes: G240, G010
Keywords: Venture capital, crisis, great recession.

1.1 Introduction

The Global Financial Crisis of 2007-2009 (hereafter crisis) has been widely considered as the worst recession period since the Great Depression of the 1930s. Despite the roots of the crisis were entrenched in excessive securitization of subprime mortgages market during the housing bubble (mid 2000s), clear signs only appeared on July 31st, 2007 when Bear Stearns liquidated two hedge funds that invested in various types of mortgage-backed securities. Following events intensely shook the financial sector leading to banking panic, bankruptcy and public bail-outs which rapidly spread globally to the real economy harsh recessions, private defaults and high unemployment rates. Venture capital intermediaries (hereafter VC), as the rest of financial sector, were not exempted from the financial turmoil.

So far, the literature has not widely analyzed the effect of the Global Financial Crisis on venture financing. Important exceptions are Block and Sandner (2009) and Block et al. (2012). The former, using a regression analysis for a sample of US internet related companies, find that the average amount of funds raised per round decreased by 20% during the crisis. This effect is detectable only in later rounds. The latter approach the question on a wider perspective, measuring the effect with descriptive statistics across industries and countries. They conclude that the crisis has considerably dropped the number of first-round investments and it has led to a severe funding gap in the amount of funds raised, especially in later funding rounds. Nevertheless, both papers do not investigate the possible startup maturity conditionality or, putting it simply, the fact that the measured effect of the crisis on VC funding could also depend on the stage of development of the funded company. Firms may have adopted different strategies to react to the financial crisis. On the one hand, investors may have simply changed the composition of the companies in their portfolios, according to many dimensions (including development stage). On the other hand, above and beyond relative shares, they may have adopted a selective approach on funding size, depending on the stage of the company and on the period considered.

This article addresses the above gap in the empirical literature by using a multiplicative interaction model, including different company stages at financing, company and firms characteristics and sector and regional effects. It will revisit the above mentioned results, testing a differential effect during the crisis for each company stage. Moreover, this study will also answer to several related questions. Building on the previous literature which highlights the high responsiveness to market changes of experienced VCs (Lerner, 1994b; Gompers et al., 2008; Cumming et al., 2005), this paper will test whether venture firms which have kept funding companies during the crisis are more experienced (according to different measures) than in the tranquil period. And if this result modifies conditional on the company development stage. Lastly, it will investigate any geographical change in VCs' funding allocation by checking whether VCs have tended to finance closer companies during the crisis, as to "keep an extra eye" on their investments. For example, geographical proximity may allow the firm's general partners a more effective monitoring, increasing face to face relations and habitual presence in the board meetings (Lerner, 1995; Cumming and Dai, 2010).

The empirical results of this study can be summarized as follows. First, descriptive analysis shows how the effect of financial crisis on venture funding depends on company stage at financing. In fact, when the conditional effect is measured, the reduction in number of deals and size of financing appears to be concentrated only on later stages, while VCs increased follow-on investments for seed and early stage companies. Second, by using a multiplicative interaction model which controls for the conditional effect on development stage of the venture-backed company, there is a *ceteris paribus* effect of boosting the size of investments on early development stages, while reducing their exposure to later stages companies. Third, there is statistically significant evidence that, during the crisis, experienced venture capitalists reallocated their investments towards seed and early stage companies more than new and relatively inexperienced intermediaries. Forth, business angel and government sponsored programs have kept sustaining venture funding during the financial crisis, particularly in first rounds. Lastly, there is not enough evidence in support of the geographical proximity hypothesis.

The paper proceeds as follows. Section 1.2 illustrates the theoretical background by analyzing the well-known VC market cyclicality, highlighting the differences with an exogenous financial shock and depicting possible channels through which the economic turmoil may have affected VC finance. Section 1.3 describes the data and the crisis time-window selection, explaining the construction of the variables used in this study. Section 1.4 shows the empirical methodology and presents the descriptive and multivariate analyses to address a number of questions related to the strategy adopted by VC intermediaries to face the economic downturn. General results will be discussed in Section 1.5, while Section 1.6 concludes.

1.2 Venture capital, market cyclicality and the Global Financial Crisis

A venture capital is a specialized financial intermediary which invests money raised from institutional investors or wealthy individuals, called 'limited partners', in promising startups characterized by prevalence of intangible assets, years of negative earnings, facing high-risk, but potentially with high-rewards. Among many distinctive VC finance characteristics, the provision of monitoring, mentoring and other value added services is key and goes along with the infusion of equity-based staged capital. The former mechanism empowers the VC firm with a significant control right and eases the problem of being held-up by the entrepreneur (Da Rin et al., 2011). Staged financing should not be confused with the company stage at financing. It refers to the maturity of the startup and the distance from the end of the venture-cycle. Venture financing usually classifies companies in four stages, from ‘seed financing’, the very first investment when the company uses money for market research and product developing, to ‘later stage’, when the company is ready to go public or being acquired. However, company stage signals also two other important features. The earlier is the stage of funded company, the greater is the potential return and the risk. VCs which prefer product potentiality over proved market acceptance invest more in early stage startups (Elango et al., 1995). In order to increase clarity, through the paper the term ‘firm’ will always identify the venture capital firm, while the term ‘company’ will refer to the startup financed.

Respect to bank financing, VC finance is optimal when the uncertainty is high, the firm’s cash flow distribution is highly risky, positively skewed, with low probability of success and low liquidation value, but high returns if successful (Winton and Yerramilli, 2008). Theory also focuses on optimality of VC advising in reducing the agency costs related to external financing (Casamatta, 2003). Stemming from these considerations, a vast stream of empirical literature has measured the effects of VC on financed company performance, finding significant improvements in productivity (Chemmanur et al., 2011), firm growth (Baum and Silverman, 2004; Peneder, 2010; Puri and Zarutskie, 2012) and innovation (Kortum and Lerner, 1998, 2000; Da Rin and Penas, 2007; Hirukawa and Ueda, 2011; Popov and Roosenboom, 2012).

In general, VCs target enterprises and sectors where information asymmetries are stronger, typically young companies in high-tech sectors. Addressing this market failure by intense scrutiny and due diligence before providing capital and by monitoring afterwards, it helps to bridge the funding gap for young and innovative companies (Hall and Lerner, 2009). However, venture cycle, from raising a venture fund to exiting and returning capital to its investors, is closely linked to financial sector in each of its steps (Gompers and Lerner, 2001). A sudden and enduring decreasing of VC finance, due to a financial shock, may have jeopardized a pivotal source of funding in key sectors for growth and economic development.

Cyclicality in venture capital investments is a well-known phenomenon. Metrick and Yasuda (2010) provide a historical account, reviewing the patterns of venture capital industry from its start, right after the Second World War, to the end of 2000s. VC market has been frequently affected by boom-and-bust phases (Cumming and Johan, 2012). This is mostly due to the uneven adjustment of supply and demand curves for VC funds in the short-run, which in turn is connected to the intrinsic nature of venture funding. Lerner (2003) illustrates the mechanism. The supply of VC funds is determined by the willingness of institutional investors to provide funds, which depends on the expected returns of VC investment in respect of the market returns in the same risk class. The demand curve is determined by the number of startups asking for funds, which varies with the rate of return anticipated by investors and the technological opportunities historically available. Return demanded by investors set up the minimum threshold for funding, while the presence of big technological opportunity (e.g. internet revolution) would increase the expected returns and the capacity of companies to meet this requirement. Supply and demand together determine the level of VC funding in the economy. However, these curves are not either fixed or smooth. Reaction to changes is slow due to information lags and illiquidity of private equity funds. Hence, investors realize the quality of their investments only after a significant amount of time and cannot adjust accordingly the capital committed, as they would do in public markets. When the adjustment happens, it is likely to fail to correctly estimate the expected revenues at the time of the investment and the impact of competitors on startups profits: it could overshoot the ideal amount, which in turn exacerbates cyclicality (Gompers, 2007).

As Figure 1.1 clearly shows, the last 16 years did not come as an exception. The total amount of funds raised per quarter (solid line), along with the number of funding rounds (dashed line), significantly fluctuated around different investment levels. Using BBQ algorithm (Bry and Boschan Quarterly), developed by Harding and Pagan (2002), it is possible to identify from the data the turning points in the total amount raised series and the chronology of funding cycles.[1] The algorithm highlights 4 peaks and 4 troughs from 1998 to 2014, indicated by black diamonds in the figure. During the biggest boom-and-bust period, the dot-com bubble, funding increased from around 5 billions per quarter at the beginning of 1998, peaking at 28 billions two years later, to crash at 4 billions in the first quarter of 2003. The following period shows a general recovery trend, with a cycle of smaller width, interrupted only by the Global Financial Crisis. During this event, the total amount disbursed halved in approximately one-year period. So did the number of rounds, decreasing from more than 1000 to about 600 per quarter. Shaded areas show economic contractions as officially registered by NBER.[2] VC funding contraction, started in the last quarter of 2007 and ended in the first quarter of 2009, seems to sync almost perfectly with the economy recession period led by the downturn. Afterwards, despite the negative predictions about a future general downsize of the VC industry expressed by many commentators at the beginning of 2009 (Mason, 2009), we observe a rapid recovery, followed by a milder contraction, forming a 4-year cycle. Starting from 2013, VC market underwent on extraordinary growth in amount invested which may possibly result into another boom-and-bust event.

In summary, between 1998 and 2014, we observe 4 full cycles of different duration and width, although with a general trend on increasing the level of amount invested and number of deals concluded. In fact, Metrick and Yasuda (2011) report how institutional investors tripled average share of portfolio allocation to private equity firms between 1997 and 2007. However,

[1] The algorithm defines a peak as y_{t-2} ; $y_{t-1} < y_t > y_{t+1}$; y_{t+2} and a trough as y_{t-2} ; $y_{t-1} > y_t < y_{t+1}$; y_{t+2}. This algorithm identifies a set of potential turning points which have to comply with an extra censoring rule: expansion and contraction phases must be at least 2 quarters long, and complete cycles must have a minimum duration of 5 quarters.

[2] See http://www.nber.org/cycles/cyclesmain.html for NBER recession definition and time-line.

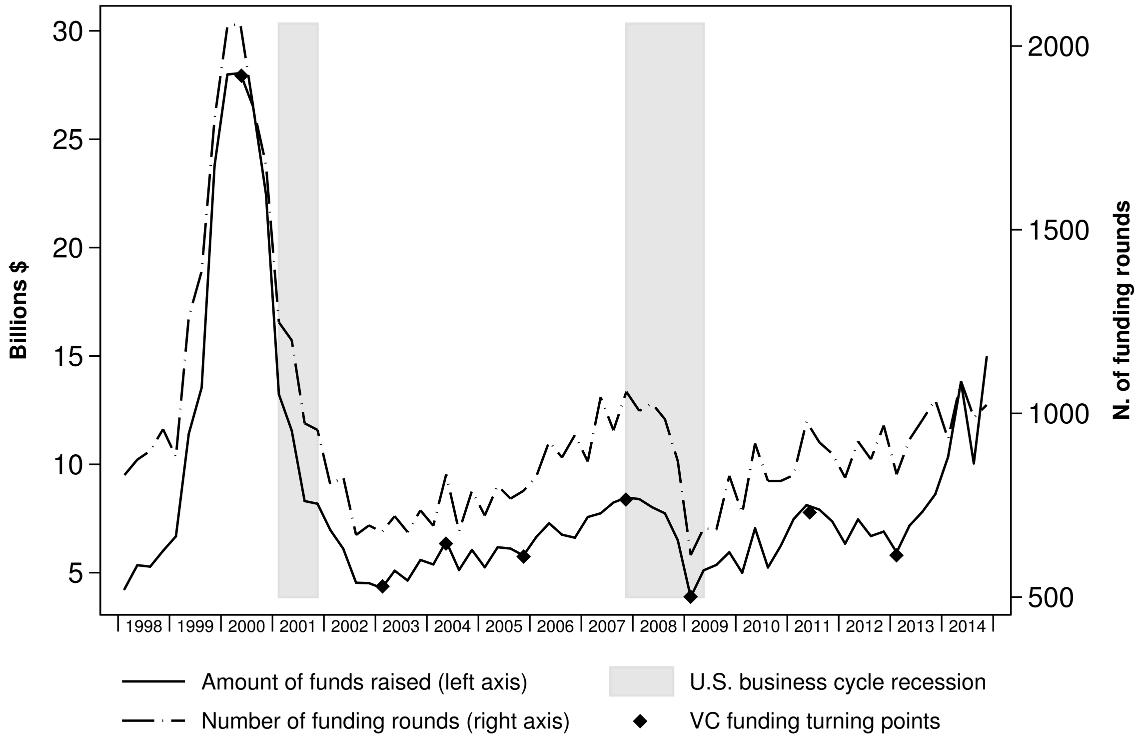

Figure 1.1: Total amount and number of deals by quarter (1998Q1 -2014Q4)

while 3 cycles, including the dot-com one, appear to be mainly driven by endogenous causes, it is apparent that the economic recession due to the financial crisis can be considered as mainly exogenous to venture capital market.[3] The VC finance contraction is largely due to the effect of VC reaction to an external change of environment which modified firms expectations and strategies.

Financial shocks may affect venture funding in manifold ways, operating in different phases of venture cycle. On the one hand, shocks may reduce the firm capacity to raise a fund or the investors' ability to meet the capital requirements. On the other hand, they may lower companies valuations and consequently their exit perspectives, which in turn influence the future capital contributions to VC funds. The first argument relates to the initial phase, when firms raise money through a vehicle, the venture fund. The average lifetime of a typical fund is around 10 years, during which investors face liquidity restrictions, though compensated by a higher return (Lerner and Schoar, 2004). A shock may negatively affect new funds formation, making new investors' search more difficult. However, as the capital committed is not disbursed upfront,

[3]Despite the argument of the fundamental contribution of shadow banking sector in the collapse of the financial system (Acharya et al., 2009), venture finance can be hardly considered part of that sector, missing the most important, and dangerous, characteristic: the asset/liability mismatch. In VC market there is not maturity transformation, as the VCs (general partners) impose illiquidity on their counterpart (limited partners) in order to ward off the liquidity shocks (Lerner and Schoar, 2004).

but at capital call demanded by VCs, firms are not completely shielded by liquidity shocks even in active funds. During an economic downturn, some of the limited partners may need to hoard liquidity to face the crisis, increasing the risk of unfunded commitment. The second argument is connected to company exits. Negative business cycle pushes down IPOs valuation and fund returns, which in turn have a negative effect on venture fundraising. Lerner (1994b), using a sample of 350 venture-backed biotechnology companies, shows how venture capitalists (in particular the experienced ones) take firms public when equity valuations are at peaks and postpone it, employing private financing, when values are lower. This finding connects us to an important strategy employed by firms during a period of expected illiquidity of exit markets (as it is during a crisis). During a cold IPO market period, firms invest proportionately more in early-stage companies in order to distance their investments from the trough. Conversely, when exit markets are liquid, venture capitalists rush to exit by investing more in later-stage firms (Cumming et al., 2005). This hypothesis will be empirically tested in this paper by analyzing the evidence of stage selective investing, during the Global Financial Crisis.

However, adaptation strategies are not limited to funding size or stage selection. A significant change in VCs' market experience or geographical proximity during a recession may be the result of an active risk reduction strategy. Gompers et al. (2008) finds that the largest response in number of investments during market booms is not by new or inexperienced venture capitalists, but rather by specialized firms with remarkable sector experience. Therefore, the involvement and the behavior of experienced intermediaries may change during a bust. Regarding geographic proximity, VCs may want to reduce information asymmetry and moral hazard problems associated with distance. In fact, proximity is a key factor that influences VCs' behavior as it significantly decreases information asymmetry and the cost of monitoring (Lerner, 1995; Cumming and Dai, 2010). Even these hypotheses will be tested in Section 1.4.

1.3 Data

1.3.1 Source of data

Data on deals, financed startups and VC firms' characteristics are collected from the commercial database Thomson One by Thomson Reuters (formerly known as Venture Xpert or Venture Economics). Thomson One dataset has been widely used in academic research and its completeness and accuracy has been assessed in Lerner (1994b) and Kaplan et al. (2002). The latter compares a small sample of VC contracts with the information provided in the dataset, concluding that it excludes roughly 15% of the financing rounds, but provides relatively unbiased measures of the amount financed. Thompson One surveys quarterly private equity intermediaries, reporting investments made by all private equity sector including venture capital, buyout

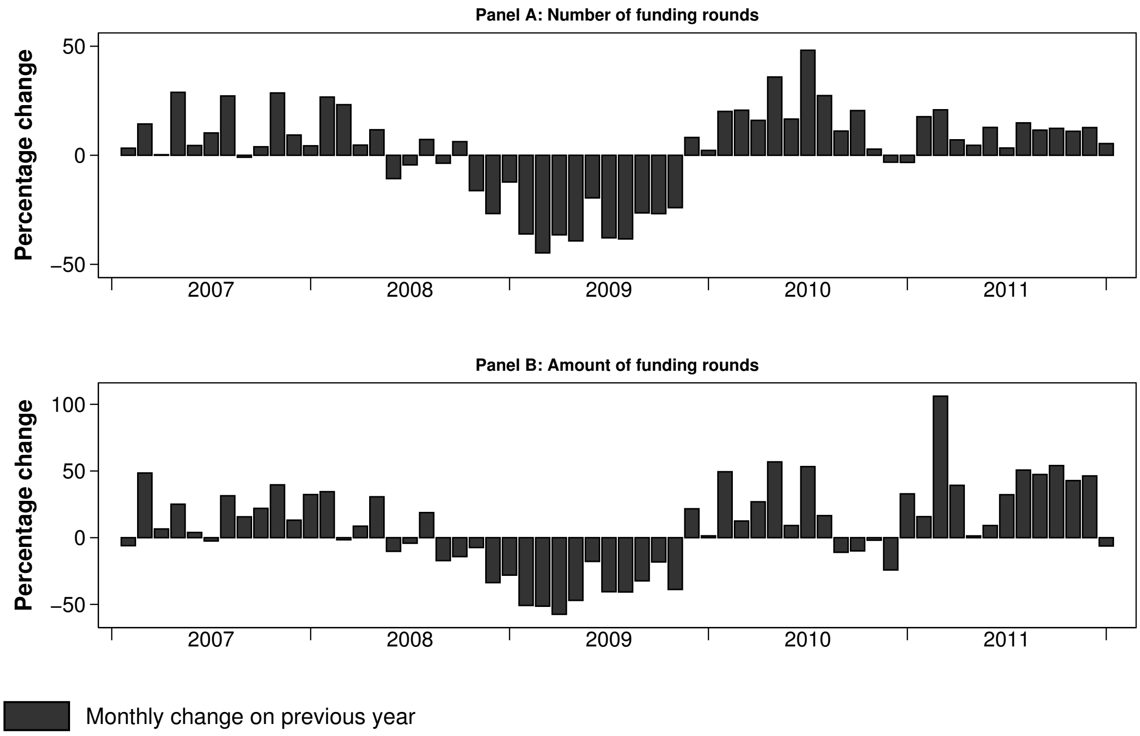

Figure 1.2: Monthly percentage change on the previous year (Jan 2007 - Dec 2011)

firms, business angels, corporate venture capital and investment banks. However, the present paper will study only venture investing, either private or public, which does not include buyout, mezzanine and fund of fund investing.

The database identifies 41,391 investment rounds between 2003 and 2014, made by traditionally venture focused firms. Approximately 30% consists in first rounds of financing, while the remaining 70% are second or later rounds. The sample is limited to funding rounds in which the amount invested is disclosed and the company headquarter is within the United States. We will start by descriptively overlooking the most important deal characteristics through the last decade and the first part of 2010's, to later focus the empirical analysis mainly on the analysis of the crisis period (2008-2009) compared to the tranquil period preceding it (2003-2008).

1.3.2 Dating the financial crisis period

In order to highlight whether any significant change happened during the crisis and to measure its consequences, we have to clearly define when the financial crisis started hitting the VC market and when its effects disappeared. Figure 1.1 shows the turning points in VC financing. However, these cut-offs do not take into account seasonal fluctuations in venture funding. In fact, the time series of VC funding data between 2007 and 2011 shows periodicity and the inspection of autocorrelation and partial autocorrelation plots finds spikes at lag 12 and 24. Block et al. (2012) use a simple method to determinate the correct time-window, adjusted for seasonality. They compare the monthly growth rate in the number of funding rounds in comparison with the previous year. For example, the starting point of an enduring switch from positive to negative growth rate is a candidate to be the initial cut-off of our time-window. Figure 1.2 employs the same methodology for both number and amount invested. Panel A depicts the percentage change in number of funding rounds. We observe negative growth from October 2008 (right after Lehman Brothers filed for bankruptcy) to October 2009, inclusive. However, the growth rate had started declining since the beginning of 2008, with an unclear situation during the months immediately preceding the Lehman Brothers crash. Panel B illustrates a similar situation with respect to the amount invested. Nevertheless, the initial cut-off can be dated earlier than in Panel A, around May 2008. Consequently, two different time-windows are adopted here. A shorter one (October 2008-October 2009), where effects seem to be more concentrated, will be presented first, while a longer one (May 2008-October 2009) will constitute the robustness check in the regression analysis, shown in the Appendix A.

1.3.3 Variables

This paper deals with the effects of the financial crisis on venture funding. The change in funding size will be addressed using both descriptive and multivariate analysis, while the related questions concerning VC experience and geographical proximity will be mostly analyzed using mean and median test difference. The unit of analysis is the funding round and each variable refers to it, to the characteristics owned by company, or VC, prior to the date of the deal. The regression dependent variable is the logarithm of the total amount raised in each funding round (*total investment*). It includes equity and debt funding and it is measured in US millions $. All other variables used throughout the paper are described as follows. *Financial crisis* dummy indicates whether the funding round occurred during the crisis time-window, while *syndication*, *business angel*, *government program* and *non-US VC* are VC-specific dummies, equals to one if the financier is an investment consortium and if there is the presence of at least one business angel, government sponsored program or a foreigner venture firm. *Lead investor* is defined as the VC firm contributing for the largest amount of cash. In a syndicated investment, the lead investor typically is in charge of overseeing most of the negotiation, legal work, due diligence, and following monitoring. *Stage at financing* describes the stage of a company when it received the financing. Thomson One defines four stages: ‘seed financing’, ‘early stage’, ‘expansion’ and ‘later stage’. *Company age* is the age (in years) of the financed company since the funding date. *VC firm age* and *Company-VC distance* are the age of the financiers and the geographical distance between VCs and company. In case of syndicated investments both measures are constructed as the weighted averages between all firms in the consortium. *General experience*,

Variable Name	Description
Financial crisis	Dummy variable equal to 1 if the investment occurred during the crisis time-windows (October 2008-October 2009 or May 2008-October 2009).
Syndication	Dummy variable equal to 1 if there is more than one investor in the funding round.
Business angel	Dummy variable equal to 1 if there is at least one business angel in the funding round. Business angel category includes angel groups and individuals. The latter have been tracked in Thomson One identifying first name and surname in investor names.
Government program	Dummy variable equal to 1 if there is at least one government sponsored program in the funding round.
Non-US VC	Dummy variable equal to 1 if there is at least one foreigner VC firm in the funding round.
Lead investor	Constructed as the VC firm with the highest investment share in the round. In case of equal share, the first financier with the highest share is considered to be the lead investor. As robustness check "lead investor" has been compared with the variable "firm preferred role" in Thomson One. Historical changes are not registered in this variable, but it refers only to the point of time of data download (Jan 2016). However, "lead investor" shows high correlation with the value "deal originator" in "Firm preferred role" variable.
Stage at financing	Company development stage as reported by Thomson one. Four different stages are considered: "seed", "early stage", "expansion" and "later stage". Excluded dummy is "seed" stage.
Company age	Constructed as the difference (in years) between investment date and company date of founding.
Lead VC distance	Constructed as the distance (in hundreds of miles) on the earth surface between company and firm headquarters (geocoded at zip-code level). It uses the Vincenty's formulae and measures the geographical distance "as the crow flies", using the coordinates of two points.
VC firm age	Constructed as the difference (in years) between investment date and firm date of founding. In case of syndicated investment, firm age represents the average age at financing, weighted by the respective investment share of each firm in the consortium.
Company-VC distance	Constructed as the distance (in hundreds of miles) on the earth surface between company and firm headquarters (geocoded at zip-code level). It uses the Vincenty's formulae and measures the geographical distance "as the crow flies", using the coordinates of two points. In case of syndicated investment, distance represents the average distance, weighted by the respective investment share of each firm in the consortium.
General experience	Similarly to Gompers et al. (2008), constructed as the total number of investments made by the lead investor from its founding date to the time of the current investment.
Sector experience	Similarly to Gompers et al. (2008), constructed as the total number of investments made by the lead investor from its founding date to the time of the current investment, but in the same sector of the funded company. It considers 17 sectors as defined by Thomson One "Moneytree industry" variable.
Specialization	Similarly to Gompers et al. (2008), measured as the percentage ratio of "sector experience" to "general experience". It indicates how much a particular lead investor is specialized in the current investment sector at the time of the investment.
Industry	All investments are aggregated in 9 broad sector dummies, which refers to the industry of the company. Dummy equal to 1 if the sector is: "Biotechnology", "Computer & Electronics", "Healthcare", "Industrial/Energy", "IT Services & Telecom", "Media and Entertainment", "Services & Retailing/Distribution", "Software", "Financial Services & Others". Excluded dummy is "Biotechnology".
Region	All investments are aggregated in 6 broad areas dummies, which refers to the headquarter region of the company. Dummy equal to 1 if the area is: "California", "East Coast", "South-West", "Midwest & South-East", "North & Other". Excluded dummy is "California".

Table 1.1: Definition of variables

sector experience and *specialization* are variables expressing VC specific characteristics in the domain of VC market experience. They will be referred only to the lead investor and calculated prior to the time of each financing round. Lastly, industry and regional effects are captured by nine *industry* dummies and six *region* dummies, referring to the industry and area of the funded company. Table 1.1 provides a detailed account on the construction of all the variables used in this paper.

1.4 Empirical analysis

1.4.1 Descriptive analysis: Empirical facts on venture financing before, during and after the crisis

Tables 1.2 and 1.3 illustrate the principal characteristics of VC funding activity. The tables include the period before, during and after the Global Financial Crisis, distinguishing between first and later rounds. Pre-crisis and post-crisis periods are 69 and 62 months long, respectively, while the length of the crisis period is 13 months. The variables employed in this first analysis refers to the investment characteristics, as number of deals, amount raised by month, syndication, investor type and sector allocation. Moreover, using contingency tables for number and raised amount, it is possible to control for stage at financing of the funded company.

The tables refer to the sub-sample of funding rounds divided by first and later rounds. The first round constitutes the initial contact between the entrepreneur and her investors. Typically, this is even when external financiers are given company ownership for the first time. Usually this happens after a period in which the entrepreneur relied mostly on her personal finance, the so called ‘bootstrap’. In comparison with later rounds, first one is characterized by higher information asymmetries and uncertainty. It is the first time the team and company business model is extensively screened and the odds of a rejection is extremely high. Later rounds represent a follow-on to sustain company needs or they signal the achievement of designed milestones. Clearly, the abandonment of the project is an option, but it is costly. Instead, incumbent VCs can play an influential role looking for new investors, which do rely on the information signaled by the quality of incumbents (Pearce and Barnes, 2006). Previous analyses on the effects of financial crisis on VC funding rely mostly on this dichotomy. Despite there is a clear prevalence of initial (later) stages companies in first (later) rounds, we may observe how even a significant amount of relatively older (younger) firms have been selected and financed in those type of rounds. This paper contributes on existing literature by going deeper than first/later rounds dichotomy, also considering the differential effects at different stage of financing.

The evolution of the average number of monthly investments through the period considered is shown in the first row of Table 1.2. There was a clear and significant dip in the number of deals during the crisis, a drop of about 30%, that were promptly absorbed in the post-crisis period. Considering the stage of the funded company, we observe that the fall is mainly concentrated at mid-level of company development, while seed and later stage financing seem more stable, with a slight increase in relative shares during the crisis period. Considering the funding amount, we observe, on average, a drop of about 800,000 $ per single investment (significant at 5%). Interestingly, results change controlling for stage of the company. Each funded company at seed stage benefited from almost a million dollars more in first investment size during the crisis

Variable	Pre-crisis Mean (Std. Dev.) (1)	Crisis Mean (Std. Dev.) (2)	Post-crisis Mean (Std. Dev.) (3)	Mean difference (2)-(1)	Mean difference (3)-(2)
Number of rounds per month:	81 (24.7)	55 (18.1)	92 (18.7)	***	***
by Stage at financing:					
Seed	20 (10.5)	16 (5.9)	16 (6.9)	-	-
Early Stage	40 (9.9)	25 (7.6)	58 (15.5)	***	***
Expansion	16 (6.9)	9 (4.7)	12 (4.7)	***	*
Later Stage	6 (3)	5 (3.3)	6 (2.4)	-	-
Raised amount per funding round:	5.89 (9.6)	5.05 (8.6)	4.73 (10.3)	**	-
by Stage at financing:					
Seed	3.46 (6.5)	4.39 (7.5)	3.69 (7.3)	**	-
Early Stage	5.22 (7.3)	4.38 (7.6)	3.79 (7.0)	**	-
Expansion	8.77 (12.9)	6.24 (8.9)	7.74 (18.7)	**	-
Later Stage	11.32 (15.7)	8.52 (13.7)	11.08 (16.5)	**	-
Investment consortium (%)	66.94	52.50	64.37	***	***
Business angel (%)	13.76	13.75	24.52	-	***
Government program (%)	7.16	10.42	6.69	***	***
Firm age (in years)	2.7 (3.8)	2.8 (3.7)	2.2 (3.3)	-	***
Industry (%):					
Biotechnology	11.71	13.61	8.17		
Computer & Electronics	10.90	8.33	3.92		
Financial Services and Others	2.76	1.67	2.03		
Healthcare	10.50	11.11	6.53		
Industrial/Energy	7.89	10.28	5.72		
IT Services & Telecom	12.18	11.81	10.67		
Media and Entertainment	10.27	9.44	13.39		
Services & Retailing/Distribution	7.66	7.08	8.22		
Software	26.13	26.67	41.37		
N funding rounds	5,617	720	5,669		

NOTE: This table shows descriptive statistics on first rounds of financing. Periods are specified as follows: “Before crisis” (Jan 2003 - Sept 2008), “During crisis” (Oct 2008 - Oct 2009) and “After crisis” (Nov 2009 - Dec 2014). Raised amount measured in mil $. Differences in mean are analyzed using two-sample t test Symbols ***, ** and * denote significance level of 1%, 5% and 10%, respectively.

Table 1.2: Descriptive analysis. VC funding before, during and after the crisis. First rounds

Variable	Pre-crisis Mean (Std. Dev.) (1)	Crisis Mean (Std. Dev.) (2)	Post-crisis Mean (Std. Dev.) (3)	Mean difference (2)-(1)	Mean difference (3)-(2)
Number of rounds per month:	200 (43.0)	181 (31.1)	213 (34.2)	-	***
by Stage at financing:					
Seed	6 (3.9)	11 (4.5)	6 (4.2)	***	***
Early Stage	34 (10.9)	46 (9.8)	77 (19.1)	***	***
Expansion	82 (19.0)	58 (12.4)	69 (12.1)	***	***
Later Stage	77 (23.1)	67 (14.2)	62 (11.9)	-	-
Raised amount per funding round:	8.44 (11.2)	7.96 (14.7)	10.43 (30.4)	**	***
by Stage at financing:					
Seed	3.19 (4.7)	6.01 (7.1)	4.71 (6.6)	***	*
Early Stage	5.45 (7.0)	6.39 (8.9)	7.69 (17.0)	***	*
Expansion	8.48 (11.8)	9.25 (21.4)	12.62 (42.6)	-	**
Later Stage	10.15 (11.9)	8.24 (11.2)	11.95 (27.9)	***	***
Investment consortium (%)	81.73	72.94	72.24	***	-
Business angel (%)	9.97	5.45	9.28	***	***
Government program (%)	2,63	4,35	4,24	***	-
Firm age (in years)	5.4 (3.8)	5.8 (4.2)	6.1 (4.4)	***	**
Industry (%):					
Biotechnology	13.19	16.02	14.54		
Computer & Electronics	16.68	12.19	7.92		
Financial Services and Others	1.70	1.49	1.41		
Healthcare	10.68	12.48	11.36		
Industrial/Energy	4.75	7.41	7.24		
IT Services & Telecom	12.49	10.86	10.01		
Media and Entertainment	6.39	8.56	8.92		
Services & Retailing/Distribution	4.58	5.07	5.35		
Software	29.52	25.91	33.26		
N funding rounds	13,787	2,347	13,222		

NOTE: This table shows descriptive statistics on later rounds of financing. Periods are specified as follows: “Before crisis” (Jan 2003 - Sept 2008), “During crisis” (Oct 2008 - Oct 2009) and “After crisis” (Nov 2009 - Dec 2014). Raised amount measured in mil $. Differences in mean are analyzed using two-sample t test Symbols ***, ** and * denote significance level of 1%, 5% and 10%, respectively.

Table 1.3: Descriptive analysis. VC funding before, during and after the crisis. Later rounds

than the previous and following periods. Conversely, companies in expansion and later stage experienced a drop in average amount invested, of 1.5 and 2 millions, respectively.

In general, results show a clear trend towards investing relatively more in younger companies and less in older ones. Other deal characteristics depict a situation which agrees with previous findings in the literature (De Vries and Block, 2011; Sohl, 2008). Syndicated investments plunged during the financial crisis, while the share of investments involving a business angel remained constant. As it would be expected, the involvement of government sponsored venture programs in investment consortia increased in connection with the economic downturn (the share moves from 7.2% to 10.4% to diminish at 6.7% with the aftermath of the crisis, both significant at 1%). Finally, age and sector shares do not seem to be significantly affected by the financial crisis.

