PRIVATE EQUITY PERFORMANCE DRIVERS

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Abstract

This paper investigates which are the key performance drivers for private equity firms. We have collected information on performances and features for 570 private equity funds raised between 1980 and 2009 and managed by 151 General Partners. They have a cumulative committed capital of more than $1 trillion, allocated across 6,620 investments. Overall, we have found a positive and concave relationship between Venture Capital funds' performances and their sizes. Moreover, we documented a strong persistence across funds managed by the same General Partner both for Buyout and Venture Capital. In addition, experience seems to be an important driver of performance for any type of PE fund. We have found a positive and concave relationship between current fund's performance and the natural logarithm of fund's sequence number. Furthermore, industry concentration is another significant driver of performance for BO funds but it is not so important for VC. Finally, we have found no evidence that geographical concentration improves or worsens performance. Interestingly, our findings hold also when we measure performance in terms of cash-on-cash multiple or quartile ranking. Moreover, thanks to robustness tests, we have shown that our main findings are strong and independent from the specific form assumed by the variables in question.

Keywords: Private Equity, Buyouts (BO), Venture Capital (VC), Performance, Persistence, Industry concentration, Size, Experience

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Introduction

There is little doubt that PE has played a vital role for thousands of companies around the world. Strömberg (2007) indicated that PE worldwide had acquired 14,000 companies worth around $3.6 trillions. Therefore, the magnitude and economic importance of this phenomenon make it an interesting area of research. The PE industry has gone through peak and thought, fluctuating wildly in the last three decades. After having boomed in 2008 with $680B[2] in fundraising, the industry went into a strong recession, from which, it would be difficult to fully recover and pre-crisis levels of fundraising and investments are just a dream today. This may be partly due to the financial constraints that some investors went through and partly to regulations, which obliged many LPs to reduce their allocations to PE, because this asset class was considered to bear excessive liquidity risk.

2012 was a flat year for the PE industry, with $320B[1] in fundraising and few transactions. Despite this poor picture of the last years, the number of firms in the market has rose steadily since 2006, reaching a peak in 2012 of almost 2,000[1] GPs. Moreover, the PE industry is becoming always more a regional phenomenon. As a matter of fact, in spite of the crisis, 2012 saw same areas of the world quite active in terms of PE activity, while other areas, such as South Europe, seemed almost dead. Furthermore, 2013 will be a crucial year for the industry, at least in terms of tax and regulatory framework, because the traditional self-regulation typical of this industry was considered, finally, incomplete and regulators are pushing for tax and regulatory developments similar to those already faced by hedge funds[3]. Undoubtedly, these regulations will increase costs for PE firms, but considering the difficult times the industry is experiencing, it would be difficult to pass these costs to investors via higher fees. Nowadays, the size of the pie is smaller than pre-Lehman gold times and LPs need to allocate their resources more consciously. Therefore, two important questions need answers. Firstly, we would need to know whether PE asset class creates value for investors. Secondly, we would like to understand what drives the PE performance: are there some elements that matter more than others or is performance just a question of luck?

[2] Preqin's data

[3] 2012 saw important developments, such as Securities and Exchange Commission's (SEC) registration and Form PF (mandated by the Dodd-Frank Wall Street Reform) and the Foreign Account Tax Compliance Act. Moreover, Alternative Investment Fund Managers (AIFM) Directive needs to be implemented by 22nd July 2013

Despite the large amount of money, which has been allocated to PE over time, the historical performance of this asset class has controversial pieces of evidence. Authors have reached different conclusions according to the sample used or the period considered. Therefore, today, we are still not able to give a definitive and unidirectional answer to whether PE had historically outperformed the market or not. Leaving returns to LPs aside, without, however, forgetting that they remain fundamental to the discussion, PE firms seem to add an economic value in a more general term. For example, Kaplan and Strömberg (2009) suggested that, thanks to changes in capital structure, management incentives and corporate governance, PE activity, on average, creates value.

The aim of this paper is to address the second question, investigating which are the performance drivers of PE funds. Traditionally, authors have addressed several factors as possible drivers. Even if these elements did not always have the same significance and magnitude in terms of explanatory power, authors seem to agree that previous performance, size and experience are important components of current performance. Moreover, market cyclicality, macroeconomic conditions, such as the level of interest rates, and competition for investment opportunities have also been addressed as important elements affecting the performance of this asset class.

Our first finding is that past fund's performance is an important driver of current performance. Persistence is present in terms of the previous and second previous fund. Moreover, persistence is important across fund's type and time with the only exception of the period 1980-1990, for which we recorded only 26 observations and we were not able to reach any robust conclusion.

Our second important finding is the concave relationship between size and performance, which is strong and significant for the overall sample. We found that the optimal size for the overall sample is $1.2B. Moreover, we have also shown that size is the most important variable in terms of magnitude, followed by experience. However, when we split the sample by type, we do not find any evidence of size effect for BO, while this effect is even more important for VC, for which the optimal size was found to be $750M.

Our third finding is a strong effect of experience on performance. Independently from how we measure experience, we found that experienced PE firms performed better. Moreover, when experience is measured with the Log (Sequence number) and its square, a positive and concave relationship between performance and experience emerges. The optimal sequence number was found to be eight. Moreover, the experience effect remains important across fund's type.

Our fourth finding is that industry concentration is another important driver of performance. However, both the significance and the magnitude of the coefficient linking industry concentration to performance vary according to the variable used to measure it. In addition, when we split the sample by fund's type, we find that industry concentration matters for BO but not for VC. We attributed this last finding to the fact that VC are already very industry-focused (i.e., 82% of VC investments is concentrated in Information Technology and Healthcare).

Our fifth finding is that geographic concentration is irrelevant in affecting the PE performance. Independently from how we measure it, the effect of this variable is significant neither for BO nor for VC. However, we cannot fully trust this evidence because of the characteristics of our sample, which is very US-focused.

It is worth noticing that these findings above are still true and even stronger when performance is measured via TVPI or quartile ranking and we have shown the reliability of our findings via a number of robustness tests.

In the last part of this paper we have addressed also whether these results were valid for subgroups by location, fund's type, vintage and size. Unfortunately, given the low presence of Non-US funds in our sample, we were not able to find any conclusive evidence for this group. Moreover, we found that our model fits better VC and funds smaller than $1B. In addition, we have shown that over time, the significance and the magnitude of explanatory variables have changed and each decade has its own story. Finally, analyzing only liquidated funds, we can state that we did not find any strong evidence that the NAV appraisal have influenced our regression analysis. In conclusion, we summarize our findings and highlight the fact that, despite the robustness of our results, data quality, sample characteristics and possible model misspecification might still affect our analysis.

The rest of this paper is organized as follows: Chapter 1 deals with the terminology and a basic background of PE industry, useful to better understand the results of the research. Chapter 2 reviews the literature, which addressed this question in the past. Chapter 3 presents the model and the results of the analysis. And before our conclusion, Chapter 4 tests the robustness of the analysis by changing variables of interest and by running the analysis for selected subsamples.

CHAPTER 1: Background on Private Equity

1.1. Definitions and Terminology

The concept of "Private Equity" (PE) can assume several meanings. As far as this paper is concerned, PE will be defined as an investment in the equity of a company that is not listed on a stock exchange (Fraser-Sampson, 2010). Moreover, the aim of this investment is the "*provision of capital and management expertise to create value and, consequently, generate big capital gains after the deal*" (Caselli, 2010, p. 4). Moreover, PE takes difference meanings in the Anglo-Saxon countries and in continental Europe. In the former, PE comprises both venture capital (VC) and buyouts (BO) while, in the latter PE is different from VC. Thus, VC refers to an early phase of financing dedicated to young and emerging companies, where the investors typically do not obtain the majority control (Kaplan and Strömberg, 2009). In this paper, we will abide with the Anglo-Saxon definition and PE will, henceforth, include investments in VC, Growth Capital and BO. In contrast, the definition will not embrace funds of funds, real estate, debt investments and hedge funds.

Our definition above draws a distinction between private and public equity because enormous differences exist between the two forms of investment. Firstly, in public equity, markets provide liquidity, while in PE a proper market does not exist. Consequently, investments in this asset class are illiquid assets. Because of this illiquidity issue, PE entails a long-term relationship, while investors in public markets can flip their stocks quickly. Therefore, in PE, reputation, networks and contacts make the difference. Secondly, investors are provided with massive information on public companies, allowing them to monitor the company behavior. Yet this information is rarely available for PE and investors willing to exercise control on private companies, have to be strongly involved in the management or sign binding contracts. Finally, public markets have a price discovery function, while the same is not true for PE. As a consequence, usual valuation techniques are hardly applicable and the price of each transaction will be strongly affected by negotiations and relative bargaining powers. As suggested by Lerner, Leamon and Hardymon (2012, p. 22), "*access to better opportunities requires active sourcing and strong negotiation*". Following on this, GPs' reputation and long track record will be showed to have fundamental roles in fundraising and performance.

In the PE world, also the core principles of corporate finance can be called into question. First of all, shareholders' value maximization is not always a strait task, because different classes of shareholders with specific objectives exist and a compromise between new shareholders and entrepreneurs is needed. Secondly, there is less separation between ownership and control, because financers in PE often manage the company. Thirdly, investors in PE want to know the exact usage of their money, while in traditional corporate finance the linkage between financing and investing is usually missing. Finally, contracts in PE are critical to mitigate conflicts between shareholders, while the classical agency theory for corporates is more focused on conflicts between managers and shareholders.

Overall, we can identify three main reasons that make the PE involvement fundamental at all phases of the life cycle of a company: *Financial Gap* to be covered with fresh money (i.e., the sources of funds are smaller than the usages and, therefore, the company needs money to cover this gap), *Certification Effect* (i.e., demonstration of the quality of a company to the other market participants) and *Network Effect* (i.e., the PE firm gives to the company the access to its buyers, suppliers, technology and entire network). Each of these effects will have a different relative importance depending on which stage of its life cycle the company stays. Moreover, PE firms are able to create value for the acquired companies, by applying financial, governance and operational engineering (Kaplan and Strömberg, 2009).

Looking inside the box called “Private Equity”, we can distinguish between six clusters, which are related to different stages of a company’s life cycle and have heterogeneous features, such as different risk-return profiles. Firstly, *Seed Financing* is the financing of a research project, with the aim of generating an output, which could eventually become a product. This PE segment is mainly focused on R&D-intensive sectors and, therefore, it is very risky. Moreover, the crucial roles of financers at this stage are the preparation, the analysis and the validation of the business plan. Secondly, *Startup Financing* is the financing of a startup to give to the company enough money to “turn on the light” and start its activities, investing mainly in fixed assets and in a minor way in working capital (WC).

Thirdly, *Early Growth Financing* is the financing of the very first stage of a company growth, during which, PE firms provide the company not only with money, but also with strong advisory services, revising, if necessary, the business plan. Even if less risky than the previous cluster, where there is big uncertainty about future business development, the risk at this stage is still high and comes from the uncertainties about sales growth development.

Because they all address young and emerging companies, these first three categories can be classified together with the broader term “Venture Capital”. Fourthly, *Expansion Financing* is the financing of the sales growth of a company. At this stage, the company needs to invest in WC and, potentially, in additional fixed assets. Given the sales potential, expansion firms could also borrow money from banks. However, PE firms are sometimes preferred to banks because they can provide the company not only with money but also with network and reputation. Up to this category, we can say that, the risk-return profile falls as we move from *Seeds* to *Expansion Financing*.

Fifthly, *Replacement Financing* is the financing of mature companies. In this phase “*the problems come from governance or corporate finance decisions*” (Caselli, 2010, p.21). A mature company can either need money to grow via a M&A campaign or need advisory services to face a turnaround situation, such as successions. Finally, *Vulture Financing* is the financing of a company in a distressed situation. This entails both restructuring and bankruptcy. The risk for the investors in this cluster is high and depends on the “*nature of the crisis*” (Caselli, 2010, p.24). As far as this paper is concerned, we will distinguish funds in two big categories: VC and BO. BO will include transactions, in which the PE firm buys majority control of an existing or mature firm, while VC will address young or emerging companies (Kaplan and Strömberg, 2009). Moreover, we will consider the *Expansion Phase* as part of the VC category. We believe that using finer categories would not be appropriate, not only because the data coverage for some subcategory is low, but also because the boundary between some clusters is blur and a fund may invest in companies at different stages, making the categorization in clusters quite discretionary.

1.2. Business of Private Equity

Once understood, what a PE is, it is time to understand what a PE exactly does. Usually a PE firm or Asset Management Company (AMC hereafter) is organized either as a partnership or as a limited liability corporation (Kaplan and Strömberg, 2009). However, depending on the legal framework in which they operate, PE firms can adopt different legal forms. While in EU you have three main vehicles to set up an equity investment (i.e., bank, investment firm or close-end fund), the Anglo-Saxon system is more various (e.g., Venture Capital Funds, Business Angels, Venture Capital Trusts etc.). A complete discussion on legal forms is beyond the scope of this paper but it is carefully presented by Caselli (2010).

Leaving legal issues aside, we have two categories of players: a general partner (GP), which is the AMC and a series of investors or limited partners (LPs)[4]. The GP raises funds from the LPs and is responsible for investing into a portfolio of companies. At the same time, the GP needs to manage these companies. The investors will expect a capital gain for the risk they are taking, while the GP will receive a fixed management fee (around 1.5-2.5% of committed capital) and a performance fee (or carried interest) around 20% (Robinson and Sensoy, 2012). In addition, GPs charge deal and monitoring fees to the companies in their portfolios.

The typical time span for a fund is 10-13 years (Kaplan and Strömberg, 2009), which can be labeled into four phases: *Fundraising* (1.5 years before year zero), *Investment Period* (0-5 years), *Management Period* (5-10 years) and *Grace Period* (10-13 years). During *Fundraising*, the AMC tries to collect money. If its target is achieved, the *Investment Period* (also called *Drawdown*) begins, during which, the AMC has to screen and select investments and to invest the money into a portfolio of companies. The following five years are devoted to return money back to investors and, at the same time, to manage the acquired companies. This phase is called *Management Period*. Finally, if at the end of the 10th year markets are down, the AMC can ask to the LPs for the extension of the fund's life for three additional years (*Grace Period*) in order to find better market opportunities to divest its assets. However, the beginning and the end of each phase is not so neat and for example, AMC can start giving money back to investors after 3 years only.

Once the LPs commit funds, they have little to say about the usage of their money as far as the AMC complies with basic covenants agreements on where or how to invest in terms of maximum allocation in each company, industry or region (Sahlman, 1990; Kaplan and Strömberg, 2009). It is also worth stressing the fact that the AMC has some "skin in the game" because it provides some capital into the fund, usually around 1% (Robinson and Sensoy, 2012).

1.3. J-Curve Effect

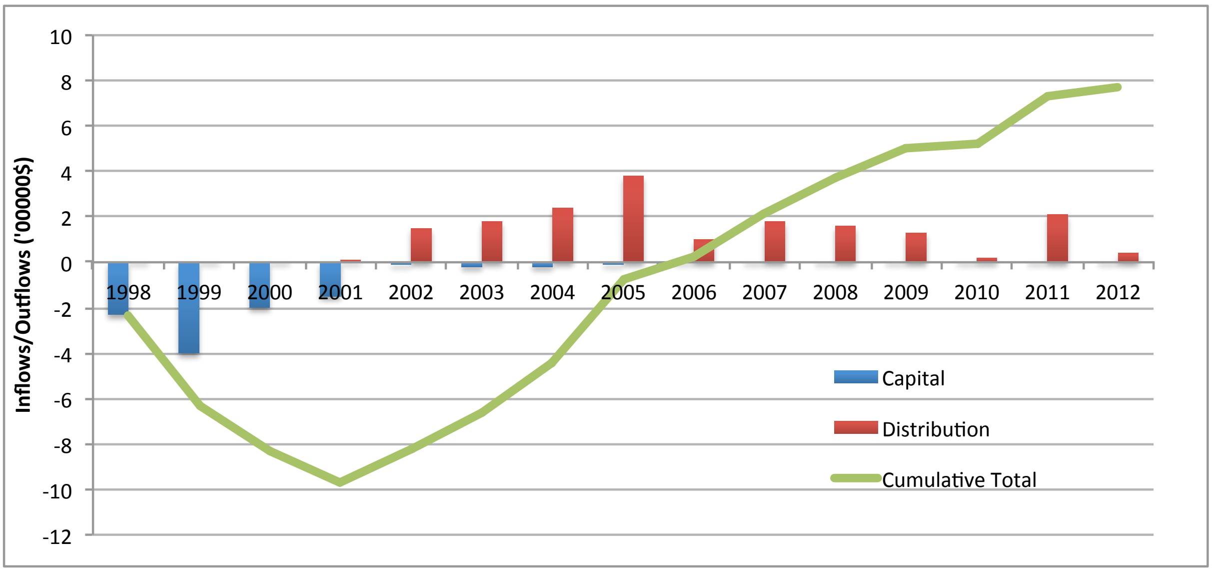
Performance measurement is critical to understand whether or not PE firms are able to create value for LPs. However, measuring performance is not an easy task. First of all, differently from other asset classes, annual returns do not accurately suit for this purpose (Fraser-Sampson, 2010). Unlike other investments, PE can be seen as

[4] Lerner *et al.* (2012) identify different clusters of LPs: Families, Foundations, HNWI, Angel Investors, Endowments, Pension Funds, Corporations, Insurance Companies, Banks, Sovereign Wealth Funds, AM firms, Funds of fund and Government agencies.

a series of cash-outflows and cash-inflows. ***Figure A*** shows a typical pattern of cash flows for a 1998 European PE fund. PE investors know neither the time nor the exact amount of these cash flows *ex-ante*. They only know the maximum cap of the investment, which is represented by the total committed capital. Being the amount and the time of these cash flows uncertain *ex-ante* and being the largest stream of cash flows distributed towards the end of the fund's life, the returns for the first years can be misleading. Furthermore, the exact drawdown period and distributions are strictly connected with the nature of each fund. Because the management fees are, at least initially, based on the capital committed rather than on that invested, they also have a stronger impact at an earlier stage of the fund's life. The same applies to costs. Therefore, because the impact of costs and fees is heavier at the beginning, annual returns, initially, can be easily negative (Fraser-Sampson, 2010).

Figure A
Cash flows for a 1998 European private equity*

A typical pattern of cash flows for a 1998 PE funds. For the first few initial years we observe only capital contributions, while distributions begin after 4 years. Moreover, payback point is reached only after 9 years.



Source: Preqin (* For legal reasons, the name of the fund cannot be disclosed)

Given the inaccuracy of periodic returns, we need to measure compounded returns over time. However, a problem persists and this well-know feature of PE is the so-called "J-curve" effect (***Figure B***). Despite being famous, this phenomenon is sometimes misinterpreted. To be brief, we can say that this effect is the consequence of the structure of cash inflows and outflows illustrated above. If we measure cumulative returns over time via the internal rate of returns (IRR) since inception till a given year X, we can see that the IRR is negative at the early stages of the fund's life. The IRR will be virtually negative till when the distributions match at least the contributions and this moment is called *payback point* (Fraser-Sampson, 2010).

As a consequence of the J-curve effect, we cannot trust recent fund's performance. Another problem is, however, to understand how long this effect will last. Not surprisingly, on this point we have diverging opinions but we know that we should avoid using the last three/five vintage years when doing any research. In the analysis below, we left out of the sample all the funds, which had been raised in the last three vintage years, and considered only vintages 2009 and older.

1.4. Measure of Performance

The PE industry relies on two methods to measure performance: IRR and cash-on-cash multiples. The IRR is a cash flow-based return measure. It considers the net residual value (NAV) of the fund as a final cash-inflow. It can be seen as the rate that equals to zero the Net Present Value (NPV) of a fund's cash flows, i.e.:

$$\sum_{t=0}^{T}\frac{D_{(t)}}{(1+IRR_{(T)})^{t}}+\frac{NAV_{(T)}}{(1+IRR_{(T)})^{T}}-\sum_{t=0}^{T}\frac{C_{(t)}}{(1+IRR_{(T)})^{t}}=\sum_{t=0}^{T}\frac{Net\ Flow_{(t)}}{(1+IRR_{(T)})^{t}}+\frac{NAV_{(T)}}{(1+IRR_{(T)})^{T}}=0$$

Where $D_{(t)}$ is the distribution for year t, $C_{(t)}$ is the capital contributed for year t, $NAV_{(T)}$ is the Net Asset Value at time T and the Net $Flow_{(t)}$ is the difference between distribution and contribution at year t.

On the one hand, the IRR solves the issue of inaccuracy of periodic returns and, at the same time, accounts for the time value of money. However, on the other hand, IRR is not free of pitfalls. Lerner *et al.* (2012) pointed out four main disadvantages: 1) "The Case of Tortoise and the Hare", 2) Lack of Systemization, 3) Paradox of multiple IRRs and 4) Aggregation Problem.

First of all, the IRR rewards those PE firms that quickly return capital to investors, favoring, therefore, early exits. However, these funds are not always the best long run performers. Therefore, the IRR favors the "Hares" at the expense of the " Tortoises". Secondly, there is a lack of systematization when calculating the IRR. For example, treatment of time, NAV appraisal, taxes, etc. Because of this lack of common standards, IRR comparison across funds may be misleading. Thirdly, if the stream of cash flows is rather complex and it experiences more than one change of sign, we will have more than one IRR. As a matter of fact, we will have as many IRRs as there are changes in the sign of the cash flows (Brealey, Myers and Allen, 2011).

Possible solutions in this case are either to look at cash multiples or to compute the NPV of each fund. Finally, we could experience challenging times when aggregating IRRs from different funds. Depending on which method we use (e.g. average IRR, pooled IRR, weighted-average IRR) we could end up with very different results.

Two additional limitations are intrinsic in the IRR. Firstly, its calculation assumes that early redistribution can be reinvested at the same fund's IRR. Secondly, this method assumes one discount rate for both cash inflow and outflow. However, it is reasonable to believe that the discount rate should be different between contributions and distributions. In sum, the IRR may tend to overstate the fund's performance. Taking all these limitations into account, *Lerner et al.* (2012) suggested that we should use the NPV of the fund as a better measure of performance. Not only the NPV accounts for the time value of money (as opposed to multiples), but it can also avoid three of the four problems outlined above (i.e. 1, 3, 4). A big pitfall of the NPV method stays, however, in the difficulty of finding a reasonable discount rate.

The second approach used by the PE industry to measure performance is a set of cash-on-cash multiples. We can identify three common multiples (Mathonet and Meyer, 2007):

$$\text{Distribution to Paid-in: } DPI = \frac{\sum_{t=0}^{T} D_{(t)}}{\sum_{t=0}^{T} C_{(t)}}$$

$$\text{Residual Value to Paid-in: } RVPI = \frac{NAV_{(T)}}{\sum_{t=0}^{T} C_{(t)}}$$

$$\text{Total Value to Paid-in: } TVPI = \frac{\sum_{t=0}^{T} D_{(t)} + NAV_{(T)}}{\sum_{t=0}^{T} C_{(t)}}$$

Where symbols are the same as above. DPI measures only the value already distributed to investors with respect to their contributions and completely disregards what is left as unrealized inside the fund. LPs' contributions could have been either invested or used to pay fees. This multiple is, therefore, more significant towards the end of the fund's life, because at the beginning little has been distributed to LPs and much of the value is still unrealized. DPI multiple is, therefore, not accurate for the first years of a fund's life or if the fund failed to invest all its allocated capital. Fraser-Sampson (2010) claimed that in the latter case, fees have been too high and the LPs lost the opportunity to invest their money elsewhere. Therefore, in this case, he suggested using a multiple of distributed over committed capital (DCC).

On the other hand, RVPI measures the amount of the investment still tied up in the fund over the paid-in capital. This measure is, therefore, more meaningful at the beginning of the fund's life, where most of the investments are still unrealized. However, possible problems may concern the NAV appraisal, which is subject to accounting valuation and, therefore, often unreliable (Phalippou and Zollo, 2005). Moreover, despite the FASB requirements to value assets at fair value every quarter and the fact that US National Venture Capital Association guidelines have become a quasi-standard, accounting practices and discrepancies may still give rise to different valuations for the same investment.

Summing the DPI and the RVPI, we can calculate the TVPI (also called "multiple"), which is a comprehensive measure of both the realized and the unrealized value. Because the TVPI is just the sum of the other two multiples, it will suffer from the same pitfalls. Therefore, the biggest issue to be addressed will be the NAV appraisal. Overall, the main drawback of using multiples is that they do not keep into consideration the time value of money but they simply add together cash flows, which occur at different points in time. This fact can be misleading in some situations because money collected before can be reinvested elsewhere. In other words, multiples fail to value the opportunity cost. Finally, we need to recall the obvious trade-off between multiples and IRR[5] and the fact that both the IRR and the multiples completely ignore any kind of risk- or market-adjustment. Because PE asset class has been found to have an equity beta higher than one (Driessen, Lin, and Phalippou, 2011; Axelson, Sorensen and Strömberg, 2012), if risk is not treated properly, these two measures may be seriously misleading.

Once that a measure of performance has been found, in order to compare performances across funds, we need to choose a basis of comparison. This can be for example, vintage year, type and geography; this comparison method is often called "peer group cohort" (Mathonet and Meyer, 2007). Measures of comparisons may be the median, the upper quartile or a capital-weighted average return[6].

[5] I.e., if the holding period increases, in order to yield the same IRR, the multiple must increase as well.

[6] In case the database comprises very small sample, Fraser-Sampson (2010) suggests that the upper quartile is better than the mean. This is so, because institutional investors do not invest in small funds and by including these funds in the sample, the average is strongly affected. This latter point, however, will not be relevant for our analysis, because our database only includes funds, in which institutional LPs invested.

Till now, we have focused on classical relative benchmark, comparing measures of performance across funds. Another approach is to compare the PE performance with that of a public market index (e.g. S&P500). This methodology is called Public Market Equivalent (PME). It is a dollar-weighted return that could have been achieved by the investors if they invested funds in the index whenever a capital contribution was made and they divested when they received any distribution from the GP. Therefore, it uses the time of the fund's cash flows in order to invest in and divest from the index. The PME is the ratio of the sum of discounted distributions over the discounted contributions. The formula for PME is:

$$PME = \frac{\sum_{t=0}^{T} \frac{1}{\prod_{\tau=0}^{t} 1 + r_\tau} D_{(t)}}{\sum_{t=0}^{T} \frac{1}{\prod_{\tau=0}^{t} 1 + r_\tau} C_{(t)}}$$

Where $D_{(t)}$ and, $C_{(t)}$ are t-year distributions and contributions and r_τ is the time-varying S&P500 return. When assessing relative performance a β of one is assumed (i.e., perfect co-movement of public and PE returns) and a PME greater than one indicates outperformance. A detailed discussion on PME is beyond the scope of this paper but an illustrative example can be found in Kaplan and Schoar (2005). Sorensen and Jagannathan (2013) showed that, when LPs has log-utility preferences and the return on their total wealth matches the market return, PME is a sound PE performance measure. Therefore, contrarily to IRR and multiples, the PME provides a market-adjustment and, if some conditions are met, it also adjusts for risk.

However, if the utility function has a different form, being the β of PE higher than one, this measure may not account for the true opportunity cost of investing in PE but still remains better than the IRR or multiple. Furthermore, the major drawback of this measure is that it is fully dependent on the index selection, which therefore becomes crucial. Historically, authors have compared PE industry with S&P500. However, recently, some doubts have risen on whether a Small-Cap Index should replace the S&P500 as a basis for comparison (Phalippou, 2012). Finally, Mathonet and Meyer (2007) pointed out the fact that if neither a relative benchmark, nor a PME benchmark can be found, an absolute benchmark remains the only solution. This means that the performance is compared with a target set by the GPs either as a fixed value or as a premium over an index.

1.5. Measurement Problems

Not only the choice of the measures of performance is challenging, but also the data used for the analysis of PE can be misleading. This is a consequence of the nature of PE, which is such that it does not produce a lot of information and we need to rely on commercial databases, on which GPs or LPs report data mostly on a voluntary basis (Kaplan, Sensoy, and Strömberg, 2002). Therefore, this lack of data is a serious issue in PE and affects any analysis. Firstly, the performance measures and the NAVs are reported few times per year. Secondly, not only the frequency of data is low but also the amount of information is scare and sometimes one doesn't have all the relevant pieces to conduct extensive analyses.

Moreover, the self-reporting can affects data accuracy considerably. Bird, Liem and Thorp suggested that if self-reporting is anonymous, as it is the case for Venture Economics, "*there is no incentive to bias performance data upwards as funds cannot be marketed through the database. Second, […] There is no incentive for a private equity manager to force early closure and so discontinue reporting returns, as long as fees can be collected*" (2011, p.12). However, they also recognize the fact that "*Selection bias, as well as the anonymous nature of the database, are an important limitation of our research, and can mean that our results are still biased either upwards or downwards*" (2011, p.13).

On the other hand, if self-reporting is not anonymous, other issues may arise, such as selection bias, survival bias and smoothness. As highlighted by Harris, Jenkinson and Kaplan, any database has its own bias and drawbacks: "*Burgiss, while providing complete data from each LP, may have a selected sample of LPs. VE* [Venture Economics] *is dependent on LPs and GPs providing information. Preqin is dependent on public filings and FOIA requests. As a result, Preqin may be missing some high performing funds that do not have public pension fund investors. CA* [Cambridge Associates] *may have a bias towards GPs who are raising new funds and, therefore, may have performed well*" (2012, p.7).

Selection bias is a natural consequence of voluntary reporting. If the fund recorded a poor performance, the manager of the fund will have little or no incentive to report it. On the one hand, if a fund has been successful it can enter the database together with "its successful history". On the other hand, if the AMC consistently perform poorly, it will never enter a database and will died anonymously. This fact gives rise to a second problem: survival bias. This bias may also affect the data, because funds, which delivered a very bad performance and eventually failed, may not be in the sample anymore or they had never entered the sample (Kaplan and Schoar, 2005). Furthermore*,* GPs start by raising smaller funds and as they gain reputation, they raise additional and usually bigger funds. On the other hand, small and unsuccessful GP may give up raising funds after a bad performance and they will not be included in the sample. This survivorship bias may create a spurious relation between size and performance (Lopez-de-Silanes, Phalippou and Gottschalg, 2010).

In addition, we have understood that a considerable part of the performance is attributable to the unrealized part of the portfolio. Therefore, the NAV appraisal is fundamental. However, not only it is subject to many computational details but managers may also have an interest in smoothing it over time to avoid strong swings in performance. As Bird *et al.* (2011) stated "*Private equity fund managers smooth reported quarterly returns, and during periods of sharp falls in public markets tend to lag valuations of the non-traded assets which make up the majority of their illiquid portfolios. This creates an artificial stability in unit prices that feeds into returns"* (p.3).