Table 1.3 presents descriptive evidence for later rounds. Surprisingly, the average number of rounds per month decreased by only 10% (from 200 in pre-crisis period to 181 during the crisis period) and this difference in mean is not significant at conventional levels. However, the pattern remarkably changes analyzing the trend by stage at financing. As noted above, the dichotomy between first and later rounds does not proxy particularly well for stage at financing. Even in later rounds, despite the increasing weight of later stages, there is a substantial part of finance still directed to companies in the initial phase of development. Through stage breakdown, almost all the differences in mean become statistically significant, describing a two-fold behavior. VCs boosted their investments in seed and early stage companies and, on the contrary, diminished the number of rounds for companies at later stages. Relative shares of investment in young companies increased, consequently reducing the investment share in older ones, in particular those in expansion stage. As for first round financing, it is worth noting that the number of follow-up financing in early stage kept growing significantly even during the post-crisis period, signaling a persistent change in venture capitalists' investment strategy. Similarly, average funding size almost doubled for seed stage, from 3.2 to 6 million \$, then reducing to 4.7 \$ right after the crisis. Early stage investment size slightly increased, while, as noted for first rounds, funding in later stage companies plummeted during the crisis to return at previous size in post crisis period. The change in syndication and government programs funding followed the pattern registered in the first rounds, while in contrast, the presence of business angels significantly diverged from first rounds, decreasing only in the crisis period.

In summary, descriptive analysis highlights a number of important results that will be later examined in depth. First, as described in the previous literature, there is a statistically significant evidence of a structural break during the crisis, compared to both pre-crisis and post-crisis periods. Temporary effects of the crisis are generally later reabsorbed or overcome. Second, unlike the above mentioned literature, this analysis shows how first/later rounds break is not sufficient to describe the differential impact of the crisis. Stage at financing is the most important discriminating factor, in particular for funding size. During the crisis, companies in their early stages benefited from more deals and investment size premium than the previous and following periods. Conversely, later stages companies discounted a loss during the crisis both in number and size of financing. Third, the analysis of deal characteristics offers a more nuanced vision to the numbers presented above. Government program and business angels sustained venture financing during the crisis (for angel financing this is true only for first rounds), while syndicated investments substantially decreased their relative share during the economic downturn. Finally, there is evidence of sector reallocation, but the data do not show a clear pattern in this dynamics. Yet, the above general picture lack of a *ceteris paribus* analysis which disentangles the partial contribution of each component. The following section using a multiplicative interaction regression model will carry out this study.

1.4.2 Regression analysis

Table 1.4 presents the findings on the relation between the effect of financial crisis, deal characteristics and average amount of funds provided by venture capitalists. The analysis is conducted at the funding round level. Thus, each round concluded between January 2003 and October 2009 represents a unit of observation. As described in Section 1.3, the crisis cut-offs are October 2008 - October 2009. A longer time-window is introduced later as robustness check. Moreover, as in the descriptive statistics, the whole sample is divided by first and later rounds, as to introduce interaction terms in the model in the clearest way.

Formally, venture funding is modeled as:

$$\begin{aligned} Log(Y_{ir}) &= \alpha + \beta_1 Crisis_r + \beta_2 Age_{ir} + \beta_3 Syndic_r + \beta_4 Angel_r + \beta_5 GovProg_r + \beta_6 NonUS_r + \\ &+ \beta_7 Stage_{ir} + \beta_8 Stage_{ir} X Crisis_r + \beta_9 VCage_r + \beta_{10} Distance_{ir} + \psi_i + \phi_i + \varepsilon_{ir} \end{aligned}$$

The response variable is the natural logarithm of the total amount of the investment (measured in million of dollars and inclusive of equity and debt financing) to company i in round r. The use of semi-logarithmic regression equation eases the interpretation, as the regression coefficients multiplied by 100 (or more precisely $[exp(\beta)-1]\times 100$ in case of dummy variables) is interpreted as semi-elasticities which gives the percentage change of the predicted y with respect to a change of x. Standard errors are given in square brackets below the coefficient estimates and are robust to heteroskedasticity, allowing for clustering by company in the case of later rounds.

Each specification includes also the average age of the firms in the consortium and the geographical distance between financed company and firm. The first and second columns of each group (namely, columns 1-2 and 4-5) fit a linear model which does not include any interaction effect. Thus, the interpretation of the dummy variable *financial crisis* is the usual semi-elasticity in respect of the average amount raised. Instead, the third column of each group (namely, columns 3 and 6) fits a multiplicative interaction model between *financial crisis* dummy and three out of four values of the variable *stage at financing*. Here, the dummy representing the effect of the crisis cannot be interpreted as such, but it is the *ceteris paribus* change in funded amount due to the crisis for the base category (*seed stage*). Relative changes for the other categories are rendered by each interaction term. In all specifications, eight industry and five regional effects (ψ and ϕ) are included to account for sector and geographic reallocation.

Column 1 fits a simple model for crisis effect on first rounds, including only some deal characteristics, industry and region effects. Not surprisingly, the regression suggests that financial crisis reduces investment size at 1% of significance. The coefficient of -.181 indicates that during the economic downturn funding reduces by about 17%. As the second column shows, once other deal characteristics, such as the syndication, the presence of angel financing, or government programs in the consortium and stage at financing are controlled for, the coefficient of the crisis dummy reduces more than two times and now is only significant at the 5% level. The crisis funding discount implied by the regression for first round financing is only at 7%. Interestingly, the estimated coefficients for *stage at financing* dummies are all highly statistically significant and confirm empirical findings of the descriptive statistics. Therefore, funding size does change according to development stage even within the type of round (first or later stage). The dollar amount of an average *early stage* round is 31% higher than a *seed* one, while *expansion* round is 81% and *later stage* is 111% bigger. Thus, size of the investment depends on the company stage in the venture cycle. As illustrated in Section 1.2, the choice to invest at different company stages is endogenous at firm level and depends on multiple factors, as for example the current state of the public markets. Neglecting to control for stage at financing may result in an omitted variable bias, inflating the crisis coefficient. The inclusion of stage at financing rules out every possible compositional effect from the regression model.

The third column adds the interaction terms between *financial crisis* dummy and *stage at financing*. Breaking down the effect of the crisis by company stage controls for firms' selection in funding size. Thus, interaction terms are interpreted as the change in funding size between pre-crisis and crisis periods at each stage of development. The regression indicates that there is no relation between crisis and funding size at *seed* stage, as the *financial crisis* coefficient is not statistically significant at conventional level. However, all the companies in other stages suffer a highly significant decrease directly proportional to their progress in the venture cycle. During the crisis, compared to the previous period, a typical *early stage*, *expansion* and *later stage* company sees its investment size decrease by 16%, 26% and 29%, respectively. VCs selectively decreased the size of funding of those closer to the end of venture cycle. In respect of the column 2, other coefficients remain substantially stable and they can be interpreted as follows. In the sub-sample of first round financing, controlling for other characteristics, an increase of one year in company age is associated with a 1% rise in funding. The low effect registered may be due to the fact that part of the company maturity is captured by the stage variables. Syndicated investments are on average 63% bigger than the individual ones. Interestingly, the presence of business angels or government sponsored investors is associated with a decrease (significant at 1%) of the amount invested by 27% and 52%, meaning that investment targets are smaller compared to those of venture firms, especially in the case of public programs. Lastly, VC experience, proxied by the average age of financier, is positively associated with an increase in funding by 2%, while distance between company and investors is positive and highly significant. A possible explanation to the latter is that, in case of geographical distance, only bigger investments may justify the cost of monitoring a distant company. However, despite the coefficient being highly statistically significant, the economic significance is low (.7% for each 100 miles of distance).

Columns 4 to 6 repeat the previous regressions for the sub-sample of later rounds. The results in column 4 indicate that financial crisis is associated with a reduction of funding size (at 1 % of significance) of about 14% for later rounds, controlling for industry and region effects as well as VC distance and age. This effect is somewhat lower than the one registered for first rounds. However, when all deal characteristics and the stage of financed companies

Dependent variable: ln(Total Investment - Million of $)						
	First rounds			**Later rounds**		
	(1)	(2)	(3)	(4)	(5)	(6)
Financial crisis (dummy)	-.181***	-.074**	.091	-.156***	-.027	.199**
	[.034]	[.031]	[.055]	[.023]	[.021]	[.085]
Company age (in years)		.010***	.010***		-.017***	-.016***
		[.004]	[.004]		[.003]	[.003]
Syndication (dummy)		.493***	.491***		.858***	.857***
		[.021]	[.021]		[.020]	[.020]
Business angel (dummy)		-.316***	-.315***		-.058**	-.057**
		[.028]	[.028]		[.026]	[.026]
Government program (dummy)		-.751***	-.744***		-.172***	-.175***
		[.033]	[.033]		[.046]	[.046]
Non-US VC (dummy)		.024	.023		.310***	.309***
		[.051]	[.050]		[.029]	[.029]
Stage at Financing dummies						
Early Stage		.271***	.294***		.288***	.310***
		[.023]	[.025]		[.039]	[.041]
Expansion		.596***	.631***		.605***	.656***
		[.034]	[.035]		[.039]	[.041]
Later Stage		.747***	.792***		.709***	.776***
		[.055]	[.057]		[.043]	[.044]
*Fin.crisis*Early Stage*			-.180***			-.068
			[.069]			[.093]
*Fin.crisis*Expansion*			-.304***			-.225**
			[.100]			[.093]
*Fin.crisis*Later Stage*			-.339**			-.362***
			[.132]			[.092]
VC firm age	.025***	.019***	.019***	.018***	.015***	.015***
	[.001]	[.001]	[.001]	[.001]	[.001]	[.001]
Company-VC distance	.012***	.007***	.007***	.010***	.003***	.003***
	[.001]	[.001]	[.001]	[.001]	[.001]	[.001]
Industry effects	YES	YES	YES	YES	YES	YES
Region effects	YES	YES	YES	YES	YES	YES
Constant	1.229***	.847***	.824***	1.864***	.715***	.660***
	[.043]	[.043]	[.044]	[.039]	[.048]	[.049]
R-squared	.126	.337	.339	.100	.272	.274
Adj R-squared	.124	.335	.336	.099	.271	.272
P-value	<.001	<.001	<.001	<.001	<.001	<.001
Observations	6,012	6,012	6,012	15,680	15,680	15,680

NOTE: Crisis period is specified as Oct 2008 - Oct 2009. Standard errors are robust and clustered at company level for later rounds. Symbols *, ** and *** denote significance level of 10%, 5% and 1%, respectively.

Table 1.4: Multiplicative interaction model for VC funding

are included (column 5), *financial crisis* coefficient turns out to be insignificant at conventional levels. All other terms are significant at 1%, with the exception of *business angel* coefficient which is significant at 5%. The omission of these characteristics can bias the results, by hiding the actual transmission mechanism which ties financial crisis to average amount invested. In fact, it is unlikely that the financial crisis uniformly influences follow-on investments causing a uniform funding gap of 14%, as for example, measured in column 4. Hence, the effect is mediated by the actions and the adaptation strategies of the VCs, which in turn determine the average effect on investments. Again, by targeting younger companies, which correlate to smaller investment needs as it is apparent from the magnitude of *stage at financing* dummies, VCs may have indirectly lowered the amount provided to each company. The regression indicates that the inclusion of company stage and deal characteristics completely absorbs every direct negative effect. However, direct effects may still be measured at different stage levels.

The sixth column again adds interaction terms between crisis and stage at financing. As for first rounds, the coefficient *financial crisis* now measures the effect of the crisis for the base category (*seed stage*). There is a premium in funding size of 22% in comparison with the tranquil period (significant at 5%). This is not surprising and it confirms the preliminary evidence of descriptive statistics. VCs not only made more follow-on deals with younger companies, but also invested on average 22% more dollars on them, controlling for all other characteristics (the descriptive analysis shows a doubling in funding size, but it does not take into account all other variables). The interaction term *fin.crisis*early stage* is not significant, meaning that there is not a statistically significant effect on the dollars invested before and during the crisis. Differently, the terms *fin.crisis*expansion* and *fin.crisis*later stage* are negative and significant (at 5% and 1%, respectively). Those companies in expansion stage discounted a 20% reduction, while for those in later stage the reduction was higher, about 30% less than previous period. As in the first rounds regression, there is evidence of a selective funding by venture capitalists, conditional on company stage at financing. In column 5, the direct average effect of financial crisis is hidden by the opposite directions of stage effects. Funding gap in follow-on investments does exist, albeit limited to later stages (expansion and later stages), while companies still in seed stage received a premium.

Regarding the other coefficients, an important question to ask is whether the sign, the significance and the magnitude of the effects estimated in the current regression are similar to those estimated for first round financing. Columns 3 and 6 show that *stage at financing* dummies in column 6 have the same sign, significance and they are of a comparable magnitude than the ones of column 3, signaling that proportional change in funding size remains fixed across first/later stage dichotomy. Also *VC firm age* has a similar sign and magnitude. However, all the remaining variables are sensibly modified compared with the regression of first rounds financing. *Company age* coefficient is negative and highly significant, meaning that, *ceteris* *paribus*, each year since the founding date decreases the funding size by 1.6%. As expected, syndicated investments correlates more with higher funding in later rounds, while controlling for other variables. A switch from a single financier to a consortium increases the funding size by 136%, more than twice the measure registered in first rounds. Business angels and government programs decrease their negative effects with average size of the funding (-5% and -16%, respectively). This pattern may reflect the substantial drop in angel and public contribution registered in later rounds. A possible explanation may be the qualitative variation on intermediaries involved in later rounds (for example a switch from wealthy individuals to organized angel groups or bigger public programs which are able to focus on more complex projects). Lastly, *non-US VC* is now positive and significant, associating the presence of a foreign VC with 36% more funding in the round. The positive sign may reflect the size needed to justify higher monitor costs, while the significance may be explained by their principal interest to later rounds, where the riskiness of new financing in foreign markets is mitigated by the information provided by the other partners.

In order to determine whether the analysis undertaken is robust with a different time-window specification, as described in Section 1.3, Table 1.A1 repeats the regression including 5 months more in the financial crisis window. Basic patterns hold, including sign, significance and magnitude of coefficients. Differences are restricted to decimals (or few percentage points in semi-elasticity interpretation). In general, enlarging the sample size soften slightly the effects, showing how the acme of the crisis in concentrated in the shorter time-window. The descriptive analysis and the multiplicative interaction regressions undertaken in this section clearly establish a more nuanced vision of the effect of financial crisis on venture finance and in particular on the existence of a funding gap for venture backed firms. Those results, together with the VC experience and proximity findings, will be discussed in Section 1.5.

1.4.3 Venture capital experience

Table 1.5 summarizes the data on venture capital experience before and during the economic downturn. Following Gompers et al. (2008), experience here is proxied by three different measures. *General experience* is the number of investments made by the lead investor from its founding date to the time of the current investment. *Sector experience* considers only same industry deals with respect to the financed company and describe the industry-specific knowledge of the venture capitalist. Lastly, *specialization* is a percentage share and indicates how much a particular lead investor is specialized in the current investment sector at the time of the investment. Obviously, the first two measures may show a positive trend due to the fact that experience increases automatically over time for venture capitalists who remain active in the market. Considering the limited time span and the magnitude of the change registered, the inclusion of a trend adjustment is not necessary. However, in order to be on the safe side, only significant differences both in mean and median will be commented. Finally, the reason of restricting the analysis of venture capital experience to the lead investor is both theoretical and computational. On the one hand, as explained in Section 1.3, lead investor does the great part of venture job in selecting and managing the deal. Followers instead rely mostly on lead investors' reputation in choosing to join the deal. Averaging venture experience among all deal participants is not going to add much information, but noise. On the other hand, due to computational constraints, is not possible to construct the measures for all the investors, accounting experience since 1946 to each investment date.

The breakdown of first rounds by company stage does not exhibit any clear pattern before the financial crisis. However, the substantial distances between average and median measures signal the presence of outliers. Average and median number of deals or specialization shares of the financier are usually very similar among stages and there is not one stage that consistently prevails over the others on different measure of experience. By contrast, during the crisis only seed stage shows a statistically significant jump (at 1%) in venture experience in all the variables. Average (median) number of deals prior to the current investment increases from 215 (58) to 350 (126), while the sector experience leaps from 39 (8) to 61 (18). Even average (median) specialization share of the investor between pre-crisis and crisis period is up from 20 (11) to 26 (16).

Later rounds depict a similar pattern. General and sector experience registers a discontinuity, with a positive and highly significant rise during the downturn. Breaking down by stage highlights an upswing in investor experience for seed and early stage companies. With respect to the previous period, average experience in seed stage doubles (or triples considering median values). Even early stage companies experience a milder increase, albeit not significant at conventional levels for specialization.

These results, measured across different dimensions, clearly show a sudden increase in average and median investors' experience of early stages companies, which cannot be accounted solely by a mechanical positive trend. This is suggestive of the fact that experienced venture capitalists reallocated their investments towards seed and partially on early stage companies more than new and relatively inexperienced intermediaries. Correlating this evidence with the boom of deals in early stages, as delineated in the previous section, it is indicative of their major role in the highlighted phenomenon. All together, the results support the hypothesis that more experienced venture capitalists are the most responsive in shaping adaptation strategies even during a recession period.

1.4.4 Venture capital proximity

Table 1.6 illustrates the evolution of geographical distance between VC firms and venture-backed companies before and during the financial crisis. Due to the limited computational

Variable	First Rounds				Later Rounds			
	Before Crisis	During Crisis			Before Crisis	During Crisis		
	Mean (Median)	Mean (Median)	ΔMean	ΔMedian	Mean (Median)	Mean (Median)	ΔMean	ΔMedian
General experience	234 (57)	255 (62)	-	-	303 (117)	341 (141)	***	**
by Stage at financing:								
Seed	215 (58)	350 (125.5)	***	***	210 (65)	426 (191)	***	***
Early Stage	258 (70.5)	228 (53)	*	*	273 (93)	342 (149)	***	***
Expansion	204 (37)	201 (46.5)	-	-	312 (118)	327 (107)	-	-
Later Stage	230 (42)	186 (60)	-	-	314 (132)	341 (152)	-	-
Sector experience	37 (7)	44 (8)	*	-	53 (17)	63 (21)	***	***
by Stage at financing:								
Seed	39 (8)	61 (18)	***	***	47 (11)	96 (42)	***	***
Early Stage	40 (9)	40 (5.5)	-	***	49 (14)	68 (20)	***	***
Expansion	31 (4)	27 (4)	-	-	52 (17)	57 (17)	-	-
Later Stage	32 (4)	36 (8)	-	-	55 (19.5)	61 (22)	*	-
Specialization	18 (9)	20 (11)	-	**	24 (17)	26 (18)	***	-
by Stage at financing:								
Seed	20 (11)	26 (16)	***	***	29 (21)	35 (28)	**	**
Early Stage	19 (9.5)	19 (10)	-	-	25 (18)	27 (19)	-	-
Expansion	16 (6.5)	15 (5.5)	-	-	23 (16)	24 (15.5)	-	-
Later Stage	17 (7)	19 (12.5)	-	-	24 (16.5)	26 (18)	*	-

NOTE: This table measures VC experience divided by first and later financing rounds. Periods are specified as follows: "Before Crisis" (Jan 2003 - Sept 2008), "During Crisis" (Oct 2008 - Oct 2009). Differences are analyzed using two-sample t test for equality of means and Mood's median non-parametric test on the equality of medians. Symbols *, ** and *** denote significance level of 10%, 5% and 1%, respectively.

Table 1.5: Venture capital experience

constraints, proximity here is calculated both as the weighted average distance using all firms in the consortium and as the pair distance between lead investor and company headquarter. However, as it is apparent from the data, both variables are closely related in magnitude and significance. First rounds do not exhibit any particular change over time, but it can be noted as average and median proximity decreases by stages. Companies at early stages are relatively closer to the investor with respect to later ones. Moreover, the difference between average and median distance points out the influence of the outlier observations. Later rounds depict a slightly different situation. Both mean and median differences decreases significantly for later stages companies and concurrently geographical distance rises for seed stage. However, the magnitudes of the mean change are still limited. Collectively, the evidence in support of the geographical proximity hypothesis remains weak, limited to later stages and not conclusive.

1.5 Discussion

Results presented in Section 1.4 revisit the empirical nexus between the Global Financial Crisis and venture financing. By including stage of development of the funded company in a descriptive and multivariate setting, a longer time span and analyzing several related questions, this paper broadens the scope of previous literature on the topic.

Descriptive analysis shows how the major recession affects venture funding with temporary effects which are later absorbed or reversed during post-crisis period. As highlighted by Block et al. (2012), total number of deals dramatically drops during the crisis, in particular in first rounds. However, once the effect is measured by stage at financing, as in the present paper,

Variable	First Rounds				Later Rounds			
	Before Crisis	During Crisis			Before Crisis	During Crisis		
	Mean (Median)	Mean (Median)	ΔMean	ΔMedian	Mean (Median)	Mean (Median)	ΔMean	ΔMedian
Company-VC distance	870 (235)	865 (141)	-	***	1,080 (735)	1,005 (591)	***	***
by Stage at financing:								
Seed	780 (93)	729 (56)	-	-	998 (200)	1,008 (538)	-	**
Early Stage	848 (236)	823 (122)	-	**	920 (369)	931 (346)	-	-
Expansion	1,026 (354)	1,072 (282)	-	-	1,073 (711)	1,012 (484)	-	**
Later Stage	915 (387)	1,121 (423)	-	-	1,165 (916)	1,049 (715)	***	***
Lead VC distance	875 (114)	910 (88)	-	-	1,090 (325)	1,004 (203)	***	***
by Stage at financing:								
Seed	789 (34)	686 (31)	-	-	979 (35)	1,048 (403)	-	**
Early Stage	839 (68)	907 (105)	-	-	934 (188)	923 (84)	-	**
Expansion	1,063 (261)	1,106 (282)	-	-	1,084 (327)	1,027 (180)	-	***
Later Stage	906 (320)	1,268 (572)	*	-	1,171 (413)	1,035 (320)	***	**

NOTE: This table measures VC proximity divided by first and later financing rounds. Periods are specified as follows: "Before Crisis" (Jan 2003 - Sept 2008), "During Crisis" (Oct 2008 - Oct 2009). Differences are analyzed using two-sample t test for equality of means and Mood's median non-parametric test on the equality of medians. Symbols *, ** and *** denote significance level of 10%, 5% and 1%, respectively.

Table 1.6: Venture capital proximity

the reduction appears to be concentrated only in later stages, while VCs increased follow-on investments for seed and early stage companies. These conclusions are still valid even considering the amount raised by each deal. In general, companies in their early stages benefited from an investment size premium compared to the previous and following periods, while later stages experienced a significant deduction. Hence, considering only first/later rounds dichotomy is not sufficient to describe the differential impact of the crisis.

The multiplicative regression model suggests that results obtained through a simple linear model which does not control for stage at financing and its interaction terms may be biased. First, the crisis effect is mediated by the adaptation strategies of the VCs, which include targeting younger companies during the financial crisis. Once stage is included, the inflated crisis coefficient reduces its magnitude by more than two times (from 17% to 7%) or turns to be insignificant (in later rounds). Moreover, strong and significant direct effects may be found conditional on company development stage. The analysis finds differential effects by stage. Seed financing benefited from financial crisis, by receiving more funds. Evidence on early stage companies is mixed, varying from a reduction of 16% in first rounds to no significant change in follow-on investments. There is clear evidence of a severe funding gap for expansion and later stages companies, in both first and later rounds. The reduction varies from 20% to 26% for expansion stage and it is between 29% and 30% for later stage companies. The key dividing line appear to be the stage of the financed companies (early/later stages) more than the stage of financing (first/later rounds).

These findings are supportive of the argument related to public market liquidity (Cumming et al., 2005) exposed in Section 1.2. The risk connected to the stock market crash of 2008-2009 is likely to have modified VCs investment strategies, boosting investments on early development stage, while reducing their exposure to later stage companies in order to postpone an IPO and avoid a lower valuation at exit. However, demand-side effects have not been introduced in this picture, yet. Entrepreneurs at first financing round may have tried to avoid general low valuations, by postponing their ‘pitch decks’ to raise money till a future positive outlook, while those in later rounds could not have avoided this deduction. Clearly, we cannot test this hypothesis with a VC commercial database. However, the presence of differential effects even in first round financing is suggestive that the impact of demand-side effects is relatively limited and that the leading mechanism is more related to supply side factors, in particular the end of venture cycle (IPOs and acquisitions).

There are other interesting findings in this paper. First, the paper finds proof in support of the hypothesis that the experienced VCs are indeed the most responsive even to negative market stimuli. There is statistically significant evidence that, during the crisis, experienced (and possibly more successful) venture capitalists reallocated their investments towards seed and early stage companies more than new and relatively inexperienced intermediaries. This argument closely relates to Lerner (1994b) and Cumming et al. (2005). Experienced VCs are more in tune with the market, adapting their investment strategy to the external conditions. Second, business angels and government sponsored programs have kept sustaining venture funding during the financial crisis, particularly in first rounds. Business angel share of investments remained constant over the crisis, but decreased in follow-on investments, while the proportional contribution of public VCs substantially increased during the downturn. Lastly, there is not enough evidence in support of the geographical proximity hypothesis. The geographical distance between investors and their investments only partially changed during the financial crisis and this dynamic is limited to later rounds.

1.6 Conclusion

Venture capital market has been historically highly cyclical and volatile as demonstrated by persisting fluctuations in number of investments and amount raised. The Global Financial Crisis shook this industry, coming as an external shock, which obliged intermediaries to adapt and react to the changing environment. This paper aims to revisit the empirical evidence by shedding new light on VCs’ behavior during a negative business cycle and measuring the effects in number of investments and funding size.

By using a multiplicative interaction model which controls for development stage of the venture-backed company, this paper concludes that VCs changed investment strategies to boosting the size of investments on early development stages, while reducing their exposure to later stage companies. There is clear evidence of a severe funding gap for expansion and later stages companies, in both first and later rounds. The reduction in funding size varies from 20% to 26% for expansion stage and from 29% to 30% for later stage companies. There is evidence that shows that most of this response is connected to the behavior of experienced venture capitalists. Collectively, the results reinforce the hypothesis of stage selective investing in order to postpone an IPO, avoiding a lower valuation at exit.

This paper contributes to the current VC discourse by highlighting how VCs reacted during the economic downturn, identifying the companies which "won" or "lost" according to their development stage, and measuring the magnitude of the funding premium or gap. The question whether the highlighted behavior has been profitable for investors is of interest for market experts and scholars, albeit out of the scope of the present paper. However, despite it could constitute a possible topic for future analyses, the evaluation still needs time to pass till the end of the venture cycle, and it requires detailed information on venture investment returns.

Implications on VC-backed companies of the strategy described above are instead of general interests for scholars and policy makers (above and beyond the positive or negative future returns for investors). The existence of a funding gap for later stage companies might have delayed, harmed, or cancelled ongoing positive improvements in innovation and growth. Conversely, the funding size premium towards seed and early stage companies might have accelerated their innovative pattern or just diverged part of the money into bigger offices. Klingler-Vidra (2016), maintaining that the surge of seed funding since the Global Financial Crisis provides an increasingly 'patient capital' to VC-backed companies, predicts that long-term value creation will prevail on short-term profits, while limiting the overall short-termism of the capital markets financial system. However, net effects are *ex-ante* unclear. Moreover, this paper accounts for just one dimension of the venture capital selection (the one connected to the stage of the company), while the Global Financial Crisis might have impacted also on other dimensions. For example, Pianeselli (2017b) carrying out a cohort analysis between 2001 and 2010, finds a strong negative effect on patent innovation for the 2009 funding cohort, even controlling for company stage and investment size. This is indicative of the presence of other selection patterns during the financial crisis, which might have impacted companies' outputs. Even this promising topic may open new avenues for future research.

1.A Appendix A

Dependent variable: ln(Total Investment - Million of $)	First rounds			Later rounds		
	(1)	(2)	(3)	(4)	(5)	(6)
Financial crisis (dummy)	-.152***	-.054**	.113**	-.108***	-.011	.168**
	[.028]	[.025]	[.044]	[.020]	[.018]	[.072]
Company age (in years)		.010***	.010***		-.017***	-.016***
		[.004]	[.004]		[.003]	[.003]
Syndication (dummy)		.494***	.492***		.859***	.858***
		[.021]	[.021]		[.020]	[.020]
Business angel (dummy)		-.315***	-.317***		-.056**	-.055**
		[.028]	[.028]		[.026]	[.026]
Government program (dummy)		-.751***	-.741***		-.173***	-.175***
		[.033]	[.033]		[.046]	[.046]
Non-US VC (dummy)		.023	.025		.310***	.310***
		[.051]	[.050]		[.029]	[.029]
Stage at Financing dummies						
Early Stage		.270***	.315***		.288***	.319***
		[.023]	[.026]		[.039]	[.044]
Expansion		.594***	.645***		.607***	.669***
		[.034]	[.036]		[.039]	[.044]
Later Stage		.748***	.834***		.710***	.789***
		[.055]	[.061]		[.043]	[.047]
*Fin.crisis*Early Stage*			-.208***			-.060
			[.056]			[.080]
*Fin.crisis*Expansion*			-.246***			-.180**
			[.081]			[.079]
*Fin.crisis*Later Stage*			-.349***			-.270***
			[.104]			[.078]
VC firm age	.025***	.019***	.019***	.017***	.015***	.015***
	[.001]	[.001]	[.001]	[.001]	[.001]	[.001]
Company-VC distance	.012***	.007***	.007***	.010***	.003***	.003***
	[.001]	[.001]	[.001]	[.001]	[.001]	[.001]
Industry effects	YES	YES	YES	YES	YES	YES
Region effects	YES	YES	YES	YES	YES	YES
Constant	1.234***	.849***	.809***	1.863***	.712***	.646***
	[.043]	[.043]	[.044]	[.039]	[.048]	[.052]
R-squared	.126	.337	.340	.099	.272	.273
Adj R-squared	.124	.335	.337	.098	.270	.272
P-value	<.001	<.001	<.001	<.001	<.001	<.001
Observations	6,012	6,012	6,012	15,680	15,680	15,680

NOTE: Crisis period is specified as May 2008 - Oct 2009. Standard errors are robust and clustered at company level for later rounds. Symbols *, ** and *** denote significance level of 10%, 5% and 1%, respectively.

Table 1.A1: Multiplicative interaction model for VC funding

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Chapter 2

Venture capital innovation over a decade of turbulence. A cohort analysis between 2001-2010

Abstract

We study the innovative outcomes of US venture-backed startups in the 2000s. By constructing a novel longitudinal dataset which tracks down patenting behavior of 10,119 companies, we confirm the existence of a generational effect in the companies selected during the Global Financial Crisis, which display a persisting lower innovative potential (of about 30%), as measured by the number of issued patents over time. Similar effects are not identified during the previous market turmoil of 2002-2003, when venture capital markets were severely hit by the Dot-com bubble burst. These results are robust to the inclusion of terms which take into account the age-related component, yearly fluctuations, and other confounding factors. Cohorts selected during the financial crisis have also lower probability to fail and lower valuation at exit. We highlight the differential consequences for innovation of external shocks which highly increase uncertainty (the Global Financial Crisis) as opposed to traditional boom-and-bust phases (the Dot-com bubble) that reduce funding availability without changing innovative capabilities of financed startups.

JEL Codes: G240, O300, G010

Keywords: Venture capital, innovation, crisis.

2.1 Introduction

As a decade, the 2000s may fit almost perfectly the definition used by Alan Greenspan (2007) for the title of his professional life memoir: "age of turbulence". Despite the book was published few weeks before the Global Financial Crisis became evident and his 18 years tenure as Chairman of the Board of Governors at Fed ended at the beginning of 2006, in the introduction, the author recognizes how this "new world", in which turbulence represents an essential condition, became finally apparent at the beginning of the 2000s, after 9/11 terrorist attack. During the decade, globalization and technology became key in shaping the interconnected and interdependent world we now live in. In particular, the Internet strengthen its grip on all aspects of political, economical and social life in Western societies, while becoming increasingly important for emerging markets and many less-developed countries. However, the benefits in efficiency and cost reduction of a high-tech globalized world must be traded off with the burden of the uncertainty, disruption and global vulnerability brought about by this interconnected world. In fact, the economic landscape of the decade was also marked by two financial and economic crises which spread globally: the Dot-com bubble burst and the Global Financial Crisis of 2007-2009 (henceforth GFC). Although both events originated from economic bubbles in the United States, which severely hit financial markets and later developed in a recession, differences in root causes, duration and intensity of the effects are evident. Even so, both crises were able to widely increase uncertainty and strike harshly the overall financial system, including venture capital market.

Indisputably, venture capital (henceforth VC) can be consider one of the pivotal pieces of the engine pushing the high-tech boom of the 2000s, which finally gave broad currency to the Schumpeterian "perennial gale of creative destruction" (Greenspan, 2007). The growing importance of this market is also confirmed by the volume of capital invested in the past four decades. According to ThomsonOne data, in 1980 the amount of VC investments directed to US companies was $580 million (constant 2010 US$). By 1990 this figure had reached $3 billion. After peaking at around $110 billion at the boom of the Dot-com bubble, it crashed at $20 during the Global Financial Crisis, to leap again at around $50 billion in 2014. However, between 2001-2010 the extreme fluctuations in venture financing reached a trough in the aftermath of the Dot-com bubble and more evidently during the GFC.

Uncertainty may have had a pivotal role in driving these temporary VC market drying-ups. In fact, there is a wide consensus that micro and macro uncertainty, here defined as the inability of firms to forecast the plausibility of future events[1], rises sharply after an exogenous shock or

[1]More formally, Knightian uncertainty (Knight, 1921) is different from the notion of risk. While risk has a single probability distribution of outcomes whose mean and variance can be quantitatively estimated and consequently hedged, uncertainty has a set of probability distributions which depend on future state of nature which is ex ante unknown.

during a recession, while it usually falls in booms (Bloom, 2014). There is also a growing body of literature which highlights the implications of uncertainty on investors' behavior. Irreversible investments accompained with uncertain future market conditions determine a raise in the value of "waiting and seeing", making the firm more likely to postpone the investments (Nishimura and Ozaki, 2007). This cautionary strategy derives from the fact that option value of waiting will be much more valuable when uncertainty is higher. However, uncertainty may also directly change the investors' selection criteria, in particular in highly risky and experimental industries, as it is the venture capital market (Nanda and Rhodes-Kropf, 2016). This is of particular interest as venture financing has proved to be key for innovation and growth. For example, Kortum and Lerner (1998) and Kortum and Lerner (2000) maintain that venture-funded companies may have accounted for 8-15% of the overall industrial innovation from 1983-1992. More recently, using Census data over a 25-year sample period, Puri and Zarutskie (2012) confirm the high-growth potentiality of venture-backed companies, finding that they account for 4-5.5% of total amount of US employment, despite they represent the .11% of new companies established from 1981-2005. Consequently, the turbulence brought about by the financial shocks of the 2000s could have modified or hindered the growth and innovative path of new venture-backed companies, originating severe long-term consequences.

However, since the Second World War, venture capital market has been generally extremely volatile, undergoing several boom-and-bust phases. Those have been depicted as "hype cycles" where the starting frenzy about a promising technology fosters excessive profit expectations and ultimately a crash (Henton and Held, 2013). Literature has often explained these repeating waves as the result of investors' overreaction or herding behavior which lead to a sharp decline in effectiveness (Gompers and Lerner, 2000; Scharfstein and Stein, 1990). Alternatively, it explained them as a rational reaction to public equity market conditions (Gompers et al., 2008). Yet, the consequences of venture market size on innovation are still unclear. On the one hand, Nanda and Rhodes-Kropf (2016) maintain that higher capital availability during peaks enables experimentation and innovation by reducing financing risk. Consequently, during troughs, when financing risk is high, VCs change the type of startup they are willing to finance towards those with proven, safer, but less innovative projects. On the other hand, Lerner (2003) supports an overfunding view, arguing that the reduced investment effectiveness during peaks lowers the impact on innovation. Therefore, the expected negative consequences for innovation of VC market drying-ups would be modest.

This paper contributes to the literature by constructing a novel longitudinal dataset which tracks down patenting behavior in order to analyze, since their first financing, innovative outcomes of US venture-backed startups in the 2000s. We examine whether the cohorts of companies selected and financed for the first time during financial crises, when uncertainty is at its highest, are persistently less innovative than those financed over ordinary periods. In particular, this study focuses on confirming the existence of a generational effect which distinguishes, as a "mark", the cohorts selected during turbulent periods from the others, while accounting for life-cycle patenting patterns and the effect of current patenting trends across all cohorts. We use the cohort analysis, a methodology increasingly popular in many disciplines of social sciences (Glenn, 2015). The empirical model identifies the alleged cohort effect on "recessionary startups", disentangling it from cyclical trends, the development stage, industry and region fixed effects, quantity of funds and other relevant factors. The sample is constituted by 10,119 American venture-backed companies, divided into ten financing cohorts (2001-2010), following each company for five years. The choice of the first venture financing as the event which shapes the cohort membership stems from the consideration that it is the initial investment selection at entry made by VC investors which determines the characteristics of the cohorts while the following rounds just sustain the company growth or signal the achievement of defined milestones. Recent empirical contributions by Moreira (2015) and Manaresi and Scoccianti (2016) on the universe of businesses document a persistent negative effect on growth of recessionary cohorts. By the same token, this paper will test a similar effect on the innovation outcomes measured by patent count and a set of patent quality proxies, focusing on a more cohesive group of startups, those which were able to get financed by venture capitalists. Despite the fundamental role of VC in fueling repeated waves of technology innovations, still, to my knowledge, this is the first empirical study which measures the cohort effect on innovative outcomes over the business cycle.

Results confirm a significant reduction of available funding coupled with a negative generational effect in the companies selected during the Global Financial Crisis which display a persisting lower innovative potential, of about 30%, as measured by the number of issued patents over time. This evidence is robust to the inclusion of terms which take into account the age-related component, yearly fluctuations, together with other confounding factors. Additionally, the generational effect identified during the GFC is not evenly distributed across industries, but it concentrates in sectors like healthcare, industrial/energy and media and entertainment. We explained this finding with degree to which formalized innovation, as accounted by patents, is an entry requirement to compete in each market. In order to find confirmation of the view of cohort effect as the result of venture capital selection of safer but less innovative projects, the paper tests the correlation of this selection with lower probability to fail and also a lower valuation at exit. Evidence confirms the previous hypothesis.

Interestingly, similar effect is not traceable during 2002 and 2003. Generational differences are not statistically significant between 2001-2008. The burst of the Dot-com bubble, despite equally reducing available funding, did not exert any significant persistent effect on innovative patterns with respect to the tranquil period. This is suggestive of a differential impact that an exogenous vs. endogenous shock may have had on the level of uncertainty which in turn is likely to affect startups selection and innovation. The historic magnitude of the Global Financial Crisis emphasizes the importance of understanding the degree to which different types of shocks affect real economy. In fact, considering the two slowdowns alike on VC perspective it is hardly supported by any evidence. Venture market itself had an essential role in boosting the unrealistic expectations on the Internet sector during the Dot-com bubble, which then can be accounted as one of the many market "hype cycles". Conversely, the Global Financial Crisis can be considered a malfunctioning of the entire financial system and it appears as mainly exogenous to VCs (Block and Sandner, 2009). Whereas both drying-ups have directly produced a severe funding gap for financed companies, leaving some good companies unfunded, it is also worth noting that VCs have reacted differently according to the type of shock, modifying the pool of selected companies, which in turn have affected the innovative potential of the financed cohorts with long-lasting negative effects. Therefore, our results suggest that the degree of risks and uncertainty perceived by investors may have been pivotal in shaping the consequences on innovation. Overall, by studying comparatively different shocks during the decade, this paper takes a step in between the alternative and conflicting predictions of the above mentioned literature on innovation consequences of market conditions. In fact, whereas the bust of 2002-2003 does not seem to have led to severe consequences on innovation, at least with regards to the following tranquil period, the sharp financial distress brought about the exogenous shock of the GFC significantly and persistently lowered innovative potential of selected startups.

This paper is related to the large body of literature which investigates the relationship between venture capital industry and innovation (Florida and Kenney, 1988; Kortum and Lerner, 1998, 2000; Lerner, 2003; Da Rin and Penas, 2007; Lerner et al., 2011; Hirukawa and Ueda, 2008, 2011; Popov and Roosenboom, 2012). Overall, research supports the positive effects of VC on R&D and patenting, in particular for the case of US venture capital market. However, empirical works have usually neglected the analysis of the over time variation on the intensive margin. One important exception is Nanda and Rhodes-Kropf (2013) who document how the degree of experimentation and innovation systematically varies over time according to the market conditions. Our results are consistent with their findings, but highlights the existence of a negative generational effect only for the GFC cohort. Our work is also complementary to the still small amount of research which demonstrate a negative impact of the Global Financial Crisis on innovation for the generality of businesses (Cosh et al., 2009; Archibugi and Filippetti, 2011; Paunov, 2012; Archibugi et al., 2013). However, this paper will limit its scope to the analysis of new venture-backed companies in the United States, hence reducing de facto any concerns on firms' heterogeneity.

The article is organized as follows. Section 2.2 traces out the conceptual framework, highlighting the theoretical and empirical findings on investment behavior under uncertainty. This section also explores the possible transmission channels to innovative outcomes. Section 2.3

describes the dataset, the measurement choice of innovation outputs and the other covariates. Descriptive statistics, empirical methodology and major findings are provided in Section 2.4. Lastly, Section 2.5 discusses the results and conclude.

2.2 Conceptual and research framework

2.2.1 Conceptual framework

In the last two decades, a burgeoning literature has deeply investigated the impact of uncertainty on economic performance. First, macroeconomic empirical studies have challenged the traditional dichotomy between business cycle fluctuations and growth, highlighting the negative effect of volatility[2] on GDP growth (Ramey and Ramey, 1995) and private investments (Aizenman and Marion, 1999). Then, theoretical works have focused on explaining the propagation channel which connects the two phenomena. Aghion et al. (2010) develop a model which links endogenous productivity growth with financial markets over the business cycle. The model shows that in the presence of imperfect credit markets, long-term productivity-enhancing investments (as R&D, for example) become procyclical, amplifying the business cycle. Therefore, a negative exogenous shock affects the composition of investments, by diminishing the ex-ante investors' willingness to commit to long-term investments in the presence of possible ex-post liquidity shocks. This underlying mechanism and its consequences on cyclical investment fluctuations are connected to the concept, as first formalized by Bernanke (1983), of "real option", which emerges with irreversible investment choice under uncertainty. When investment is irreversible, but the flow of information on future returns arrives over time, the optimizing agent may be better off if she "wait and see", postponing the commitment while choosing the optimal investment timing. Bloom (2009) confirms the existence of a major real option effect following large macro shocks. Firms pause their hiring and investment behavior generating a short-term drop on real economy outcomes with a medium-run rebound which drives back to trend on the long-run. A corresponding micro literature complements these findings by focusing on investment behavior under uncertainty measured at firm-level. The cautionary effect, whereby uncertainty lowers firms' responsiveness, is confirmed. Moreover, the option value is increasing in the magnitude of the shock. In particular, R&D persistence implies a positive marginal effect of uncertainty if firms are reducing their knowledge investments, while the same effect will be negative, if firms are increasing R&D (Bloom, 2006; Bloom et al., 2007).

Collectively, the reviewed literature suggests the existence of a "delay effect" which tem-

[2]The concepts of volatility and uncertainty are somewhat different. A phenomenon is volatile if it fluctuates, but it is also uncertain when this fluctuation is unpredictable. In general, many papers use them as equivalents, since these characteristics are often paired. For example, Ramey and Ramey (1995) demonstrate that the negative effect of volatility stems in particular from its unpredictability.

porarily pauses investment activity in the presence of uncertainty shocks. The value of waiting and seeing, the real option value, surges during these phases and investors may prefer to wait and not to commit until uncertainty is cleared. Interestingly, this framework may also apply to investment decisions into new ventures made by VCs. Venture capital is an equity-based, specialized form of private equity investment which focuses on young innovative companies characterized by high-growth potential, a scalable business, albeit facing high failure risks. Typically, funds, raised from institutional investors and wealthy individuals (limited partners or LPs), are independently managed by venture capitalists (general partners or GPs), which, usually after a decade, liquidate their assets and compensate the limited partners to start a new cycle (Hall and Lerner, 2009). On their jobs, VCs are normally exposed to manifold risks, constantly mitigated by their risk-reducing behavior. Fiet (1995), comparing agency and market risks, maintains the preeminence of the latter for venture capitalists. Agency risk stems from the divergence of interests between entrepreneur and investor. Nevertheless, VCs have learned how effectively protect themselves with stringent legal terms and covenants in their contractual provisions. Moreover, the supply of staged financing is another powerful instrument to hold the real option together with a significant control power over entrepreneurs. Therefore, venture capital investors devote a larger amount of time to the screening process in order to reduce market risk which is related to the size, growth and level of competitiveness of the reference industry of their investments. However, an exogenous uncertainty shock may negatively affect the market risk as well as expose the VCs to the liquidity risk of their counterpart (limited partners). The latter is related to the notion of financing risk, that is the uncertainty on the capacity to continue financing future promising investments. This could be due to the negative outlook for future fund raising or even the inability of LPs to provide the committed fund at GPs' capital calls. As a result, some VCs may temporary delay their investments as a precautionary mean to acquire more information.

Yet, temporary halting the investment decision is not the only system adopted to reduce vulnerability to shocks. Investors may systematically modify the type of projects financed or its riskiness according to the level of uncertainty on future perspectives. For example, during an uncertain phase some investors may be more concerned about the expected illiquidity of a cold IPO exit market, funding proportionately more early-stage companies in order to distance their investment from the expected exit time, avoiding a lower valuation at exit (Cumming et al., 2005). Conversely, Ruhnka and Young (1991) analyzing venture capital investing decisions, hypothesize a behavioral framework of VCs risk-reducing strategies connected to the notion of "ideal level of risk". This strategy reduces the risk of failure, by allocating relatively more funds to later stage companies. By investing in companies at the end of venture cycle, VCs prioritize the avoidance of very low or negative final portfolio rates of return at the expenses of the probability of above-average returns. Moreover, Nanda and Rhodes-Kropf (2016) model a rational investor behavior in the presence of high financing risk which directly targets less innovative firm. When uncertainty is high (for example, during a crisis) a trade-off appears between the commitment of more upfront funding to protect the company from the future impacts of the shock and investment staging to preserve the real option. They predict that with incomplete contracts, the higher is the option value, the stronger is the impact of financing risk. Shocks change the type of selected startups towards companies with lower option value, consequently decreasing the degree of experimentation and innovation of their investments. The main implication of their model is that financial market conditions significantly affect companies experimentation. Therefore, the diffusion of radical innovation requires hot financial markets with low financing risk. One noteworthy aspect of this risk mitigation mechanism is that it is part of a rational equilibrium and it does not require any behavioral explanation which violates the axioms of expected utility theory. In fact, the increasing financing risk lowers net present value of the investment. Investors rationally leave unfunded those projects which now exhibit a negative value. However, behavioral factors could further magnify by this effect. For example, loss aversion, a concept formalized in prospect theory (Kahneman and Tversky, 1979), can even increase investors' responsiveness under uncertainty.

2.2.2 Transmission channels

These complementary predictions on the effects of uncertainty shocks seems to fit the recessionary environment in the 2000s. There is a clear consensus on the fact that uncertainty rises strongly in recessions, as it happened in particular during the Global Financial Crisis (Bloom, 2014). Moreover, periods of crisis which reflects on venture funding and selection can also have direct and indirect consequences on the level of innovation of venture-backed companies. In fact, venture capital which funnels money from financial markets into high-risk asset class, while mitigating information asymmetries and moral hazards problems through constant monitoring and mentoring has proved as one of the most valid mechanism to finance radical innovation (Kortum and Lerner, 2000). Based on the above conceptual framework, the following paragraph will hypothesizes three main supply transmission channels through which uncertainty can modify the innovative patterns of venture-backed cohorts. Section 2.4 will test the presence of a generational effect in the VC selection (proxied by the different cohorts of companies) which directly influences innovation, while controlling for funding fluxes and startup stage shifts which indirectly may impact innovative performance too.

Funding gap: Uncertainty shocks temporary halt or reduce investment commitments, leading to VC market drying-up. Beyond the fact that a lower number of companies can get financed which in turn decreases the aggregate number of patents, the downsize of investment flows to cash-constrained new entrepreneurs or the lack of refinancing opportunities at later rounds hinder company technological development and innovation.

This hypothesis controls for the importance of cash constraint vs. abundance in shaping the company innovative path. This is coherent with the "wait and see" strategy of the investors highlighted before which may reduce funding size or delay refinancing rounds during periods of high uncertainty. However, literature predictions on the effect on innovation are not unanimous. The recent strand of empirical research which spurred after the Global Financial Crisis points to the possible long-lasting negative effect of liquidity constraints on innovation. Block and Sandner (2009) show that the crisis deeply affected the number of first-round VC investments on Internet companies, while the average amount of funds raised per round decreased by 20%. Block et al. (2012) find a severe funding gap in the amount of funds raised across sectors, especially in later funding rounds. In contrast, Lerner (2003) soften the implication for technological innovation of venture funding drying-ups. Periods of booms are often accompanied by diminishing venture funding effectiveness as a result of general over-funding of specific sectors. Therefore, short-run fluctuations in venture financing which do not turn in prolonged undershooting of venture funding levels are likely to have modest implications on innovation.

Stage shift: Uncertainty shocks modify the selection of investments in the VCs' portfolios. Two alternative hypotheses emerge. Investors adjust their choices towards early-stage companies if the expected liquidity conditions of IPO exit markets are negative. Alternatively, investors reduce the risk of achieving very low or negative returns by investing in "safer" later stage companies. They trade off the lower expected returns with a reduced variability and a closer exit date.

Pianeselli (2017a), analyzing venture funding over the Global Financial Crisis, finds evidence consistent with the stage shift hypothesis, which is connected to the liquidity of public markets. VCs changed investment strategies, boosting the size of funding on early development stages, while reducing their exposure to later stages companies. Independently from the chosen strategy in response to the shock, a shift in stage selection may indirectly affect innovative performances in case there is significant relationship between company development stage and patenting rates. In fact, Mann and Sager (2007) show that the majority of companies apply for the patent protection at relatively earlier stage of their venture cycle. The fact that patents are obtained long before they become useful to defend the intellectual property from competition, it suggests that patent is a way to protect young startups from investors' expropriation. Therefore, any swing in stage composition of the investments' portfolio may indirectly influence the rate of patenting. Moreover, comparing the patenting behavior of software startups with those in biotechnology industry, the authors note a differential propensity to patent between industries and from sector to sector within the same industry. Even this factors may affect patenting and will be held constant in the following analysis.

Generational effect: Venture capitalists react to periods of high uncertainty not only by temporary decreasing the amount committed or reshaping the development stage composition of their portfolio, but they directly select less innovative startups in order to lower the riskiness of their investments. The lower tolerance for failure reflects on VCs choice and represents a generational characteristic. Therefore, it is common to the companies selected and funded on the same uncertain period (the cohort) and it represents a persistent effect with long-lasting consequences on innovation performances.

This hypothesis originate from the theoretical framework analyzed before. Highly experimental startups are the most damaged by uncertainty shocks which may severely hinder their initial financing or diffusion. Empirical results seem to confirm the existence of this pattern. Nanda and Rhodes-Kropf (2013) find that venture-backed companies first financed during periods of low uncertainty were more likely to be in the tails of the outcome distribution (they were both more likely to fail or being highly innovative and profitable). Depending on the external environment and the economic cycle, investors change accordingly their willingness to experiment. They find that startups receiving their initial funding in cold investment periods had a lower bankruptcy rate, but their valuations at exit were significantly lower, they filed less patents in the years following their funding (controlling for capital received), and had less patents citations. This evidence is suggestive of the fact that economic turmoils are less likely to be connected to the Schumpeterian gales of creative destruction which instead link with economic booms, when levels of experimentation and failure tolerance are higher. In fact, Archibugi et al. (2013), using a sample of British firms, show how during the Global Financial Crisis creative accumulation prevailed over creative destruction with innovation concentrated on incumbents more than new companies. During times of crisis, innovation progresses more in a cumulative fashion than during tranquil periods.

2.3 Data and variables

2.3.1 Source of data

This paper uses four main sources of data. The base sample, which determines the financing cohorts and all related information on venture-backed companies, is constructed by using the VC deals in the commercial database Thomson One by Thomson Reuters. Currently this database (previously known as Venture Xpert or Venture Economics), due to its availability to universities and research centers, represents the industry standard in venture capital academic debate and its characteristics has been widely analysed in Da Rin et al. (2011), Lerner (1994b) and Kaplan et al. (2002). Thomson One identifies 10,119 venture-backed companies financed for the first time between 2001 and 2010. This number is limited to venture investing funding rounds (excluding other private equity deals as mezzanine capital, LBOs etc.) in which the amount invested is disclosed and the company head-quarter is within the United States.

Data on US granted patents are collected from PatentsView platform and updated through the end of 2015[3]. PatentsView initiative was established in 2012 and it is a collaboration between US Patent & Trademark Office (USPTO), US Department of Agriculture (USDA), and other institutions in order to increase the value and scope of the analysis of patenting activity at micro-level. The PatentsView data warehouse is sourced from USPTO bulk data files, which are then probabilistically disambiguated and geocoded, in order to longitudinally link inventors and assignee with patents characteristics[4]. The automatic disambiguation process distinguishes 430,162 distinct assignees and 5,231,384 patents, granted between January 1976 to December 2015. The number of granted patent is the result of domestic and foreign companies or single inventors which successfully applied to the agency to protect their inventions, products or intellectual properties in the US market. Therefore, all unissued patent applications will not appear in this list. As in all relational databases, there is a unique key which connects assignee to granted patents and to related tables reporting patent or assignee characteristics. This paper will heavily employ those information to construct the variables and the final matched sample. Their use is explained in details in the Section 2.3.3 and in the Appendix 2.A.

The present work carries out a systematic attempt of micro-level integration between our base sample of first-time venture-backed companies between 2001-2010 and their pre- and post-innovation outcome measured as patent count and patent quality, taken from PatentsView tables. Clearly, matching different sources which do not share a unique identifier is problematic and time-consuming. Among others, Hall et al. (2001) and more recently Lotti and Marin (2013) attempted such an effort, highlighting common problems and caveats. The former also briefly list all previous similar projects, since the first ‘Productivity, Innovation, and Entrepreneurship Program’ at the National Bureau of Economic Research (NBER) in 1978. An automatic STATA® routine has been developed in order to harmonize names, perform exact matching, geocode companies at zip-code level and carry out approximate matching applying the Jaro-Winkler string similarity algorithm to each possible pair between the base sample and the assignees list. Lastly, all results has been recursively filtered out in order to correct possible false positive while minimizing the need of manual double-check. The procedure found 3,277 applicants which has been funded by VCs for the first time between 2001 and 2010. This signals that almost a third of the base sample is involved in patenting activity. Overall and up to the end of 2015, these applicants have successfully registered at USPTO 42,111 patents. The result is a novel dataset which tracks down patenting activity of a generality of newly funded and usually very small

[3]The data was accessed and downloaded on 1st March, 2016 as bulk download in tab delimited format from the website http://www.patentsview.org/download

[4]See ‘Methods and Sources’ at http://www.patentsview.org/web for detailed information on PatentsView project’s methodology

private equity companies over 10 years time. All the procedures are documented in detail in the Appendix 2.A.

Data on US patent application which include issued and unissued documents are collected from the "Historical Patent Data Files" at USPTO[5]. USPTO project is the first to apply the NBER higher-level classification to patent applications[6]. The Office of Chief Economist at USPTO developed a probability-matching algorithm to fill each patent application into one of the thirty-six NBER subclasses (Marco et al., 2015). In fact, patent classification of unpublished, pending or abandoned applications can be difficult to obtain otherwise. USPTO micro data have been aggregated at year and NBER subclass, reporting the number of applications and the patent allowance rate. Those numbers have been subsequently matched by year and NBER subclass with the granted patents and used in a multivariate setting to partially control for demand-side effect or variation at specific patent-class level.

Finally, data on company exits are obtained matching the list of VC financed companies with IPO issuers or acquisition targets of the transactions registered in Standard & Poors Capital IQ (CIQ) financial dataset[7]. A continuous variable reports the gross offering amount for IPOs or the acquisition transaction value. The matching found 482 companies in the base sample which launched an initial public offering, and 1,717 which were acquired by other companies. In order to evaluate each cohort on the same time-span, the analysis will consider exit events happened within six years from first financing. Accordingly, the sample restricts to 268 IPOs and 1,186 acquisitions.

2.3.2 Measuring innovation

The present paper investigates the innovation outcome of selected cohorts of venture-backed companies, as measured by their patenting activity. During the decade between 2001-2010, the aftermath of a high-tech speculative bubble and the Global Financial Crisis of 2007-2009 severely impacted and shaped selection and funding of innovative startups. This section will explain how the innovation is measured and accounted for in the following analyses.

Since the seminal contribution of Kuznets (1962), the lack of a unique satisfactory measure of inventive activity has always been highlighted as one of the major flaws in understanding the economical impact of innovation and new technology. In particular, the literature has hitherto proposed several different proxies which closely relates to the three main phases of innovative process (Acs and Audretsch, 2005): (a) input measures of the innovation effort, such as the amount of R&D investments or the share of highly-specialized workers within the company;

[5]The data was accessed and downloaded on 1st March, 2016 as bulk download in STATA® format from the website https://www.uspto.gov/learning-and-resources/electronic-data-products/historical-patent-data-files

[6]Hall et al. (2001) with NBER developed a higher-level classification by aggregating over 400 US administrative patent classes (USPC) into 36 technological (and economically relevant) categories.

[7]The data was accessed and downloaded on 1st December, 2016 using CIQ excel plugin

(b) measures of intermediate output related to patenting activity; and (c) measures of final innovative output, usually survey-based questions addressed directly to companies or to industry experts. The present study will employ intermediate innovative output measures related to the number of patented innovations and their "quality".

The measurement choice is primarily imposed by data availability. Neither detailed balance sheets information nor survey-based data on innovation outcomes are publicly available for private-equity startups. Nevertheless, there are also several reasons why the choice of patent data seems to be appropriate to the analysis undertaken. In fact, Scherer (1983) posits that the major challenge on the reliability of patent measures resides in a thorough understanding of the nexus among R&D, patent production and innovation, the so called "propensity to patent". Uncertainty on the parameter stability undermines the efficiency of the measure. In particular, the propensity to patent an invention of given quality may vary across company and industries, while the underlying technological (and economic) value of the invention varies among patents (Scherer, 1965). However, a sample made of cohesive units with similar characteristics is likely to ease the concerns about the stability of the propensity to patent across companies. In fact, venture capital investments concentrate on few high-technology industries with rapid growth opportunities, selecting more innovative companies with high patent production (Da Rin et al., 2011). Moreover, the remaining variation of the propensity to patent across industries, technology classes and time periods will be controlled by using industry fixed effects and suitable control variables.

Crucially, US patent documents are mainly designed for administrative purposes in order to guarantee the inventor with "the right to exclude others from making, using, offering for sale, or selling the invention throughout the United States" (35 U.S.C. §154 (a)(1)). However, they also represent a unique source of detailed information which allows researchers to evaluate the technological and economical importance of the patented invention. Patents include information on inventors, inventions, technological areas, companies and geographical locations. Moreover, they report citations to previous patents and to the scientific literature. These information open new avenues to investigate spillovers and diffusion in terms of citations networks, but also allow to measure the technological breadth of patents, and its expected market value, tackling the significant "value" heterogeneity among patents (Hall et al., 2001).

All patent-based measures present advantages and drawbacks. On the one hand, patent count while linking directly the grant of an intellectual property right to a cumulative measure of innovation output, fails in fairly capturing the heterogeneity in economic value and technological importance of all granted patents (Lanjouw et al., 1998). On the other hand, patent quality indicators explicitly attempt to embrace and rank patent value heterogeneity, but the exact meaning and definition as well as the practical measurement of patent quality is still the subject of intense scrutiny in the innovation and technological change discourse (Squicciarini et al., 2013). As a result, here the descriptive and multivariate analyses will take into consideration several aspects of patenting, measuring as outcomes a wide array of indicators in the domain of both patent count and quality.

2.3.3 Variables

The dataset consists of an annual balanced panel of 10,119 US venture-backed companies tracked for five yearly periods since their first financing. The innovation output is the regressand and it is measured by a set of proxies related to patenting activity. Table 2.1 details the content of each variable used in this paper, here we briefly describe them and discuss their economic significance. PATGRANT is the count of company successfully granted patents processed in each period. ORIGINALITY is a measure of the breadth of the knowledge sources the patent relies on. Higher concentration of backward citations on one or few technological classes indicates the patent is following a single line of invention, whereas lower concentration signals the patent is building an original (and more valuable) contribution on a wide array of technologies. GRANTLAG reports the time elapsed between the application date and the date when the patent was granted. Popp et al. (2004) mantain that the grant lag is not completely exogenous to the applicant, but instead depends on the features of the application itself. For example, motivation and efforts undertaken by the applicant are one of the main driver of shorter grant procedures. Moreover, recent theoretical and empirical evidence correlates both effort and length of patent review with potential value (Harhoff and Wagner, 2009; Régibeau and Rockett, 2010). CLAIMS is the count of the claims contained in the patent. They are validated by examiners and define the extent of the legal protection conferred by a patent. As the patent fee structure is based on the number of claims included, the straight count may also capture the expected market value of the patent (Squicciarini et al., 2013). Lastly, PATSCOPE represents the patent scope which is a proxy for the breadth of the intellectual property. Lerner (1994a) shows also a positive and significant impact of patent scope on company valuation. It is measured by the number of International Patent Classification (IPC) subclasses to which patent is assigned by examiners.

All other variables used throughout the paper are described as follows. Companies are grouped by COHORT representing the year of first venture financing. These dummies control for shared common characteristics or experiences, determined by the year of venture selection, and investigate possible persistent effects on innovation. YEAR captures the influence of aggregate time trends, while STAGEATFIN describes the stage of the company when it received the financing. TOTINVEST is the total amount raised by companies in each year. It includes equity and debt funding and it is measured in million constant dollars. PATAPP is calculated as the overall number of applications at USPTO in the same year and NBER subclass of the venture-backed patents. For example, the proportion of innovation which are actually patented in each class may be directly influenced by endogenous company choices (common to venture and non-venture financed companies) or indirectly from the (exogenous) arrival of a huge technological opportunity in a specific technology class. By controlling the over time variation of the propensity to patent at technology class level, it will be possible to disentangle the general trend from the cohort specific effect. Moreover, patent allowance rate of the applications at USPTO may change by year and technological class. An exogenous (to the company) change of patent office policy may decrease (or increase) the number of granted patents, confounding our results. By the same token, CLAIMSCTR, GRANTLAGCTR and PATSCOPECTR will control the over time general variation for patent quality regressions. Unfortunately, due to computational constraints, the construction of such a control for the originality measure is not possible here. OUTBUSINESS, IPO and EXITVALUE are all indicators used in the robustness tests as dependent variables to verify the degree of success in VC investments by cohort. They represent, respectively, the company status, the presence of IPO exit and the exit transaction amount in million of constant dollars. Lastly, industry and regional effects are captured by nine INDUSTRY dummies and six REGION dummies, referring to the industry and area of the funded company. Table 2.2 describes the sample size by cohort, industry and region. Sectoral composition in Panel A shows that observations distribute almost uniformly across high-tech industries. Software startups receive the highest share of venture funding, while investments in fin-tech are still very low. It also indicates that all sectors have been evenly hit by venture market drying-ups during the aftermath of the Dot-com bubble and GFC.

During the 2000s innovation has been highly concentrated even at geographical level. Figure 2.1 compares the geographical distribution of venture capital investments (Panel A) with innovation intensity by area (Panel B), measured as the number of patents granted to venture-backed companies. Research documented the tendency of venture capital firms and financed companies to concentrate in few locations. Lerner (1995) and Cumming and Dai (2010) find the presence of strong local bias in VC investment decisions. Chen et al. (2010) examine the location decision of venture industry, pointing out how VCs and companies cluster in highly-successful areas in order to exploit agglomeration externalities, in particular in the metropolitan areas of San Francisco, Boston, and New York. Panel A substantially confirms this prediction for our sample of financed companies, but the picture is more nuanced. Venture financing spreads beyond the "venture capital centers" of the coasts, reaching almost all US territory and developing other important clusters even in urban areas of America's heartland. By contrast, innovation intensity by area depicted in Panel B shows a different situation. Patenting appears very concentrated and high innovation remains a prerogative of few venture capital centers, where at substantial inflows of venture investments correspond an important outflow of patent production. Once metropolitan areas of San Francisco, New York, Boston and Los Angeles/San Diego are excluded, few other areas remains significant for patenting activity.

Variable Name	**Description**
BWCITATION	The variable reports the number of citations made by each granted patent irrespective of NBER subclass or citation category (cited by applicants or examiners).
CLAIMS	The variable reports the number of claims contained in each patent which in turn defines the extent or the scope of the protection conferred by the patent.
CLAIMSCTR	The variable measures the average number of claims contained in each patent at patent class and year level for all patents deposited at USPTO (irrespective of company financier). This variable, used as control in a multivariate setting, is matched with each company observation by NBER subclass and year. In case of a company which applies in the same year for multiple patents belonging to different classes, CLAIMSCTR represents the weighted average number of claims.
COHORT	The variable indicates the year in which the company has been funded by VCs for the first time. 9 dummies are included, varying from 2002 to 2010. Excluded dummy is 2001.
INDUSTRY	All investments are aggregated in 9 broad sector dummies, which refers to the industry of the company. Dummy equal to 1 if the sector is: "Biotechnology", "Computer & Electronics", "Healthcare", "Industrial/Energy", "IT Services & Telecom", "Media and Entertainment", "Services & Retailing/Distribution", "Software", "Financial Services & Others". Excluded dummy is "Biotechnology".
IPO	Dummy variable equal to 1 if the company exited through an IPO within 6 years from first venture financing.
EXITVALUE	The variable reports the gross value of the exit only for those companies which underwent an IPO or have been the target of a company acquisition within 6 years from first venture financing. It is constituted by the Gross Offering Amount of the issue venture financing. This is equal to the share x price value. It represents the market valuation at the issuance and includes the discount due to the underwriters. In case of acquisition, this variable reports the Total Transaction Value of the acquisition only for those companies which within 6 years from first venture financing. This is equal to total consideration paid for the transaction. It represents the company valuation at the issuance but it does not include total other consideration, consideration paid to options, warrants, or rights holders, total deferred, earnout, or contingent payments, net assumed Liabilities, and adjustment size.
GRANTLAG	The variable reports the length of the period between the filing date of the application and the date of the grant. This is calculated in days for each patent issued by venture-backed companies.
GRANTLAGCTR	The variable measures the average length (in days) of the grant lag period at patent class and year level for all patents deposited at USPTO (irrespective of company financier). This variable, used as control in a multivariate setting, is matched with each company observation by NBER subclass and year. In case of a company which applies in the same year for multiple patents belonging to different classes, GRANTLAGCTR represents the weighted average grant lag.
NASDAQ INDEX	The variable reports the closing value of the NASDAQ Composite index on the day of the IPO or acquisition of the company. NASDAQ Composite is a stock market index of more than 3,000 stocks listed on the Nasdaq exchange whose composition is heavily weighted towards high-tech companies.
ORIGINALITY	Similarly to Trajtenberg et al. (1997), constructed as the Herfindahl index of concentration of backward citation among 36 NBER technological subclasses. $ORIGINALITY_i = 1 - \sum_{k=1}^{N_i} \left(\frac{BWCITATION_{ik}}{BWCITATION_i}\right)^2$ where k is the index of patent class and N_i is the number of the different patent classes to which the citing patent i belongs. Thus, for each different cited patent class, the ratio gives the proportion of citation made by patent i to patent class k out of the total citation of patent i. By construction, the patent originality indicator ranges between 0 and 1. If a patent cites previous patents that belong to a wide set of technology fields the originality score will be high, whereas the narrower are the technological roots as measured by NBER subclasses, the lower is the score. The term $BWCITATION_i$ here is calculated only for the cited patents with the NBER subclass reported.
OUTBUSINESS	Dummy variable equal to 1 if the company status according to Thomson One is either "Defunct", "Bankruptcy - Chapter 7" or "Bankruptcy - Chapter 11". Company status is updated at 31st December, 2015.
PATALLOWRT	The variable reports the patent allowance rate of all applications at USPTO (irrespective of company financier and granted status) in the same year and NBER subclass of the venture-backed company patent. It is measured as the percentage ratio of issued patents to the total applications. In case of a company which applies in the same year for multiple patents belonging to different classes, PATALLOWRT represents the weighted average patent allowance rate.
PATAPP	The variable reports the number of all applications at USPTO (irrespective of company financier and granted status) in the same year and NBER subclass of the venture-backed patents. In case of a company which applies in the same year for multiple patents belonging to different classes, PATAPP represents the weighted average number of applications. All numbers are later rescaled, diving them by 100 in order to achieve meaningful coefficients.