In conclusion, we need to highlight two points. Firstly, when reporting comes from LPs via Freedom of Information Act, the selection and survivorship biases can be avoided. However, the NAV smoothness issue persists and additional sample distortions may arise, because databases will be biased towards bigger and well-known funds. Finally, we need to be aware of these biases, which we can manage but not avoid and, therefore, we need to learn to live with them.

CHAPTER 2: Some Evidence on Private Equity Performance Drivers

2.1. General Performance

Before investigating which are the drivers of PE returns, we need to evaluate the general performance of this asset class. Interestingly, despite the large proliferation of PE funds in the last decades, whether or not this asset class was successful remains a question mark and researches have delivered heterogeneous outcomes. Today, we still do not have conclusive evidence of whether this asset class was able to beat the market or not. However, while older studies are much more controversial because of limited sample period and low-quality data, more recent ones offer a more optimistic picture of PE. In this section, we focus mainly on the set of literature that tries to measure the net-of-fees fund-based performance derived from cash flows rather than the gross-of-fees performance at individual investment level.

Ljungqvist and Richardson (2003), using a relative small sample composed by 19 VC and 54 BO funds, documented a substantial outperformance of 5-8% per year depending on the benchmark employed. The mean (median) outperformance was 8.06% (6.04%) with respect to S&P500 and 6.28% (4.01%) with respect to the Nasdaq. Moreover, they estimated a beta for this asset class higher than one (i.e., 1.12 for VC and 1.08 for BO) but found that even risk-adjusted performance was in excess of the index. Along similar lines of thought, Jones and Rhodes-Kopf (2003), basing their analysis on 1,245 funds from VE database, recorded a certain degree of outperformance, but this time, it was mainly attributable to VC. They found an annual alpha of 4.68% for VC and 0.72% for BO[7]. On the one hand, Kaplan and Schoar (2005), using a sample of 746 funds (from VE) and measuring performance in terms of IRR and PME, showed that PE asset class was not able to beat the S&P500 with a net-of-fees performance approximately equal to that of the index[8]. Overall, the PME was 1.05 but VC drove this tiny outperformance, while BO underperformed the index.

In sum, looking at these three first studies, we can say that they all recorded similar positive performances for VC, but BO performance remains controversial. However, the limited sample period and the low-quality data used by these old studies (Stucke, 2011) make results less relevant today. Furthermore, strong cross-fund heterogeneity and inappropriateness of the benchmark asked for further studies. Controversial studies are also Phalippou and Zollo (2005a) and Phalippou and Gottschalg (2006), which, however, reported much more negative results. The former, using VE database and implementing strong and consistently negative corrections[9], documented that PE funds with vintage 1980-1996 underperformed the S&P500 index by -3.3% per year. Phalippou and Gottschalg (2006) highlighted an underperformance of PE of -3.83% per year with respect to the S&P500. Only gross-of-fees performance was in excess of 2.96% with respect to the index. Some year later Phalippou and Gottschalg (2009) obtained a similar negative picture, indicating that the average PE fund underperformed the S&P500 net-of-fees by -3% per annum and of -6% adjusting for risk.

[7] Unfortunately, these numbers were not statistically significant.
[8] PME of 1.21 for VC and 0.93 for BO.
[9] Firstly, they adjusted the database for sample-selection bias. Secondly, they used aggregated cash flows across all fund. Finally, they wrote off the "living-dead" investments.

In theory, this underperformance may be justified in three ways, which were underlined by Phalippou and Gottschalg (2009). Firstly, it may be a price investors have to pay in order to gain access to better funds. Thus, if they want to join the "good club", LPs have first to participate in inexperienced and poor-performing funds. Secondly, LPs may have some side-benefits in investing in PE in terms of future commercial relationships (i.e. consulting work or underwriting securities). Finally, mispricing may be a third explanation. Thus, LPs may have misvalued this assets class because of the lack of skills or they may have not been completely aware of the full impact of the fee structure on performance. In practice, however, this puzzling performance may be attributable to poor quality data, downward corrections[10] and strong heterogeneity of performances[11].

Lopez-de-Silanes, *et al.* (2010) highlighted the tendency for high performing fund to remain consciously smaller and for less performing funds to increase their size and live out of management fees, delivering a minimum acceptable return. Furthermore, they spotted the fact that less-sophisticated investors may be more confortable to invest in larger and known firms, which their study identified as poorer performers. The authors investigated, therefore, reasons that allow poor performers to survive. Firstly testing fund-selection strategies is hard and investors sometimes identify top performers looking only at few excellent investments rather than at the entire track record. Secondly, investors allocate money for reasons other than returns such as side-benefits. Finally, larger institutions tend to invest in large-scale firms because they need to invest a large amount of money in PE asset class.

As mentioned before, a recent study by Stucke (2011) highlighted a strong bias in the VE database used by Kaplan and Schoar (2005) and by Phalippou and Gottschalg (2009). Apart from having limited sample period, their data was poor with missing cash flows. New cash flows were not recorded and IRRs were consequently downward biased. Moreover, in the case of Phalippou and Gottschalg (2009),

[10] Phalippou and Gottschalg (2009) results are more negative than those obtained by Kaplan and Schoar (2005) mainly because, while the latter authors assumed a residual value for living dead investments equal to the book value, the former assumed it equal to zero. Moreover, Phalippou and Gottschalg (2009) weighted the fund performance by present value of investments rather than by committed capital and considered additional funds, which, on average, performed worst. Their findings are also worst than those of Ljungqvist and Richardson (2003) mainly because of the sample used. The latter authors' sample had a larger presence of US, larger and experienced funds. It was also disproportionately biased towards BO. Moreover, the fact that data came from a single investor, made problematic any sort of generalization because of the strong heterogeneity across GPs outlined for example by Lerner, Schoar and Wongsunwai (2007).

[11] Lopez-de-Silanes, et al. (2010), differently from the studies above, performed an analysis at investment level, employing 7,453 investments coming from fundraising private placement memorandums. They found that while the first quartile delivered more than 50% IRR, the worst 25% either were unprofitable or failed. Moreover, they identified outliers and fat-tail distribution of returns as causes for inaccuracy of performance measurement.

performance was even poorer because of the treatment of the NAV, which was written-down to zero in case of inactive funds. The discovery of VE biases, the availability of new databases with more accurate data and the possibility to employ a longer sample period gave origin to new studies, which reported, on average, a more positive picture for PE performance, especially for BO funds.

Robinson and Sensoy (2011), using a unique sample of 990 funds, reported a net-of-fee outperformance over the S&P500 index of 1.5% per year. Moreover, even if this asset class co-moved with public markets, it was able to outperform the S&P500 independently from the mood of the market. In contrast to many prior researches, outperformance was stronger for BO than for VC funds. However, while the authors recorded better performance compared with Kaplan and Schoar (2005) in terms of PME, the same cannot be said if we look at IRR. This highlights potentials for misleading conclusions when IRR at fund level is used to measure performance.

Harry, Jenkinson and Kaplan (2012) recorded an outperformance of 3% over S&P500 using Burgiss data for circa 1,400 US funds. US Buyouts outperformed the S&P500 by 20-27% over the life of the fund. They found that BO had a yearly average (median) excess return over S&P500 of 6.6% (3.3%). The capital-weighted average (median) excess return was 3.7% (3%). In line with Robinson and Sensoy (2011), they reported a PME for BO exceeding one for vintages 1980s, 1990s and 2000s. On the other hand, VC outperformed in 1990s but not in 2000s, recording a PME less than one and very poor returns in 1990 and 2002. These results remained valid even when benchmarked against Russell 3000, Russell 2000 or NASDAQ.

Higson and Stucke (2012), using a sample of 1,169 funds from CA, which covered almost 85% of US buyouts, reported, indeed, a significant outperformance. Capital-weighted IRR for liquidated BO funds (i.e., 1980-2000) was in excess of the S&P500 by 434 bps per annum. The picture improved to 809 bps per year when they considered also partially liquidated funds (i.e., 1980-2005) and to 544 bps over the entire sample (i.e., 1980-2008). Also by changing the benchmark with S&P600 Small-Cap the outperformance persisted[12]. However, they also noted a strong cross-sectional variation with only three out of five funds performing better than the Index. Moreover, being the average larger than the median return, the distribution was positively skewed with large outliers driving excess returns. They also considered Kaplan and Schoar (2005) and Phalippou and Gottschalg (2009) performances

[12] In this case, they recorded a weighted-average IRR spread of 184 bps for the entire sample (1980-2008) and of 481 bps for funds of vintages 1980-2005 only.

downward biased but suggested that those low performances were, indeed, not surprising and consistent with a vision of the world where "*rent-seeking fund managers fully appropriated the excess return through fees and carried interest, leaving net returns to investors that are no better than a random drawing from S&P*" (Higson and Stucke, 2012, p.25).

Phalippou (2012), commenting on Robinson and Sensoy (2012) and Harry *et al.* (2012), raised the issue of size effect, calling into question the use of the S&P500 as the right benchmark for PE asset class: "*the S&P500 index significantly underperformed small cap and mid cap stocks, which are the size categories in which private equity funds mainly invest*" (p.1). This size effect has been stronger in recent times, because large-size stocks have significantly underperformed small ones. One attempt to keep size into account was, indeed, done by Robinson and Sensoy (2012) via a "tailored PME". Moreover, Phalippou (2012) argued that even when outperformance was found, additional costs had not been considered. Firstly, the risk in PE may be higher and therefore the risk premium should be larger. Secondly, the investor's cost of having capital committed to GPs is usually not quantified. Thirdly, illiquidity cost may be high and was estimated around 1% per year (Sorensen, Neng and Yang, 2011). Fourthly, additional costs related to consultants and lawyers are relevant and should be considered. For example, Bird *et al.* (2011) after adjusting for equity risk, illiquidity, leverage and volatility clustering, found no evidence of excess performance for PE asset class.

Finally, we must be aware of these difficulties when measuring performance and even if it is difficult to show the existence of a positive alpha, "*the current state of research does not allow a strong conclusion in the other direction, either*" (Phalippou, 2012, p.15). Conclusive results may be, indeed, possible, only if "*data were comprehensive, unbiased and more widely available*" (2012, p.15).

2.2. Drivers of Performance

We have understood that performance measuring is not an easy task and given the relative youth of the industry, we should still wait some years to judge PE performance in full, with particular attention to the pre- and post-crisis period, with which authors have not fully dealt yet. Keeping these difficulties in mind, we can now focus our attention to drivers of performance, in order to understand whether there are some patterns in performance. Over time, many authors have come up with models and theories that not always deliver consistent results, mainly because of the data inaccuracy outlined above. Moreover, uncertainties still exist not only on whether PE as an asset class was able to beat the market in the last decades, but also on which are the key performance drivers. Studies have reached different outcomes because they were affected by factors such as sample size and database used, performance variable considered, time framework and other technicalities about the treatment of NAV and aggregation of returns. However, the main elements on which authors (***Table I***) have focused their attention over time are the following:

a) Cyclicality
b) Size
c) Persistence
d) Experience
e) Industry concentration
f) Geographical concentration
g) Fund's type
h) Other variables

2.2.1. Cyclicality

While we cannot reach a definitive conclusion on PE general performance, there is no doubt that the industry is cyclical and performance is, therefore, affected by the economic cycle. This is somehow disappointing given the fact that PE was thought to be only marginally dependent on public market and, therefore, considered an asset class apt to portfolio diversification. However, authors agree on the fact that PE shows a strong cyclicality and the term "Boom and Bust" has become a distinguishing feature of this industry. This cyclicality can be shown under three aspects: cyclicality in fundraising, in investment volume and in performance.

Firstly, the cyclicality of fundraising has been associated with the impact of public market on this asset class (Lerner *et al.*, 2012). During period of bull market, there would be more IPOs and sales done at a higher valuation. LPs will receive back a larger portion of what they invested and if they need to maintain a fixed allocation to PE, they will accelerate their investment rate, allocating more funds to this asset class. On the hand, GPs, leveraging on recent stronger performance, have an easier life to raise new funds. The reverse is true during periods of bear market. Moreover, Kaplan and Schoar (2005) have showed that capital flow into individual GPs is linked to past performance: "*Better performing partnership are more likely to* *raise follow-on funds and larger funds. This relation is concave, so top performing partnership grow proportionately less than the average performers*" (p.1791).

Secondly, movements in public market also affect investment volumes for both BO and VC. On the one hand, the volume of BO investments is associated with public market through the availability of cheap financing and the ability to leverage and this would, in turn, affect performance. In contrast with the basic notion of cost of capital (i.e., *ceteris paribus*, return to equity increases with leverage), Axelson, Jenkinson, Strömberg and Weisbach (2012) showed that leverage is negatively related to BO returns (measured relative to returns on public stock markets). One reasons for this poor performance is an agency story in which GPs overpay for deals at times of hot credit market when leverage is cheap and largely available. On the other hand, the financial markets affect the volume of VC investments because of the appetite for better possible exits.

Thirdly, there is a strong cyclicality in PE performance. On the one hand, when the public market is booming, also PE performance is very good because exits will occur at higher valuation multiples than those paid at entry, while PE performance is poor in periods of bear market. On the other hand, the time of fundraising and inventing can affect performance. Kaplan and Schoar (2005) showed that fund raised in boom years are more likely to perform poorly. This poor performance is linked to the fact that during bull markets valuation of investments is high and, because of the cheap available debt, the competition over each investment is stronger. The authors also showed that, if the market conditions improved in the three years following the fundraising, the probability to raise a new fund would increase significantly and they also showed that established funds are less subject to cycle than new entrants. Moreover, Kaplan and Strömberg (2009) documented a negative relation between vintage year fundraising and performance. Thus, larger capital inflows into the PE are associated with poorer subsequent performances.

Another issue, which makes the industry cyclical, is the link between holding period and performance. Phalippou and Zollo (2005b) and Lopez-de-Silanes *et al.*[13] (2010) observed that funds that keep their investments longer have lower performances, while "quick flips" performed better. Even if this could be due to a fast operational and financial therapy and/or to the ability to buy cheap and sell expensive, it is also an endogenous characteristic of the industry because PE firms

[13] Lopez-de-Silanes *et al.* (2010) recorded a better performance of the quick flips (i.e., investment held for less that 2 years) over investments held for more than 6 years

will have an incentive to exit successful investments earlier to show a good track record (Gompers, 1996) and extend the holding period of unsuccesfull ones to wait for better opportunities. This element has in instrinsic cyclicality, because during bear market, when valuations are low, PE firm longer the holding period in the hope that better time to sell will come and, by doing so, *ceteris paribus*, their IRRs fall.

Lopez-de-Silanes *et al.* (2010) showed that there exists a strong connection between private and public equity. One standard deviation increase in market return increases IRR by 13.7%. Robinson and Sensoy (2011) reported that when public valuation is high, both PE contributions and distributions are more likely and larger, however, *"distributions are more sensitive to public markets than calls are, implying a positive correlation between public and private equity returns*" (p.4). Moreover, they found that VC are more cyclical than BO. On the same line of reasoning, Higson and Stucke (2012) recorded a strong cyclicality in returns (both in term of IRRs and TVPIs). They noticed that funds set up toward the end of each of the past three decades were delivering poorer returns. On the other hand, the first six vintage years of each decade outperformed the S&P600 Small-Cap. Furthermore, they reported a downward trend in absolute returns over all 29 vintage years.