PATGRANT	The variable reports the count of successfully granted patents at company level in each 1-year period. First period starts the day of the first funding round and ends one year later. Multivariate analysis considers 5 periods since the date of the first VC financing. Patent count by period is based on the date of application filing (reported in the field "date" of table "application" in PatentsView) and reports only entries successfully granted by December 2015.
PATSCOPE	Similarly to Lerner (1994a), develops a proxy for patent scope based on the International Patent Classification (IPC) scheme. The variable is the count of the number of distinct 4-digit IPC subclasses to which patent is assigned by examiners. The greater is this number, the higher is the breadth and the technological and economic value of patents.
PATSCOPECTR	The variable measures the average patent scope at patent class and year level for all patents deposited at USPTO (irrespective of company financier). This variable, used as control in a multivariate setting, is matched with each company observation by NBER subclass and year. In case of a company which applies in the same year for multiple patents belonging to different classes, PATSCOPECTR represents the weighted average patent scope.
REGION	All investments are aggregated in 6 broad areas dummies, which refers to the headquarter region of the company. Dummy equal to 1 if the area is: "California", "East Coast", "South-West", "Midwest & South-East", "North & Other". Excluded dummy is "California".
STAGEATFIN	Company development stage as reported by Thomson One at the date of venture financing. Four different stages are considered: "Seed", "Early Stage", "Expansion" and "Later Stage". Excluded dummy is "seed" stage.
TOTINVEST	The variable reports the total amount invested by VCs at company-level in each one-year period. First period starts the day of the first funding round and ends one year later. Multivariate analysis considers 5 periods since the date of the first VC financing. In case of multiple rounds to the same company within a period, it sums all the occurrences. The variable is equal to 0 for periods with no funding registered. All amounts are inflation adjusted (in 2010 real terms) using GDP Implicit Price Deflator in United States, calculated by Organization for Economic Co-operation and Development, GDP Implicit Price Deflator in United States, retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/USAGDPDEFAISMEI, January 4, 2017.
YEAR	The variable indicates the calendar year of the first period (equal to the year of first financing) and following 4 periods. 13 dummies are included, varying from 2002 to 2014. Excluded dummy is 2001.

Table 2.1: Definition of variables

Panel A: Sample by industry and cohort

Industry	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Total Companies	Total Obs
Biotechnology	108	108	90	107	119	147	143	137	90	118	1,167	5,835
Computer & Electronics	210	115	114	153	116	103	111	93	50	50	1,115	5,575
Healthcare	77	78	89	93	105	132	139	124	87	87	1,011	5,055
Industrial/Energy	71	55	43	62	68	86	134	139	67	79	804	4,020
IT Services & Telecom	183	66	66	103	130	175	163	147	95	112	1,240	6,200
Media & Entertainment	67	41	38	57	94	149	164	155	81	136	982	4,910
Services & Retailing/Distribution	88	47	46	71	80	82	105	97	60	64	740	3,700
Software	308	247	225	244	279	288	310	316	219	333	2,769	13,845
Financial Services and Others	39	22	21	38	31	22	45	26	16	31	291	1,455
Total	1,151	779	732	928	1,022	1,184	1,314	1,234	765	1,010	10,119	50,595

Panel B: Sample by region and cohort

Region	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Total Companies	Total Obs
California	365	250	268	357	409	477	497	450	272	343	3,688	18,440
East Coast	379	235	226	260	288	362	400	389	237	346	3,122	15,610
SouthWest	122	91	85	84	113	118	120	91	67	99	990	4,950
Midwest & SouthEast	190	146	106	158	131	155	210	198	130	163	1,587	7,935
North & Other	88	57	47	69	81	72	87	106	58	59	724	3,620
Total	1,144	779	732	928	1,022	1,184	1,314	1,234	764	1,010	10,111	50,555

NOTE: Panel A shows the distribution of the sample by industry and cohorts. Columns report the number of unique companies by industry in each cohort. Last column reports the number of the whole panel dataset by industry. Panel B shows the distribution of the sample by region and cohorts. Columns report the number of unique companies by region in each cohort. Last column reports the number of the whole panel dataset by industry. Sample size differences are due to missing values.

Table 2.2: Sample characteristics

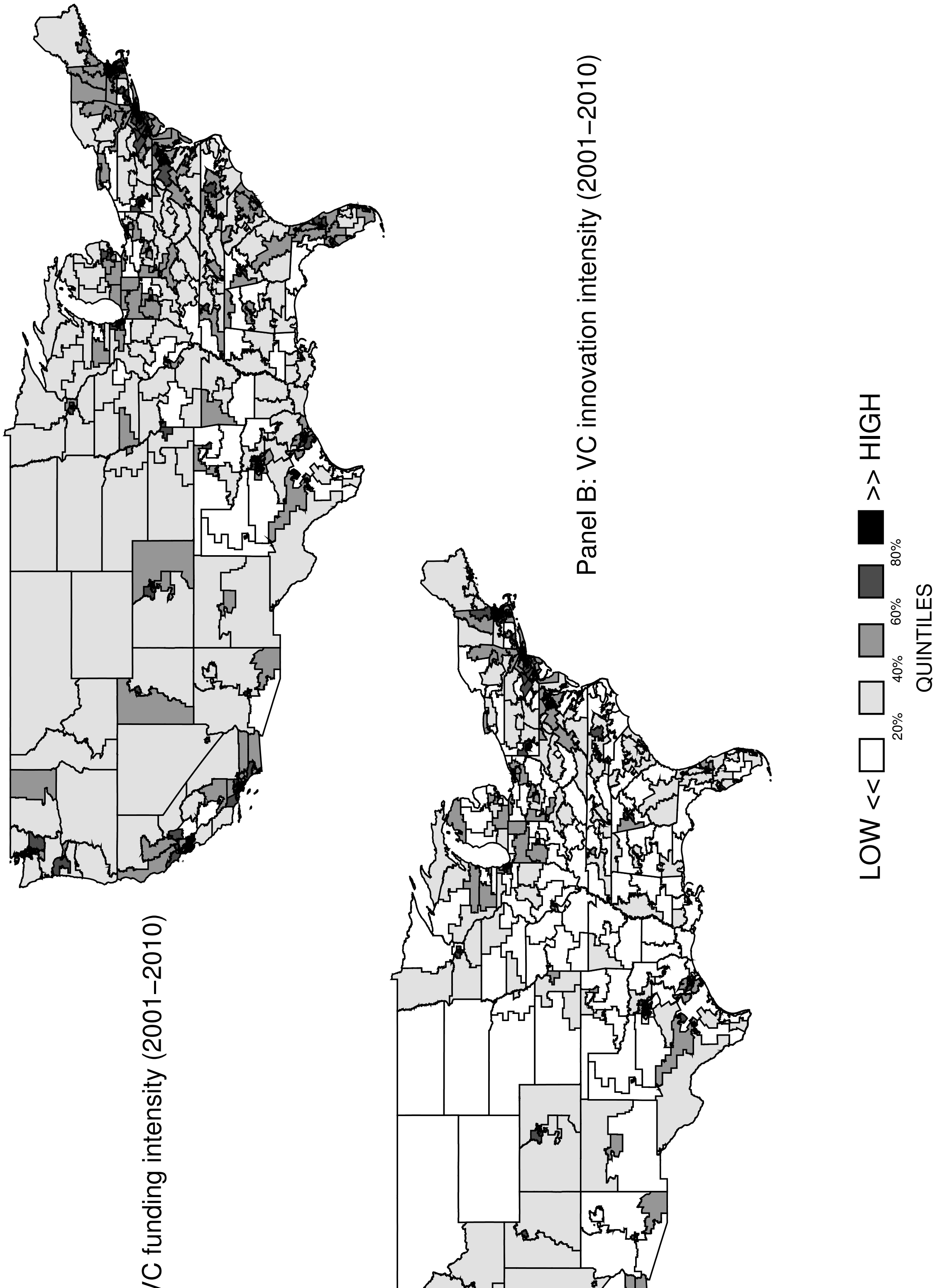


Figure 2.1: Geographical distribution of VC financing and innovation (2001-2010)

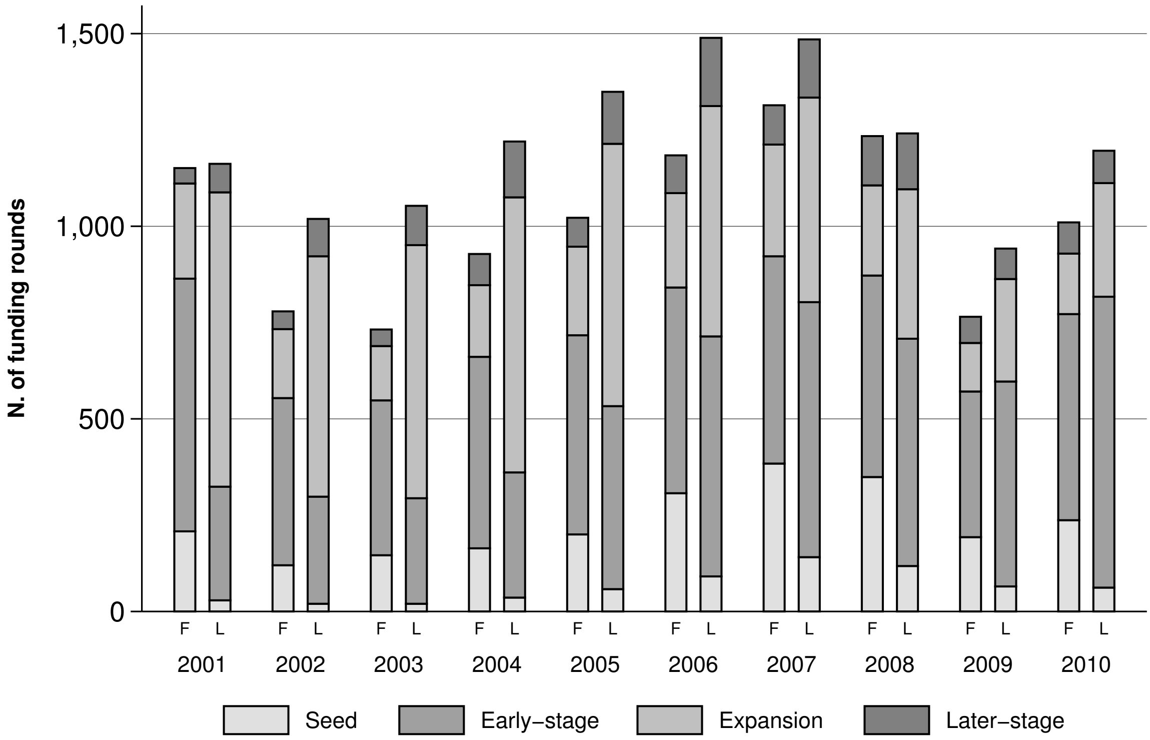
2.4 Empirical findings

2.4.1 Venture capital funding and patenting over the decade

Before turning to the multivariate analysis, this section presents the novel dataset obtained from the matching procedure by descriptively exploring general dynamics of venture capital funding and patenting activity between 2001-2010. Figure 2.2 plots the number of funding rounds by cohort and stage of the company at financing. It also differentiates for each cohort, the count of venture capital deals between first and later rounds. While the left bar depicts the number of companies selected (and funded) for the first time by venture capitalists, the right one sums all additional financing rounds directed to the same companies within five years since the first round. Staged instead of full upfront financing is a typical instrument used by VC in order to hold significant control rights on their investments. Moreover, first and later rounds serve different purposes. First round aims to select and provide the company with initial capital required, while follow-on financing holds up and guides the company growth towards defined milestones.

The visual analysis of the graph clearly identifies a general positive trend in the middle of the decade and two VC funding contractions connected to the burst of the Dot-com bubble (which for VC market started in 2001 but exerted most of its effects in 2002 and 2003) and the intense financial turmoil of the Global Financial Crisis. Both events substantially decreased the number of deals respect to the previous periods. The number of first rounds (left bars) decreased by almost 40% between 2001-2003 and again between 2008-2009. Considering the stage of the funded company, we observe a proportional drop in all the four stages of development. The evolution of follow-on rounds (right bars) exhibits a smoother path during the first part of the decade, whereas the reduction in the number of rounds it is still significant for the 2009 cohort. The number of follow-on investments, directed to the companies initially financed in 2002-2003 and in 2009, reduced by 10% and 40%, respectively. However, by solely analyzing ex-post realizations of follow-on deals, it is hard to distinguish a change in the VC strategic staging behavior from a deterioration of the companies performance (Da Rin et al., 2011).

The graphical illustration of the total amount disbursed (Figure 2.3) may help to shed some more light on this phenomenon. In fact, the impact of the financial crises on venture financing is also evident when funding size is taken into account. The amount available to companies at their first round (left bars) almost halved between 2001-2002, reaching the local minimum in 2003 at $4.7 billion. The following periods show a general recovery trend interrupted in 2008. In 2009 funding continued to shrink at fast pace (by 51% in one-year period), crashing at $3.8 billion. The last year of the decade shows a limited upswing in venture investment, signaling the end of the contraction. Interestingly, the investment flow following the first financing (right



NOTE: This figure provides a graphical illustration of the number of funding rounds divided by year of first financing (cohort) and company development stage at financing. The "F" bars show the number of "first" financing events by cohort. The "L" stands for "later" and in- dicates the number of follow-on rounds to the same companies, within 5 years since first event.

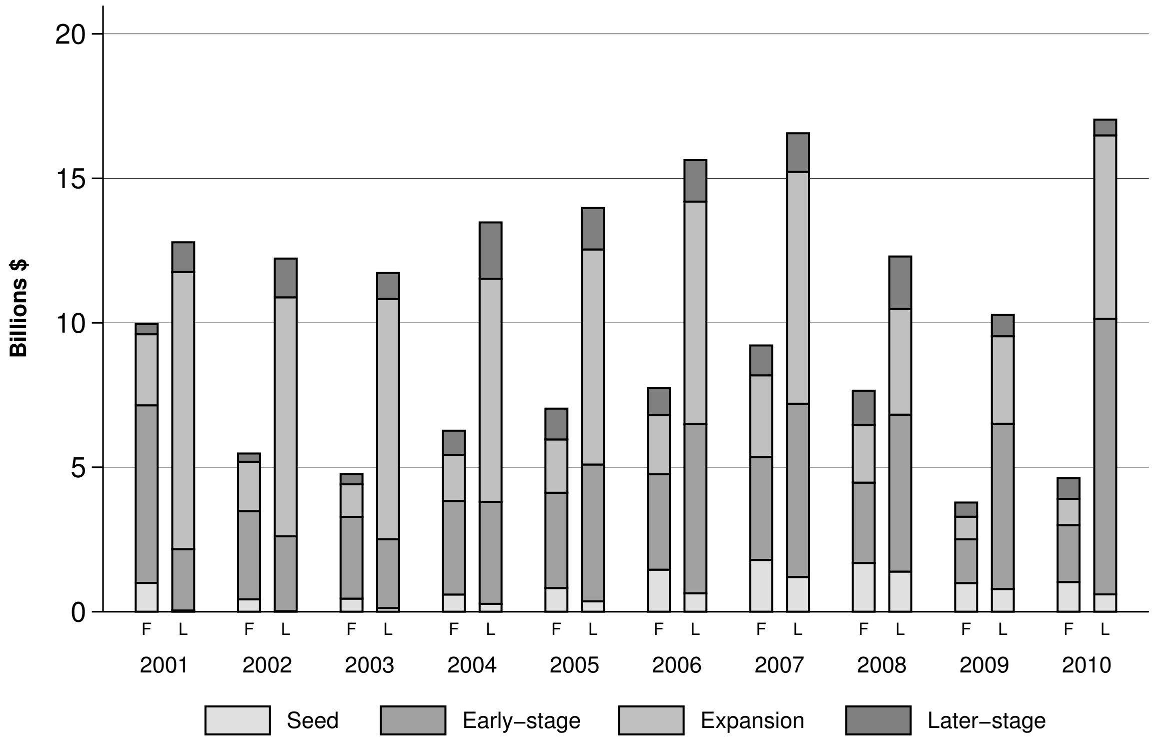
Figure 2.2: Number of funding rounds by cohort and stage at first financing (2001-2010)

bars) confirms the evidence highlighted in Figure 2.2. The cohorts financed for the first time during the aftermath of the Dot-com bubble have experienced only a slight reduction in the financing flows during the following five years. Conversely, the sum of follow-on financing dropped from $17 billion for the 2007 cohort to $12 billion raised by the 2008 one, reaching the minimum at $10.5 billion for the 2009 cohort. However, the figure shows how even the medium term consequences of the Global Financial Crisis are clearly over after 2009. In fact, the amount of follow-on investments directed to companies selected in 2010 moved back to the pre-crisis level ($17 billion). Furthermore, the analysis of the stage breakdown of first rounds (stacked left bars) highlights two differential maturity selection patterns in funds allocation. During the aftermath of the Dot-com bubble funding crunch was mainly concentrated in relatively younger companies. On the contrary, in 2009, VCs reduced their investments relatively more in expansion and later stage companies.

Overall, the figures clearly show that venture financing have indeed been affected by both financial downturns. The number of deals and the amount of funds provided, substantially lowered in connection with the two events. However, there is descriptive evidence which points out the deeper impact of the Global Financial Crisis on venture-backed companies. In particular, the amount invested in first financing and follow-ups reached the minimum values in 2009. Moreover, in the same year VCs seem to have selectively allocated their investments towards companies at earlier stage of development.

In order to examine the innovation performances of the venture-backed companies, Figures 2.4 and 2.5 present evidence of the patenting activity of the ten cohorts during the 2000s decade. Companies in each cohort share the year of first financing (and selection) as common characteristic. The vertical axis of Figure 2.4 reports the aggregated number of successfully granted patents registered in each one-year period by all the financed companies in the cohort. The horizontal axis displays the time elapsed since the first financing (time t). Patenting activity is followed from the year before the financing (t_{-1}) to the last year available ($t_{+13} = 2014$). Therefore, there are available fifteen one-year periods for the first cohort (2001) and only six for the last (2010).

Figure 2.4 provides many general insights. First, the figure clearly depicts a distinct common dynamics for all the cohorts. Patent count per period steadily increases in the first part of cohort life after financing, to later peak and slowly decrease to a lower level than the pre-financing one (t_{-1}). Evidently, the aggregated nature of the data does not allow to identify the nature of this pattern. The mortality of companies or a diminishing innovative push at company level are both valid explanations to this result. Second, venture-backed companies starts patenting even before venture capital involvement, but at a lower level. Moreover, 2009 and 2010 cohorts are the smallest at entry. Third, variability in patenting levels seem to increase after venture financing. Differences among cohorts on vertical axis steadily increase with time. Lastly, the



NOTE: This figure provides a graphical illustration of the total amount disbursed (in 2010 real terms) in funding rounds divided by year of first financing (cohort) and company development stage at financing. The "F" bars show the the amount provided in "first" financing events by cohort. The "L" stands for "later" and indicates the amount provided in follow-on rounds to the same companies, within 5 years since first event.

Figure 2.3: Total amount by cohort and stage at first financing (2001-2010)

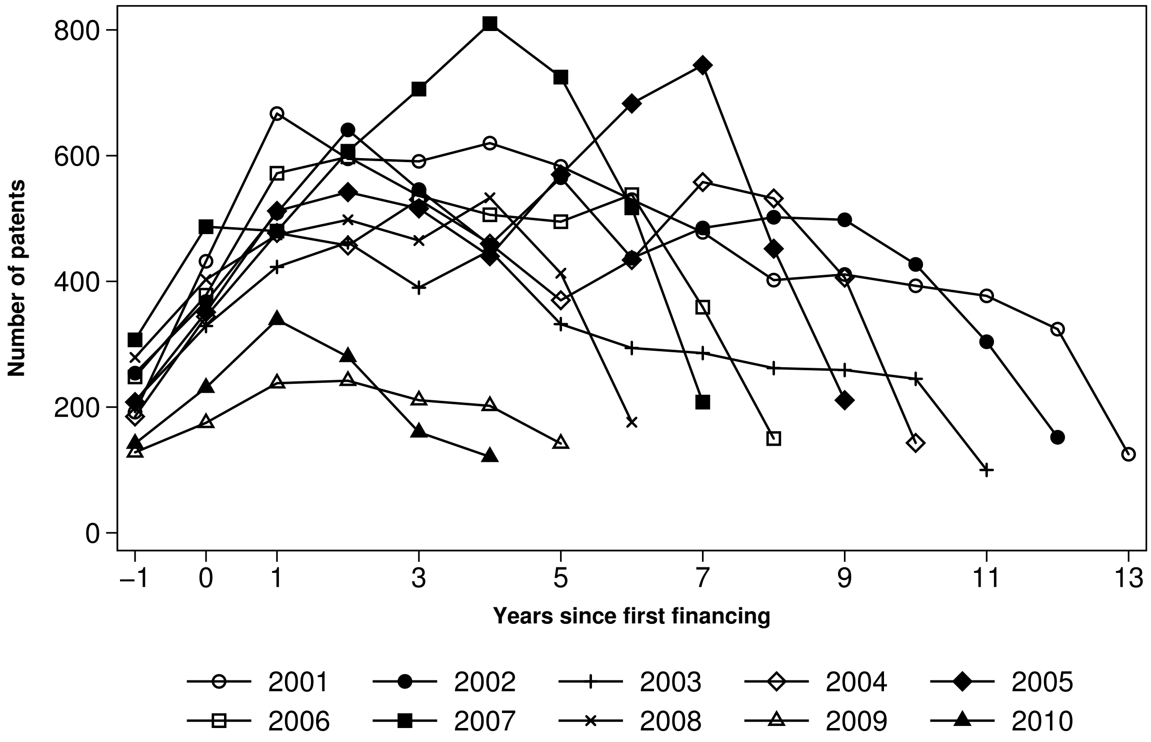


Figure 2.4: Total patent number by cohort (2001-2010)

figure shows a well-defined differential pattern between 2001-2008 and 2009-2010 cohorts. Both groups consistently cluster at different levels. The cohorts of companies financed during the Global Financial Crisis report a constant underperformance which increase with time. Note that 2010 curve, albeit starting from similar level at t_{-1}, exhibits a steeper slope for the first two periods, signaling an improving performance after the end of the slowdown. However, the spread between curves start decreasing at t_{+2} followed by a sharp drop which reverses the curves in the last two periods. This effect is likely to be due to the so called "truncation" (Hall et al., 2001). The problem arises as the period considered comes closer to end of the dataset. It is possible that application filed has not been granted yet at the time of data retrieval (updated up to the end of December 2015), resulting in missing observations bias. Truncation may have also affected the last part of 2009 time series. Graphically, only time t_{+5} shows a clear drop of patenting activity. Caveats are then required and will be discussed in the next sections.

Aggregated number of patents tend to be related to the venture investment activity. The bigger is the cohort of companies, the higher is the probability of a larger patent count. In order to rule out funding activity contribution, while focusing only on underlying innovative potential of the financed companies, Figure 2.5 plots on vertical axis the average number of patents per company within the cohort. This figure ranks innovation output by cohort above and beyond the absolute number of its members. As it is apparent, most of the characteristics highlighted

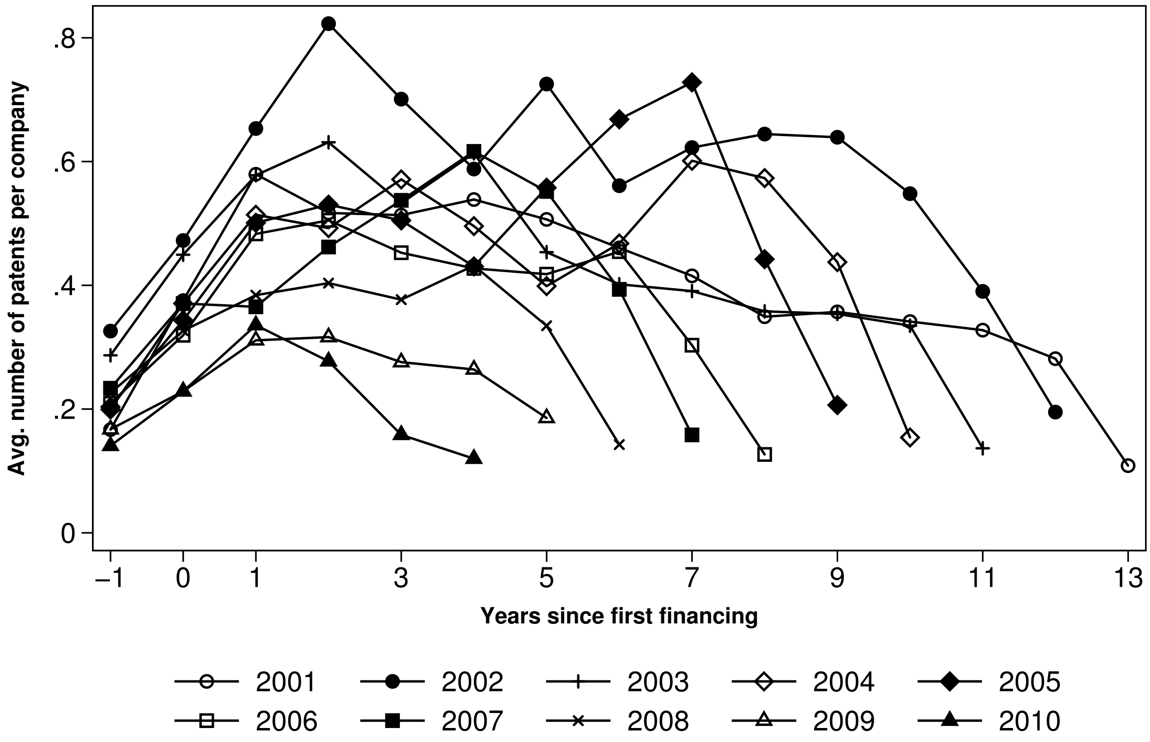


Figure 2.5: Average number of patent per financed company by cohort (2001-2010)

in the previous paragraph are still valid. In particular, clusters and trends remain very similar. The companies financed in 2009 have a significant lower level of patents per company with respect to the previous cohorts. There is a switch in the ranking of the most prolific cohorts in term of patenting, once cohort size is taken into account. However, on average, patenting by company remains always below one for all cohorts. This is suggestive of the concentration of the innovative activities. In fact, over the decade, many venture-backed companies were not involved at all in patenting.

Turning to the analysis of granted patents, Figure 2.6 gathers further descriptive evidence on their characteristics and quality. All graphs depicts the evolution of the ten cohorts by averaging their innovative performances over the five years following the first financing. Figure 2.6a considers only companies which have successfully granted at least one patent (and therefore are considered as assignee in USPTO records). It shows how the decrease of patenting during the GFC may be partially connected with a lower number of patents per assignee. The average (median) number of patents owned by each company is about 8(4) during the first part of the decade. In connection with the financial downturn of 2009, mean number shrinks to less than 6 while median is 3, but this value has lowered since 2005. This is indicative that this reduction is localized especially in the upper part of the distribution. Thus, between 2009-2010 the category of top innovators was less prolific than the past cohorts. We start analyzing the

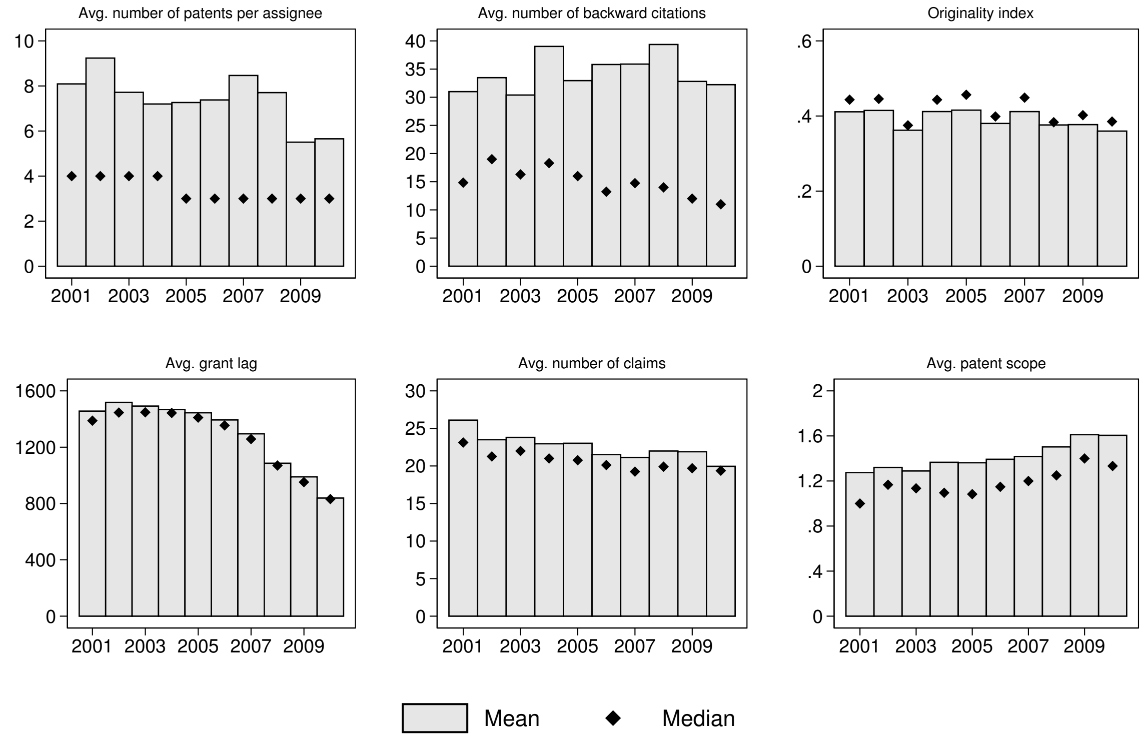


Figure 2.6: Patent characteristics by cohort (2001-2010)

quality of the patents registered by the different cohorts by considering the average number of backward citations included on patent applications (Figure 2.6b). Literature finds that absolute number of backward citations is positively related to the value of a patent, but could also signal the type of innovation (incremental vs. radical innovation) (Harhoff et al., 2003; Squicciarini et al., 2013). Citations fluctuates around 30 during the negative cycle, but increases at about 40 between 2004-2008, during a relatively tranquil period. Even, the originality index (Figure 2.6c), which measures the concentration of backward citations among different technological classes, remains close to .4 with a slight decrease during the last years of the decade. A relevant shortening of time in granting procedure is highlighted in Figure 2.6d. There is a continuous trend in mean and median reduction of grant lag since 2006. The time elapsed between the application date and the grant date reduced from about 1400 days to 850 in 2010. Also the average number of claims decreases during the decade, but at moderate pace (Figure 2.6e). On the contrary, patent scope which accounts for the technological and economic value of patents, slightly increases during the decade, and in particular in the last two years (Figure 2.6f). Overall, with the exception of the average grant lag the dynamics of patent quality during the 2000s remains limited with mixed evidence. There are weak signs of quality deterioration over time exhibited by the reduction in backward citations, originality and number of claims. Whereas the decrease of grant lag and the improvements in patent scope are evidence of quality increasing.

Summing up, the descriptive evidence in this section shows interesting general features about venture funding and innovative output of the 2000s. During the decade, the burst of the Dot-com bubble and the GFC have seriously affected the cohorts selected and financed for the first time in these periods. Number of rounds and amount provided significantly decrease in both periods, but the effects appear deeper and more enduring for the Global Financial Crisis. This picture is confirmed by the evidence provided for patenting. With respect to the other cohorts, 2009 and 2010 cluster on a lower level of aggregated patent count and number of patent per assignee. This difference is noticeable before financing, and it is increasing in company age. Moreover, in comparison with venture funding which spreads beyond the well-known venture capital centers of the coasts, patent production appears more geographically concentrated on few urban areas of east and west coast. Lastly, the quality of the patented innovation, as measured by several different indicators, does not appear to respond much to the economic slowdowns. They fluctuates around similar level or move following historical trends. Yet, this evidence alone neither helps in framing the whole picture of the venture innovation over the decade, nor can assess the single contribution of the manifold aspects which influence patenting. Thus, the following sections will describe the empirical methodology and examine this relationship in a multivariate context.

2.4.2 Empirical methodology

Cohort models aim to rule out the life-cycle age-related component and the aggregate yearly fluctuations from the time-invariant effect of cohort membership. In this paper, the cohort effects capture the secular trends on patenting behavior which differentiate various cohorts, net of age and year fixed-effects. The former controls the effect of the venture-cycle position on the number and quality of granted patent, while the latter holds constant the synchronous but temporary shocks in patenting which may affect the sample during different periods. Therefore, in the presence of systematic life-cycle patenting pattern, a shift on age selection would not impact on the cohort coefficients. However, this methodology is not exempted from strong assumptions. So, cohort data decomposition assumes that every interaction effect among age, cohort, and years is not statistically significant (Deaton, 1997). For example, here we assume that the shape of patenting behavior by age does not significantly depend on the cohort analyzed.

Clearly, linear age-period-cohort (APC) models suffer from a fundamental identification problem: there is perfect linear dependence between these effects. Without independent variation among those variables, a model including APC effects cannot be identified. Literature has developed several techniques to overcome this well-known problem (Glenn, 2015). The simplest solution is omitting one of the variable, but it comes at the cost of forgoing one of the three dimensions. Alternatively, Deaton and Paxson (1994) developed a normalization which requires that year effects sum to zero. Nevertheless, here we do not need any normalization to break the perfect multicollinearity. We can simply substitute age with the ordinal variable "stage at financing" as reported by Thomson One. This variable registers the starting point and the progress of the startup through the venture-cycle across four stages. The evolution through the different stages of development may be slightly related to the years since the first financing (age), but the latter is independent from the starting stage. Arguably, it is the development stage that influences patenting the most. Hence, the life-cycle component is controlled in the regressions by three stage dummies.