Phalippou and Zollo (2005b), using a database for 705 funds showed a strong pro-cyclicality. They found that not only public stock market returns but also macroeconomic conditions deeply affected fund performance. Performance is positively correlated with average GDP growth rate and negatively correlated with average level of interest rates (in particular corporate bonds yield) that prevailed during the life of the investment. Interestingly, like hedge fund, PE funds were found to exhibit tail risk (i.e. non-linear systematic risk). Taking a different perspective, Gompers and Lerner (2000) and Ljungqvist and Richardson (2003) showed that one important variable affecting the PE return is "money chasing deals". This effect was partly explained by Kaplan and Schoar (2005), stating that the industry reduction of overall performance in PE industry in periods of high entry into the market was mainly driven by the poor performance of new entrants, while established funds' performance was mainly unaffected. In contrast, Phalippou and Zollo (2005b) and Phalippou and Gottschalg (2009) found no evidence of money chasing deal.

Finally, given the cyclicality of PE, authors have tried to assess whether the systematic risk of this asset class is priced and affects performance. However, measuring the beta of PE industry is not an easy task and the only point of agreement among authors is that beta should be in excess of one for both BO and VC funds. Reyes (1990) reported betas from 1.0 to 3.8 for VC, Gompers and Lerner (1997) of 1.08 and Peng (2001) found a very high beta of 4.66 on the Nasdaq index. Even if of smaller magnitude, also Cochrane (2005) believed that the beta is in excess of one. Phalippou and Zollo (2005b) reported an average beta of 1.7 and 1.6 for BO and VC funds respectively. Moreover, they documented that smaller funds had a higher beta than bigger ones[14]. Recently, Axelson *et at.* (2012) reported an average PE beta of around 1.9 with an annualized volatility of 95% and strong variation across investment type. To sum up, we can say that authors agree on the fact that PE beta is higher than one. However, do not have strong evidence that there is a relation between systematic risk and performance. Phalippou and Zollo (2005b) and Ljungqvist and Richardson (2003) found that systematic risk was not an important determinant of performance.

2.2.2. Size

If managers were skilled, better managers would attract more investors and this would lead these managers to manage bigger funds. These funds, in turn, would have a larger bargaining power in transactions and, therefore, could buy companies cheaply. Moreover, management fees and costs have a lower effect on net-of-fee performance for larger funds. From this, it follows that there should be a positive relation between fund's size and performance. However, on the other hand, as the size continues to increase, negative effects come into play. Firstly, there would be a lack of enough profitable transactions. Secondly, diseconomies of scale would arise because of a reduced attention partners can put in each company in the portfolio. Thus, at least in theory, we should expect a concave relationship between fund's performance and size. However, studies relating these two variables have reached different conclusions mostly because it is not easy to separate the size effect from other dimensions such as reputation, economies of scale and learning.

Ljungqvist and Richardson (2003) showed that excess IRR increases with the log of real size and decreases with its level and found the optimal fund size to be between \$1.1B and \$1.2B. However, this effect was not significant for BO subgroup. Kaplan and Schoar (2005) documented a positive and concave relation between size and PME, suggesting decreasing returns to scale. However, by splitting the sample by type of investment, the relation remained statistically significant only for VC. Also

[14] 1.65 for smaller fund and vs. 1.56 for larger.

Robinson and Sensoy (2011) reported a significant concavity effect between PME and Log (Size). Indeed, the quadratic effect was stronger than that showed by Kaplan and Schoar (2005) and justified by a stronger competition prevalent during the timespan considered by Robinson and Sensoy, which worsened performance of very large funds. Despite reporting poorer performance for smaller funds, Phalippou and Zollo (2005b) found no evidence of concavity. The same conclusion was reached by Phalippou and Gottschalg (2009). However, when they added past performance to the regression, size and all the other variables lost their significance.

It is worth noticing, however, that the poorer performance of very big funds is not indicating that managers of larger assets are unskilled. Berk and Green (2004), looking at the mutual fund industry, argued that, in equilibrium, better managers manage larger funds, but because larger funds present diseconomies of scale, these managers earn the same expected return as their less-skilled colleagues. Therefore, even with some caution because of the industry differences (e.g. in contrast with mutual funds, PE managers cannot increase the fund's size immediately but only with their next fund) we can extend this finding to PE industry.

Higson and Stucke (2012), studying the performance of 1,169 US BO funds, found a weak positive relation between size and performance. However, this relation was stronger for funds set up in the first part of each decade because they were less affected by subsequent economic downturn. Moreover, they did not find any concavity effect and argued that the concavity found by Robinson and Sensoy (2011) was due to the presence of truncated data in later vintage years. Harris *et al.* (2012) reported a lack of relation between fund size and performance for BO funds in line with Kaplan and Schoar (2005). However, controlling for vintage year, they found a positive and concave relation between PME and fund's size for VC. Nonetheless, the significance of the relationship remained only marginal.

Not only the funs's size was found to be an important performance driver but also the scale of the GP. Lopez-de-Silanes *et al.* (2010) showed the existence of diseconomies of scale in PE at both fund and firm level. Measuring firm's scale in terms of simultaneously held investmentsm, they showed that firms that invested simultaneously in fewer companies performed better. The plausible rationale was that as the scale increase, the benefits of higher knowledge utilization rate might be outweighed by larger communication costs. They also showed that neither the firm's nor the fund's unobservable characteristics were the main drivers of diseconomies of scale and that greater diseconomies of scale were present in more hierarchical firms with managers with different backgrounds, because of a harder information flow.

2.2.3. Persistence

Differently from mutual funds, where persistence has been hardly detected, the majority of researchers believe that past fund's performance is an important variable in determining the current fund's performance. Explanations for this finding may stay in the quality of the managers, who if were able to perform well in the past, would more likely perform well it in the future. Managers' skills can be either M&A skills or operational (i.e. industry-specific) skills. A second explanation for persistence may reside in the practices or relations set up by the GP, which will affect positively the different subsequent funds and cause, therefore, persistence in returns. Moreover, network, contacts and reputation give the GPs access to proprietary deal flows, affecting in a positive way all the GP's funds.

Kaplan and Schoar (2005) found a statistically and economically strong persistence across funds for the same GP, for BO and even more for VC raised in 1980s and 1990s. They recorded that GPs, whose previous fund outperformed, are more likely to outperform the industry also with their next fund. Moreover, persistence was assessed not only in terms of the previous fund, but also in terms of the second and third previous fund[15] and was shown neither to be caused by time overlaps, nor by investment overlaps. Aigner, Albrecht, Beyschlag, Friederich, Kalepky and Zagst (2008) recorded a higher probability for top-ranked GPs to be top performers also with their following funds. Phalippou and Gottschalg (2009) considered persistence the most important factor in explaining current fund's performance and also Robinson and Sensoy (2012) reported a significant persistence for BO and VC in terms of PME. Finally, a recent paper by Harris, Jenkinson, Kaplan and Stucke (2013), confirmed the previous findings for pre-2000 funds, documenting persistence, especially for VC funds. On the other hand, while persistence for VC remained statistically and economically significant also for post-2000 funds, the authors found mixed evidence of persistence for BO post-2000.

2.2.4. Experience

Experience is fundamental in PE industry because by gaining experience GPs can increase their reputation and network. As outlined above, the two fundamental roles

[15] However, because of the reduced sample size when the third pervious fund is considered (i.e. the sample size is reduced from 746 to 128 observations) the coefficients for this variable are positive but not significant.

played by GPs are the *Network* and the *Certification Effect*. The former consists in giving to the acquired company access to its buyers, suppliers, technology and entire network. The latter can be seen as a beneficial effect for the acquired companies in terms of reputation and certification among other financial players (e.g. banks). A combination of these effects would allow the target to grow faster and potentially increase its value. However, these effects are hardly directly measureable but both are strongly related to experience. In order words, if a GP has operated in the market for many years, it would have a larger network and higher number of contacts. And it would have probably developed a strong reputation, on which it can leverage.

Experience can be measured either in terms of firm's age or fund's sequence number. However, looking at experience factors, we can then hardly attribute the effects back to network, contact, reputation or other less obvious variables. One of the first studies relating performance to the fund subsequent number was Gompers and Lerner (1999), which found a positive relation between the two variables. Kaplan and Schoar (2005) recorded that funds with a higher sequence number (in log term) have significantly higher PME. Moreover, introducing the squared term of the log of sequence number, they showed that the relation was convex although insignificant. Also Phalippou and Zollo (2005b) found that inexperienced funds' performance was poorer. Moreover, in their analysis, experience measured as fund's sequence number seemed to be the best determinant of performance.

Ljungqvist and Richardson (2003) measured experience with a dummy variable taking value one if the was a first time fund, zero otherwise and documented a positive but not significant performance for first-time funds. In contrast, Phalippou and Gottschalg (2009) found a lower performance for this category of funds. They noticed also that fund sequence number was positive but not always significant and, therefore, they considered it not as good as fund's size to proxy skills. Finally, using PE firm's age as a proxy for experience, Lopez-de-Silanes *et al.* (2010) showed that this variable was only weakly related to IRR.

2.2.5. Industry Concentration

In theoretical terms, if a PE firm is specialized in a sector or industry, it should deliver better performance, thanks to its deeper specific knowledge. Phalippou and Zollo believed that *"Being focused enables GPs to work with smaller and more specialized teams that may learn faster via a high number of similar deals. An additional benefit is that GPs build tight links with the industry which may improve* *performance"* (2005b, p.13). Moreover, diversification may also be a negative fact for two reasons. Firstly, unskilled managers may diversify because they have failed in another sector or industry and want to start again but cannot do so in the previous sector/industry. Secondly, managers have an incentive to build reputation at the expense of LPs. Therefore, they may invest in different industries (but also different countries or PE types) in order to establish a track record in that specific market.

Jones and Rhodes-Kropf (2003) found that idiosyncratic risk should be related to fund return because PE firms are required to hold a large amount of specific risk. Therefore, more concentrated funds should perform better to fairly rewards investors for bearing more risk. To test the Jones and Rhodes-Kropf's hypothesis, Ljungqvist and Richardson (2003) tested whether portfolio diversification was a determinant of performance. They implemented a regression using four measures of diversification (i.e. the number of portfolio companies, the percentage of investment in the dominant industry, the percentage of invested capital in the dominant industry and the Herfindahl index). However, independently of the measure used, they did not find a relation significant at any reasonable confidence level.

Also Phalippou and Zollo (2005b), using the number of investments made as a proxy for idiosyncratic risk, did not find evidence that idiosyncratic risk is priced for PE. Nevertheless, differently from Rhodes-Kropf (2003) the relation between number of investments and performance and between Herfindahl index (i.e. index for industry concentration of investments) and performance was positive but not significant. Moreover, the effect seemed to be driven by the investments in high-tech industries.

Gompers, Kovner and Lerner (2009) found that the specialized VC firms performed better on average. This outperformance was attributable to the specialized human capital, which can not only screen and select better investments, but also manage more efficiently the acquired firms. Finally, Lopez-de-Silanes *et al.* (2010) showed that performance is only weakly positively affected by idiosyncratic risk measured as the volatility of PE firm portfolio. Alternatively, they tested whether investors of diversified funds with more investments required lower returns because they bore less idiosyncratic risk and showed that higher industry concentration and a lower number of industries in the portfolio improve performance.

2.2.6. Geographical Concentration

As outlined above, if the PE performance depends on macroeconomic features, the location of the investments may have an important effect on performance. Moreover, the development of the industry is at different stages in the US, in EU and in the emerging markets. We can say that PE industry was born in the US and strongly developed during the 1980s. Only in the following decade, it became important in the EU, where it is, therefore, still less mature compared to the US. Finally, PE activity was also developed in the emerging markets, where still today, the industry saturation is much lower. This geographical difference is becoming more evident in the last years of economic recession, during which, the PE performance was very poor in some regions, while not that bad in others.

Fraser-Sampson (2010) compared the performance for BO and VC across regions. He found that European BO have consistently outperformed the US ones during the 1990s. The author attributed this outperformance to market imperfections present in Europe. However, the reverse was true for VC. US VC funds have outperformed the European counterparties during the 1990s. The difference in performance was attributed to the superiority of the US model (i.e., focus on very early stage, presence of few big winners-home runs and search for value-adding strategies). Also Hege, Palomino and Schwienbacher (2009) reported a strong outperformance of US VC funds over EU ones. Phalippou and Gottschalg (2009) agreed on US VC outperformance, but, looking at TVPI multiple, they found a slight outperformance also for US BO. These findings may be due to the macroeconomic conditions of the local economy or/and to the relative maturity of the PE industry, which, in Europe is at a lower point in the learning curve. Interestingly, Lopez-de-Silanes *et al.* (2010) documented a significant underperformance of investments in emerging countries. This last finding goes against the big amount of money that flowed into emerging country PE industry in the last years but this poorer performance may be due to the interaction of many factors such as costly learning, lower leverage, poorer legal environment and limited exit routes.

2.2.7. Type of funds

Looking at PE asset class may give a misleading image of the performances of two different categories of funds: BO and VC. Therefore, it is interesting to look at how these two types of fund performed over time. Ljungqvist and Richardson (2003) reported a stronger outperformance for BO[16] than for VC and attributed it to fact that BO had used a higher amount of leverage than VC. Also Robinson and Sensoy

[16] Cumulative alpha (Profitability Index-PI) for BO and VC was of 33.69% (27.13%) and 28.08% (15.11%) respectively. The PI is the present value of the cash flows received by LP, over present value of paid-in capital using realized S&P500 as discount rate. A PI larger than one indicates outperformance.

(2011) and documented that VC underperformed BO both in terms of PME and IRR. In line with Robinson and Sensoy (2011), Harris *et al.* (2012) found a PME for BO exceeding one for vintages 1980s, 1990s and 2000s. However, VC outperformed in 1990s but not in 2000s, recording a PME less than one and very poor returns in 1990 and 2002. On the contrary, Jones and Rhodes-Kropf (2003) reported a stronger outperformance for VC funds (alpha 4.68%) than for BO funds (alpha 0.72%). Also Kaplan and Schoar (2005) documented that VC with a PME of 1.21 performed, on average, better than BO funds (PME of 0.93). However, the results of these two last studies are very sensitive to time period and dominated by the strong VC performance in the 1990s. Finally, in contrast to other previous studies, Phalippou and Gottschalg (2009) did not find a significant difference between these two groups.

2.2.8. Other Variables

In addition to the variables we have considered, authors have also focused on other, less evident drivers of performance. For example, Lopez-de-Silanes *et al.* (2010) showed that small investments outperform larger ones. They documented the existence of a negative relation between investment size within the fund's portfolio and its performance**.** However, even if IRR and multiple decrease for larger investments, it is objectionable whether one should prefer a lower IRR on a larger investment or a higher IRR on a smaller investment. In other words, even if in terms of IRR an investment is better, it must not necessarily be so in terms of NPV.

Managers' compensation could also affect performance in theory. However, Robinson and Sensoy (2012) documented that, in contrast with mutual fund industry, in PE, higher compensation or lower managerial ownership is not associated with worst net-of-fee performance[17]. This is consistent with an equilibrium, in which, PE firms benefiting from higher compensations are able to earn back their pay by delivering higher gross performance. Moreover, they found that compensation could affect the holding period because the GP has private information on investments. Therefore, the GP can play around the timing of exit and, doing so, it may have an impact on performance. GPs have incentives to cluster distributions around "waterfall dates" to earn the carried and to delay distributions on "living dead" investments to earn management fees, when these fees are based on the invested capital.

[17] Note, however, that during boom years, fundraising is easier and fund sizes increase. The overall pay goes up and moves towards fixed compensation (management fees) and away from variable component (carry).

Chapter 3: Empirical analysis

The main purpose of this paper is to investigate which are the key performance drivers of PE funds. Before highlighting our main findings, we will first describe the sample data and then the variables used in our analysis.

3.1. Data

Data was collected using several sources and databases. Performance measures (e.g., IRR, quartile, TVPI, DPI) were collected via Preqin. Fund features (e.g., size, number of investments, regions and industries of investments) were collected via CapitalIQ. Finally, historical market returns (e.g. S&P500) were collected via Bloomberg. ***Table II*** gives details on the source of each variable.

A first important remark is that, as outlined above, each database has its own drawbacks and biases. In our case, however, selection and survivorship biases are minimized because Preqin collects data not only via GPs voluntary contributions but also through public institutions via freedom of information legislations and published reports of listed fund of funds. However, because Preqin depends on public filings and FOIA requests and, as underlined by Harris *et al.* (2012), may miss some funds, which are not in the public pension funds' portfolios. Also CapitalIQ, which we used to collect fund's characteristics, is missing important data. For instance, there is no data for some funds, while for others only one or two investments are recorded and it is unlikely that these few investment depict the real and complete picture accurately.

A second remark is that GPs' selective reporting in our sample was also minimized by the fact that only the funds that had also been reported by large public LPs (e.g., The California Public Employment Retirement Fund, The Regents of the University of California, Oregon Public Employees Retirement Funds, etc.) have been considered. However, if this selection reduced selective reporting, it created a strong bias toward US-based, larger and more experienced funds because public institutions, usually, invest in well-known GPs with a long and positive track record.

3.2. Sample Descriptive Statistics

Starting from 6,224 funds present in Preqin universe, ***Table III*** shows that the sample was reduced to 2,405 funds when we had excluded funds that had:

- No IRR performance reported
- Size less than $5M or unreported (in line with previous research)
- Vintage outside the range 1980-2009

- Special focus or features (e.g., real estate, fund of funds, etc.)

In addition to the previous selection criteria, we cross-matched data from CapitalIQ in order to get information about funds' features. As a consequence, we reduced the sample according to two criteria:

- The fund had at least three investments reported in CapitalIQ
- All other features needed were accessible in CapitalIQ

As a result, our sample is composed by 570 funds from 151 PE firms (Appendix B). Performance data has been also cross-checked using reports from large institutional LPs[18]. 68% of these funds are BO and 32% VC. Moreover, 87% of the funds are located in the US, 11% in EU, and 2% in other countries. The total number of investments is 6,620, accounting for more that $1 trillion. 78% of these investments were located in the US, 15% in the EU, 5% in Asia, and the rest in Latin America and in Africa & Middle East (***Table IV***). Using CapitalIQ classification, we can spot eleven different industries, reported in ***Table V*** together with the number (percentage) of investments in each industry. Interestingly, for BO funds, the only outstanding industry is Consumer Discretionary accounting for 23%, while the rest of the investments are widespread among the other industries. For example, Information Technology, Industrial and Healthcare account for 17%, 16% and 12% respectively. In contrast, VC investments are much more concentrated and mainly focused on Information Technology (47%) and Healthcare (35%), leaving to all the other industries a marginal 18%.

Table V
Investments by industry for BO and VC

The table shows the number (percentage) of investments in each industry for BO and VC. 82% of VC investments are concentrated in Information Technology and Healthcare, while BO investments are more equally distributed.

Industry	BO	VC	All
Information Technology	715 (17%)	1,128 (47%)	1,843 (28%)
Healthcare	492 (12%)	832 (35%)	1,324 (20%)
Consumer Discretionary	970 (23%)	155 (6%)	1,125 (17%)
Industrial	686 (16%)	89 (4%)	775 (12%)
Financials	356 (8%)	62 (3%)	418 (6%)
Energy	245 (6%)	35 (1%)	280 (4%)
Materials	226 (5%)	10 (0%)	236 (4%)
Telecom Services	185 (4%)	50 (2%)	235 (4%)
Consumer Staples	203 (5%)	17 (1%)	220 (3%)
Utilities	88 (2%)	3 (0%)	91 (1%)
Others	63 (1%)	14 (1%)	77 (1%)
Total	**4,229 (100%)**	**2,395 (100%)**	**6,624 (100%)**

[18] Note that funds, in which none of the institutional LP invested, were also excluded.

Furthermore, the average BO fund invests in 4.32 industries while the VC only in 2.79. Overall, for all PE funds, we have an average number of investments of 11.62, but VC have a higher average with 13 investments per fund (***Table VI***). This number is lower than previous research's estimates and we attributed the difference to a lack of data for older funds (i.e. 1980-1990, where the average number of investments is 7.8) and to the fact that some recent funds have not yet invested the full amount of capital committed (e.g. the average 2004-2009 number investments is 9.7). On the other hand, these two issues have a lower effect for funds between 1991-2003, for which, the average is higher and totals 13.3 investments per fund.

We have already said that our sample is more US- and BO-focused compared with previous studies and with commercial databases For example, in Jones and Rhodes-Kropf's (2003) VE sample 70% of funds were VC. Similarly, Kaplan and Schoar's (2005) sample had 78% of VC. Because we selected only investments held by large LPs, our sample is more similar to that of Ljungqvist and Richardson (2003), which collected data from a unique LP and had 74% of BO funds.

Moreover, we have an underrepresentation of less experienced funds. First-time funds are 10%, second-time funds are 13% and third-time funds amount to 15%. Previous studies had higher percentages of first-time funds. For example, Robinson and Sensoy (2012) had 35% first-time funds and 23% second-time funds in their sample. This underrepresentation is due to the fact that large public institutional investors do not usually invest in first-time fund but they usually prefer to wait for the GP to have acquired some experience and a demonstrable track record. Moreover, full fund's characteristics are hard to be found for first-time funds.

Finally, the sample presents a bias towards larger fund. The average (median) size is \$1.77B (\$800M) for the entire sample, \$494M (\$304M) for VC and \$2.38B (\$1.3B) for BO (***Table VII***). Because average values are higher than median ones, we observe a positive skewness driven by big outliers (Appendix B). This last finding is obvious in light of the fact that data is coming from large LPs, which tend to invest in larger funds. Note that to minimize the effects of outliers and to make the distribution more similar to a normal one, we took a logarithmic transformation of size in our analysis. Moreover, ***Figure C*** and ***Table VIII*** report the average size by vintage year and the comparison with that of Preqin's universe. Preqin has an average size of \$607M, smaller than that of our sample. Moreover, the BO average size is \$1.06B, while the average size for VC is \$217M.

We believe that the larger averages of our sample are attributable to three factors. Firstly, public institutions prefer bigger funds. Secondly, for smaller funds less data about fund's features was available and it caused the elimination from our sample. Thirdly, we included vintages 2005-2008, over which we recorded an average size of $3.2B and, therefore, the historical average increased abnormally. Note that, also Preqin's universe has median size smaller than the average, indicating positive skewness. Average and median size are higher also compared with previous research, especially when compared with old studies, because fund's size has increased over time. For example, Kaplan and Schoar (2005) reported an average size of $172M for the entire sample, with BO being much larger than VC ($416M vs. $103M), while, Harris *et al.* (2012) reported that the mean BO fund's size was $390M, $782M and $1.42B for the 1980s, 1990s and 2000s respectively. The average VC fund's sizes over the last three decades was lower and respectively $77M, $191M and $358M. Also Robinson and Sensoy (2012) reported higher numbers with respect to previous studies. Thus, the average (median) fund's size was $208M ($106M) for VC and $988M ($313M) for BO funds, with an overall average of above $700M.

Looking at the IRR, we can state that the average (median) value over the entire sample is 15.16% (10.75%). Being the average smaller than the mean, the distribution is characterized by strong positive skewness (Appendix B). Moreover, the first (third) quartile IRR is 20.48% (4.73%) and the size-weighted average IRR is 10.96% (10.98% for BO and 10.85% for VC). This last evidence indicates that very larger funds performed more poorly in terms of IRR, because size-weighted is higher than equally-weighted average. This is a hint for the concave relation between size and performance, which will be analyzed below. Moreover, we notice a quite large dispersion in returns, with a minimum return of -30.50%, a maximum of 118.40% and a standard deviation of 20.92% *(**Table IX**)*. VC have a higher average IRR compared with BO (i.e., 16.63% vs. 14.47%). Interestingly, the median (first quartile) is 11.85% (20.63%) for BO and 8.55% (20.05%) for VC. Therefore, even if the average IRR is higher for VC, this is only driven by large outliers. Moreover, VC have almost doubled standard deviation than BO (29.30 vs. 15.41). Looking at Preqin's restricted universe of 2,405 funds, the average IRR is 14.07%. The minimum is -100% and maximum 1015.5% with a standard deviation of 35.41%. We can notice that our sample has a slightly higher mean but much more concentrated returns, with a lower standard deviation and smaller range. This is a positive aspect because it allows avoiding outliers to affect deeply the analysis. Preqin's entire universe recorded an average (median) IRR of 14.15% (11.9%) for BO and 13.47% (6.95%) for VC funds. Overall the average (median) IRR for both BO and VC funds is 13.79% (9.30%). Finally, the average IRR of our sample is also in line with previous researches[19].

Looking at the TVPI, we can observe a multiple over the entire sample of 1.80x. Dividing the sample by fund's type, we observe a higher multiple for VC than for BO (i.e., 1.99x vs. 1.71x). Furthermore, we can detect a significant heterogeneity in the sample, with a maximum (minimum) multiple of 19.62x (0.27x) for VC and 8.29x (0.29x) for BO. The variability is higher for VC with a standard deviation of 2.06 and 0.81 for VC and BO respectively. Overall, the standard deviation over the entire sample is 1.35. The median (first quartile) TVPI is 1.48x (2.06x) (***Table X***). Also in this case we can detect a right skewness being the average higher than the median TVPI and the presence of some outliers (Appendix B). Therefore, in order to avoid misleading effects on our results, as for the case of IRR, a logarithmic transformation on this variable has been implemented. Looking at Preqin's restricted universe, we notice an average (median) TVPI of 1.72x (1.36x). However, the dispersion of observations is much larger, with minimum multiple of 0.0x, a maximum of 42.45x and a standard deviation of 1.82 (35% larger than in our sample). Finally, the Preqin's entire universe average (median) TVPI is 1.51x (1.25x).

It is interesting to observe how the vintage average IRR and TVPI have evolved over time (***Figure D***). Firstly, both these two performance measured refer to the 31st December 2012. Excluding 1980s funds, for which the limited number of observations does not allow reaching strong conclusions[20], we can see that the median IRR has been positive over the last two decades. Moreover, in line with what was observed by Higson and Stucke (2012), also in this sample we can notice a downward trend in absolute value for IRR and a strong co-movement with the 6-year rolling average S&P500. In addition, ***Figure E*** shows that the excess IRR over the 6-year rolling average S&P500 was always positive between 1990 and 2007 but with some fluctuations. Also the TVPI multiple shows cyclicality and a downward trend over time. Finally, we recorded a high correlation between TVPI and IRR[21]. ***Figure F*** compares VC and BO median IRR and TVPI over the time period 1990-2009 and,

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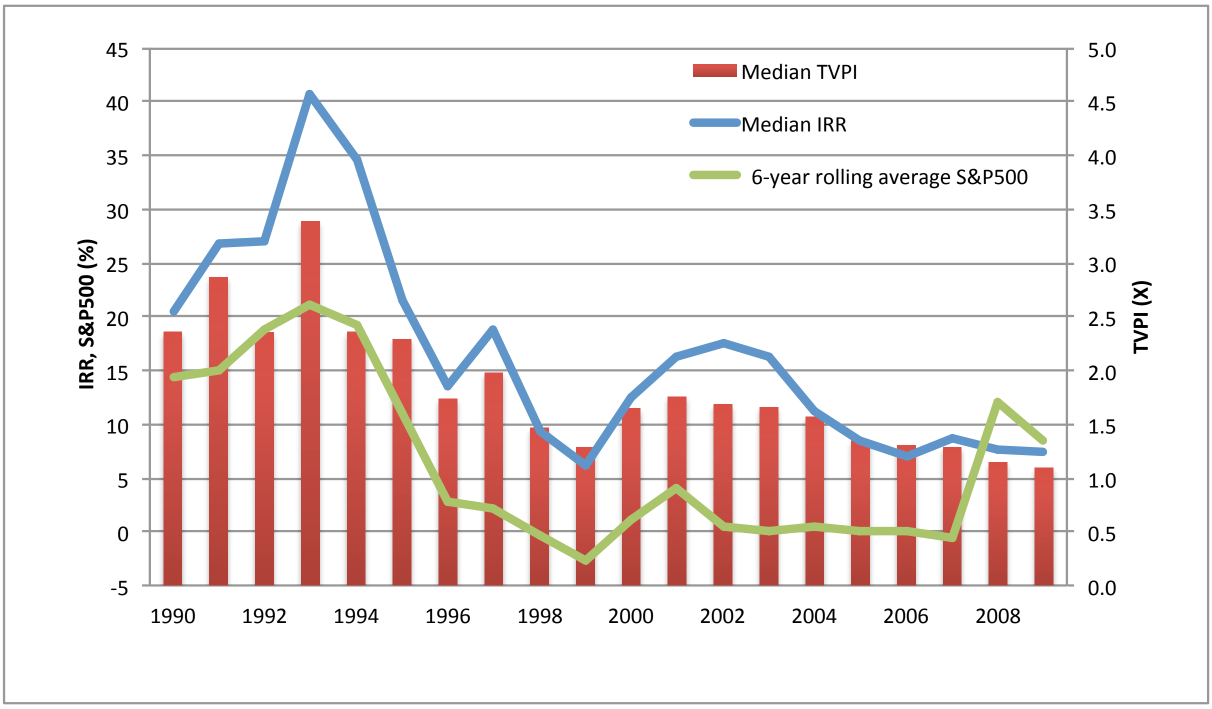
[19] For example Kaplan and Schoar (2005) reported an equally-weighted average IRR for their sample of 17%.
[20] The lack of enough observations for the 1980s is due to a poorer coverage by Preqin for this decade.
[21] The correlation between IRR and TVPI was 0.95 between 1990 and 2009.

confirming the findings of Harris *et al.* (2012), shows that the VC, on average, have outperformed BO in 1990s but underperformed in 2000s.

Figure D

Median IRR and TVPI and 6-year rolling average S&P500 return (1990 – 2009)

The figure shows the evolution of the vintage median IRR and TVPI. Moreover, it shows a 6-year rolling average S&P500 return (i.e. a typical PE duration is between 6 and 7 years). Because vintages 2004 and onwards are not fully realized (particularly 2006 and later) we cannot fully trust the data for the latest period. Moreover, also the rolling averages S&P500 for the last five years have been calculated over shorter periods. We notice a strong cyclicality for both IRR and TVPI and a co-movement between these two measures and the market. Moreover, we notice a strong correlation between IRR and TVPI. Note that median values have been preferred to average because the latter suffer from the presence of outliers.