In order to test the sensitivity to the size of funding, our specification includes a variable which controls for the amount of capital (in real terms), raised by companies in each one-year period. This measure is also entered into the regressions with a one-year lag to take into account a possible delay in response of the dependent variable. Moreover, variation in patenting behavior may also be accounted by the compositional changes of cohorts. For example, if the sector composition changes systematically over the years, aggregate patenting will display a variation which is not only indicative of corresponding cohort effect, but it also captures a different propensity to patent across industries. Consequently, industry and region fixed effects are employed throughout, as illustrated in Table 2.1. However, nine sectors and five regions fixed effects may be not sufficient to absorb all the confounding factors. In principle propensity to patent may vary also within industry, at specific sub-sector level. Moreover, exogenous shocks on patenting may be not effectively controlled by the period component, if the arrival of technological opportunity is restricted to a specific sector and not to the aggregate economy. Lastly, patent examiners have very specific scientific background and work in "art units" which examine cases in the same area of technology. Level of scrutiny or set of explicit rules may vary at unit level, above and beyond the inventors' abandonment rate which is likely to depend more on market and economy conditions. Differences in patent allowance rates across technological area are therefore relevant and widely recognized in patent literature (Carley et al., 2013). As a result, if not sufficiently controlled, this variability may also bias the results of the cohort analysis. In order to partially address all these issues, we include a set of controls, one for each response variable analyzed, which refers to the universe of patents registered at US Patent Office. They report the number of applications (irrespective of company financier and granted status) for patent count and the average patent quality for the generality of granted patents in the same technological category (NBER subclass) and same year of the sample observation. Moreover, in the main specification for patent count, the ratio of issued patents to the total of applications presented by the universe of businesses is added to control the exogenous variation in patent allowance rate by technological class and year. The share of patents of new venture-backed startups over those belonging to the generality of businesses is very small, hence the overall variation captured by these set of controls may be considered as mainly exogenous to the companies in our sample.

Formally, the main empirical model takes the form:

$$Y_{ict} = \alpha + S\kappa + T\zeta + C\beta + \Gamma\chi + F^{(t,t-1)}\lambda + \theta + \psi + u_{ict}$$

where the patenting outcome of interest (Y) of startup i, belonging to cohort c, and observed in year t, is estimated as the linear combination of company development stage S, time T and cohort C, a set of controls Γ for common patenting behavior, the funding raised F, industry and region fixed effect (θ and ψ), and an error term (u_{ict}). Dependent variables are alternatively the number of issued patent, the number of backward citations, the patent originality, grant lag, number of claims and patent scope. As we aim to test the existence of a time-invariant cohort effect, common to all companies selected on the same year, the model specification cannot absorb also the firm-specific fixed effect, but the standard error is clustered at firm level.

Lastly, truncation problem highlighted in the graphical analysis must be addressed here. As we have seen, truncation appears when the years of analysis approach the temporal limit of the dataset, resulting in yet missing observations. When the scope of the analysis is focused on relatively recent events, there is an evident trade off between the length of the examined period and the extent of truncation bias. Graphically, Figures 2.4 and 2.5 show that such a problem is evident for years 2014 and 2015. First of all, we dropped 2015 from the sample. Consequently, by limiting the study on patenting outcomes to the year of financing and to the following four one-year periods, we exclude much of the possible truncation bias in every cohort, but in the 2010 one. The effect is clearly visible on the graphs, where 2014 represent an important turning point for the last cohort. Thus, caveats are needed when interpreting the results for this cohort. However, in order to verify that truncation is not significantly confounding the cohort effects, as robustness check, cohort analysis for patent count is replicated reducing the panel time dimension to three and four periods. The fact that this test yields similar results is more reassuring on the robustness of the evidence presented in the next paragraph.

2.4.3 Multivariate analysis

This section addresses the question of the existence and the magnitude of a generational effect which persistently lowers innovation output of the startups first financed during downturns. Here regression analysis is employed on patent count and patent quality measures, holding constant all the possible factors which influence patenting behavior as well as accounting for aggregate time trends and other confounding factors. Moreover, the next section will check the robustness of the analysis, and extend its scope by including a test for ex-post probability of failure and successful exit by cohort.

Table 2.3 reports the results of the regression on the number of obtained patents by each

Dependent variable: Number of issued patents						
	APC model + funding			APC model + funding + other controls		
	(1)	(2)	(3)	(4)	(5)	(6)
Cohort 2002	.151	.173	.169	.062	.075	.083
	[.154]	[.152]	[.151]	[.126]	[.125]	[.123]
Cohort 2003	-.107	-.006	-.012	-.175	-.162	-.162
	[.140]	[.139]	[.139]	[.119]	[.119]	[.115]
Cohort 2004	-.294**	-.144	-.151	-.213*	-.190*	-.182*
	[.132]	[.129]	[.129]	[.113]	[.113]	[.109]
Cohort 2005	-.278*	-.058	-.067	-.154	-.127	-.136
	[.147]	[.144]	[.144]	[.124]	[.124]	[.123]
Cohort 2006	-.366**	-.060	-.074	-.200	-.188	-.209
	[.164]	[.161]	[.161]	[.150]	[.152]	[.151]
Cohort 2007	-.355**	.036	.020	-.178	-.133	-.121
	[.157]	[.159]	[.159]	[.147]	[.147]	[.142]
Cohort 2008	-.577***	-.122	-.139	-.288*	-.228	-.198
	[.172]	[.163]	[.163]	[.148]	[.147]	[.144]
Cohort 2009	-.855***	-.352**	-.370**	-.434***	-.364**	-.394**
	[.180]	[.176]	[.176]	[.168]	[.167]	[.165]
Cohort 2010	-.872***	-.351**	-.371**	-.476***	-.407**	-.414***
	[.181]	[.175]	[.176]	[.160]	[.159]	[.156]
Stage at Financing dummies						
Early Stage		.521***	.518***	.236***	.229***	.212***
		[.083]	[.083]	[.068]	[.067]	[.066]
Expansion		.906***	.892***	.480***	.451***	.418***
		[.089]	[.089]	[.074]	[.074]	[.073]
Later Stage		.951***	.937***	.454***	.426***	.382***
		[.111]	[.111]	[.094]	[.094]	[.092]
Total Investment			.002***	.002***	.001***	.001***
			[.000]	[.000]	[.000]	[.000]
Total Investment (1 year-lag)					.006***	.005***
					[.002]	[.002]
Patent Allowance rate				.068***	.068***	.064***
				[.001]	[.001]	[.001]
Overall Patent Applications						.003***
						[.000]
Years effects	YES	YES	YES	YES	YES	YES
Industry effects	YES	YES	YES	YES	YES	YES
Region effects	YES	YES	YES	YES	YES	YES
Observations	50.555	50.555	50.555	50.415	50.415	50.415

NOTE: This table reports the results of the Poisson regressions over the number of issued patents. Symbols *, ** and *** denote significance level of 10%, 5% and 1%, respectively.

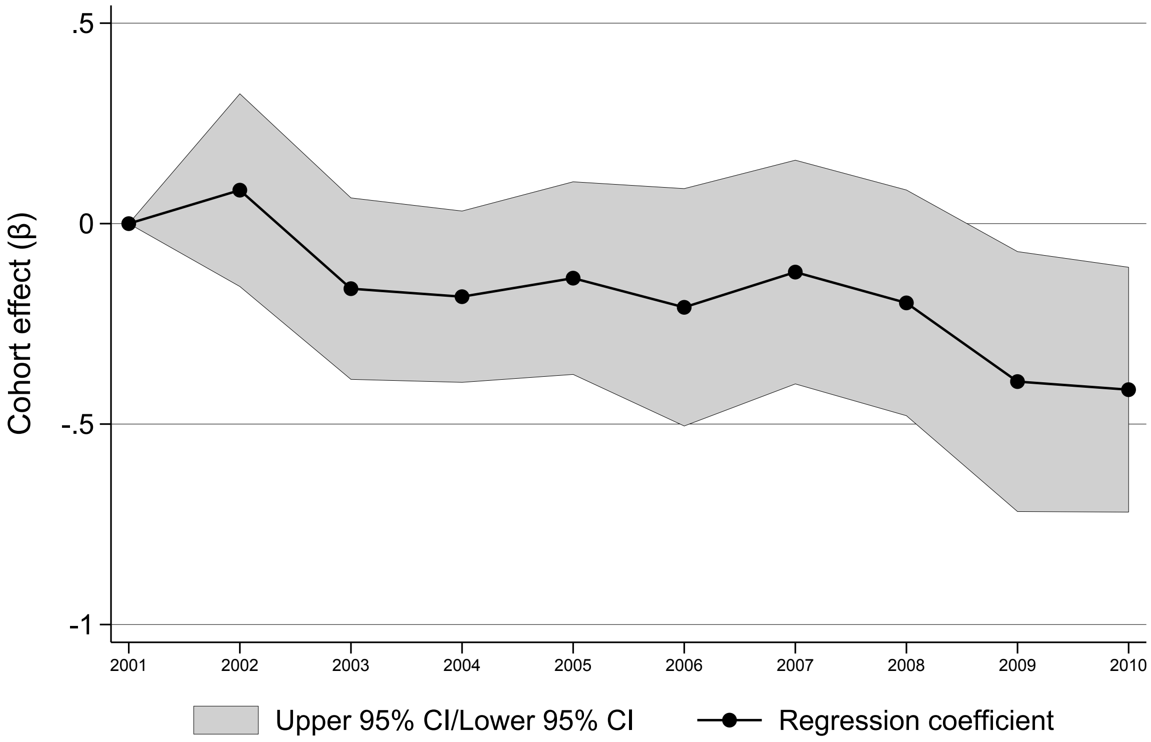
Table 2.3: Poisson regressions of patent count

startup in the five years following its financing. The outcome analyzed is a count variable which take non negative integer values, with a great amount of small numbers, including zero. Normality assumption of linear regression cannot hold here, therefore count dependent variable is estimated through a Poisson regression model. Poisson coefficients of continuous explanatory variables, multiplied by 100, are interpreted as the percentage change in expected number of patent, ceteris paribus. Alternatively, dummy variable effect is interpreted as $[exp(\beta)-1]\times 100$ change with respect to the base category (omitted dummy). First three columns fit an age-period-cohort model, augmented with funding size variable in order to jointly test all the three supply-side transmission channels hypothesized in Section 2.2.2. The remaining columns will test its robustness to the addition of other variables which control for possible confounding factors.

Column 1 starts testing the existence of the cohort effects over the period analyzed, taking 2001 as base category, and controlling just for yearly fluctuations which equally affect all cohorts, industry and region fixed effects. Although this represents a very simple baseline, it is useful to preliminary confirm the descriptive evidence, holding constant industry and region reallocation. As it is apparent from the table, cohorts financed in the aftermath of the Dot-com bubble patented significantly more than following cohorts. Magnitude of the negative effect seems to grow towards the end of the sample, when the coefficient spikes from -.58 to -.85 during the Global Financial Crisis. Being selected and financed by VCs for the first time in 2009 instead of 2001, implies a reduction of 57% in expected number of issued patents. Yet, this dramatic effect is not surprising. Figures 2.4 and 2.5 have showed a persistent lower level of patenting especially concentrated in 2009 and 2010 cohorts. Moreover, 2001, 2002 and 2003 cohorts were among the most prolific groups both in total and in average number of issued patents per company. However, these coefficients may be upward biased, also capturing all the other effects associated with the specific group selected in each year (e.g. a lower funding or a shift in development stage). Column 2 makes a further step, presenting a complete APC model. We account for the age composition of each cohort, by adding the ordinal level variable of stage at financing. This inclusion substantially change the picture. First, the significance and the magnitude of the stage at financing dummies confirm the differential impact of development stage on the number of issued patents. Average patenting steadily grows through all steps of venture-cycle. For example, the coefficient of the "expansion stage" dummy implies that, other factors being equal, the expected number of patents for a startup in that stage is almost 1.5 times higher than a comparable "seed" startup (coefficient is .906, significant at 1%, that is equivalent to a difference of 147%). Second, all cohorts coefficients, but 2009 and 2010 ones, are now insignificant. Much of the negative cohort effect registered in column 1 is explained by the movements in development stage composition associated to each cohort. However, even when controlling for stage at financing, yearly fluctuations, industry and region fixed effects, the cohorts financed during 2009 and 2010 still experience a persistent negative effect. The model estimates a 30% reduction in patenting for the two financing years with respect to the 2001, while there is not any significant difference for 2002-2008 cohorts. In column 3 the amount of funding size provided by venture capitalists is added to the APC model. Through this variable we control for under funding which may hinder innovation process. The coefficient is highly statistically significant (at 1%), but economically low. In fact, it implies a 20 basis point increase in expected number of patents. The other coefficients remain substantially unchanged. The fact that 2010 effect remains as negative as 2009 even though economic environment was recovering is still puzzling. Descriptive statistics highlighted the role of truncation bias in explaining this outcome. The next section will deal with this problem testing the robustness of the results and easing the concerns on their validity.

Columns 4-6 extend the cohort analysis, by testing the robustness of the estimates to the inclusion of three different variables which controls for patent office specific allowance policies, the lag in the effect of funding and the patenting trends at patent class. In column 4, average patent office allowance rate, at technology class and year level, enters positive and highly significant in the regression. This coefficient therefore highlights the fact that, as expected, part of the variability in patenting is explained by the different allowance policies in each "art unit". In fact, as the allowance rate widely varies across technology fields, movements across technological areas among cohorts may confound their effects. Once allowance rate is controlled for, the impact of stage at financing generally reduces while 2009 and 2010 coefficients increase their magnitude and statistical significance (from 5% to 1%). However, changes in the effects are limited (4 percentage points more for the 2009 cohort) and substantive interpretation does not change. Interestingly, negative cohort effect for 2009 and 2010 is robust to the inclusion of the lagged funding (column 5). Despite patenting seem to respond significantly more to the investment disbursed in the previous year, the effects of of both coefficients remain significant but low (60 basis points for previous year and 10 basis points for the same year funding). Lastly, adding the overall number of patents, to control for the exogenous arrival of technological opportunities (column 6), substantially confirms the previous results. Sign and significance are very similar. The expected reduction in the number of patents for startups selected in 2009 is 31% in the APC model augmented with funding size (column 3), while it rises to 32.5% when considering also other confounding factors (column 6).

Figure 2.7 graphically summarizes the evolution of the cohort effect estimated in column 6. According to the VC market trends illustrated in the descriptive analysis, we divided the decade in three periods: the aftermath of the Dot-com bubble (2001-2003), the tranquil period between 2004-2008 and the period following the Global Financial Crisis (2009-2010). The figure clearly identifies a common trend between 2001-2008. There is not any statistical significant evidence which differentiates the cohort selected up to 2008 from the base category of 2001, holding constant other factors. However, things change when considering the cohorts following the GFC. The analysis confirms the existence of a common negative generational effect which persistently (up to the fifth year after financing) lowers the number of issued patents. The *ceteris paribus* estimated negative difference is around 30%, irrespective of the model specification used. Interestingly, we find that every transmission channel hypothesized in Section 2.2.2 exerts a significant impact on innovative outcome. In particular, both funding size and progress in development stage have a positive and significant effect on patenting. Failing to control for these factors may bias the cohort effects when the former correlate with cohort selection.



NOTE: This figure plots the cohorts coefficients estimated through the Poisson regression $Y_{ict} = \alpha + S\kappa + T\zeta + C\beta + \Gamma\chi + F^{(t,t-1)}\lambda + \theta + \psi + u_{ict}$ where Y is the number of issued patents in the five periods following first financing. The 2001 cohort is normalized to zero. Confidence interval (at 95%) is included in the shaded area.

Figure 2.7: Cohort effect on issued patents (2001-2010)

Dependent variable: Number of issued patents	Biotech	Computer & Electronics	Healthcare	Industrial & Energy	IT Services & Telecom	Media & Entertainment	Services & Retail./Distr.	Software
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cohort 2002	.054	.326	-.217	.003	-.317	-1.191***	.983**	.394*
	[.199]	[.246]	[.280]	[.319]	[.375]	[.399]	[.483]	[.223]
Cohort 2003	-.063	-.332*	-.220	-.257	.205	-1.435***	-.953**	-.100
	[.256]	[.187]	[.282]	[.351]	[.257]	[.445]	[.415]	[.195]
Cohort 2004	.506*	-.113	-.408	-.782**	-.287	-.549	-.987*	-.072
	[.284]	[.191]	[.255]	[.354]	[.229]	[.434]	[.525]	[.221]
Cohort 2005	.110	.090	-.685**	-.669*	-.335	.030	.655	.065
	[.214]	[.240]	[.310]	[.349]	[.277]	[.423]	[.990]	[.232]
Cohort 2006	.158	-.349	-.750**	-.461	-.040	-1.937***	-.511	.707*
	[.247]	[.224]	[.330]	[.358]	[.425]	[.560]	[.899]	[.373]
Cohort 2007	.229	.096	-.464	-.499	-.298	-1.415*	.456	.014
	[.254]	[.283]	[.310]	[.352]	[.304]	[.730]	[.939]	[.245]
Cohort 2008	.197	.069	-1.036***	-.413	-.208	-1.510**	-.141	.207
	[.262]	[.284]	[.312]	[.361]	[.361]	[.706]	[1.019]	[.289]
Cohort 2009	-.034	.004	-.936***	-1.001***	-.171	-2.746***	-.175	.293
	[.310]	[.390]	[.361]	[.371]	[.430]	[.852]	[.932]	[.277]
Cohort 2010	.179	-.562	-.825**	-.958**	-.159	-2.666***	-1.392	.329
	[.283]	[.357]	[.346]	[.390]	[.461]	[.827]	[1.030]	[.340]
Stage at Financing dummies								
Early Stage	.294***	.083	.223**	.316	.349**	-.110	-.389	.166
	[.098]	[.151]	[.107]	[.207]	[.167]	[.355]	[.348]	[.179]
Expansion	.504***	.228	.297**	.283	.597**	.616	.044	.258
	[.121]	[.159]	[.140]	[.208]	[.299]	[.388]	[.346]	[.180]
Later Stage	.700***	.140	.263	.107	.644**	-.400	-.572	.251
	[.189]	[.190]	[.204]	[.222]	[.327]	[.407]	[.420]	[.168]
Total Investment	.004***	.013***	.014***	.003***	.006*	-.002	-.003	-.000
	[.001]	[.002]	[.004]	[.001]	[.003]	[.004]	[.006]	[.000]
Total Investment (1 year-lag)	.011***	.011***	.012***	.002	.007**	.006*	.011***	.014***
	[.002]	[.002]	[.004]	[.002]	[.003]	[.003]	[.003]	[.004]
Patent Allowance rate	.055***	.065***	.058***	.062***	.079***	.102***	.104***	.074***
	[.002]	[.002]	[.003]	[.002]	[.008]	[.005]	[.006]	[.002]
Overall Patent Applications	.007***	.002***	.004***	.004***	-.001	-.003**	.001	.001**
	[.001]	[.000]	[.001]	[.001]	[.001]	[.001]	[.002]	[.001]
Years effects	YES	YES	YES	YES	YES	YES	YES	YES
Region effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	5.824	5.545	5.026	4.006	6.183	4.893	3.680	13.824

NOTE: This table reports the results of the Poisson regressions over the number of patent issued in each industry. “Financial Services and Others” has been omitted due to its limited number of observations and heterogeneity. Standard errors (in square brackets) are robust and clustered at company level. Symbols *, ** and *** denote significance level of 10%, 5% and 1%, respectively.

Table 2.4: Poisson regressions of patent count - Sectors

Another important aspect which should be considered in this analysis is that the previous results may be driven by a concentrated effect on few specific sectors rather than being a generalized trend across all industries. In fact, the degree of innovation captured by patents can be a quite stable requirement in specific high-tech sectors, while other industries are able to hold profitable projects at different levels of innovation. For example, the variability in innovative level incorporated in businesses belonging to the biotechnology or software industries may be much lower than the ones competing in services, retail or entertainment. On average, step in the biotech market requires inevitably large degree of innovation, while a project in other sector can be economically viable even if it does not absorb an high level of formalized innovation, as accounted by patents. Ex ante, we expect that over time variation on innovation and patenting would be more evident in sectors where they do not represent a tacit requirement to effectively compete, but where investors are more likely to effectively face the choice between a safer or a more innovative project.

To address this question, Table 2.4 replicates the cohort analysis at industry level. As can be seen, the analysis confirm that a strong cohort effect appear in healthcare, industrial & energy and media & entertainment and it is especially concentrated during the GFC. For the 2009 cohort, with respect to 2001, the model estimates a reduction in these sectors ranging from 61% to 94% (statistically significant at 1%), while the other sectors have not significantly changed their patenting behavior, once all other factors are held constant. However, media & entertainment which shows the most negative cohort effect, reduced its patenting even before the GFC, but the estimated negative effect peaked for the 2009 cohort. Conversely, cohort effect is non existent in other industries. For example, cohort dummies of software industry are generally positive, even if not significant at conventional level. Arguably, the aggregation choice can influence the sign and significance of the combined categories. Here a broader aggregation is preferred in order to have sufficient sample size in each industry for a cohort study. However, even if caveats should be borne in mind when interpreting this results, a more detailed sector-based analysis is out of the scope of the present paper.

So far, the multivariate analysis has embraced only the quantitative dimension of patenting. However, as explained in the descriptive analysis, measurements of innovation should include also the concept of patent intrinsic value. Although every patent to be accepted should meet defined innovative standards, underlying technology may greatly differ in quality and novelty, resulting in a highly skewed distribution of values (Griliches, 1990). To examine the extent to which external conditions influenced also the intrinsic quality of issued patents, Table 2.5 reports regressions which use measures of patent quality as dependent variable. Therefore, cohort analysis has been re-run via linear regression, but limiting the sample to those companies which actually patented over the period analyzed. As explained in Section 2.3, data availability limited the extent to which all aspects of quality can be controlled for. In particular, due to

Dependent variable: Patent Quality Indicators	Patent Scope	Backward Citations	Originality Index	Number of Claims	Grant Lag
	(1)	(2)	(3)	(4)	(5)
Cohort 2002	.003	-1.281	.025*	-.220	6.866
	[.018]	[3.249]	[.013]	[.555]	[20.043]
Cohort 2003	-.025	-4.060	-.001	.118	8.771
	[.018]	[3.494]	[.013]	[.531]	[21.054]
Cohort 2004	-.003	.622	.026*	.770	14.214
	[.020]	[3.322]	[.013]	[.578]	[20.863]
Cohort 2005	-.016	-1.638	.035**	.553	25.739
	[.022]	[3.532]	[.014]	[.533]	[21.274]
Cohort 2006	-.014	-.142	.030**	.509	33.406
	[.023]	[4.186]	[.015]	[.576]	[21.810]
Cohort 2007	-.040*	-2.765	.048***	.521	53.666**
	[.023]	[3.877]	[.016]	[.601]	[22.580]
Cohort 2008	-.028	1.084	.053***	.841	42.474*
	[.028]	[5.140]	[.017]	[.670]	[22.915]
Cohort 2009	-.003	-3.554	.049***	1.036	56.759**
	[.032]	[4.683]	[.019]	[.727]	[23.786]
Cohort 2010	-.048	-1.392	.059***	.693	43.506*
	[.035]	[5.193]	[.019]	[.683]	[24.658]
Stage at Financing dummies:					
Early Stage	-.004	-2.693	.035***	-.090	-8.183
	[.013]	[3.510]	[.007]	[.304]	[8.954]
Expansion	-.018	-.756	.051***	-.649*	-12.254
	[.014]	[3.792]	[.008]	[.340]	[10.002]
Later Stage	-.017	-4.132	.043***	-.681*	-19.396
	[.017]	[4.131]	[.010]	[.377]	[12.249]
Total Investment	-.000	.038	.000	.001	.016
	[.000]	[.048]	[.000]	[.002]	[.049]
Total Investment (1 year-lag)	-.000	.250***	.001***	.012	-.128
	[.000]	[.072]	[.000]	[.008]	[.203]
Patent Quality Control	.986***			1.284***	1.006***
	[.007]			[.013]	[.006]
Years effects	YES	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES	YES
Region fixed effects	YES	YES	YES	YES	YES
R squared	.722	.091	.034	.570	.818
R squared adj	.722	.088	.032	.569	.817
P-value	<.001	<.001	<.001	<.001	<.001
Observations	14.780	14.780	14.780	14.780	14.780

NOTE: This table reports the results of the linear regressions over the patent quality indicators. Due to computational power constraints we were not able to estimate the corresponding patent quality control for “Backward Citations” and for its derivate “Originaly Index”. Standard errors (in square brackets) are robust and clustered at company level. Symbols *, ** and *** denote significance level of 10%, 5% and 1%, respectively.

Table 2.5: Linear regressions of patent quality

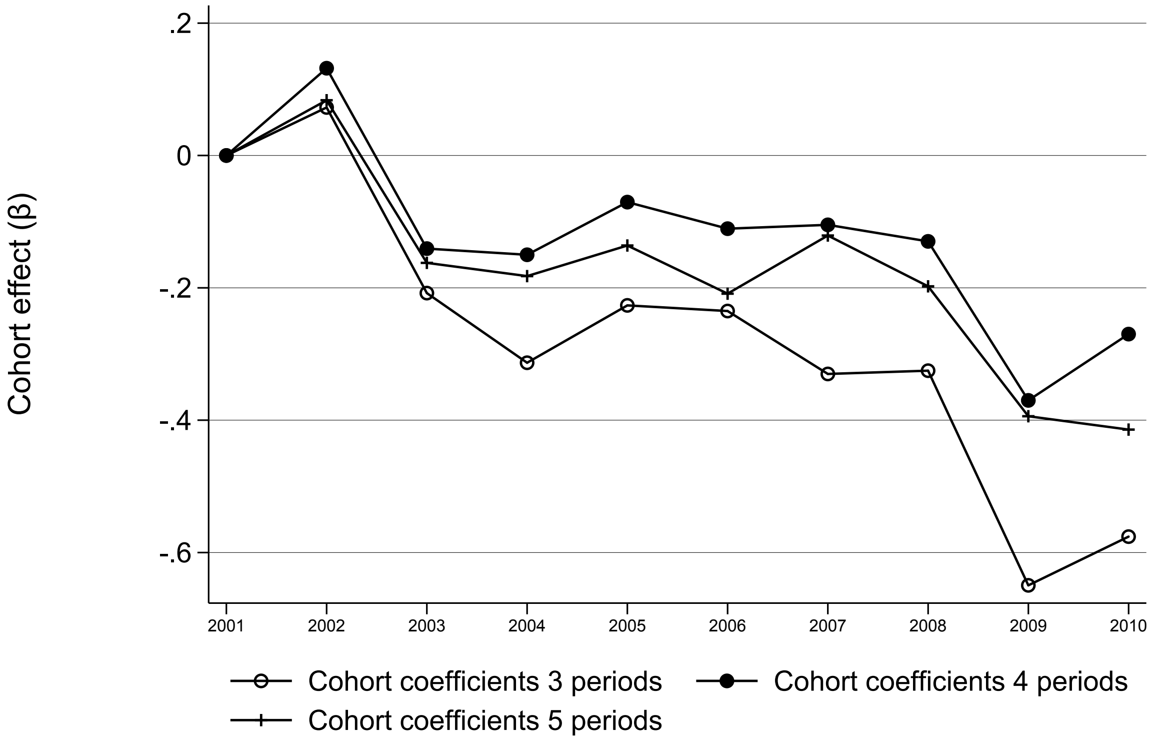
the closeness to the period of analysis, measure of generality and patent diffusion has been excluded from the current study. Indeed, all those measures are based on forward citations (citations received by the patent in force from subsequent patents) which need a sufficient time lag to be effectively captured. We rely on backward citations (originality), patent scope, claims and grant lag. The results highlight that there is not any significant change at cohort level in the domain of quality, with the exception of the improvements in originality and grant lag (columns 3 and 5). However, the latter do not refer to a specific period, as it is in the patent count analysis, but they seem to be connected to a gradual improvement over time (started at least from 2005). Nevertheless, the lack of strong evidence in support of a generational effect using the previous proxies, does not imply that the overall innovative content of patents has not been persistently influenced by the startup selection during uncertainty shocks. Trajtenberg et al. (1997), who also introduced these measures in the literature, find that proxies based on forward citations are the closest to the concept of a seminal and novel innovation, while backward citations mostly fail to account for these aspects. Hence, the extent to which financed startup has produced patents with less (or more) innovative value during the financial shocks of the 2000s remains an open question, that should be reassessed once more data will be available.

Overall, the previous analyses confirm the presence of a generational effect which selectively lowers the innovation capabilities of startups selected and financed during financial shocks connected to venture capital market drying-ups. However, results limit this finding to the cohort selected in 2009 when the effects of the Global Financial Crisis were at its highest. On the contrary, cohorts selected during the aftermath of the Dot-com bubble when funding available shrank similarly to 2009, are not significantly different from the tranquil period in the middle of the decade, when funding showed a positive trend. This evidence is robust to the inclusion of life-cycle age-related components, aggregate yearly fluctuations and funding provided over time. Moreover, even accounting for other confounding factors does not substantially change this conclusions. Companies selected during the Global Financial Crisis displays an enduring innovative gap (on average 30%), holding constant other factors. Sector based analysis points to the fact that this negative cohort effect is concentrated (and much higher) on industries where high degree of formalized innovation is a less pressing entry requirement. For example, biotechnology and software companies did not experience any innovation gap during GFC. Lastly, patent quality of venture-backed companies, as measured by backward citations, patent claims, scope and grant lag, does not appear to have been significantly affected by the financial shocks of 2000s.

2.4.4 Robustness checks

In this paragraph several tests are run to check the robustness of the previous results. First, truncation problem is addressed here. As previously discussed, patent count truncation can be a substantive issue, especially when analyzing recent years (as we did for GFC). The descriptive statistics highlighted a lower patenting level between 2009-2010 and multivariate analysis confirmed the presence of a negative generational effect of those cohorts with respect to the 2001. Although the empirical strategy made sure to distance, as much as it could, the period analyzed from the truncation point, major concerns on the validity of the results must be eased here. These concerns derive from the fact that patent count may blur the line between negative cohort effect and truncation. We want to be sure that the estimated effect is a genuine cohort effect and not only an artifact of truncation. Therefore, we run again the cohort analysis reducing the number of periods after financing to three and four. The idea is to artificially increase the lag between application date and the end date of the dataset. By doing so, we are not interested in the magnitude of the effects, but in checking similar trend of cohorts coefficients with respect to our baseline with five periods. Figure 2.8 plots the cohorts coefficients estimated by using three and four periods and the baseline with five periods, while the whole cohort analysis is reported in Table 2.B1, in the Appendix 2.B. The robustness test substantially confirms the consistency of the previous cohort analysis. As it is clear from the figure, we exclude that truncation is a major driver of the results for 2009 cohort. By observing the trends in cohort coefficients, it can be concluded that a negative and significant cohort effect exists even when the lag is increased to four years (three years safety-lag is the rule of thumb suggested by Hall et al. (2001)). However, as previously noticed, truncation seem to be a relatively bigger problem for 2010 cohort. When safety-lag is increased, 2010 seems to perform better than the previous year, leaving 2009 as the acme of the negative effects. This finding suggests a cautious interpretation of the last coefficient. However, it also reinforces the view of the 2009 negative cohort effect as the result of a external shock which persistently, but temporary lowered innovative potential of the financed startups, later reabsorbed once the GFC faded out.

Second, after ensuring the existence of the negative cohort effect for the GFC cohort and, that it is robust to truncation bias, we need to find confirmation that this is attributable mainly to VC selection. We first test the preexistence of the innovative gap for the GFC cohorts observed in the the descriptive statistics. If the negative cohort effect is indeed the result of the selection of safer but less innovative projects, this lower potential should be traceable even before the VC financing. A lower ex-ante level of issued patents would confirm this selection mechanism. Despite previous literature points out the facilitating role of patents in accessing to funding (Hoenen et al., 2014; Farre-Mensa et al., 2016), evidence from our sample points out that relatively few startups, mostly outliers, significantly patented before first financing. In fact, the validity of patent count as a proxy of innovative content of the project appears to be reduced when variability is low. Table 2.B2 in the Appendix 2.B, reports the result of a very simple Poisson regression which account for cohort effect and industry and region fixed effects. Results show that companies selected during the 2000s do not exhibit any significant difference in



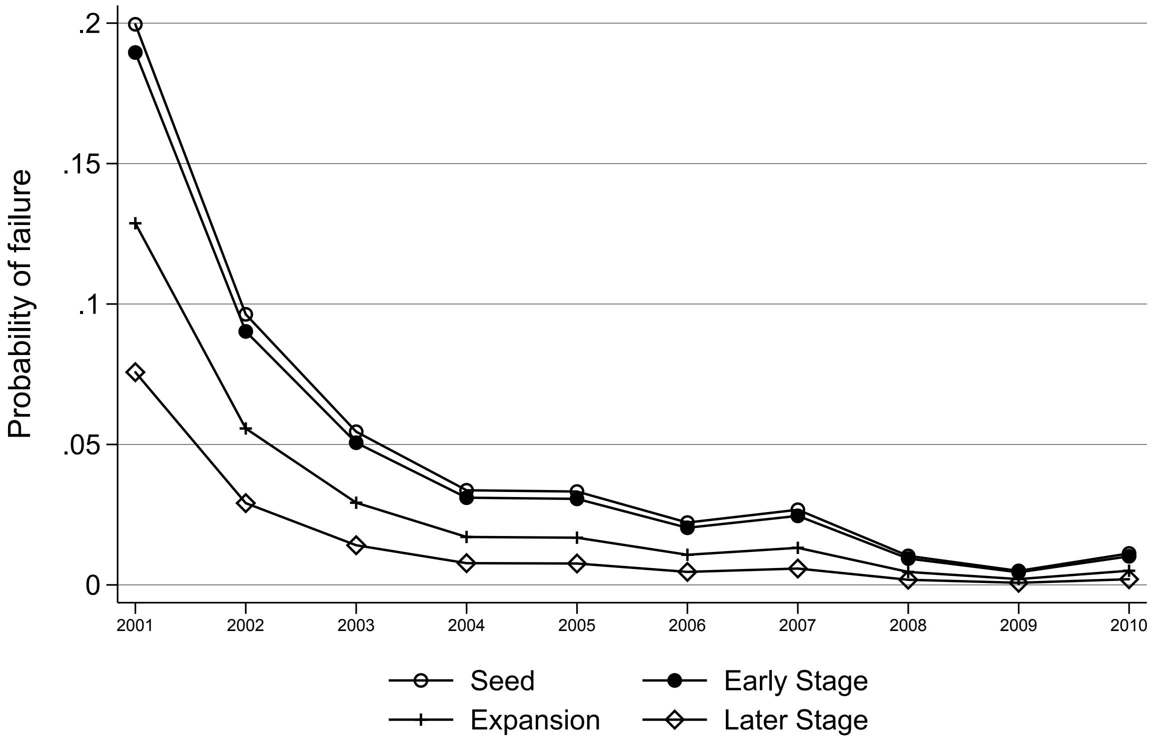
NOTE: This figure plots the cohorts coefficients estimated through the Poisson regression $Y_{ict} = \alpha + S\kappa + T\zeta + C\beta + \Gamma\chi + F^{(t,t-1)}\lambda + \theta + \psi + u_{ict}$ where Y is the number of issued patents in the three/four/five yearly periods following first financing. The 2001 cohort is normalized to zero.