Some words must be spent on the vintage year selection and NAV treatment, which has been used in the TVPI and as last cash flow in the IRR calculation. On the one hand, by restricting the sample to liquidated fund (i.e. 1980-2003), we do not need to worry of whether the NAV was correctly reported. However, the sample size would be reduced significantly from 570 to 329 funds. On the other hand, if we require a larger sample size, we need to trust the NAV appraisal. Because we have considered funds whose vintage is 2009 or older, our sample will necessarily include non-liquidated funds and, therefore, we will use the Preqin's value. As highlighted by Higson and Stucke (2012), "*NAV initially records the purchase cost of investments. NAV is written down if the recoverable value falls below cost but, since 2006, industry guidelines and GAAP (SFAS157, IAS39) require NAV to be recorded at 'fair value', that is, written up to current value as well as written down*" (p.4). Having this in mind, even if managers could smooth the NAV, boosting it before new fundraising, we will consider this as an exception and take the NAV as a fair measurement of residual value. Moreover, robustness tests will be conducted to show that our findings are independent from this assumption.

3.3. Rationale of the model

In this paper, we would like to test a number of hypotheses. Firstly, we investigate whether persistence is an important factor in PE industry. If managers had skills and performed well in the past, we would expect them to perform well also with their next fund. If this were true, previous fund's performance would affect the performance of the current fund. Moreover persistence may not only derive from operational and deal-related skills, but also from the established relationships, networks and reputation.

Secondly, better and skilled managers would attract more funds and increase their fund's size. Bigger funds would have a stronger bargaining power in deal execution and performance will be less affected by fixed fees and costs. Therefore, there would be a positive relation between size and performance. However, at certain point, the benefits of being large would be offset by drawbacks. Not only there would be a limited number of profitable transactions, but also diseconomies of scale would arise because of a reduced attention partners can dedicate to each company in the portfolio and a more difficult communication. These last factors would, in turn, have a negative effect on performance. Overall, putting positive and negative effects of size together, we expect a concave relationship between size and performance.

Thirdly, we have learned that PE is an environment where experience, network, contacts and reputation make the difference. Experience can be measured by the number of funds a GP has opened, by the years it has been active in the market or by the cumulative fundraising. An established GP, with a strong network and high reputation will have a competitive advantage over newcomers and, therefore, we expect experienced PE firms to perform better.

Fourthly, not only network, contacts and reputation, but also industry-specific knowledge affect performance. Industry and geographic concentration may increase the specific knowledge and network. These elements, in turn, will be useful not only to have access to better deals in that specific industry or region, but also to evaluate better the investment opportunities. Moreover, specific knowledge would play also a fundamental role ex-post, when the PE firm has to manage the acquired companies. Consequently we expect specialized and focused GPs to perform better.

Finally, we also investigate how these factors affect BO and VC and whether their effects has been different over time and across regions. Therefore:

- ***Hypothesis 1****: There is a positive correlation between consequent fund's IRR for the same GP. This shows persistence in performance.*
- ***Hypothesis 2****: The relation between fund's size and performance is positive and concave.*
- ***Hypothesis 3****: PE firms with more experience deliver higher performances.*
- ***Hypothesis 4****: Funds that focus on a particular industry/sector will perform better than funds with a lot of investments in many disparate industries. Moreover, also geographical focus may be beneficial in terms of performance.*

3.4. Methodology and Variable description

In order to test our hypotheses, we will rely on a regression analysis by means of least squares estimators. In particular, our general specification will be:

$$y_i = a + \boldsymbol{bX}_i + e_i$$

Note that below we provide several diagnostic tests to asses the soundness of the regression tool in our analysis. The dependent variable y_i is the Log (1 + IRR - Preqin's benchmark)[22]. The benchmark is based on 4,448 funds of vintages 1980 to 2012 as of 30th June 2012 and determined based on the vintage year, region and the fund's type (VC vs. BO). When robustness tests will be conducted, the dependent variable would be in turn the log of the TVPI multiple, the fund's quartile and a dummy variable taking value one if the fund was in the top 25% in terms of IRR, zero otherwise. The explanatory variables are briefly described below, while a complete analysis with graphical representation and descriptive statistics is available in Appendix B:

- Previous performance (Persistence): the natural logarithm of one plus the previous fund's IRR.
- Size: the natural logarithm of the fund's size (in $M) and its quadratic form. A logarithmic transformation has been implemented in order to have a variable more similar to a normal distribution. While the square has been used to test the concavity of the relation between size and performance.
- Experience: the natural logarithm of the sequence number and its square.

[22] The log transformation makes the distribution more similar to a normal one and avoids the impact of outliers.

- Industry concentration: the natural logarithm of the maximum number of investments in the dominant industry over the total number of investments.
- Regional concentration (90%): a dummy variable which takes value one if the number of investments into the dominant geographical area, over the total number of investments is in excess of 90%, zero otherwise.
- Venture Capital: a dummy variable which takes value one if the fund is a VC, zero if the fund if BO.
- S&P500: average return from S&P500 in the 3 years following fundraising. It is an assessment of market conditions in which the PE firm operated during the investment period.
- “Hot market” dummy: a dummy variable, which takes value one if the S&P500 index increased for four consequent years, zero otherwise.

The previous variables have been used to develop the basic model specifications. Moreover, in order to conduct robustness tests and subgroup analysis we employed other variables reported in ***Table XI***. We have considered the correlations and multicollinearity issues between variables and a series of diagnostic checking is provided below to test the soundness our analysis.

3.5. Results

In our basic specification, we look at the effects of previous fund’s IRR, size, sequence number and fund’s type on performance (***Table XII***). In order to avoid that vintage year differences may affect our analysis, we employed a series of dummies to impose a vintage year fixed effect[23]. With this specification we can address the hypothesis 1 to 3, while we will deal with hypothesis 4 below. The overall significance of the model is very high[24] and the goodness of fit is decent. The adjusted R^2 is 9.4% and all the variables are significant at 5% confidence level. Note that, because we have included past performance, we reduced the sample from 570 to 514 observations (i.e., 56 observations are first-time funds with no previous fund)[25].

Firstly, as expected, past performance plays an important role. The coefficient of Log (1+ Previous fund’s IRR) is 0.115 and it is significant at 1% confident level. Therefore, previous fund’s performance has an influence on current performance.

[23] Note that, however, because we had used as dependent variable Log (1+IRR-bechmark), we kept the vintage effect already into account. However, we believe it is still usefull to insert this fixed effect.
[24] i.e., p-value of F statistics is 0.000
[25] Alternatively, we have used a dummy for first-time funds and kept all 570 observations. By doing so, even if the signs and significance of the coefficients are only slightly affected, the explanatory power of the model is reduced.

However, the way in which the variable is measured has some pitfalls. Firstly, LPs do not already know the previous fund's IRR when they invest in the second fund. Secondly, we have overlap in performances between the current and previous fund because they will benefit/suffer from same macroeconomic conditions. Despite these limitations, we have also found that the current performance is positively affected by the second-previous fund's IRR. However, by doing so, we lose 176 observations and the significance of the variable is low[26].

A second important finding is that, in line with that of Kaplan and Schoar (2005), size has a positive and concave effect on performance. The coefficients are significant at 6% and 5% confidence level for Log (Size) and Log $(\text{Size})^2$ respectively. This confirm our hypothesis and shows that performance increases in size, but this effect is valid only up to a point, after which, a further increase in size is detrimental for performance. This optimal point has a size value of \$1.2B for the entire sample and \$750M for VC subsample[27]. Looking at the standardized betas, we can detect that size is the most important variable in terms of magnitude. A standard deviation increase in size leads to an increase of 0.74 in performance. However, the effect is partially offset by the quadratic negative term.

Thirdly, experience is a very important driver of performance, second after size in terms of magnitude. The coefficient for the Log (Sequence number) and the Log $(\text{Sequence number})^2$ are respectively 0.131 and -0.073 and both significant at 1% confidence level. This positive and concave relation has important insights. The experience effect is positive on performance up to the optimal point (i.e., sequence number 8). Afterward, opening a new fund turns out to have negative consequences on performance. We can explain this by the fact that benefits of experience are outweighed by other elements in a similar way as the fund's size[28]. Finally, the dummy variable, which accounts for differences in fund's type, is significant at 3% confidence level. On average, VC seems to have performed better than BO in terms of IRR of circa 1.7%[29]. However, when we performed a separated analysis for BO and VC (see subsample analysis below), we found no evidence that VC consistently outperformed BO and the winner will be determined by the time period and the measure of performance employed.

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[26] This finding is in line with Kaplan and Schoar (2005).

[27] The relation between size and performance is not significant for BO (see the subsample analysis).

[28] Both for size and experience, the introduction of a quadratic term casues high collinearity. However, we will show, through the use of dummy variables, that multicollinearity does not affect the significance of our results.

[29] $e^{(0.017)}-1= 1.7\%$.

In order to test hypothesis 4, we extended our regression model by inserting variables in order to account for industry and geographical concentration. Firstly, we introduced the industry concentration variable in *specification 2*. The effect of this variable is positive but small. Therefore, specialized funds, concentrated in a single or few industries, performed better and this effect is significant at 5% confidence level. Moreover, two important facts occurred. Firstly, the significance of size is slightly reduced. Secondly, the dummy variable accounting for the fund's type is no longer significant. On the contrary, the regional concentration (*spec.* 3) has a negative effect on performance but it is not significant at any reasonable confidence level. This result was not expected *ex-ante* but it is probably due to the characteristics of our sample, which has a strong US bias and, therefore, does not allow an effective analysis across regions. *Specification 4* put together the industry and geographical concentration and shows a similar picture as above.

Up to this point, we have employed a year fixed effect, to keep cyclicality and other omitted variables into account. However, in order to show which is the effect of cyclicality, we run a regression where the average S&P500 return for the first 3 years after fundraising has been added but the fixed year effect omitted (*spec.* 5). We can see that, good economic conditions in the years after fundraising, improve the performance of a fund. This may result form the fact that a period of optimism makes easier and faster the company operational improvements. However, we have also found that if fundraising occurred at a peck of a market cycle (i.e., after that the S&P500 has increased for four consequent years), the fund would, on average, perform worst. This may be due to the fact that bull market allows easier access to leverage, which has been shown to be negatively related to BO returns because of a stronger competition on deals with consequent overpayment (Axelson *et al.*, 2012).

3.6. Diagnostic Checking

Before performing robustness tests and subsample analysis, we want to dedicate this brief session to the understanding of whether the regression tool was appropriate. It is useful, therefore, to make some diagnostic checking for the breakdown of regression assumptions. Simplifying, the basic assumptions, which must be satisfied to employ the regression tool, are the following:

1) $E(\mu_t)=0$: average value of the error terms is zero
2) $Var(\mu_t) = \sigma^2 < \infty$: constant variance of the error terms (homoscedasticity)
3) $Cov(\mu_i, \mu_j) = 0$: no autocorrelation between error terms

4) Cov (μ_i, X_i) = 0: no correlation between error terms and independent variables
5) μ_t ~ N (0, σ^2): normally distributed residuals

The first assumption is satisfied by the simple fact that we included a constant in our model. A second important assumption it that the variance of the residuals associated with the dependent variable does not change across the dimension of any independent variable, that is, there is no heteroscedasticity. In order to test for heteroscedasticity, we can conduct several diagnostics. We opted for a White's test. We squared the unstandardized residuals of the regression and used them as dependent variable in a second regression, in which, the independent variables are the independent variables of the original regression, their squared terms and the cross products. Finally, we multiplied the number of observations (514) for the R^2 (0.20) and compared it with a chi-squared critical value. Accomplishing this test, we detected some heteroscedasticity. We, therefore, computed the heteroscedastic robust standard errors for *specification 1* and *5* by implementing the code developed by Hayes and Cai (2007). Results are reported in *specification 1-HR* and *5-HR*. By doing so, we can notice that despite the fact that the errors for all the variables increased, any important changes in the significance of the variables occurred with the exception of size, whose significance was slightly reduced.

Thirdly, we are confident that no autocorrelation between error terms exists because the value of the Durbin-Watson test was 2, indicating no autocorrelation. Fourthly, the violation of assumption four happens if one or more independent variable, which are related to the dependent variables are omitted. As far as this assumption is concern, we are aware that the model does and could not include all the possible relevant dependent variables. For example, different strategies of PE firms may be an important variable to be included that may cause the violation of this assumption. However, in our regression, a year fixed effect has been used at least to help to reduce this problem. Fifthly, by looking at the histogram and the distribution of the residuals (Appendix B) we detected a certain degree of non-normality. The standardized residuals have a positively skewed and leptokurtic distribution. The values for Shapiro-Wilk (***Table XIII***) and for Jarque-Bera tests[30] confirmed the non-normality of the distribution. However, this is not a serious issue as long as the independence assumption holds. Furthermore, because of the large sample size,

[30] The Jarque-Bera test gives a value of 85.6, which indicated that the varaible departs from a normal distribution.

violation of the normality assumption is rather inconsequential[31]. Moreover, we can attribute the rejection of normality assumption to the presence of large outliers.

Finally, we can firmly state that there is no collinearity problem because the bivariate Pearson correlations (Appendix B) are rather small. The only noteworthy correlations are, obviously, those between the Log (Size) and its quadratic transformation and those between Log (Sequence number) and Log (sequence number)^2. Moreover, the VC dummy has a modest correlation with size and industry concentration but the correlation is still lower than 60%. No other correlations are higher than 40%. Also looking at VIF coefficients we reached the same conclusions. Apart from the obvious high correlations outlined, all the other VIF coefficients are smaller than 2, indicating no multicollinearity. Overall, we can state that the use of the linear regression is a decent tool for this analysis.

Chapter 4: Subsample analysis and Tests on Robustness

4.1 Other Performance Measures

We would like, now, to understand whether we can replace the variables used above with others with similar meanings but different forms, leaving the results of the analysis unchanged. Firstly, we are interested on whether the used explanatory variables affect other measures of performance than the excess IRR, such as the TVPI and the quartile ranking. Results for this section are reported in ***Table XIV***. Note that in all these specifications a vintage year fixed effect has been employed to avoid that vintage specific characteristics affected the analysis.

Firstly, we replace the Log (1 + IRR - Benchmark) with the TVPI multiple (*spec. 6*). Given the fact that the relevance and the signs of almost all the variables' coefficients remained unchanged, we can state that our model is rather robust. The most striking feature of the new regression is the impressive increase of the goodness of fit of the model (i.e., the adjusted-R^2 went from 10.2% to 33.9%). Secondly, previous fund's performance is still significance at 1% confidence level and the form and significance of the relationship between size and performance did not change. Thirdly, experience and performance show again a positive and concave relationship, with strongly significant coefficients (i.e. 1% confidence level). Contrarily to previous specifications, however, the industry concentration lost its significance.

[31] This is a result of the central limit theorem, according to which, as the sample size increases, the statistics will asymptotically follow a normal distribution even if the error depart from normality.

Finally, the dummy distinguishing between fund's types changed its sign, indicating that, *ceteris paribus*, VC performed, on average, poorly in terms of TVPI. This finding is interesting and indicates that VC IRRs are mostly driven by short holding periods.

As a second test, we used as dependent variable a dummy, which takes value one if the fund performance ranked in the top 25%, zero otherwise. However, being this variable binomial, we performed a binomial logistic regression (*spec. 7*). Note that the same explanatory variables as in *specification 4* were exploited. Despite the fact that the general interpretation for these coefficients is slightly different than that in a linear regression, we can see that most of the coefficients maintained the same signs and remained significant, with the exception of experience, which seemed not to matter anymore. Therefore, it does not matter how many funds you have opened before to asses the likelihood to be in the top-performing quartile. On the contrary, previous performance and size remained strongly significant. Moreover, our previous findings remained unchanged for industry and geographical concentration. Industry focus is an important explanatory variable for PE performance while the coefficient for geographical concentration, even if positive, was not significant at any reasonable confidence level.