Figure 2.8: Cohort effect on issued patents (2001-2010) - 3/4/5 yearly periods following financing

their pre-financing patenting performance. Still, the fact that there is not evidence also against the selection hypothesis is suggestive of the fact that we may not have sufficient variability in the pre-financing patenting to capture this effect.

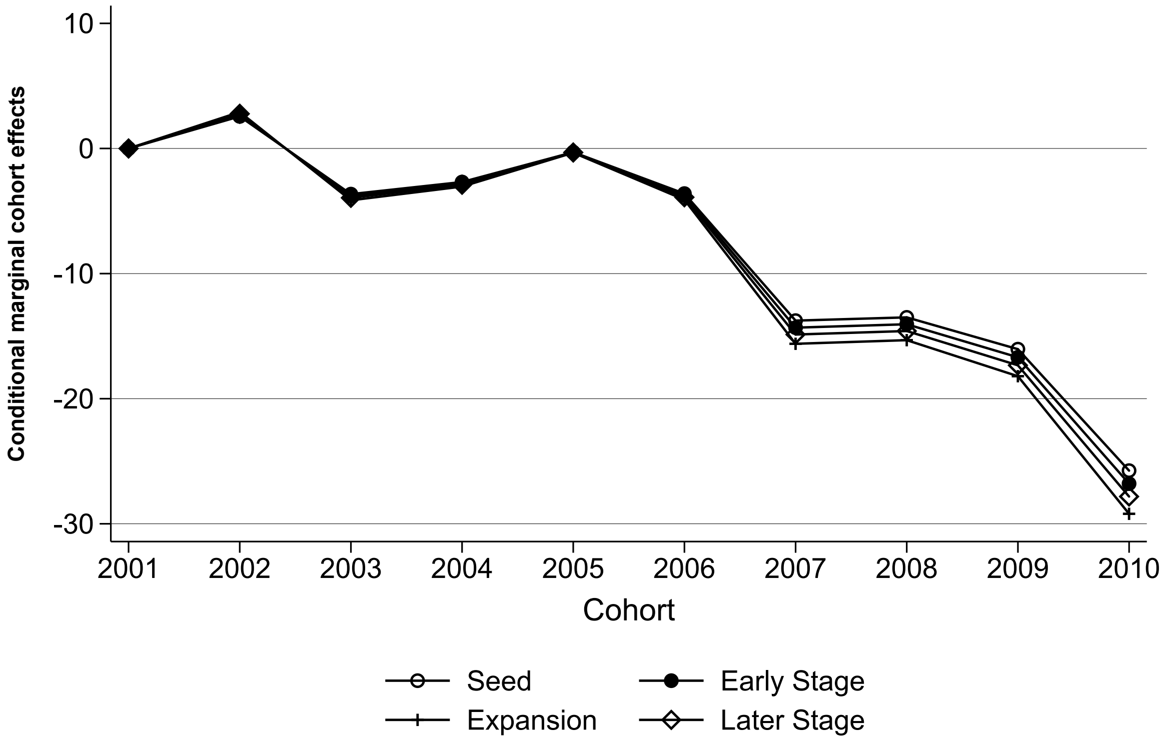
Therefore, we turn to test the ex-post outcome of financed companies, exploiting the trade-off between safety of the project vs. innovative and experimental content. In fact, if the selection hypothesis holds, less innovative cohorts should correlate with lower ex-post failure rate, but, also conditional of being survived, with lower exit rates and valuations in IPOs or acquisitions. This is somewhat similar (even if it constitutes the other side of the coin) to the findings in Nanda and Rhodes-Kropf (2013), where companies funded in very active investment markets were more likely to go bankrupt, but conditional on success, they had higher valuation at exit. As analyzed before they attribute this result to the higher degree of experimentation favored by a lower financing risk during hot markets. Conversely, in 2009 during GFC, we expect higher financing risk to determine lower experimentation, but also lower risk taking and average returns. We determine the probability to fail by cohort running Probit regression on cohort effects, stage at first financing, the amount of investment provided over the first five years, industry and region fixed effects. Table 2.B3 in the Appendix 2.B reports the full specification. The amount of investment provided is not statistical significant at conventional level, while fixed effects does not add much to the explanatory power of the model or alter the cohort coefficients. Hence postestimation is based on a parsimonious model which includes cohort and stage at first financing and it is plotted in Figure 2.9. The four lines indicates the ex-post probability to fail for each company development stage at the date of VC selection. As expected, companies at early stages are on average more risky than those at later stages. The failure rate of a early stage company selected in 2001 is almost 20%, while on the same year the odds for a later stage is only 8%. Moreover, this gap appears to be enduring over time. Focusing on cohorts, startups financed in 2009 have the lowest rate of bankruptcy with respect to the other cohorts. However, there are caveats associated with this trend. Companies financed in the first part of the decade may have been mechanically more exposed to failures related to the normal firm dynamics. Moreover, the phenomenon of "living dead" may be more sizable for relatively recent cohorts. This phenomenon relates to those companies that did not officially filed for bankruptcy but lay, for a long time, in-between positive exit and failure. Nonetheless, the fact that failure rate for the 2009 cohort is lower at each stage with regards to the immediately preceding and following cohorts is suggestive that these factors are not determinant in shaping this effect. We conclude that the evidence supports the hypothesis of the selection of less experimental and relatively safer projects during the year when the effects of the Global Financial Crisis were at their maximum.

Lastly, we check the correlation of the negative cohort effect for innovation with lower valuations at exit. Initial public offerings and acquisitions values are widely used as indicators of



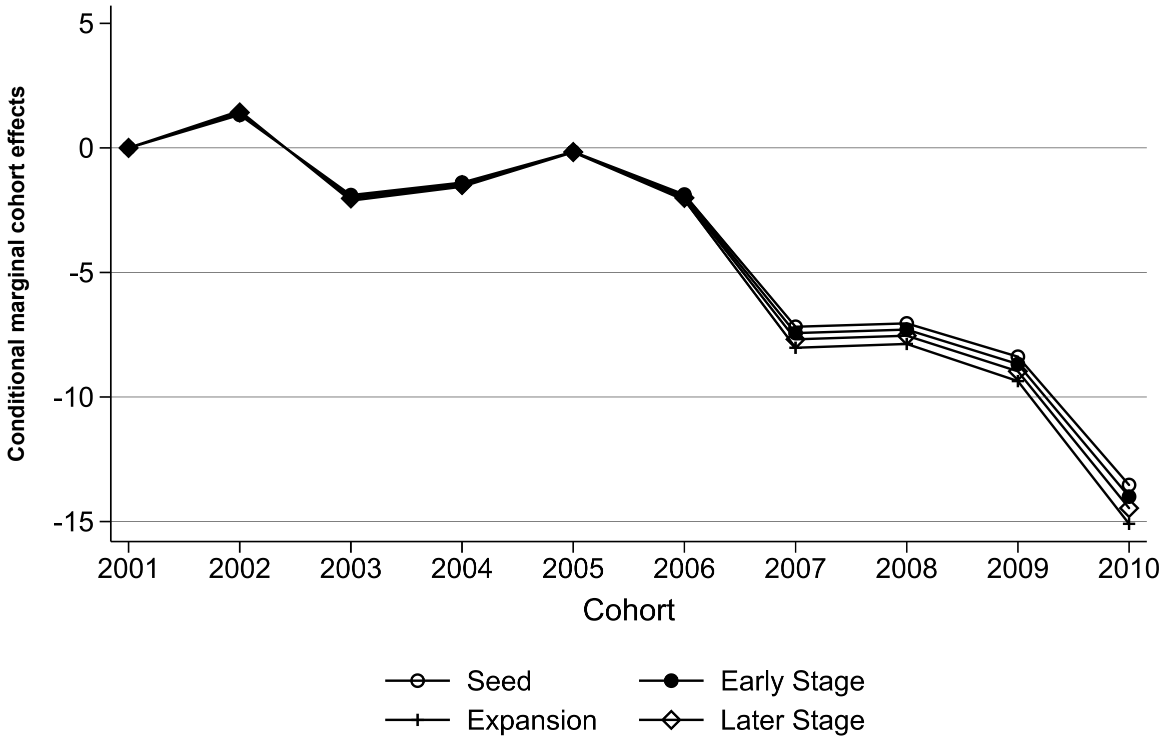
NOTE: This figure plots the probability of failure estimated through the Probit regression for each cohort at different level of stage at first financing. In order to ease the interpretation this post-estimation does not consider industry and region differences. The results are robust to the inclusion of these variables. Full model is reported in Table 2.B3 in Appendix 2.B

Figure 2.9: Probability of failure by cohort and stage at first financing



NOTE: This figure plots the means of the marginal effects of cohort variable on the expected value of the truncated outcome in million $ estimated through the Tobit regression for each cohort at different level of stage at first financing. In order to ease the interpretation this post-estimation does not consider industry and region differences. The results are robust to the inclusion of these variables. The 2001 cohort is normalized to zero. Full model is reported in Table 2.B4 in Appendix 2.B

Figure 2.10: Conditional marginal effects by cohort and stage at first financing - IPOs



NOTE: This figure plots the means of the marginal effects of cohort variable on the expected value of the truncated outcome in million $ estimated through the Tobit regression for each cohort at different level of stage at first financing. In order to ease the interpretation this post-estimation does not consider industry and region differences. The results are robust to the inclusion of these variables. The 2001 cohort is normalized to zero. Full model is reported in Table 2.B4 in Appendix 2.B

Figure 2.11: Conditional marginal effects by cohort and stage at first financing - Acquisitions

successful VC investments and they are positively correlated with investor revenues (Ljungqvist and Lu, 2007; Phalippou and Gottschalg, 2009). According to this line of reasoning, a drop in investment degree of experimentation, in order to follow a "safer path" will also negatively mark the ex-post level of success. We regress the valuation at exit in million dollars on financing cohort, stage at first financing, the total amount of funding provided to the company, a dummy equal to 1 if the exit is an IPO and industry and region fixed effects. The value of the Nasdaq Composite Index on the date of the company exit is added to proxy the stock market sentiment towards high-tech companies returns which may highly affect valuations. This regression poses several identification problems which must be taken into account. First, odds of success are not ex-ante similar. In fact, companies financed in 2001 had 16 years to go public or being acquired, while 2010 ones only six. In order to achieve a fair evaluation of each cohort we have to consider the same time-span. Therefore, for all cohorts the response variable is restricted to the valuation of those exits which happened within six years from first financing, while the rest of y is equal to zero. Second, we proxy successful investment with market valuation which is observable only conditional on company exit (and we further truncated it with the six years clause). Hence the response could be imagined as a latent variable, while we are able to observe only the subset which corresponds to our conditions. This also implies that a non trivial fraction of y piles up at zero, violating the normality assumption. Tobit model appears to be convenient in this truncated scenario with a corner solution response. Table 2.B4 in Appendix 2.B reports the estimated coefficients. Crucially, the latter measure the partial effects of the regressors on the latent variable, while the interest of the analysis is on the conditional expectation on the observed outcome $E(y|y > 0, x)$. The mean of the marginal effects on the expected value of the truncated outcome are plotted in Figures 2.10 and 2.11 for IPOs and acquisitions, respectively. They are estimated by holding constant (at means) the continuous variables, and plotting the differential cohorts effects conditional to stage at financing and IPO/acquisition dummy. Evidence confirms that less innovative cohorts are also, *ceteris paribus*, those with the lower valuations at exits. Being selected and financed in 2009 instead of 2001, correlates with an average reduction of \$18 million IPO value and \$9 million for acquisitions. The 2010 cohort registers even stronger reduction. Moreover, all the partial effects for cohorts 2007-2010 are statistical significant at conventional level (see Table 2.B4 in Appendix 2.B).

2.5 Conclusion

Venture capital market in the last decade was characterized by periods of economic turbulence and high uncertainty. Two financial shocks, punctuated by economic recessions, were spaced out by a recovery period in the middle of 2000s. Despite the fact that both crises led to temporary VC market drying-ups, difference on root causes and intensity are evident. Beyond the immediate effect on capital availability of market drying-ups, literature has not yet analyzed the longer-term consequences for innovation of investment selection under recent periods of high uncertainty, as the aftermath of Dot-com bubble and the Global Financial Crisis. Therefore, this paper applies the cohort analysis to the companies selected by VCs between 2001-2010 in order to investigate this topic.

Results confirm the presence of a generational effect in the companies selected during the Global Financial Crisis which display a persisting lower innovative potential, as measured by the number of issued patents over time. Interestingly, similar effect is not traceable during 2002 and 2003, when Dot-bubble burst severely hit venture capital market too. Cohort effects are non existent between 2001-2008. These results are robust to the inclusion of terms which take into account the age-related component, yearly fluctuations, together with other confounding factors. Additionally, the generational effect identified for the 2009 cohort is not evenly distributed across industries but it concentrates in sectors like healthcare, industrial & energy and media & entertainment. We explained this finding with degree to which formalized innovation, as accounted by patents, is an entry requirement to compete in each market. In order to find confirmation of the view of cohort effect as the result of venture capital selection of safer but less innovative projects, the paper tests the correlation of this selection with lower probability to fail and also a lower valuation at exit. Evidence confirms the previous hypothesis. Overall, this paper points to the differential consequences for innovation of venture investors reaction to external shocks which highly increase uncertainty (as the Global Financial Crisis) as opposed to phenomena which can be depicted as traditional boom-and-bust phases (Dot-com bubble) that are able to reduce funding availability without anyway changing innovative capabilities of financed startups.

Our results and their interpretation provided here have two main limitations. First, our conceptual framework assumes that the GFC may have affected the supply-side of venture capital selection and funding. The existence of a negative cohort effect may also derive from demand-side effects, with more innovative entrepreneurs opting out from the venture pitching when valuations are low. Despite conventional wisdom suggests that the value of "waiting and seeing" is much higher for VCs than entrepreneurs, this is ultimately an empiric question. Unfortunately, commercial database registers only venture funding ex-post realizations and it is not suitable to properly address this question. Second, in Section 2.4 we fail to identify clear cohort effects on measures of patent quality. Nevertheless, conclusions on changes on the value of patents are limited from the omission of forward citations and patent diffusion measures, due to the lack of necessary time lag. It will be important to include also these measures once they will be available. Both these considerations represents important extensions to the present work which we leave to future research.

2.A Appendix A - The matching procedure

This appendix briefly documents the main steps of the STATA® matching routine developed here to integrate venture capital data in Thomson One with patent data taken from PatentsView tables. As highlighted in the text, the lack of a common company identifier between the different sources is a fundamental problem. Therefore, we needed to develop a procedure of exact and approximate matching which equally balances two contrasting aims: ensuring high probability of correct assignment, while reducing (as much as possible) the need for manual double-checking.

We started from the list of names of financed startups identified in Thomson One. This provider also indicates all the known alternative names (aliases) for each financed startup. Company alias can be used to provide a shorter business name for marketing purposes or alternatively, it is the result of a name change after the registration. This is not uncommon at early stage of company operation. In fact, when the brand is not established yet, the (marketing) costs are likely to be limited. Hence, each company can be commonly identified by more than one name. Failing to account for this fact could reduce the quality of matching by increasing the share of unmatched pairs (false negative). We then created a list of company names and aliases with unique identifiers at company level.

We proceeded first with a set of commands of general cleaning similar to the ones in the NBER Patent Data Project[8] and used also in Lotti and Marin (2013). We repeatedly run these commands to eliminate punctuation, special characters and double spaces. All letters were transformed in lower cases and we got rid of abbreviations and acronyms not useful to uniquely identify the company. We eliminated duplicates taking into consideration both company identifier and name (including the principal name and aliases). Finally, we added to this list information regarding company location, sector and georeferentiated points (latitudes and longitudes of headquarters, obtained from zip codes).

We then moved to the list of patent assignees available in PatentsView data. Information is organized in a relational database with different tables connected by primary keys. The list of names have been harmonized at origin by the PatentsView project[9]. We proceeded with the general cleaning commands used for startup names. Lastly, we merged this list of cleaned names with the table reporting geographical location (latitudes and longitudes) of each assignee, disambiguated by the PatentsView project.

Once we completed all the preparatory tasks, we carried out the actual matching procedure. We started from the exact matching of venture-backed companies and assignees. Exact correspondence was evaluated according to multiple criteria. The main criterion was the exact

[8] https://sites.google.com/site/patentdataproject/

[9] More information on project's methodology is available in 'Methods and Sources' at http://www.patentsview.org/web

name correspondence between each possible pair. Moreover, the quality of the matching was evaluated through different steps according to the geographical distance (using the Vincenty's formulae which measures the geographical distance using the coordinates of the two points) and name length, measured in words and letters, assigning to manual inspection exact matches of short names. The procedure ended with 164 ambiguous exact matches which were manually inspected using additional information from Google Patents[10] and Standard & Poor's Capital IQ. We confirmed the correspondence of 96 pairs and discarded the remaining part.

The last step consisted in performing the approximate matching, evaluating all the possible unmatched pairs. Approximate or probabilistic matching is necessary when small changes in company name, due to misspelling or name variation, make exact matching unsuccessful. In order to identify possible matches, we used the Jaro-Winkler algorithm which measures the edit distance between two strings. The metric is scaled between 0 (not similar at all) and 1 (exact match). This procedure requires to evaluates each element of the one vector with all the elements of the other vector, returning a score for each pair. We had 12,352 unmatched company names and 385,101 unmatched assignees which amount to a total of 4.7 billions possible pairs. In order to speed up the process, the routine excluded from the evaluation pairs composed by company names/assignees with a single word, but different initials. After having assigned a score of similarity to each possible pair, the procedure kept only the best match for each company name. An automatic procedure left only the pairs with a score greater than or equal to .97, evaluating it with geographical proximity. When geographical information were missing or contrasting with the text match, pairs were assigned to the class of ambiguous matches and manually verified using alternative sources as above specified for exact matching. Out of 5,589 ambiguous matching we assigned 406 as real match, the rest were discarded. Finally, we created a unique identifier which connected Thomson One data with the patent based information available in the remaining tables of PatentsView. We used these tables to construct the indicators used in this paper.

[10] https://patents.google.com

2.B Appendix B

Dependent variable: Total number of issued patents			
	3 yearly periods	**4 yearly periods**	**5 yearly periods**
	(1)	(2)	(3)
Cohort 2002	.073	.132	.083
	[.129]	[.128]	[.123]
Cohort 2003	-.208	-.141	-.162
	[.130]	[.120]	[.115]
Cohort 2004	-.313**	-.150	-.182*
	[.132]	[.116]	[.109]
Cohort 2005	-.226	-.070	-.136
	[.153]	[.135]	[.123]
Cohort 2006	-.235	-.111	-.209
	[.185]	[.166]	[.151]
Cohort 2007	-.330*	-.105	-.121
	[.174]	[.153]	[.142]
Cohort 2008	-.325*	-.130	-.198
	[.185]	[.160]	[.144]
Cohort 2009	-.650***	-.370**	-.394**
	[.205]	[.182]	[.165]
Cohort 2010	-.576***	-.270	-.414***
	[.203]	[.170]	[.156]
Stage at Financing dummies			
Early Stage	.206***	.207***	.212***
	[.066]	[.066]	[.066]
Expansion	.294***	.354***	.418***
	[.074]	[.074]	[.073]
Later Stage	.240**	.322***	.382***
	[.109]	[.100]	[.092]
Total Investment	.006***	.004**	.001***
	[.002]	[.002]	[.000]
Total Investment (1 year-lag)	.006***	.006***	.005***
	[.002]	[.002]	[.002]
Patent Allowance rate	.064***	.063***	.064***
	[.001]	[.001]	[.001]
Overall Patent Applications	.002***	.003***	.003***
	[.000]	[.000]	[.000]
Years effects	YES	YES	YES
Industry effects	YES	YES	YES
Region effects	YES	YES	YES
P-value	<.001	<.001	<.001
Observations	30.252	40.332	50.415

NOTE: This table reports the cohorts coefficients estimated through the Poisson regression $Y_{ict} = \alpha + S\kappa + T\zeta +$ $+ C\beta + \Gamma\chi + F^{(t,t-1)}\lambda + \theta + \psi + u_{ict}$ where Y is the number of issued patents in the three/four/five yearly periods following first financing. The 2001 cohort is normalized to zero. Symbols *, ** and *** denote significance level of 10%, 5% and 1%, respectively.

Table 2.B1: Poisson regressions for patent count - 3/4/5 periods after financing

Dependent variable: Total number of issued patents before financing			
Cohort 2002	.327	Cohort 2007	.129
	[.270]		[.243]
Cohort 2003	.164	Cohort 2008	.323
	[.253]		[.261]
Cohort 2004	.349	Cohort 2009	.015
	[.308]		[.276]
Cohort 2005	.004	Cohort 2010	.412
	[.241]		[.316]
Cohort 2006	.249	Industry effects	YES
	[.242]	Region effects	YES

NOTE: This table reports the cohorts coefficients estimated through the Poisson regression $Y_{ic} = +C\beta + \theta + \psi + u_{ic}$ where Y is the total number of issued patents before first financing. The 2001 cohort is normalized to zero. Symbols *, ** and *** de--note significance level of 10%, 5% and 1%, respectively.

Table 2.B2: Cohort effects for patenting before first financing

Dependent variable: Startup bankruptcy				
	(1)	(3)	(2)	(4)
Cohort 2002	-.468***	-.460***	-.456***	-.427***
	[.079]	[.079]	[.079]	[.080]
Cohort 2003	-.755***	-.759***	-.757***	-.736***
	[.092]	[.093]	[.093]	[.093]
Cohort 2004	-.988***	-.986***	-.982***	-.973***
	[.096]	[.096]	[.096]	[.097]
Cohort 2005	-.997***	-.992***	-.989***	-.962***
	[.093]	[.093]	[.093]	[.095]
Cohort 2006	-1.164***	-1.167***	-1.160***	-1.132***
	[.098]	[.098]	[.097]	[.100]
Cohort 2007	-1.088***	-1.088***	-1.088***	-1.068***
	[.089]	[.091]	[.091]	[.091]
Cohort 2008	-1.465***	-1.470***	-1.474***	-1.449***
	[.123]	[.123]	[.123]	[.125]
Cohort 2009	-1.719***	-1.733***	-1.735***	-1.699***
	[.199]	[.200]	[.200]	[.202]
Cohort 2010	-1.430***	-1.440***	-1.441***	-1.390***
	[.130]	[.132]	[.132]	[.133]
Stage at Financing dummies:		-.036	-.032	-.049
Early Stage		[.062]	[.061]	[.062]
		-.289***	-.290***	-.322***
Expansion		[.078]	[.078]	[.080]
		-.591***	-.595***	-.643***
Later Stage		[.152]	[.152]	[.152]
			-.001	
Total Investment			[.002]	
Industry effects	NO	NO	NO	YES
Region effects	NO	NO	NO	YES
Pseudo R^2	0.143	.152	.153	.159
Wald χ^2	452.56	495.75	496.31	501.14
P-value	<.001	<.001	<.001	<.001
Observations	10.119	10.119	10.119	10.119

NOTE: This table reports the results of the Probit regressions for probability of failure. The model is specified as follows:$Y_{ic} = \alpha + S\kappa +$ $+C\beta + F\lambda + \theta + \psi + u_{ic}$ where response variable (Y) take the value 1 if the startup went bankrupt between 2001 and 2015, 0 otherwise. Total investment (F) reports the amount provided by investors during the first 5 years after first financing. Coefficients are not post est--imated. Symbols *, ** and *** denote significance level of 10%, 5% and 1%, respectively.

Table 2.B3: Probit regressions of probability of failure by cohort

Dependent variable: Exits values in constant million $						
		(1)	(3)	(2)	(4)	(5)
Cohort 2002		28.286	25.263	29.312	6.953	11.214
		[32.707]	[32.050]	[31.974]	[30.895]	[30.861]
Cohort 2003		-17.750	-17.603	7.345	-20.207	-16.324
		[35.898]	[35.380]	[34.988]	[35.273]	[35.171]
Cohort 2004		-1.285	-1.570	9.637	-17.250	-11.959
		[31.969]	[31.423]	[31.171]	[31.032]	[31.064]
Cohort 2005		-16.283	-13.007	24.534	-6.583	-1.316
		[35.037]	[34.760]	[36.128]	[36.207]	[35.932]
Cohort 2006		-4.063	-1.817	16.291	-20.432	-16.138
		[30.328]	[30.013]	[30.036]	[29.741]	[29.843]
Cohort 2007		-38.435	-39.374	-18.089	-70.451**	-64.043**
		[31.347]	[31.013]	[30.266]	[32.054]	[31.615]
Cohort 2008		-40.807	-36.067	-25.832	-67.764**	-62.773*
		[32.778]	[32.421]	[31.938]	[33.743]	[33.682]
Cohort 2009		-49.167	-45.309	-32.819	-76.435*	-75.356*
		[38.379]	[37.919]	[38.334]	[42.223]	[42.665]
Cohort 2010		-77.212**	-83.498**	-55.269	-126.838***	-125.980***
		[36.574]	[37.285]	[36.743]	[42.272]	[42.328]
Stage at Financing dummies:						
	Early Stage	42.185*	37.700*	34.750	28.491	23.968
		[21.838]	[21.496]	[21.641]	[22.930]	[22.541]
	Expansion	108.930***	107.183***	88.661***	83.850***	75.518***
		[25.982]	[25.606]	[24.910]	[25.784]	[25.452]
	Later Stage	93.674***	92.308***	83.347**	54.210	46.501
		[33.594]	[33.126]	[33.289]	[34.626]	[34.320]
Total Investment			.882*	.393**	.296**	.322**
			[.456]	[.194]	[.121]	[.129]
IPO dummy				642.132***	406.981***	416.449***
				[73.243]	[49.242]	[48.466]
Nasdaq composite index					.139***	.140***
					[.017]	[.017]
Industry effects		YES	YES	YES	YES	NO
Region effects		YES	YES	YES	YES	NO
Pseudo R^2		0.008	0.012	0.054	0.112	0.111
F		3.15	3.16	4.51	4.49	6.57
P-value		<.001	<.001	<.001	<.001	<.001
Observations		10.111	10.111	10.111	10.111	10.119

Table 2.B4: Tobit regressions of exit values by cohort

Chapter 3

Upwind sailors. Financial profile of innovative and non-innovative Italian firms during the double-dip recession

Abstract

We examine the innovative activity of a large sample of Italian non-financial companies during the recessionary period of 2008-2012. By developing a four-status classification based on patenting behavior we descriptively account for firms' financial characteristics related to profitability, capital structure and operating performances. We find that more than 80% of innovation is concentrated in the manufacturing sector. Among innovators, the majority engages in occasional innovation, while very few (mostly large) firms maintain a persistent level of high inventive capacity. On a over time perspective, firms in the sample have slightly increased average patenting during the crisis with respect to the previous five years. The empirical analysis finds that Italian innovators are on average relatively large, mature and established. Their higher cash-flow and lower indebtedness clearly signal that they fund their activities mostly with internal resources. Moreover, they grow faster than non innovators, even during a recessionary period. The global picture that emerges is largely consistent with the hierarchical view of pecking-order theory. As we move from non-innovators to great innovators the use of cash flow to fund operations increases, while leverage decreases. However, the direction of causality is not addressed here.

JEL Codes: G300, O300, G010

Keywords: Italian firms, financial profile, innovation, crisis.

3.1 Introduction

The gap in innovation has been considered one the main reasons why the performance of Italian economy is lagging behind those of the other European partners (Bugamelli et al., 2012). According to the "2016 Global Innovation Index" report[1], Italy is out of the top 25 world's most-innovative economies. It ranks at 29th place, followed by Portugal and Greece, but overtaken by all the rest of Western economies. However, the relatively poor innovative outcome of Italian production system is not a recent problem. In 2002 the number of Italian successful applications to the European Patent Office were 74 per million inhabitants, while the European average was 158 (Scellato, 2007).

This paper aims to shed further light on the innovative performance of Italian firms between 2008-2012. By using a large dataset of 162,959 Italian non-financial enterprises, we have been able to descriptively analyze the financial characteristics of companies together with their patenting behavior. This study explores to what extent the financial structure of innovative firms is different from non-innovative ones and to what extent this difference increases with the ability to achieve a sustained patenting over the years. One of the main contribution of this paper is represented by overcoming the classical dichotomy innovators vs. non-innovators, to adopt an enhanced categorization in four innovative classes (non-innovators, occasional, medium and great innovators), based on their degree of patenting between 2008-2012. Consequently, we will use the between-group differences measured on a large set of financial ratios to define each specific financial profile.

After describing the size of the patenting activity in Italian firms and the relative contribution of each sector to the over time innovation, we will focus only on the manufacturing sector which alone accounts for the great majority of Italian inventions. The empirical analysis investigates the existence of systematic patterns in terms of cash flow, profitability, capital structure and growth which differentiate firms at different level of innovation. We will first employ a non-parametric analysis with the whole set of indicators, to later move towards a multivariate analysis to account for other relevant variables that might affect financial strategy. Moreover, the choice of the window period (2008-2012) is not accidental. During this period the Italian economy was severely hit first by the Global Financial crisis and later by the Sovereign Debt crisis. Both financial turmoils developed in a strong double-dip recession, which severely hit the Italian industrial system. Beyond taking into consideration the big influence of the recessionary period in the interpretation of the results, data allows also to investigate the degree of persistence of patenting activity during the crisis period (2008-2012) with respect to the previous tranquil period (2003-2007). While this paper does not attempt to provide any causal interpretation or

[1]This annual report of countries' innovative capabilities is jointly published by Cornell University, INSEAD, and the World Intellectual Property Organization. The latest edition is available at https://www.globalinnovationindex.org/home

explanation, it does provide a wide description of the phenomenon, reporting specific patterns and suggesting interesting areas for further research.

The remainder of the paper is organized as follows. Section 3.2 reviews the existent literature on the financial structure of innovative firms, while Section 3.3 describes the data, the methodology and provides summary statistics on the sample. Section 3.4 presents the results of the non-parametric analysis, followed by the regression analysis. Section 3.5 concludes.

3.2 Financial structure and innovation

The problem of selecting the right type of capital to finance investments whose yields are uncertain have been long debated both in theoretical and empirical literature. The main contribution dates back to the famous (and challenged) paper by Modigliani and Miller (1958), which deals with the notion of the cost of capital and its implications in explaining firms' investment behavior. Authors maintain that in a world of perfect information, efficient capital market and without bankruptcy costs, firms are indifferent to the capital structure. Every project with a positive net present value is financed either with internal or external funds at the same cost on the margin. Theories of capital structure and financial behavior departed from this initial contribution, highlighting the effects of the presence of capital market imperfections.

With particular regard to R&D investments, the existence of asymmetric information and moral hazard are among the most important reasons why more innovative companies may favor specific sources of finance (Hall and Lerner, 2009). Asymmetric information stems from the divergence of level of information between firms and their potential investors on the projects risk and quality. The lemon market developed by Akerlof (1970) models the presence of strong informational asymmetries which can degrade the quality of goods traded in the marketplace inducing adverse selection phenomena. Innovative projects may exacerbate this problem. In fact, time and specific capacities are required to realize the quality of long-term projects. This, in turn, elevates lemon's premium demanded by investors, resulting in a higher cost of financing for innovative firms. In the extreme case, adverse selection could lead to a market freeze with funding dry-up.

Additionally, moral hazard problems may arise from the possible conflicting aims between ownership and management. Management could be more reluctant than shareholders in undertaking risky long-term projects or they may indulge in activities unrelated to company's interests. The choice of different capital structure can affect managers discipline and incentives and could also be considered a mean of easing agency problems.

The main implication of imperfect capital markets is that financial factors and constraints influence firm's investment decisions. Following this line of research which departed from the classical Modigliani-Miller approach, many authors have focused on specific problems which may affect firms' investment behavior. Myers and Majluf (1984) postulates the existence of an ordered hierarchy in financial sources in terms of costs. Their "pecking order theory" of capital structure suggests that when informational asymmetries and agency problems are high, firms prioritize their financing sources first relying on internal funds, then choosing debt and lastly, issuing new equity. This ordering derives from the high dilution cost of issuing new equity when information is asymmetric between managers and investors. Selling shares may signal to investors that firm is overvalued. If expected revenues were high, current owners would have instead remained as the only residual claimants. As a result, investors will place a lower value to the new equity issuance, increasing in turn the financing cost for firms. Therefore, when the relative inexpensive internal resources are depleted, firms are likely to prefer debt over equity among external sources, in order to lower the cost of financing.

A complementary approach followed by Aghion and Bolton (1992) focuses on firm's control rights and it partially reshuffles the rank order of financing sources. This stems from the consideration that when a substantial part of firm's capital is constituted by intangible assets, the possibility to use debt is limited by lack of collateral. Consequently, the lower is the assets tangibility, the more control rights on firm are demanded in return by outside investors. Firms will primarily use internal sources, but after their depletion, their choice among external sources will depend on project's scope and assets tangibility. Traditional firms with enough collateral will follow the original pecking order choosing first debt and then equity. On the other hand, risky innovative firms with low collateral will be required to grant more control rights to investors, hence favoring equity over debt. This effect could be also magnified by the impact of bankruptcy costs on innovative firms. It is likely that the majority of their assets are in the form of knowledge capital or specialized equipment. All these assets have none or very low degree of redeployment and liquidation. This characteristic increases the risk in lenders, discouraging the use of loans in innovative activities.

A rich stream of empirical literature has developed from this theoretical base to analyze the financing of innovative activities[2]. A substantial part of this research deals with the identification of financing constraints and the existence of a funding gap for innovation (Fazzari et al., 1988; Scellato, 2007; Mohnen et al., 2008; Hottenrott and Peters, 2012; Hall et al., 2015). Coherently with the descriptive scope of this paper, we are more interested here in highlighting the differences of financial characteristics between innovators and non-innovators, describing their financial choices. Hall (1992) explores the degree of correlation among leverage, cash flow and R&D expenditures in a large panel of U.S. manufacturing firms from 1973 to 1987. She underlines two main facts: the positive relation of R&D investment and cash flow and the strong negative correlation between R&D and degree of leverage. The predominant role of internal resources is also pointed out by Himmelberg and Petersen (1994). By using different econometric

[2]See Hall and Lerner (2009) and Kerr and Nanda (2015) for comprehensive surveys of the literature

specifications in a panel of 179 high-tech US firms, they find a large and statistically significant relationship between R&D and internal finance proxied by cash flow. Similarly, Ughetto (2008) using a GMM estimation finds that Italian manufacturing firms favor cash flow over debt when financing R&D expenditures. However, also company size may affect this choice. While external financing is very hard for small innovative firms, a relatively easier access is found for larger companies. Baldwin et al. (2003) find similar results using survey data for 3,000 small Canadian firms. Moreover, Aghion et al. (2004) analyze the use of debt financing and R&D investments directly from balance sheets data for large and medium-sized U.K. publicly traded firms. They find a non-linear relationship between innovative expenses and debt ratio. Use of debt is sizable when R&D is low. When R&D intensity grows, debt ratio significantly falls. On the contrary, they discover a linear relationship with new equity issuance. Reporting more R&D increases the probability of issuing shares at each level of R&D intensity. Using a similar sample on a slightly longer period, Casson et al. (2008) confirm the previous results. Both papers empirically confirm the validity of the "control rights" approach where the rank in the pecking order changes with innovation intensity. By the same token, further causal evidence is brought by Atanassov (2005) and Magri (2014). By analyzing a large panel of US companies from 1974-2000, the former finds that firms which use equity and bonds have a larger number of patents and patent citations than those which rely on bank loans. The latter, using survey data on 10,720 Italian manufacturing firms, establishes that issuing equity increases the probability of investing in R&D by 30-40%. However, this effect is significant only for small, young and highly leveraged firms. This finding is closely related to the literature which investigates the effect of ownership on innovation. A recent study by Acharya and Xu (2016) analyzes the effect of being publicly-traded on firm's patenting behavior, finding a differential effect of listing. They find that publicly traded firms in industries more dependent on external finance generate more patents of higher quality and novelty than private firms. On the other hand, publicly-held firms do not show any significant improvement when they belong to industries where the use of external capital is residual.

Lastly, also the strategic choice of holding cash or other liquid assets to provide a certain degree of operational flexibility may significantly differentiate innovative and non-innovative companies. Evidence is not unanimous. On the one hand, this financial slack may be necessary in promoting experimentation, long-term vision and innovation. Therefore, it should be considered as a critical strategy of highly innovative firms as it provides insulation against cash flow volatility, allowing to maintain R&D investments even during recessionary periods (O'Brien, 2003). As a consequence, piling up significant amount of liquid assets as a precautionary cushion could have particularly helped innovative firms to pursue their research activities during the double-dip recession. On the other hand, other authors point also to the negative effects of an excessive buffer of resources which may increase inefficiency and the diversion of funds on dubious projects (Jensen, 1986). For example, Nohria and Gulati (1996) find a curvilinear effect of slack on innovation with an inverted U-shaped relationship. Both too much or too little slack may be damaging to innovation.

3.3 Dataset and summary statistics

This paper explores the financial profile of Italian firms to shed more light on the distinctive ways in which more innovative firms differentiate with respect to non-innovative ones. In particular, the analysis complements evidence on innovative outcomes between 2008-2012 with those on financial structure over the period 2006-2012. The choice of a reliable indicator of innovation which can differentiate among groups is key. Many previous studies which relate firms' characteristics with innovative patterns usually focus on industry-specific technological trajectories and sectoral systems of innovation (Pavitt, 1984; Malerba and Orsenigo, 1997; Bogliacino and Pianta, 2013). Therefore, innovative classification is mainly based on firm's sectoral affiliation. Among the literature employing firm-level approaches, authors have proposed several different proxies which closely relates to the three main phases of innovative process (Acs and Audretsch, 2005). This analysis adopts an intermediate output measure, such as patenting.

Ideally, we would like to classify the innovative profile of each firm using an input measure of the innovation effort, such as the amount of yearly R&D investments. Unfortunately, this kind of information is solely available for few, usually very large, firms as the disclosure of this data in the balance sheet is not compulsory under the Italian law[3]. Alternative approaches use survey-based information stating either the amount of innovative input or the number of innovative output. Among the drawbacks in the use of such indicators, the relatively small number of surveyed firms and concerns on the quality of the response are the most important. Nonetheless, even the use of patents as innovative proxy has bright sides and caveats. On the one hand, economic literature has highlighted the positive relation of patenting with R&D expenditures (Trajtenberg, 1987; Lerner and Zhu, 2007; Arora et al., 2008). On the other hand, sectoral change in propensity to patent, the existence of trade secret protection and non patentable innovation represent the major drawbacks in the use of patents as indicator of innovative performance (Mansfield, 1986; Archibugi and Pianta, 1996).

Above all, the choice of patents allows to analyze a relative wider set of firms and permits to define the profile of innovators according to the over time persistence of their patent produc-

[3]Some firms voluntarely add further information on R&D expenditures in the footnotes of their balance sheets. However, even accounting for these extra information, in our sample, the number of non-missing observations hardly goes beyond a hundred. Among the few studies which directly measures the R&D intensity from balance sheets, Aghion et al. (2004) take advantage of the change of accounting regulation in United Kingdom in 1989 which made R&D reporting compulsory for large and medium-sized firms.

tion. In fact, one of the main contribution of this paper is represented by the categorization of Italian firms in four innovative classes, based on their degree of patenting during 2008-2012. This taxonomy derives from a methodology developed in Cefis (2003) for the patent time series of 577 U.K. firms. The author investigates the nature of patenting behavior, finding high persistence among innovators (in particular at the extremes) and the presence of a threshold effect at the first patent. After the first one, additional patenting becomes easier (or more formally, the probability to acquire an extra patent increases). The conclusions are straightforward. Innovation (and its persistence) is not a random phenomenon, but it derives from a systematic heterogeneity across firms. This implies that persistence is indeed an important ingredient for high innovative performance, but its determinants are still not known. Stemming from these results, the present paper applies a similar framework to a large cross-section sample of Italian firms, to investigate the common financial characteristics of each status. Evidence will be interpreted according to previous theoretical predictions, taking also in consideration the specific recessional environment of 2008-2012 in the interpretation of our results.

The analysis will proceed by analyzing descriptively the general characteristics of the overall sample of firms divided in a two-status framework (innovators and non-innovators). After accounting for the relative contribution of each sector to the over time innovation activity, we will focus only on the manufacturing sector which alone accounts for the great majority of Italian inventions. Subsequently, the financial structure of manufacturing firms will be observed according to the belonging to four different status, defined as follows. The "non-innovators", those firms having, on average, a yearly patenting equal to zero (they never had a patent granted between 2008-2012). The "occasional innovators", those whose yearly patenting is positive, but below one patent each year. "Medium innovators" represent those companies having per year between one and five granted patents. Lastly, "great innovators" are defined as those firms having granted at least six patents per year.

Our taxonomy modifies the original presented in Cefis (2003) in manifold ways. First, we consider here only granted patents, while the previous work considers applications regardless to its outcome. Moreover, we use patents as a proxy of formalized novel inventions. Many assignees after filing once for the protection of the original invention (usually at the domestic patent office or at the main reference market) are entitled to file subsequent applications in other countries for the same invention, in order to receive a similar protection effective as of the date of the first application. This study accounts for the worldwide patenting of Italian firms, but considers only the first patent at the priority date (which is also the closest available to the date of invention). Therefore, all the subsequent applications in other patent offices for the same invention have been ignored in order to avoid double-counting. Henceforth the word "patent" refers solely to the original one as represented by the priority patent application. Second, we also add the group of "non-innovators", as the focus here is on the main differences across groups. Lastly, our ranking conditions are somewhat less stringent than the original ones. The clauses to qualify for each innovative status should be met on average and not on each year. This choice derives from the necessity to smooth out the possible truncation effect, evident in the last two years of the period.

3.3.1 Dataset

This work relies on micro-data provided by the commercial database Orbis from Bureau van Dijk. It includes a collection of wide range of detailed data on private and public companies. Due to its availability to researchers and the presence of harmonized information on world-wide companies, collected mostly from the local chambers of commerce, the use of this source is increasingly popular in economic research. However, large differences in availability and coverage over time and across countries are still present. Excluding few exceptions, coverage degree raises with the size of the companies, which in turn diminishes the gap between aggregated micro and macro data and increases the representativeness of the whole production system. A detailed overview of the database and comprehensive evaluation of its advantages and disadvantages is presented in Ribeiro et al. (2010).

The coverage of Italian firms is wide and stable through all the period of the analysis. Moreover, by considering a single country, harmonization problems of financial structure data are less of a concern here. Balance sheet data, profit and loss statement, company ownership and patents and intellectual property information, all included in Orbis, are of main interest in this study. The whole sample consists in Italian based non-financial companies which have been incorporated before 2006 and whose total assets or operating revenues amounted to more than two million euros at least in one of the years between 2006-2012. The choice of these thresholds stems from the criteria adopted (together with staff headcount criterion) by the European Commission in the definitions of small and medium-sized enterprises in use at Community level[4].

By limiting the analysis to the companies which complies with those assets or the turnover ceilings, the sample will select only micro companies in the right tail of size distribution and all the small, medium and large Italian companies available in Orbis. While on the one hand the selection of relatively larger firms improves the overall coverage for the set of financial indicators used throughout this paper (reducing the presence of missing values), on the other hand it could be detrimental for the external validity of the described innovative output. In order to test the degree of information loss, we measure that our sample accounts for more than 70% of overall Italian patenting, while the remaining part includes many sole proprietorship which are hardly of interest in our study. Moreover, all international branches of Italian corporations

[4]Size criteria for micro, small and medium-sized enterprises are defined in the EU recommendation 2003/361 available at http://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32003H0361 and further descripted in the Appendix 3.A

have been eliminated, while Italian branches of multinational corporations have been left in the sample.

Balance sheet and income statement data have been collected yearly and used to construct micro-level financial ratios and indicators for each year. All variables, with the exclusions of age and time-invariant firms' characteristics, have been first winsorized at the 1^{st} and 99^{th} percentile and later aggregated in two periods, pre-crisis (2006-2007) and crisis (2008-2012), by considering the firm-level means. Detailed descriptions of these metrics together with descriptive statistics are provided in Section 3.3.3, while Appendix 3.A reports the construction of size, sector and other firms' characteristics. Lastly, the whole patenting history of the sample firms has been bulk downloaded and then opportunely evaluated in order to construct the innovative groups, as above specified. Overall, the sample consists in 162,959 non-financial Italian firms, which have been granted, from their incorporation to 2012, with 83,654 priority patents.

3.3.2 Summary statistics

This section describes the overall sample composition and the patenting behavior at sectoral level. Table 3.1 focuses on the innovative performance by size and company ownership. We start by using a simple two-innovative-status modality. Firms are either non-innovators, if they have not been granted with at least one patent between 2008-2012 or else, innovators. Table 3.1 shows how micro and small companies (as defined by the European Commission and explained in Appendix 3.A) represent the large majority in the sample. Overall, 141,669 firms belong to these classes, and represent 87% of the sample. However, their contribution to innovation is negligible. Only 412 micro and 1,163 small firms have successfully applied for at least one patent between 2008-2012. The absolute numbers of innovators are even smaller for medium and large companies, 1,107 and 597, respectively. However, when the relative shares within each size group is taken into account, innovators become more relevant in medium and, more evidently, among large companies (6.5% and 15%, respectively).

As highlighted in Section 3.2, ownership structure could be also relevant for innovative output. In our sample, 30% of public companies (usually medium and large firms) are innovators. In order to have a meaningful comparison, we can contrast it with the share of innovators in the generality of large firms, which is only 15%. As expected, independent companies have the lowest incidence of innovators (1.09%). Among enterprises within a business group, the share of innovators increases, but its relative importance remains very low (2.67%). We can further analyze ownership structure by considering the nationality of the ultimate owner. Among the firms owned by an Italian holding company, innovators represent only 2.45%. This frequency rises to 5.30% when taking into consideration only the group of firms owned by an international holding company.

Table 3.2 reports the absolute number and relative shares of patenting by sector and year.

Firms characteristics			
Size	**Non innovators**	**Innovators**	**Total**
Micro	79,034	412	79,446
	99.48%	0.52%	100%
Small	61,060	1,163	62,223
	98.13%	1.87%	100%
Medium	16,138	1,107	17,245
	93.58%	6.42%	100%
Large	3,448	597	4,045
	85.24%	14.76%	100%
Publicly traded			
Private company	159,564	3,230	162,794
	98.02%	1.98%	100%
Public company	116	49	165
	70.30%	29.70%	100%
Corporate group			
Independent company	66,777	734	67,511
	98.91%	1.09%	100%
Business group	92,903	2,545	95,448
	97.33%	2.67%	100%
of which:			
Domestic holding	85,922	2,154	88,076
	97.55%	2.45%	100%
International holding	6,981	391	7,372
	94.70%	5.30%	100%

NOTE: Innovators are defined as those firms with at least one priority patent granted between 2008-2012. The construction of size and ownership structure is defined as in the Appendix 3.A

Table 3.1: Sample characteristics by innovative group

This table represents the number of priority patents granted to the sample firms. For completeness, we report the sum of granted patents before the year 2006[5]. The last column of the table shows also the sectoral composition of the whole sample.

[5]For the sake of clarity, it is important to underline that we do not consider any dynamics before 2006. Hence, these figures should not be interpreted as the general patenting before the year 2006, but only as the patenting by the sample firms before that year.

Sample by sector and year

Sector	Before 2006	2006	2007	2008	2009	2010	2011	2012	Total Patents	Total Companies
Accomodation & Food	141	2	0	4	2	4	2	1	156	4,410
	0.22%	0.07%	0.00%	0.13%	0.06%	0.11%	0.10%	0.08%	0.19%	2.71%
Agriculture, Forestry, Fishing & Mining	1,483	66	71	100	90	62	31	12	1,915	3,994
	2.27%	2.46%	2.66%	3.34%	2.64%	1.77%	1.60%	0.99%	2.29%	2.45%
Construction & Real Estate	3,457	38	56	72	98	83	29	8	3,841	51,915
	5.30%	1.41%	2.10%	2.41%	2.88%	2.37%	1.50%	0.66%	4.59%	31.86%
Energy, Gas & Water Supply	232	6	6	7	15	9	3	3	281	2,680
	0.36%	0.22%	0.22%	0.23%	0.44%	0.26%	0.15%	0.25%	0.34%	1.64%
Information, Communication & R&D	2,125	124	161	136	130	87	45	31	2,839	4,237
	3.26%	4.62%	6.03%	4.54%	3.82%	2.48%	2.32%	2.55%	3.39%	2.60%
Manufacturing	49,701	2,263	2,208	2,418	2,800	2,963	1,688	1,019	65,060	41,601
	76.18%	84.25%	82.70%	80.79%	82.21%	84.56%	87.19%	83.80%	77.77%	25.53%
Other Sectors	381	32	15	13	15	17	9	3	485	6,223
	0.58%	1.19%	0.56%	0.43%	0.44%	0.49%	0.46%	0.25%	0.58%	3.82%
Other Services	1,478	47	65	92	85	105	47	53	1,972	8,945
	2.27%	1.75%	2.43%	3.07%	2.50%	3.00%	2.43%	4.36%	2.36%	5.49%
Retail Trade	569	6	12	17	16	28	15	7	670	7,771
	0.87%	0.22%	0.45%	0.57%	0.47%	0.80%	0.77%	0.58%	0.80%	4.77%
Transportation & Storage	914	33	14	42	39	20	17	32	1,111	5,908
	1.40%	1.23%	0.52%	1.40%	1.15%	0.57%	0.88%	2.63%	1.33%	3.63%
Wholesale Trade	4,762	69	62	92	116	126	50	47	5,324	25,275
	7.30%	2.57%	2.32%	3.07%	3.41%	3.60%	2.58%	3.87%	6.36%	15.51%
Total	**65,243**	**2,686**	**2,670**	**2,993**	**3,406**	**3,504**	**1,936**	**1,216**	**83,654**	**162,959**
	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

Table 3.2: Patenting behavior by sector and year

Table 3.2 clearly depicts a general positive trend in the total number of patents granted to Italian assignees. Patenting by year steadily grows from 2,686 in 2006 to 3,504 in 2010. However, the last two years of the sample show a sharp drop in the number of granted patents. In 2011, they reduce to 1,936, plummeting to 1,216 in 2012. This sudden change in the patenting dynamics is most likely connected with the presence of patent truncation. The problem arises as the period analyzed comes closer to the end of the dataset (Hall et al., 2001). In fact, it is possible that the missing patents are those which have not been granted yet at the time of data retrieval. Nonetheless, the possible effects of the truncation bias have been already discussed in the previous paragraph, as well as the way to ease some of the effects. Interestingly, the number of patents granted to the firms in the sample before 2006 is sizable. Almost 80% of the firms' patent portfolio has been produced before 2006, showing how patenting represents a long lasting and established behavior for Italian innovative firms.

The sectoral breakdown points out two important evidences. On the one hand, according to the number of firms, sample is mostly composed by construction, manufacturing and wholesale trade companies. Construction and real estate is the most relevant sector within the sample. Almost 32% of firms belong to this industry. Firms in manufacturing sector represent more than 25% of the total number of firms, while wholesale trade companies account for almost 16% of the sample. Together these three sectors amount to 118,791 firms and represent 73% of the overall sample. Therefore, each of the remaining eight sectors consists in a very small share (less than 5% each) of the total number of Italian firms. On the other hand, patenting appears to be much more concentrated in only one sector: manufacturing. This is not a surprising outcome. Most of the previous literature dealing with R&D and patenting focuses indeed on this sector. In our sample more than 80% of patents belongs to firms in this sector[6]. Moreover, this share appears to be stable over time, even before 2006. Consequently, the share of patenting of the other sectors is usually very small including high-tech sectors such as information, communication and R&D.

Summing up, the descriptive evidence in this section shows interesting general characteristics of the innovative activity engaged by Italian firms. First, data shows that this activity is relatively limited with respect to the generality of companies. The share of innovators, measured as the number of firms which patented inventions to the overall number of firms, is negligible for micro and small and very low for medium companies. Even among large firms, defined as those with more than 250 employees and a turnover higher than 50 million euros, almost 85% of active companies have not successfully applied for at least one patent. This poor performance seems to improve slightly in publicly traded firms and to a less extent in firms owned by international holding groups. Second, patenting behavior of Italian firms appears to proceed

[6]Evidence, not shown here, illustrates how concentration particularly increases at high level of innovation. Among "great innovators" (firms which steadily produce at least six patents each year) manufacturing companies amount to 49 out the 51 total number of firms in this class.

in a stable cumulative fashion. The significant stock of patents obtained before 2006 suggests that innovation is the result of a long lasting and clustered process. Lastly, there is a clear-cut evidence that innovation, as measured by patents, is mostly due to manufacturing firms. In fact, this sector steadily represent over 80% of patenting between 2006-2012 and about 76% before the year 2006.

3.3.3 Descriptive analysis of the manufacturing sample

Preliminary results illustrated in the previous section, which have underlined the particular prevalence of manufacturing firms among innovators, might be a substantive problem in the analysis of the financial characteristics of innovative and non-innovative firms. Financial literature has highlighted how companies' financial structure reveals significant patterns of inter-industry variations (Gupta, 1969; Hall et al., 2000). In fact, many financial ratios may systematically relate to features typical of the different industries. Hence, particularly in cross-sectional studies, differences among innovative groups may be severely confounded by sector-based compositional effects. Disentangling each contribution in a descriptive non-parametric analysis, as the one of the next section, can be hardly accomplished. On the other hand, the information gains resulting by considering the whole sample does not seem very high. Manufacturing constitutes more than 80% of domestic innovative output. Therefore, the between variation in the remaining sectors is very low. In order to introduce a coherent set of results, henceforward the study will exclusively focus on the financial profile of the subsample of 41,601 Italian manufacturing firms. In this paragraph we will present descriptive evidence on time-invariant firms' characteristics, relating them to the diverse innovative performances. We will also depart from the simple bimodal classification, to adopt the more complex four-status categories, as introduced before. The next section will present the financial profile of each non-innovative and innovative group through the analysis of a rich set of financial ratios, while testing the between group differences with a non-parametric test. Finally, we will later move towards a regression analysis testing the robustness of the evidence in a multivariate setting.

Table 3.3 reports the number of manufacturing firms, granted patents, size and ownership structure by group of innovative activity. According to the patenting performance between 2008-2012, each firm belongs either to non-innovators, occasional innovators, medium innovators, or great innovators. As expected, the majority of firms are considered non-innovators. Almost 94% of companies have never been granted with at least one patent. Conversely, occasional innovators, those firms whose inventive activity may be regarded as discontinuous (proxied by the fact that have received less than one patent per year), represent the largest group among innovators (2,196 companies which represent 5.28% of the overall sample). Persistent innovative activity is very limited and clustered among relatively few companies. Medium innovators (those which constantly produce more than one and less than six patents) are 367,

Manufacturing firms characteristics						
		Non innovators	**Occasional innovators**	**Medium innovators**	**Great innovators**	**Total**
N. of firms		38,989	2,196	367	49	41,601
		93.72%	5.28%	0.88%	0.12%	100%
N. of original patents		0	3,522	3,455	3,911	10,888
		0.00%	32.35%	31.73%	35.92%	100%
Size						
	Micro	9,611	213	7	0	9,831
		97.76%	2.17%	0.07%	0.00%	100%
	Small	21,454	866	46	1	22,367
		95.92%	3.87%	0.21%	0.00%	100%
	Medium	6,636	824	145	6	7,611
		87.19%	10.83%	1.91%	0.08%	100%
	Large	1,288	293	169	42	1,792
		71.88%	16.35%	9.43%	2.34%	1000%
Publicly traded						
	Private company	38,943	2,178	354	39	41,514
		93.81%	5.25%	0.85%	0.09%	100%
	Public company	46	18	13	10	87
		52.87%	20.69%	14.94%	11.49%	100%
Corporate Group						
	Independent company	16,346	542	34	0	16,922
		96.60%	3.20%	0.20%	0.00%	100%
	Business group	22,643	1,654	333	49	24,679
		91.75%	6.70%	1.35%	0.20%	100%
	of which:					
	Domestic holding	20,765	1,428	244	32	22,469
		92.42%	6.36%	1.09%	0.14%	100%
	International holding	1,878	226	89	17	2,210
		84.98%	10.23%	4.03%	0.77%	100%

NOTE: Innovative classes are defined by the average number of priority patent granted between 2008-2012. The construction of size and owner--ship structure is defined as in the Appendix 3.A

Table 3.3: Manufacturing sample characteristics by innovative group

while great innovators (those with at least six patents per year) are only 49, representing .88% and .12% of the sample, respectively. Despite the unequal size of groups, their relative contribution is almost even. Each of the three accounts for almost a third of total inventive activity. The 49 great innovators produced 3,911 patents between 2008-2012, almost 36% of the total amount of patented inventions. This is not very surprising. Cefis (2003), using a sample of 577 British manufacturing companies, finds that great innovators represent 2.37% of the companies, but account for 77.85% of patents requested. These differences may suggest a less degree of persistence of innovative activities in Italian firms with respect to the British ones, but they may also reflect different size composition of the smaller British sample. Size decomposition offers more insights on the inventive activity. Innovation is positively affected by size. In particular, the presence of innovative firms among micro and small firms is negligible and mostly represented by discontinuous outcome. Even the innovation among medium firms is mainly constituted by occasional patenting. Among the almost 30% of large firms which are innovators, half of the companies occasionally engages in patenting, while the other half persistently pursues this strategy. This suggests that high degree of innovation persistence is traceable almost exclusively in large organizations, at least for the inventive activity captured by patents. This may be related to the nature of persistent innovation which requires a set of capabilities, skills and structures that are hardly available in smaller organizations as well as by the typical specialization of production of Italian manufacturing firms.

Table 3.3 also illustrates the ownership structure by innovative groups. The share of innovative firms is much higher for publicly traded than private companies. Almost half of listed companies have patented at least once during 2008-2012 and the majority of those can be regarded as persistent innovators. By comparing these frequencies with those of large firms, we notice that public companies have a higher propensity to be innovative in each group, especially in the great innovators one. The bottom part of the table shows how companies belonging to a business group are relatively more innovative than independent companies. This is more evident for firms owned by international groups than for those belonging to domestic holdings.

Before presenting the analysis of the financial profile of innovative and non-innovative companies, we have here the opportunity to shed more light on the over time persistence of the innovation of Italian firms. The previous tables have delineated a very clear picture. The majority of manufacturing firms do not innovate at all, some engage in occasional innovation, while very few (mostly large) firms maintain a persistent level of high inventive capacity. However, this broad view is based only on the average patenting of five-year data. There are several substantive reasons which suggest to enlarge the scope of this analysis. On the one hand, innovation is a complex phenomenon. The likelihood of losing momentum may be significantly higher on a longer time span. On the other hand, Table 3.2 has highlighted how manufacturing firms in the sample had an exceptionally high number of patents even before 2006. Hence, this evidence

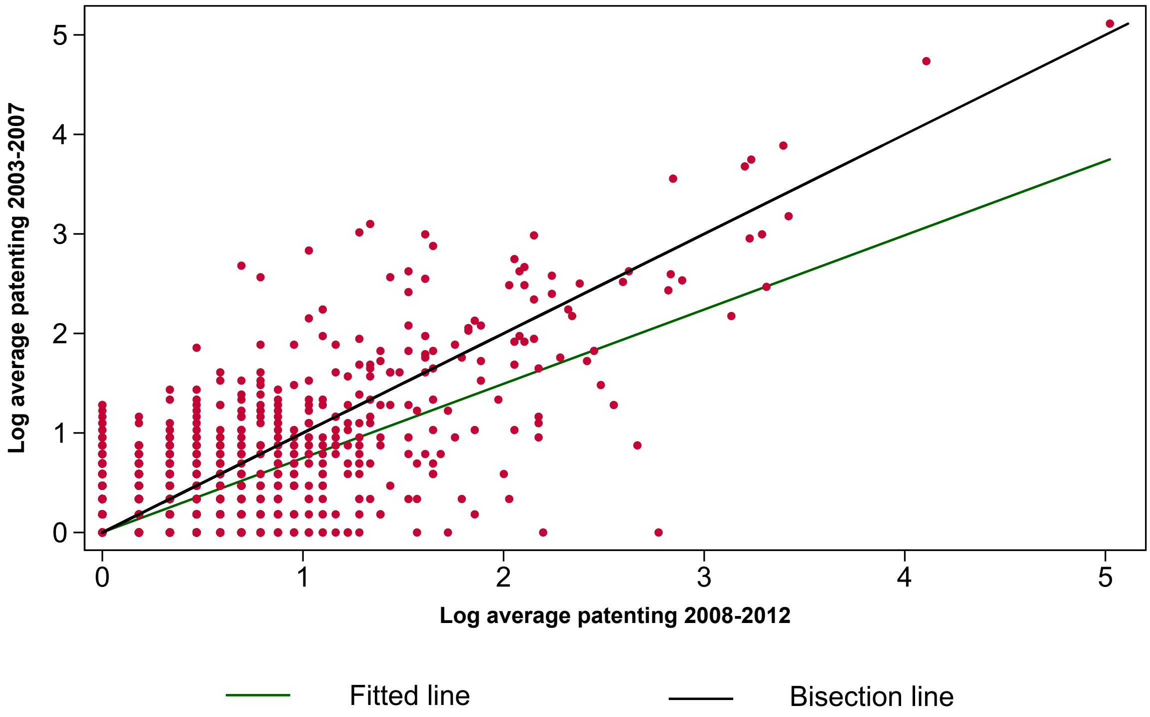


Figure 3.1: Over time average change in patenting behavior at firm level

points to the existence of an established long-term patenting pattern within firms. Lastly, years 2008-2012 represent a very harsh and unprecedented recessionary period which may have affected the innovative outcomes as well as the rest of firms' performances (OECD, 2012; Paunov, 2012).

Figure 3.1 graphically illustrates the over time change in firm-level average patenting between 2003-2007 and 2008-2012. Each point of the scatter plot displays the value of firm's average patenting in both periods. All values have been transformed in natural logarithms in order to smooth out and ease the visual interpretation[7]. Bisection line represents the pattern of perfect persistence, while fitted line is the estimated average trend. All the points above the 45 degrees bisection line represent firms which on average have innovated less than the past, while the opposite is true for the points below the bisection line. By construction, the logarithmic threshold for occasional innovators is .7, while all points above 2 are considered as great innovators.

The visual analysis over 10 years of patenting highlights several interesting points. First, as also indicated by the slope of the fitted line, the points below the bisection are more than those above. On average, patenting has slightly increased with respect to the previous five years.

[7]The exact transformation is $l = ln(1+x)$ where x represents the value of average patenting in each firm and period. Therefore, by calculating $x = exp(l) - 1$ we can get back to the original data.

Second, the majority of the improvements derives from the change among firms previously classified as occasional and medium innovators. This evidence connects directly to the third consideration. Strong persistence is clear only at very high level of patenting. At low level firms may change their behavior adapting to small shocks or simply following a diverse and unpredictable pattern with respect to the past.

The claim that innovation activity intensified during the crisis may seem at first counterintuitive. However, Archibugi et al. (2013), using the Community Innovation Survey to analyze the effect of the 2008 crisis on U.K. firms conclude that the cumulative nature of innovation tends to be higher during the crisis than in tranquil periods. They found that previous innovators intensified their innovative efforts during the crisis. The descriptive evidence presented above suggests a similar pattern. More speculatively, it is likely that the effects of the crisis on firms' innovation have been harsher for relatively younger and smaller enterprises than those in our sample. In fact, it is important to remark that the innovators described by our sample are not small startup companies, but rather established firms with instruments and capacities to pursue innovation even in times of crisis. The financial characteristics of the latter innovators are indeed the main goal of this study and the content of the next section.

3.4 Empirical results

This section will analyze a set of key financial ratios related to profitability, capital structure and operating performance of firms. When balance sheet and income statement indicators are reduced to a common order of magnitude, it is possible to investigate whether there is a significant pattern of variation related to the diverse innovative performances. The aim of this study is to characterize the most important financial features which differentiate non-innovators from occasional innovators and, in turn, the latter from persistent innovators (medium and great innovators). Moreover, this section will devote particular attention to the presence of financial flexibility also defined as financial slack, and whether this is a distinctive feature of innovative firms. As highlighted by the literature surveyed in Section 3.2, firms with excess financial resources, such as debt capacity and liquid reserves may have been more resilient to the unexpected adverse shocks. For example, a firm that has such a resource cushion may be capable of keep funding R&D projects even on a recessionary period like the one between 2008-2012. Coherently with the descriptive approach of this paper, causality here will not be addressed. Despite we will also use predetermined financial ratios with respect to innovative output, the relationship between financial structure and innovation activity may be multifaceted and persistent and the causal nexus generally may run both ways. Before presenting the results, Table 3.4 gives an overall introduction of the set of financial ratios used throughout this section, describes their construction and reports the most relevant descriptive statistics.

3.4.1 Non-parametric analysis

This paragraph will provide a description of the financial structure of innovators and non-innovators. Ratios are constructed yearly and averaged for two available periods: a short period before the crisis (2006-2007) and a longer period during the crisis (2008-2012). As described above, innovative groups are defined using the invention activity of 2008-2012. Therefore, for each financial characteristic we will carry out a twofold comparison. First, we will compare the ex-ante financial profile with respect to the ex-post inventive performance (represented by the belonging to each group), then we will also consider how the financial performance changes during the period of crisis. The emphasis of the study, however, remains focused in outlining the empirical profiles of each type of Italian innovative firm during the double-dip recession.

The description of the financial phenomena will rely on measures of central tendency and dispersion, while the Wilcoxon rank-sum test, also known as the Mann-Whitney test will verify the systematic difference between the two conditions (Wilcoxon, 1945; Mann and Whitney, 1947). The rank-sum test is a powerful non-parametric test, which requires very limited assumptions. In particular, it is more appropriate when the sample size is small, there are outlying observations and the normality assumption for the corresponding parametric method (t-test) does not hold. Given the ordered nature of our groups, we will test each group with the one immediately preceding (e.g. occasional vs. non-innovators or great innovators vs. medium innovators). The major limitation of this analysis is constituted by the lack of a *ceteris paribus* comparison. As underlined in the previous section, innovative activity seems to be positively related with size. However, even financial structure may be affected by the firm's dimension as well as by other characteristics not controlled for. Hence, the last paragraph will test the results of the financial analysis using a multivariate setting, pointing out which characteristic remain significant holding constant the other relevant variables.

Our comparison starts with the analysis of profitability ratios. All the metrics try to address the fundamental question of the adequacy of firm's returns to its investment. The main determinants of firm's profitability and returns are represented by the managerial ability to efficiently use assets to generate sales and control costs. However, each ratio evaluates a specific aspect of the company's performance, providing different information depending on the stage of an income statement and the choice of the denominator.