Finally, we used a discrete variable, taking the number of the fund's quartile (i.e., 1= top 25%, 2, 3 and 4= worst 25%) and exploited a multinomial logistic regression to understand whether, also in this case, our explanatory variables were significant determinants of performance (*spec. 8*). The coefficients in the model had the worst 25% of the funds as reference case. The variables, which drive top-quartile funds' performance, are the same as in *specification 7* and, again, the experience is not significant. However, we can see that experience is important to be classified in the second quartile with respect to the worst 25%. On the other hand, while size affect positively the likelihood to be in the top 25%, it does not matter for the likelihood to be in the second-best 25% with respect to the worst quartile.

We have understood that most of our findings are valid independently from how we measure fund's performance. Now, we are interested to understand whether these results are also valid for subsamples and, later, we will conduct robustness tests on explanatory variables.

4.2. Subgroup Analysis

The above results are valid for the entire sample. However, they may not hold for subsamples. Therefore, we investigate this fact in this section by dividing the sample in smaller groups by fund's type, vintage, size, geography and industry and looking at whether the results remain valid or not.

4.2.1. Fund type

We would like to understand whether there is any difference in performance drivers for VC and BO. In the previous specifications, we used a dummy variable for VC and, even if the coefficient had often a low significance, it was usually positive. This fact may indicate that, historically, VC performed, on average, better than BO. However, even if the average IRR for VC is higher than that for BO, the reverse is true for the median and the first quartile. Moreover, not only VC exhibit very high variation in returns with a standard deviation two times higher than that of BO funds, but they also underperformed, on average, in terms of TVPI multiple. This last finding indicates that VC returns are mostly driven by short holding periods. To sum up, unfortunately, we are not able to reach strong conclusions on the relative performance of VC versus BO. Instead of using the dummy for VC, we can split the sample by type and look distinctly at BO and VC, in order to spot differences in performance drivers (*spec. 9-10* in ***Table XV)***.

Looking at BO funds, we can immediately spot that the size effect is no longer significant[32]. This finding is in line with what suggested by Metrick and Yasuda (2009), that is, BO is a much more scalable business than VC and, therefore, size is a less relevant driver of performance. On the other hand, past performance has a strong positive effect, significant at 2% confidence level. Also industry concentration matters a lot in terms BO performance with a coefficient significant at 1% confidence level. Moreover, looking at the unstandardized betas, we can see, that experience has the strongest effect on current performance. Thus, a one standard deviation increase in Log (Sequence number) increases the performance of 0.465. However, because of the concavity of the relation, this positive increase will have a decreasing marginal effect, pecking at 7 years. Previous performance and industry concentration have a magnitude of 1/3 with respect to experience.

Looking at the regression for VC funds, we can see that our model fits this category much better, with a large increase in the goodness of fit with respect to the regression for BO only (i.e., R^2 increases from 3.9% to 19%). Firstly, past fund's performance has a slightly less strong effect on current performance. In contrast with

[32] This finding is consistent with Kaplan and Schoar (2005).

BO, moreover, size is the most important performance driver for VC[33]. The relation between performance and Log (Size) is positive and concave. However, because of the concave shape, the positive effect is marginally decreasing and the function reaches its maximum at $750M. Also the relation between experience and performance is positive and concave and the effect is stronger than for BO. Indeed, this is the second most important performance driver for VC. Moreover, differently from BO, the effect of industry concentration is not very significant. This lack of significance may be due to the fact that VC are much more industry-focused than BO and 82% of their investments is in Technology and Healthcare. This causes the lack of enough spread of observations across industries and made the coefficient not significant. Another reason for the insignificance of this variable for VC is the strong deviation from normality with a long right tail and many observations taking value zero, that is, funds that are completely concentrated in one industry[34] (Appendix B).

4.2.2. Vintages

At this point of the paper, we are fully aware of the cyclicality of the PE industry. In order to account for that, we have used a series of dummy variables to keep the vintage year effect fixed in almost all the performed regressions. Moreover, also the use of the Preqin's benchmark helped to keep vintage year differences into account. Now, we want to be more precise and analyze the vintage subsamples (***Table XV***). Firstly, we have shown before that when we plot IRR and TVPI versus vintage years, we can see wild fluctuations. This is also true for the Preqin's universe (***Figure G)***. Moreover, it is also interesting to see whether, over time, the performance has been affected by the same drivers. Therefore, we divide the sample in three subgroups, which represent the three past decades (i.e., 1981-1990, 1991-2000, 2001-2009) and analyze performance drivers for each decade. Note that for the period 1981-1990 we have only 26 observations and, therefore, being the statistical significance of the model rather low, it is useless to make any sort of inference[35].

For the decade 1991-2000 (*spec. 12*), we have 192 observations (78 VC and 114 BO) and, therefore, we can make more confident statements. The effect of size is still positive, concave and significant. Moreover, we found the usual concave relationship between performance and experience measured as a Log (Sequence number). However, the quadratic term is, now, significant only at 14% level. We can

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[33] Thus, a one standard deviation increase in Log (Size) increases the performance of 1.537

[34] These funds have a concentration of 100% and the Log (Industry concentration) = Log (100%)=0.

[35] None of the variables for this decade was shown to be significant at any reasonable level (*spec. 11*).

justify this lower significance with the fact that only few GPs in the 1980s had reached a level of experience, which can be considered harmful for performance. In contrast with previous specifications, however, industry concentration has lost its significance. Finally, past fund's performance is playing an important role in driving current performance with a coefficient of 0.14 significant at 3% confidence level.

For the period 2001-2009 we recorded 296 funds (74 VC and 222 BO funds) and documented three important pieces of evidence (*spec. 13*). Firstly, size does not play an important role anymore[36]. However, this low significance may be justified by the large BO presence in this subsample (75%), for which, as previously shown, size is not a relevant performance driver. Secondly, in contrast to the past decade, industry concentration matters. The coefficient for Log (Industry concentration) is significant at 1% confidence level and second in terms of magnitude after experience. Also this finding is linked to the high presence of BO (for which this variable is important) in the sample. Finally, we find a positive and concave effect of experience on performance[37]. As a final remark, we can notice that the effect of previous performance is stronger when compared with that of the past decade and significant at 1% confidence level.

A final step is to investigate whether the NAV appraisal was affecting the outcome of our analysis. Therefore, in *specification 14*, we considered only funds with a vintage year 2003 or older, ending up with 286 funds. First of all, we have a much more equal distribution of funds between categories with 169 BO and 117 VC. Secondly, we can see, that our main findings still hold but we can spot one major change with respect to the analysis over the entire sample. Indeed industry concentration does not matter anymore, because, consistent with what we have shown before, industry concentration seems to matter only for the decade 2001-2009. To sum up, we can state that we did not find any strong evidence that the NAV appraisal have influenced our regression analysis and we attribute the lack of significant for the industry concentration to a changed environment in PE industry rather than to any sort of NAV misreporting.

4.2.3. Size

In *specifications 15-18* we investigate whether the effects we have previously underlined are valid across subsample by size. We have analyzed funds smaller than

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[36] Log (Size) and Log $(Size)^2$ are not significant at any reasonable confidence level.
[37] Both coefficients for experience are significant at 3% confidence level.

$500M, smaller than $1B, larger than or equal to $1B, and larger than $3B. Doing so, we have found interesting pieces of evidence (***Table XVI***). Overall, we can say that our model fits best funds smaller than $1B. However, this is not surprisingly, because in this group we have 147 VC out of 277 funds and we have shown that our model fits VC better. As a consequence, in *specification 15*, we can see that almost all the variables are significant, with size playing the most important role. Second and third places are, respectively, for experience and past performance.

If we look, instead, at funds larger than $1B (*spec. 16*), we find results similar to the regression for BO subgroup, for which experience and industry concentration were the most relevant performance drivers. Surprisingly, however, past fund's performance, even if positive, is not significant. In addition, putting together the findings from the first two regressions, we can conclude, that size plays a strong positive role at the beginning, that is, when the fund is relatively small and loses its importance as the fund's size increases. On the other had, it seems that, as the fund's size increases, experience and industry concentration matter much more. In addition, previous fund's performance is no more a discriminant feature, probably because all the funds, which were able to raise a fund larger than $1B, had already a good track record and, therefore, previous fund's IRR loses its explanatory power.

Specifications 17 and *18* also offer interesting insights. Firstly, regional concentration seems to have a negative effect on performance for funds smaller than $500M. The effect is rather small but significant at 5% confidence level. Therefore, for smaller funds, it seems better to diversify geographically. Secondly, we can look at very larger funds (i.e. size larger than $3B), for which out of 102 funds, we have only one VC. We can see that our model poorly fits big funds and the only significant variable is past performance. However, we suspect that this significant, may be due to overlaps in performances between the current and previous fund, benefiting/ suffering from same macroeconomic conditions. In this cluster, the usual drivers of performance are difficult to hold, because for example, if you are able to open such a huge fund, you have already acquired enormous experience and good track record. Moreover, the size effect would be hardly detectable, because size is already very large. Therefore, we conclude that our model fits poorly funds larger than $3B.

4.2.4. Geography

We need to recall, once again, that in our sample most of the funds were US-based. Therefore, there could be a suspicion that the results we have drawn are valid for the

US funds but not for funds located elsewhere or vice versa. Therefore, we split the sample according to the geographical location of the fund, and, in particular, we compared US with Non-US funds (*spec. 19-20* in ***Table XVI***). We can see that, while the findings outlined above remain true and sometimes coefficients have an even larger magnitude for the US subsample, the same cannot be said for the Non-US funds. While the sign of the majority of the coefficients did not change, the significance of each coefficient was either very low or null. Interestingly, the sign of the previous fund's IRR become negative but the coefficients is not significant. The low significance of the coefficients in the Non-US sample, however, can be attributed to the lower number of observations for this sample (i.e., only 63 observations) because our sample is strongly US-biased.

4.2.5. Industry

We have shown, that industry concentration is an important driver of BO performance, especially for the last decade. We want now understand whether the industry, in which the GP invests can influence its performance (***Table XVII***). First of all, we extended our regression with 10 dummy variables (i.e. one less than the number of industries), which take value one if at least on investments in that industry was made, zero otherwise (*spec. 21*). The industry classification comes from CapitalIQ, and we can distinguish eleven industries (i.e., Consumer Discretionary, Industrial, Healthcare, Materials, Telecom Services, Energy, Information Technology, Consumer Staples, Financials, Utilities and Others). We need to be aware of the fact that each performance observation would be associated at the same time with more than one industry because we do not have IRRs at investment level but only at fund level. Therefore, this analysis, even if sound in theory, has some drawbacks in practice and is not 100% precise.

From this regression, we can see that when we enter these new dummies, the magnitude and significance of the other coefficients are only slightly affected. Moreover, we can notice that the only three industries that seem to have a significant effect on performance are Energy, Information Technology and Consumer Staples[38]. The magnitude of the coefficients is similar to the effect of previous fund's IRR. In *specification 22* we regressed current performance against variables that count the

[38] Coefficients are all positive and significant at 10% confidence level for Energy and 5% level for the other two industries.

number of investments in that particular industry[39]. Doing this, we can highlight two interesting findings. Firstly, size loses its significance. Secondly, only Information Technology and Consumer Staples seem to have a relevant impact on performance. Their coefficients are positive and significant at 1% confidence level.

Finally, we run eleven unreported regressions, one for each industry as a stand-alone. Note that because the same return is considered for different industries at the same time, we cannot make strong and precise statements and we limit ourselves to describe some interesting findings. First of all, performance is an important variable of current performance for investments made in Consumer Discretionary, Industrial, Healthcare, Telecom Services and Information Technology. Size is a relevant variable only for two industries, that is, Industrial and Healthcare. On the other hand, experience seems to matter for all the industries but Energy and Financial. Finally, industry concentration is an important driver of performance for Industrial, Materials, Energy, Information Technology and Utilities.

4.3. Test on robustness

4.3.1. Size

In previous specifications, we have measured size in logarithmic terms together with its quadratic form to investigate the possibility of a concave relationship with performance. Looking at the standardized betas of *specification 4*, we can see that size plays the most important role[40]. Moreover, we can detect a significant concave relationship. These results, however, remain valid only for VC when we split the sample by fund's type and we can justify this by the fact that BO is a much more scalable business than VC. In ***Table XVIII*** we looked at different specifications of the model. If Log (Size) or this variable together with its quadratic form are employed as only independent variables (*spec. 23-24*) the coefficients of the regression are not significant. This could be explained by the large number of omitted variables, such past performance, which make the model highly unreliable.

Actually, by introducing also past performance in our model (*spec. 25*), we can see that both coefficients of size are again significant at 10% confidence level and the fitness of the model improves remarkably. In *specification 26*, we replace the variable Log (Size) and Log $(Size)^2$ with a dummy variable, which takes value one if

[39] Also in this case we used a vintage year fixed effect.
[40] A change of one standard deviation in Log (Size) increases the performance of 0.672.

fund’s size is larger than \$500M, zero otherwise. By doing so, we can observe that the coefficient is negative and significant at 10% level. Therefore, on average, funds larger than \$500M underperformed smaller funds. However, this variable does not take into account the concave relationship and negative effects on performance for very large funds prevail, on average, on positive effects on medium funds.

Finally, it is interesting to notice whether the concave relationship found for VC was affected by multicollinearity because of the use of both Log (Size) and Log (Size)^2 in our regression. Therefore, we created three dummies[41] accounting for different sizes (i.e. size smaller than \$400M, between \$400-800M and larger than \$800M). When we employed the dummies for smaller and larger funds, leaving out the intermediate, we found negative coefficients. On the other hand, if we used only a variable for size between \$400-800M, the coefficient is positive[42]. This shows that the concavity effect is rather robust and not materially affected by collinearity.

4.3.2. Experience

We have measured experience with the natural logarithm of the sequence number and its quadratic form and we have obtained three important findings. Firstly, the relation between experience and performance is positive and concave. Secondly, both coefficients are significant at 1% confidence level. Finally, looking at standardized betas, we can see that experience is the second most important driver of performance after size[43]. The concave relationship between experience and performance can be explained by the fact that the positive aspects of experience are outweighed by other elements in a similar way as for the fund’s size. For example, managers can have different time horizons and those closer to retirement, who have acquired larger experience, may opt for bigger funds at the time of fundraising even if they already know that the performance would be not excellent. Another reason explaining this relationship is that, when managers have acquired a large experience and, therefore, a strong reputation, they can charge higher fees. Consequently, even if they performed better on a gross-of-fee basis, they would underperform net of fees.

We want, now, to investigate the robustness of these findings (***Table XIX***). In *specification 27*, we regressed current performance over previous performance and the Log (Sequence number) only, while in *specification 28* we added its quadratic

[41] We have 3 categories: 1) x<400M, 2) \$400<=x<800M, 3) x>\$800M. Accordingly, we used 2 dummies.
[42] Note, however, that the significance of these coefficients is rather low.
[43] A one standard deviation increase in Log (Sequence number), increased the performance by 0.615, while at the same time, we have an offsetting negative effect because of the quadratic term.

term. Interestingly, while in the former case the coefficient for experience is positive but not significant, in the latter case, in which the quadratic term is added, both coefficients are significant at 1% confidence level.[44] In order to avoid doubts on whether the concave relation was affected by multicollinearity[45], we used a series of dummy variables as we did for size. Therefore, we employed three dummy variables, which account for different experience levels[46]. We found that the coefficient of the dummy for low-experience funds (i.e., up to 3 funds opened) and for over-experienced (i.e., more than 14 funds) are negative, while they are positive for medium level of experience. This finding confirms the robustness of the concave relation between performance and experience.