Variable Name	Definition	Num. Obs.	Mean	St. Dev.	Min	Max	Median
Age	Constructed as the difference (in years) between financial year of the data and company date of founding.	41,601	23.25	14.70	4.00	156.00	21.00
Cash flow / Operating revenues	Constructed as the percentage ratio of company's internal cash flow to its operating revenues. This metric evaluates the ability to to turn sales into cash.	41,509	4.76	7.81	-84.27	48.70	4.04
Cash Ratio	Constructed as the ratio of company's total cash and cash equivalents to its current liabilities. This metric evaluates the ability to repay short-term debts.	41,587	0.23	0.40	0.00	3.08	0.08
Cash / Total assets	Constructed as the ratio of company's total cash and cash equivalents to its total assets. This metric measures the share of company's assets that are cash or can be converted into cash immediately.	41,588	0.08	0.09	0.00	0.54	0.04
Current ratio	Constructed as the ratio of company's current assets to its current liabilities. This metric evaluates the ability to pay short-term obligations. It includes stock valued at the cost of acquiring on current assets.	41,601	1.64	1.10	0.24	9.29	1.31
Debt ratio	Constructed as the percentage ratio of company's total âĂŞ long-term and short-term âĂŞ debt to total assets. This metric measures the proportion of a company's assets that are financed by debt.	41,601	20.60	17.06	0.00	75.66	18.02
EBITDA return on assets	Constructed as the percentage ratio of company's EBITDA profit generated to total assets. This metric evaluates the company's profitability, allowing a meaningful comparison between companies with different capital structure, debt structure and geographical locations.	41,510	8.34	6.40	-24.17	37.27	7.45
Interest coverage	Constructed as the ratio of company's earnings before interest and taxes (EBIT) during to the amount interests paid on its debts during the calendar year. This metric evaluates the company's ability to repay interest on its outstanding debt with available earnings.	41,191	23.87	64.17	-85.46	610.00	2.93
Leverage	Constructed as the percentage ratio of company's total debt (loans and long-term debt) to its sum with shareholders' funds. This metric measures the proportion of capital which comes in the form of debt.	41,591	39.08	29.04	0.00	100.00	37.76
Liquidity ratio	Constructed as the ratio of company's liquid current assets (cash, accounts receivable and short-term investments) to its current liabilities. This metric evaluates the ability to pay short-term obligations. Also known as 'Acid test ratio', it ignores illiquid assets such as inventory.	41,601	1.24	0.95	0.13	7.82	0.97
Profit margin (pre-tax)	Constructed as the percentage ratio of company's profits before taxes to its operating revenues. This metric evaluates the profitability excluding taxes which are not function of operations.	41,601	0.81	13.35	-138.68	39.20	1.97
Return on assets (ROA)	Constructed as the percentage ratio of company's net income generated to total assets. This metric evaluates the company's profitability and efficiency in using its assets to generate earnings.	41,601	1.47	4.66	-26.69	22.78	0.81
Return on equity (ROE)	Constructed as the percentage ratio of company's net income generated to shareholders' funds. This metric evaluates the company's profitability using the capital shareholders' have invested.	41,469	1.17	24.54	-329.73	80.91	3.84
Solvency ratio (Assets)	Constructed as the percentage ratio of company's shareholders' funds to total assets. This metric measures the amount of assets on which shareholders have a residual claim in case of liquidation.	41,601	29.64	20.14	0.00	87.93	25.82
Tangibility	Constructed as the ratio of company's tangible assets amount (including fixed and current assets) to the value of total assets. This metric measures the proportion of assets that has a physical form and can be used as collateral.	41,600	0.25	0.20	0.00	0.87	0.21
Turnover Growth	Constructed as the over time growth rate of operating revenues. This metric measures the rate of expansion (or contraction) of business.	41,562	4.63	14.63	-77.25	239.47	2.92

Table 3.4: Definition of time-variant variables

Table 3.5 includes five common profitability measures. EBITDA return on assets is the summary measure of operating profitability. The between group variation is limited both in 2006-2007 and 2008-2012. The average EBIDTA profits represent between 10% and 12% of company assets before the crisis and 7% and 9% during the crisis. Wilcoxon test confirms the significance of the difference between innovators and non-innovators, but exclude within innovators differences in profitability (occasional vs. persistent innovators). Return on assets and on equity, measure respectively, company effectiveness to deploy assets to make profits and the ability of earning returns on its equity investment. Both indicators signal a significant increase in return when we move from non-innovators and from occasional to persistent innovators. As expected, all groups registered an evident drop in company returns during the crisis, but returns of persistent innovators seem to reduce to a less extent. Cash flow on operating revenues indicates the company's ability to turn sales into available cash. This is a fundamental metric. The more the company is efficient in increasing operating cash flow, the more it can invest in fixed capital, R&D, repay its debts or distribute dividends to shareholders. As it is clear from Table 3.5, differences between groups are statistically and economically significant. Both means and medians, before and during the crisis, rise with the degree of innovation. Great innovators are two times more efficient than non-innovators attaining a constant higher flow of cash. Interestingly, the differences between groups and the magnitudes of this ratio remain almost unchanged even during the recession. Lastly, (pre-tax) profit margin indicates the income that a firm is able to generate from its sales after adjusting for all expenses. Here expenses exclude taxes as they are not function of operations. Also this metric confirms an increase of profits at higher level of innovation. Differences between groups are statistically significant at conventional level (with the exclusion of the difference between great and medium innovators in 2008-2012). Overall, profitability is unambiguously larger at higher level of innovation activity. Groups differences are statistically significant in all comparisons between innovative vs. non-innovative firms and in the majority of comparisons between occasional vs. persistent innovators.

The analysis proceeds by introducing financial structure indicators. Capital structure ratios describe the way a firm finances its overall operations and growth by using different sources of funds, but also reveal the distribution of returns among investors, firm's liquidity and what would happen in a liquidation scenario. Section 3.2 has surveyed the theoretical and empirical literature which connects financial structure to the innovation financing. Here, we will investigate the structure of the Italian innovative and non-innovative firms.

Table 3.6 reports five key structure ratios. Cash ratio evaluates the firm's ability to repay short-term debts with the cash amount held by the company. Among liquidity indicators, this is the most conservative as it includes among current assets only cash or cash equivalents. Table 3.6 illustrates that the amount cash relative to the current liabilities is higher for more innovative firms. Moreover, only non-innovative firms seem to have increased precautionary

Financial analysis								
Profitability ratios	**EBITDA return on assets (2006-2007)**				**EBITDA return on assets (2008-2012)**			
	Mean	**Stand. Dev.**	**Median**	**Wilcoxon test** $((n)-(n_{-1}))$	**Mean**	**Stand. Dev.**	**Median**	**Wilcoxon test** $((n)-(n_{-1}))$
Non innovators	10.37	7.81	9.02	-	7.41	6.68	6.63	-
Occasional innovators	11.51	7.63	10.28	***	8.67	6.35	7.77	***
Medium innovators	11.94	8.55	10.44		9.12	7.50	8.20	
Great innovators	12.27	10.22	10.82		9.35	8.57	8.82	
	Return on assets (ROA) - (2006-2007)				**Return on assets (ROA) - (2008-2012)**			
	Mean	**Stand. Dev.**	**Median**	**Wilcoxon test** $((n)-(n_{-1}))$	**Mean**	**Stand. Dev.**	**Median**	**Wilcoxon test** $((n)-(n_{-1}))$
Non innovators	2.29	5.09	1.09	-	1.08	5.12	0.61	-
Occasional innovators	2.97	5.22	1.77	***	1.82	5.10	1.17	***
Medium innovators	3.66	6.02	2.46	***	2.22	6.46	1.98	***
Great innovators	5.12	6.60	4.43	**	3.08	6.84	3.04	
	Return on equity (ROE) - (2006-2007)				**Return on equity (ROE) - (2008-2012)**			
	Mean	**Stand. Dev.**	**Median**	**Wilcoxon test** $((n)-(n_{-1}))$	**Mean**	**Stand. Dev.**	**Median**	**Wilcoxon test** $((n-n_{-1}))$
Non innovators	6.36	29.61	6.58	-	-1.23	29.27	2.76	-
Occasional innovators	8.07	27.28	8.15	***	1.62	25.75	4.24	***
Medium innovators	7.61	29.24	9.57		-0.69	36.00	5.51	
Great innovators	16.46	18.08	13.11	*	6.90	22.30	11.61	*
	Cash flow / Operating revenues (2006-2007)				**Cash flow / Operating revenues (2008-2012)**			
	Mean	**Stand. Dev.**	**Median**	**Wilcoxon test** $((n)-(n_{-1}))$	**Mean**	**Stand. Dev.**	**Median**	**Wilcoxon test** $((n)-(n_{-1}))$
Non innovators	5.54	7.11	4.19	-	4.29	9.46	3.90	-
Occasional innovators	6.17	6.11	5.06	***	5.44	7.19	4.94	***
Medium innovators	7.92	7.69	6.74	***	6.73	9.97	6.37	***
Great innovators	9.61	8.85	8.48	**	6.85	9.86	8.19	
	Profit margin (pre-tax) - (2006-2007)				**Profit margin (pre-tax) - (2008-2012)**			
	Mean	**Stand. Dev.**	**Median**	**Wilcoxon test** $((n)-(n_{-1}))$	**Mean**	**Stand. Dev.**	**Median**	**Wilcoxon test** $((n)-(n_{-1}))$
Non innovators	3.60	9.52	2.87	-	-0.58	17.21	1.60	-
Occasional innovators	4.78	8.32	3.70	***	2.27	12.04	2.38	***
Medium innovators	5.98	10.51	4.93	***	2.68	15.97	3.40	***
Great innovators	7.63	12.88	7.19	*	3.54	17.31	4.28	

NOTE: The table reports descriptive statistic and Wilcoxon non-parametric test. Symbols *, ** and *** denote significance level of 10%, 5% and 1%, respectively.

Table 3.5: Wilcoxon test on the profitability ratios

Financial analysis

Structure ratios	**Cash ratio (2006-2007)**				**Cash ratio (2008-2012)**			
	Mean	**Stand. Dev.**	**Median**	**Wilcoxon test** $((n)-(n_{-1}))$	**Mean**	**Stand. Dev.**	**Median**	**Wilcoxon test** $((n)-(n_{-1}))$
Non innovators	0.19	0.33	0.06	-	0.25	0.46	0.07	-
Occasional innovators	0.19	0.30	0.08	***	0.24	0.41	0.08	***
Medium innovators	0.22	0.35	0.10	**	0.28	0.48	0.10	*
Great innovators	0.30	0.48	0.15		0.27	0.39	0.15	
	Cash / Total assets (2006-2007)				**Cash / Total assets (2008-2012)**			
	Mean	**Stand. Dev.**	**Median**	**Wilcoxon test** $((n)-(n_{-1}))$	**Mean**	**Stand. Dev.**	**Median**	**Wilcoxon test** $((n)-(n_{-1}))$
Non innovators	0.08	0.10	0.03	-	0.08	0.10	0.03	-
Occasional innovators	0.08	0.10	0.04	***	0.08	0.10	0.04	***
Medium innovators	0.08	0.10	0.05		0.08	0.10	0.04	
Great innovators	0.09	0.11	0.07		0.09	0.10	0.06	
	Debt ratio (2006-2007)				**Debt ratio (2008-2012)**			
	Mean	**Stand. Dev.**	**Median**	**Wilcoxon test** $((n)-(n_{-1}))$	**Mean**	**Stand. Dev.**	**Median**	**Wilcoxon test** $((n)-(n_{-1}))$
Non innovators	21.37	18.78	18.45	-	20.27	17.74	17.06	-
Occasional innovators	21.71	17.87	19.71	**	21.34	17.11	19.06	***
Medium innovators	19.02	16.13	17.15	**	19.09	16.20	16.42	**
Great innovators	10.18	11.75	5.80	***	11.98	13.09	6.29	***
	Liquidity (2006-2007)				**Liquidity (2008-2012)**			
	Mean	**Stand. Dev.**	**Median**	**Wilcoxon test** $((n)-(n_{-1}))$	**Mean**	**Stand. Dev.**	**Median**	**Wilcoxon test** $((n)-(n_{-1}))$
Non innovators	1.14	0.80	0.93	-	1.28	1.09	0.97	-
Occasional innovators	1.09	0.62	0.92		1.19	0.82	0.95	
Medium innovators	1.16	0.75	0.96		1.27	0.96	1.00	*
Great innovators	1.37	1.05	1.06		1.18	0.64	1.03	
	Solvency ratio (Assets) - (2006-2007)				**Solvency ratio (Assets) - (2007-2012)**			
	Mean	**Stand. Dev.**	**Median**	**Wilcoxon test** $((n)-(n_{-1}))$	**Mean**	**Stand. Dev.**	**Median**	**Wilcoxon test** $((n)-(n_{-1}))$
Non innovators	25.49	19.54	20.70	-	30.99	21.53	27.04	-
Occasional innovators	27.97	18.21	24.05	***	33.62	19.75	30.81	***
Medium innovators	32.50	17.68	30.51	***	37.25	19.15	34.81	***
Great innovators	40.21	21.38	39.37	**	40.75	20.82	37.03	

NOTE: The table reports descriptive statistic and Wilcoxon non-parametric test. Symbols *, ** and *** denote significance level of 10%, 5% and 1%, respectively.

Table 3.6: Wilcoxon test on the structure ratios

Financial analysis								
Potential slack	**Leverage ratio(2006-2007)**				**Leverage ratio (2008-2012)**			
	Mean	**Stand. Dev.**	**Median**	**Wilcoxon test** $((n)-(n_{-1}))$	**Mean**	**Stand. Dev.**	**Median**	**Wilcoxon test** $((n)-(n_{-1}))$
Non innovators	42.75	32.74	43.05	-	37.76	30.07	35.26	-
Occasional innovators	41.31	30.14	41.43		37.36	27.76	36.19	
Medium innovators	35.09	27.04	34.86	***	32.51	25.19	29.91	***
Great innovators	21.19	21.57	14.00	***	22.88	21.61	15.13	**
Available slack	**Current ratio (2006-2007)**				**Current ratio (2008-2012)**			
	Mean	**Stand. Dev.**	**Median**	**Wilcoxon test** $((n)-(n_{-1}))$	**Mean**	**Stand. Dev.**	**Median**	**Wilcoxon test** $((n)-(n_{-1}))$
Non innovators	1.50	0.93	1.23	-	1.70	1.25	1.32	-
Occasional innovators	1.52	0.72	1.33	***	1.70	0.99	1.40	***
Medium innovators	1.62	0.89	1.37	*	1.78	1.11	1.47	
Great innovators	1.89	1.19	1.49	*	1.70	0.84	1.48	

NOTE: The table reports descriptive statistic and Wilcoxon non-parametric test. Symbols *, ** and *** denote significance level of 10%, 5% and 1%, respectively.

Table 3.7: Wilcoxon test on the financial slack measures

reserves during the crisis. Mean significantly rises while median remains stable, suggesting the presence of outliers. The relevance of very liquid assets could be measured also by the cash to total assets ratio. This indicator measures the share of company's assets that are cash or can be converted to cash immediately. The Wilcoxon test reports a significant difference only between innovators and non-innovators. Additionally, cash surplus in innovative firms is relatively smaller than the one measured to the current liabilities. Debt ratio is one of the two main indicators of financial leverage and can be interpreted as the proportion of a company's assets that are financed by debt. It also indicates the degree of financial risk of the firm. There is strong significant evidence that more innovative companies finance less their assets through debt with respect to less or non-innovative firms. This is true at each level of innovation and before and during the economic crisis. Liquidity ratio, also known as acid test ratio, is similar to cash ratio but less stringent. It includes accounts receivable and short term investments among liquid assets (but excludes inventory). However, here the non-parametric test does not reject the null hypothesis, almost for all group differences. Lastly, solvency ratio which measures the extent of the residual claims of shareholders on assets, confirms the picture delineated before. The use of debt is limited among innovative firms, which instead finance their assets with shareholders' funds. Before the crisis the ratio amounted to 25% for non innovative firms and 40% for great innovators. During the crisis, this share slightly increased for non-innovative firms (to 31%) while remained unchanged for great innovators. Moreover, all group differences are significant at conventional levels (with the exclusion of great innovators vs. medium innovators between 2008-2012).

Table 3.7 introduces other two relevant measures of financial structure: leverage and current ratio. Those ratios are also commonly used by literature to approximate the concept of financial slack (see Daniel et al. (2004) for an excellent meta-analysis on the topic). Leverage ratio accounts for the debt capacity or potential slack, while current ratio exhibits the degree of liquidity or available slack. Leverage ratio measures the proportion of capital which comes in the form of debt. The main difference here is between persistent innovators and occasional/non-innovators, both before and during economic crisis. The average(median) leverage of great innovators is 20%(14%) for great innovators, while average/median leverage for occasional/non-innovators accounts to more than 40%. There is evidence of deleveraging among non-innovators from 2006-2007 to 2008-2012, while average debt remained unchanged for persistent innovators. Innovators and in particular persistent ones seem to have a higher potential slack with respect to non-innovators and this slack remained available even during the crisis. However, it is likely that this evidence is driven by credit constraint faced by innovative firms more than the deliberate strategy to save potential slack. In fact, as underlined in Section 3.2, debt is an unsuitable mean of financing for innovative firms which lack of adequate collateral.

A more appropriate mean of acquiring flexibility during recessionary periods is constituted by available slack. Current ratio is the least stringent test of liquidity as it incorporates all current total assets of a company (both liquid and illiquid) and relates them to the firm's current liabilities. The test strongly rejects the null hypothesis for innovators and non-innovators, but the same evidence between occasional and persistent innovators is weak and limited to the pre-crisis period. Overall, differences in available slack seem to be small in magnitude and limited in statistical significance.

Table 3.8 reports the last set of indicators. They include both operating efficiency and the margin of safety a company maintains during its operations as well as other characteristics such as the tangibility of its assets and the turnover growth rate. Interest coverage evaluates the ability of a company to pay the interest on its outstanding debt with its available earnings. The higher is the safety margin, the more a company can adapt to financial hardship. Means and median widely diverge, but they are both above the safety level in all groups (the rule of thumb indicates 1.5 as the minimum acceptable level to avoid that interest expenses burden triggers bankruptcy). Differences between groups are significant only between innovators and non-innovators, showing a higher ability to repay interests for the former companies. Tangibility indicates the proportion of assets which have a physical form and can be used as collateral. As expected, innovative firms show lower level of tangible assets which in turn may be related to the lower level of indebtedness. Non-parametric test confirm the significance of this difference only between innovators and non-innovators, while tangibility in medium and great innovators does not seem to be statistically different from the one in occasional innovators. Lastly, sales growth appear to be higher in innovators than non-innovators. Interestingly, all four groups experienced a substantial drop in sales growth rate during the economic crisis. However, the

Financial analysis								
Other ratios	**Interest cover (2006-2007)**				**Interest cover (2008-2012)**			
	Mean	**Stand. Dev.**	**Median**	**Wilcoxon test** $((n)-(n_{-1}))$	**Mean**	**Stand. Dev.**	**Median**	**Wilcoxon test** $((n)-(n_{-1}))$
Non innovators	27.04	58.35	3.10	-	23.33	69.90	2.38	-
Occasional innovators	30.81	69.81	4.13	***	31.13	83.07	3.35	***
Medium innovators	34.81	71.47	5.04		37.16	95.46	4.80	
Great innovators	37.03	67.68	4.73		31.65	70.93	5.43	
	Tangibility (2006-2007)				**Tangibility (2008-2012)**			
	Mean	**Stand. Dev.**	**Median**	**Wilcoxon test** $((n)-(n_{-1}))$	**Mean**	**Stand. Dev.**	**Median**	**Wilcoxon test** $((n)-(n_{-1}))$
Non innovators	0.22	0.19	0.17	-	0.27	0.21	0.21	-
Occasional innovators	0.18	0.14	0.14	***	0.22	0.17	0.18	***
Medium innovators	0.17	0.12	0.14		0.20	0.15	0.17	
Great innovators	0.16	0.11	0.14		0.17	0.10	0.17	
	Turnover growth (2006-2007)				**Turnover growth (2008-2012)**			
	Mean	**Stand. Dev.**	**Median**	**Wilcoxon test** $((n)-(n_{-1}))$	**Mean**	**Stand. Dev.**	**Median**	**Wilcoxon test** $((n)-(n_{-1}))$
Non innovators	14.35	34.28	8.84	-	2.53	15.26	1.18	-
Occasional innovators	14.91	29.38	10.57	***	3.84	11.86	2.12	***
Medium innovators	15.36	30.84	11.06		4.17	11.54	2.36	
Great innovators	20.77	43.62	7.94		7.08	11.83	4.42	*

NOTE: The table reports descriptive statistic and Wilcoxon non-parametric test. Symbols *, ** and *** denote significance level of 10%, 5% and 1%, respectively.

Table 3.8: Wilcoxon test on the operational and other ratios

extent of this reduction is attenuated in persistent innovators with respect to non-innovators.

3.4.2 Regression analysis

The previous analysis has summarized the most important financial characteristics of the sample firms, delineating the financial profile of each innovative group. Evidence suggests that innovative firms are more profitable, less indebted, grow faster and have a higher flow of cash, but a less degree of asset tangibility. Moreover, group differences seem to widen with innovation intensity. Lastly, these features appear to be stable over time. The objective of this section is to observe whether the differences in terms of profitability, capital structure, debt management are robust to the inclusion of size, age and other relevant variables. Therefore, we implement a multivariate model which estimates the marginal effect of the most relevant financial ratios on the number of patenting activity at firm level between 2008-2012. The outcome represents a count variable which takes non negative integer values, with a great amount of small numbers, including zero. We approximate this process by fitting a Poisson regression model.

In Table 3.9, we present our estimates for the years 2006-2007 and 2006-2012. The independent variables include indicators of cash flow, profitability, financial leverage, liquidity, tangibility and growth. The specification includes also firm's size, age and the number of past patents (2003-2007). We include first the predetermined values of the financial ratios with respect to the ex-post innovative activity (columns 1-2). Then, we run the regression over all sample period (2006-2012) in columns 3-4. In order to test the robustness of results to the choice among different metrics in the domain of profitability, financial leverage and liquidity, we run again the original regressions (columns 1 and 3) with different proxies (columns 2 and 4). Profitability is proxied alternatively with profit margin and EBITDA return on assets. Leverage is proxied with leverage ratio or debt ratio. Finally, liquidity is represented by current ratio or liquidity ratio. Variance inflation factors (VIFs) have been examined to detect multicollinearity. All of the VIF scores are below 3 and the mean VIF score is 1.5.

The estimates for the period 2006-2007 (column 1-2) show a large and highly significant effect of the cash flow to operating revenues ratio. Each percentage point increase, rises the expected number of patents by 5.3% (6%, in column 2, where different proxies are considered). The effect is sizable given that the previous analysis highlighted a cash flow ratio difference of several percentage points between extreme groups. Profitability is not associated with a significant effect on patenting, both as profit margin and EBITDA profits. Conversely, leverage is related to a lower level of patenting. Even accounting for the lower level of tangible assets in innovative firms, each percentage point rise in leverage (which means a relative increase in indebtedness), the decrease in expected number of patents ranges between .6% or 1.4%, depending on the choice of the ratio denominator. Interestingly, and contrary to the (weak) evidence of the previous analysis, liquidity turns out to be negative and highly significant. The

Dependent variable: Total number of granted patents 2008-2012					
		2006-2007		**2006-2012**	
		(1)	(2)	(3)	(4)
Cash flow		.053***	.060***	.045***	.046***
		[.012]	[.008]	[.009]	[.010]
Profitability		-.003	-.012	-.005	-.001
		[.010]	[.008]	[.007]	[.010]
Leverage		-.006***	-.014***	-.007***	-.013***
		[.002]	[.003]	[.002]	[.003]
Liquidity		-.210***	-.333***	-.246***	-.389***
		[.076]	[.099]	[.070]	[.090]
Tangibility		-2.855***	-2.708***	-2.731***	-2.596***
		[.408]	[.345]	[.309]	[.295]
Growth		.004**	.004**	.025***	.025***
		[.002]	[.002]	[.003]	[.003]
Age		.006*	.006*	.006**	.006**
		[.003]	[.003]	[.003]	[.003]
Past patenting		.011***	.011***	.011***	.011***
		[.001]	[.001]	[.001]	[.001]
Size					
	Small	.783***	.813***	1.131***	1.127***
		[.113]	[.115]	[.145]	[.147]
	Medium	2.453***	2.488***	2.800***	2.805***
		[.136]	[.137]	[.176]	[.179]
	Large	4.129***	4.144***	4.465***	4.459***
		[.137]	[.139]	[.163]	[.168]
Constant		-2.798***	-2.681***	-2.998***	-2.961***
		[.229]	[.211]	[.210]	[.200]
Pseudo R^2		0.45	0.45	0.46	0.46
Wald χ^2		2785.5	3051.9	2424.3	2557.7
P-value		<.001	<.001	<.001	<.001
Observations		39,960	40,003	41,471	41,478

NOTE: This table reports the results of the Poisson regressions over the number of granted patents between 2008-2012. Symbols *, ** and *** denote significance level of 10%, 5% and 1%, respectively. Standard errors are robust to heteroskedasticity.

Table 3.9: Poisson model - Effect of financial characteristics on patenting

negative effect also increases when liquidity is accounted excluding relatively illiquid assets, such as inventories (column 2). However, the magnitude of the effect estimated here is low. The maximum average difference in liquidity ratios between groups was around .2 which in turn represents a maximum estimated reduction in patenting of 4-6%. Anyway, the negative coefficient of liquid assets may be puzzling at first and at odds with the positive and significant effect of cash flow. However, the two ratios describe different aspects. While cash flow ratio accounts for the ability to acquire cash resources to finance operations and investments which might suggest a higher capability of employing internal resources, liquidity signals instead the company's decision of holding a certain amount of cash or liquid assets with respect to its current liabilities. Therefore, as highlighted in Section 3.2, excessive resource cushion may also result in possible inefficiencies and unproductive use of cash. Sales growth rate and firm's age correlates positively with number of granted patents. The effects are both significant at conventional levels. A much stronger role is played by past patenting performance and the dimensional variables. In fact, each patent acquired in the previous five years rises the number of expected (ex-post) patents of 1.1%. This result represents a strong confirmation of the persistent fashion of Italian innovation. Lastly, size coefficients suggest that on average larger firms are able to produce more patents than the smaller ones and this effect is highly statistically significant for all the categories[8]. Columns 3-4 run again the same regressions to test the stability of coefficients on a longer time-span which includes also the recessionary period. Sign, significance and magnitude remain virtually unchanged. The only exception is the growth rate coefficient which significantly rises, signaling how successful innovation correlates more with sales growth in the longer period which includes the crisis.

Overall, the multivariate analysis substantially confirms the previous evidence. With the exception of profitability, all the financial profile outlined before is confirmed. Firms which successfully patented during the crisis are on average relatively large, established and with previous history of innovation. Their indebtedness is relatively lower than non-innovators, as it is also their collateral. Lastly, they show a relatively faster growth and a higher ability to produce cash flow out of their sales. The interpretation of these final results together with the previous evidence will be discussed in detail in the next section.

3.5 Conclusion

This paper examined the financial profile of Italian non-financial companies according to their inventive activity. The analysis complemented the evidence on patent-based innovation between 2008-2012 with the companies' financial characteristics over the period 2006-2012. In Section

[8]The very high coefficients of size are due to the choice of the base category. Overall, micro enterprises are responsible of very few patents, which in turn reflects on the very high relative effect of the other categories.

3.3.2 we described the overall sample characteristics and the patenting behavior at sectoral level. We showed that patenting is very limited in size and clustered in specific firms and sectors. The share of innovators is negligible for micro and small companies and very low for medium companies. Even among large firms, almost 85% of active companies have never applied for at least one patent. This poor performance improves slightly when firms are publicly traded and to a less extent in firms owned by international holding groups. Moreover, there is a clear-cut evidence that Italian innovation, as measured by patents, is mostly concentrated in manufacturing firms. In fact, this sector has steadily represented over 80% of patenting between 2006-2012 and about 76% before the year 2006. The significant stock of patents obtained before 2006 suggests that innovation at firm level is an enduring phenomenon.

In Section 3.3.3 we concentrated on the inventive performance of manufacturing firms dividing the sample in four-status categories. We delineated a very clear picture. The majority of manufacturing firms does not innovate at all, some engages in occasional innovation, while very few (mostly large) firms maintain a persistent level of high inventive capacity. Medium and great innovators are .88% and .12% of the total sample, but accounts respectively for 32% and 36% of the total amount of patented inventions. In particular, the 49 great innovators (those with more than six patents per year) are constituted almost exclusively by large companies with more than 250 employees. Therefore, the present evidence supports the view that firms consistently devoted to the introduction of new and original inventions are almost completely constituted by large organizations, at least for the inventive activity captured by patents. This may be related to the nature of persistent innovation which requires a set of capabilities, skills and structures that are hardly available in smaller organizations as well as by the typical specialization of production of Italian manufacturing firms. When we considered the over time change in firm-level average patenting between 2003-2007 and 2008-2012, we highlighted how average patenting has slightly increased with respect to the previous five years. The majority of the improvements derives from the change among firms previously classified as occasional and medium innovators. However, strong persistence is clear only at very high level of patenting. This evidence suggests that innovators (and in particular the persistent ones) are established firms with instruments and capacities to pursue innovation even in times of crisis.

Section 3.4 drew the financial profile of each type of innovator by employing a wide set of key financial ratios related to profitability, capital structure and operating performance of firms. The non-parametric descriptive analysis showed the existence of significant group differences both between innovators and non-innovators and, within the innovators, between occasional and persistent ones. Group differences widen with innovation intensity, but remain stable over time. The multivariate analysis confirmed that those differences were robust to the inclusion of size, age and other relevant variables. Innovators are on average relatively large, mature and established. The higher cash-flow and lower indebtedness clearly signal that they fund their activities with internal resources. Even accounting for the lower tangibility of their assets, these effects are economically and statistically significant. Moreover, the higher is the innovation activity, the faster is their average turnover growth. Innovators adapted also better to the crisis, showing a lower growth reduction during the recessionary period. Lastly, the (limited) negative effect of available slack points out that innovators avoided the accumulation of unproductive financial cushions, even in a period of crisis. This is coherent with the negative vision of excessive liquid resources, highlighted by part of the literature, and suggests that innovation is a long-term activity that is clustered more in firms with relatively stable flow of internal resources.

The global picture that emerges from these results is largely consistent with the hierarchical view of financing. As we move from non-innovators to great innovators, the use of cash flow to fund operations increases, while leverage decreases. Direction of causality is however not addressed here. Overall, Italian innovation shows bright and dark sides. On the one hand, the majority of Italian innovators represent a coherent unit of good performers, endowed with a long-term vision, skills and means to pursue innovation and even to overcome adversities, such as the 2008-2012 recession. On the other hand, their number is extremely limited with respect to the generality of Italian productive system. They are mainly concentrated in manufacturing sector and definitely not sufficient alone to reverse the poor performance of Italian economy in the last two decades. In order to start a significant catching up with the majority of European countries, a positive change both in extensive and intensive margin is required. Italy needs both the entry of new innovators and a significant increase in patenting performance among the persistent innovators. Only forty-nine great innovators in manufacturing sector is hardly a sufficient number for a highly industrialized nation, such as Italy. Lastly, the extent to which startups and smaller firms excluded in this analysis may have experienced a different pattern during 2008-2012 with respect to the ones included in this sample remains to be explored and it is left for future research.

3.A Appendix A - Construction of time-invariant variables

Time-invariant firms' characteristics have been derived from Orbis Bureau van Dijk database. This section reports a brief description of the construction of these variables.

The main factors which determines the size classification, as defined by the European Commission in the EU recommendation 2003/361, are the staff headcount and either turnover or total assets. Table 3.A1 reports the official ceilings. In the recommendation, the European Commission explains that the criterion of staff numbers is the most important, while a financial criterion is introduced to measure also the real scale and performance of an enterprise. The choice of combining operating revenues (turnover) with total assets derives from the necessity to account for sector-based turnover differences which could bias the overall wealth evaluation of the businesses. Therefore, micro firms have less than 10 employees and either turnover or assets smaller than 2 million euros. Similarly, small (medium) firms are defined as those with less than 50 (250) workers and which meet at least one of the two financial criteria (10 million euros in assets or revenues for small firms and 43 million euros in assets and 50 million euros in turnover). All enterprises above these thresholds are considered as large. Crucially, these factors change year by year. Therefore, all the figures are evaluated at pre-crisis levels, by averaging those values in the years 2006-2007.

Size	Staff headcount	Total assets	or	Operating revenues
Micro	< 10	$\leq 2m$		$\leq 2m$
Small	< 50	$\leq 10m$		$\leq 10m$
Medium	< 250	$\leq 43m$		$\leq 50m$
Large	≥ 250	$> 43m$		$> 50m$

Table 3.A1: Size definition cut-offs

The sectors considered here are based on the values of NACE rev.2, the statistical classification of economic activities in the European Community (Eurostat, 2008), reported by Orbis for each firm. Through these codes, sectors have been constructed by aggregating each NACE division (a two-digit value) in meaningful groups. Financial corporations (divisions 63-66) have been excluded from the analysis, while those companies without a sectoral code have been dropped from the sample. Table 3.A2 reports the 11 aggregated sectors, with the corresponding sections and divisions of NACE rev.2 classification. Table 3.2 in Section 3.3.2 employs this classification to describe the sample and the relative weight of each sector.

Sector	Nace rev.2 section	Nace rev.2 division (d)
Agriculture, Forestry, Fishing and Mining	A+B	$d \leq 9$
Manufacturing	C	$d > 9 \cap d \leq 33$
Energy, Gas and Water supply	D+E	$d > 34 \cap d \leq 43$
Construction and Real estate	F+L	$d > 40 \cap d \leq 43 \cup d = 68$
Wholesale trade	G	$d > 44 \cap d \leq 46$
Retail trade	G	$d = 47$
Transportation and Storage	H	$d > 48 \cap d \leq 53$
Accomodation and Food	I	$d > 54 \cap d \leq 56$
Information, Communication and R&D	J+M	$d > 57 \cap d \leq 63 \cup d = 72$
Other Services	M+N	$d > 68 \cap d \leq 75 \cup d > 79 \cap d \leq 82$
Other Sectors	N+O+P+Q+S	$d > 76 \cap d \leq 79 \cup d > 83$

Table 3.A2: Sector aggregation according to the Statistical classification of economic activites (NACE rev.2)

The variable “publicly traded” indicates if the ownership is dispersed among the general public and it is freely traded in stock markets (public company) or it is a company owned and traded exclusively privately (private company). It derives from the original variable “listed-delistedunlisted” in Orbis and it is evaluated in the year 2006.

The values of the variable “corporate group” derives from the original variables “noofcompaniesincorporategroup” and “guocountryisocode” which respectively reports the number of companies in the business group and the nationality of the ultimate owner (in case of business group). The latter is assigned to “international holding” if the value is different from Italy. All these variables are evaluated in the year 2006.

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