Moreover, we can replace the Log (Sequence number) with variables that measure experience but have different forms. Firstly, we used as a dependent variable a dummy variable, which takes value one if the PE firm has already opened at least 2 funds before the current one and zero otherwise (*spec. 30*). Secondly, we employed a dummy variable, which takes value one if the PE firm has been for more than 10 years in the business (i.e. the time between the PE firm foundation and the vintage year of the fund), zero otherwise (*spec. 31*). Thirdly, we measured experience through the natural logarithm of the cumulative fundraising of the PE firm excluding the current fund (*spec. 32*). In all these three cases, the coefficient for experience is positive and economically and statistically significant. Therefore, we are quite confident on the robustness of this variable, which we have found to be a very important driver of PE performance.

To sum up, we can say, that experience has a positive effect on performance independently from how it is measured. Moreover, when a quadratic term is added to the regression, the concavity of the relation emerges.

4.3.3. Industry Concentration

We have previously shown that industry concentration is an important performance driver. By specializing in a sector or industry, managers can not only bargain better transactional terms and evaluate opportunities more consciously, but they can also manage the acquired companies in a more efficient way. Previously, we have measured industry concentration with the natural logarithm of the maximum number

[44] Also in *specification 4* without its squared term, the coefficient for experience is positive but not significant.
[45] Because, as for size, we introduced both the Log(Sequence number) and its quadratic form.
[46] I.e., we distinguished between 4 levels of experience according to the fund sequence number: 1) fewer or equal to 3; 2) more than 3 and fewer or equal to 8; 3) more than 8 and fewer or equal to 14; 4) more than 14.

of investments in the dominant industry over the total number of investments. Its coefficient was 0.045 and significant at 3% confident level. We proceed with the analysis of the robustness of industry concentration in the same way as we did for experience, by replacing the original variable with a similar one, which we believe having analogous effect (***Table XX***).

We can measure industry concentration via a dummy variable, which takes value one if at least 2/3 of the portfolio is concentrated in one industry, and zero otherwise (*spec. 33*). In this case, we can notice three important pieces of evidence. Firstly, the significance of all coefficients remains almost unchanged. Secondly, the goodness of fit of the model improves slightly. Finally, even if the magnitude of the coefficient for the industry concentration is halved, its significance improves at 1% confidence level. Alternatively, we can measure industry concentration via the fund's standard deviation of the number of investments in each industry. In this case (*spec. 34*), we still find a positive and significant coefficient for industry concentration, but both its magnitude and significance decrease. To sum up, industry concentration is an important driver of performance. However, both its significance and its magnitude vary according to the variables used to measure it.

4.3.4. Persistence

Up to now, we have measured previous fund's performance via previous fund's IRR and we found it to be an important performance driver. This is consistent with findings of several authors and in line with the view of PE industry as a world where track-record matters and managers are able to add some value. It is also interesting to notice that previous fund's IRR remains an important and significant variable also when we use it as unique explanatory variable (*spec. 35* in ***Table XX***). Thus, coefficient for persistence is still positive and significant at 1% confidence level. However, the overall model is rather poor because of the high number of omitted variables, some of which, we have shown to play an important role. Another pitfall is the fact the macroeconomic conditions may affect simultaneously consequent funds, creating a spurious relation between current fund's performance and previous fund's performance, which is, indeed, dependent only on the overlaps of performances.

An alternative solution to measure persistence is to include in the regression the previous fund's quartile (*spec. 36*). In this case, the coefficient for persistence is negative and significant at 1% confidence level. Therefore, in line with our original hypothesis, if the number of the quartile of the previous fund was higher (i.e. as we move from the first quartile -top 25%- to the second and so on), the performance of the current fund is, on average, lower. Moreover, the goodness of fit of the model improves slightly and all the other relationships remain almost untouched in terms of magnitude and significance. To sum up, persistence remains an important driver of performance also when it is measured in in terms of previous fund's quartile.

4.3.5. Geographical Concentration

We have shown, that regional concentration did not play any relevant role in our model. The coefficient of the dummy variable, which takes value one if the number of investments into the dominant geographical area accounts for at least 90% of the total investments and zero otherwise, was not significant at any reasonable confidence level. Moreover, also measuring regional concentration using different variables, it still remains not significant (***Table XX***). For example, *specification 37* measures geographical concentration with a dummy variable, which takes value one if the PE firm invests only in one industry, zero otherwise. *Specification 38*, instead, measures geographical concentration with a dummy variable, which takes value one if more than 2/3 of the investments are focused in one region only. Coefficients for geographical concentration in both specifications are negative and not significant. Therefore, we can conclude that, in our sample, geographical concentration is not an important driver of performance.

However, it is difficult to make any strong generalization out of this finding because this lack of significance may be due to several factors intrinsic in our data or model. Firstly, our sample is strongly US-biased. Therefore, geographical analysis may be not totally relevant given the sample characteristics. Secondly, part of the geographic effect may have already been considered in the Preqin's benchmark, when the Log (1+IRR-Benchmark) is used as dependent variable. Finally, the lack of significance may be due to the fact that, nowadays, PE firms have contacts and network all around the world. This means that the location of the investments may be of second importance and, therefore, the regional concentration does not affect performance anymore. However, if this were true, regional concentration should be and important performance driver for the 1980s. However, because the sample size for this period is very small, we are not able to show if this was the case.

Conclusions

In this paper we collected data for 570 funds raised by 151 GPs between 1980 and 2009. The total number of investments recorded in our sample was 6,620, which account for more that $1 trillion. Our main purpose was to understand which are the factors that drive PE performance. After assessing its soundness for our specific analysis via diagnostic checking, we exploited the OLS regression as a tool to test our hypotheses and we reached interesting conclusions.

Our first finding is that persistence, measured in terms of previous fund's IRR or quartile, is an economically and statistically significant driver of current fund's performance. The coefficient for Log (1 + previous fund's IRR) was found to be positive and significant at 1% confident level. This is in line with our hypothesis for persistence in PE industry. The reasons for this persistence are, however, hardly identifiable and a complete discussion is beyond the scope of this paper. We have found this persistence to be important across fund's type and time with the only exception of the period 1980-1990, for which we recorded only 26 observations and we were not able to reach any robust conclusion.

Our second important finding is the concave relationship between size and performance. This relationship is strong and significant for the overall sample. We have also shown that size is the most important variable in terms of magnitude, followed by experience. However, when we split the sample by type, we do not find any evidence of size effect for BO, while this effect is even more important for VC. This is an interesting fact, in line with Kaplan and Schoar (2005) and attributable to the fact that BO is a much more scalable business than VC and, therefore, size has a less relevant impact on performance. The concavity effect could be attributable to many reasons. Initially, as the size increases, we can have economies of scale and learning. However, at a certain point, which we believe to be around $750M for VC, the positive effects of being large are offset by the absence of enough profitable deals opportunities and some diseconomies of scale coming from a limited attention managers can dedicate to each transaction and from a more difficult and costly communication.

Our third main finding is a strong economically and statistically significant effect of experience on performance. Independently from how we measure experience, we found that experienced PE firms performed better, on average. Moreover, when we measure experience with the Log (Sequence number) and its square, the concave feature of the relationship emerges. In addition, experience remains an important performance driver across fund's types and decades.

Our final finding is that industry concentration is another relevant driver of performance, especially for the decade 2001-2009. However, both the significance and the magnitude of the coefficient linking industry concentration to performance vary according to the variable used to measure it. In addition, while this variable is significant at 1% confidence level for BO, it is not significant for VC funds. The lack of significance for industry concentration in VC is attributable to the fact that VC investments are already very concentrated. Indeed, 82% of the investments are in Technology and Healthcare. We have also considered geographical concentration. However, because of the characteristics of our sample, which is very US-biased, we were not able to find any evidence that regional concentration affected PE performance in any matter. Independently from how we measure regional concentration, this variable remains irrelevant. In addition, geographic concentration affects neither BO nor VC performance.

It is worth noticing that these findings above are still true and even stronger when performance is measured via TVPI or quartile ranking. Interestingly, BO perform better than VC in terms of TVPI but not in terms of IRR, suggesting a short holding period for VC. Moreover, we have performed a number of robustness tests for the explanatory variables, which showed the reliability of our findings.

In the last chapter of this paper we have addressed also whether these results were valid for subgroups by location, fund's type, vintage and size. Unfortunately, given the low presence of Non-US funds in our sample, we were not able to find any conclusive evidence for this subgroup. Moreover, we found that our model fits better VC and funds smaller than $1B. In addition, we have shown that over time, the significance and the magnitude of our variable have changed and each decade has its own story. Finally, analyzing only liquidated funds, we can state that we did not find any strong evidence that the NAV appraisal has influenced our regression analysis.

In conclusion, we would like to state that this paper gives a contribution to the current literature on this topics. On the one hand, it confirms some results found by previous researches. On the other hand, it offers some elements of novelty, especially when the industry concentration factor is analysed. However, even if our findings are robust, sample characteristics and data quality still affect our analysis.

Firstly, our sample is strongly US-biased and has a larger presence of BO, experienced and larger funds, in which institutional LPs are more confident to invest. Therefore, we can run the risk to overestimate performance because of a bias towards better funds. Secondly, despite the good quality of Preqin's data, we are still missing important information about vintages in the 1980s. Moreover, CapitalIQ was missing relevant pieces of information about investments and, therefore, the analysis may not be completely accurate. However, we need to live with the fact that because of the nature of PE industry, precise and complete data is not available. Finally, we should be aware that also possible misspecifications of our model might affect our analysis.

Model misspecification may derive from many aspects. Firstly, we could have a problem of reverse causality. For example, we have found that more experienced and reputed GPs outperformed. This may be due to the fact that they hire skilled managers, who are then able to execute better deals or bring more efficient operational improvements. However, it may also be the case that better investee firms choose more experienced GPs and this may create a problem of reverse causality, which we were not able to assess because we missed data about the identity of the 6,620 investments. Secondly, a large number of variables may have been omitted from the analysis. This creates, in turn, an important concern. However, we tried to limit this problem via the use of Preqin's benchmark in our dependent variable and with the use of a fixed vintage year effect in most of our regressions.

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Appendix A

Tables

Table I
Literature on PE performance

The table reviews past literature showing the database used, sample characteristics and the main outcome

Reference	Source	Sample	Benchmark	Performance	Drivers: effect on performance	R^2, Beta
Jones and Rhodes Kropf (2003)	VE 1980-1999	Total 1,245 VC= 70% BO= 30%	S&P500	$Alpha_{VC}$ = 4.68% $Alpha_{BO}$ = 0.72% Not significant	- Idiosyncratic Risk - Number of investments	$Beta_{VC}$= 1.80 $Beta_{BO}$= 0.66
Ljungqvist and Richardson (2003)	Unique 1981-2001	Total= 73 VC= 26% BO= 74% US=91.1% EU=7.4% LatAm=1.5%	S&P500 NASDAQ	Outperformance: 5.7-8.1% yearly PI= 25 (vs. S&P) PI= 9.96 (vs. NASDAQ)	- Size (+) (not for BO) - "Money chasing deals" - BO outperform VC (because higher leverage)	R^2= 3.7-5.7% $Beta_{VC}$= 1.12 $Beta_{BO}$=1.08
Kaplan and Schoar (2005)	VE 1980-1996	Total=746 VC= 78% BO= 22% US=100%	S&P500	Average fund return (net of fees) similar to S&P500 but strong cross-section variability.	- Previous fund performance - Size (concave) - Experience (convex) - Cyclicality - Competition	R^2 = 17-30%
Phalippou and Zollo (2005a)	VE 1980-1996	Total=983 VC= 72% LBO= 28%	S&P500 NASDAQ	Underperformance-3.3% per year PI=1.05 (vs. S&P) PI=1.04 (vs. NASDAQ)		
Phalippou and Zollo (2005b)	VE 1980-1996	705 funds VC= 77% BO= 23%	S&P500	PI_{LBO} = 1.02 PI_{VC} =1.07 But significant underperformance if corrections are implemented.	- Corporate bond yield - Return of public stock market during the life of the investments - Length of the investments - Size and Experience	R^2 = 11% $Beta_{all}$= 1.60 $Beta_{VC}$= 1.58 $Beta_{BO}$= 1.73
Phalippou and Gottschalg (2006)	Unique 1980-1993	Total=852 VC= 72% BO= 28%	S&P500	Underperformance of - 3.8% (net of fees) p.a. PI_{BO} = 0.91 PI_{VC} =0.81 Gross-of-fees IRR=2.96%		
Phalippou and Gottschalg (2009)	VE 1980-1993	Total = 852 VC= 72% BO=28% EU= 36% US=64%	S&P500	Underperformance of - 3% (net of fees) p.a. PI=0.88 PI_{BO}=0.75 PI_{VC}=0.77	-Previous performance -Manager experience -Fund Size -EU focus -First-fund	R^2 = 4-16%
Lopez-de-Silames *et al*. (2010)	Unique 1971-2005	Total=254 Investments= 7,453 (filtered) BO =100%	CRSP US stock index	Median IRR=21% (gross) Median PME=1.27 (gross) EM underperformance	-Duration -Size of each investment -Public equity movement -Diseconomies of scale -Hierarchical firms	R^2 = 6 - 12%
Robinson and Sensoy (2011)	Unique 1984-2009	Total = 990 VC= 30% BO= 55% Other=15%	S&P500	Outperformance: 15% $MedianPI_{BO}$ =1.10 Mean PI_{BO} =1.20 Median PI_{VC}= 0.81 Mean PI_{VC}=1.03		
Harris *et al*. (2012)	Burgiss 1984-2012	Total = 1373 VC= 56% BO= 44%	S&P500 Russel3000 Russel2000 NASDAQ	US BO outperformed S&P500 of 20%-27% over the life of the fund. VC outperform in 1990s but not in 2000s	-Aggregate commitments -Size	
Robinson and Sensoy (2012)	Unique 1980-2010	Total= 837 VC= 35% BO= 65%	S&P500	Outperformance: 2.5% p.a. PME_{BO}=1.18 PME_{VC}=1.03	-Higher compensation or lower managerial ownership is not associated with worst net-of-fee performance.	
Higson and Stucke (2012)	CA 1980-2010	Total = 1,169 US =100% BO=100%	S&P500 S&P600 Small-Cap	Outperformance of 450 bps (1980-2000) and 800 bps (1980-2005)	-Cyclicality -Size	

Table II
Sources of Data

The table illustrates the sources of all the data used in the analysis. Note that the original variables have been transformed in our analysis.

Dependent Variables		
Variable	**Source**	**Notes**
IRR-Benchmark	Preqin	Dec 12
TVPI	Preqin	Dec 12
DVPI	Preqin	Dec 12
Quartile	Preqin	Dec 12

Independent Variables		
Variable	**Source**	**Notes**
Vintage	CapitalIQ	1980-2009
Size	CapitalIQ	$M
Type of fund	CapitalIQ	BO, VC
Sequence number	CapitalIQ	Units
Cumulative fundraising	CapitalIQ	$M
Number of investments	CapitalIQ	Units
Number of investments by country	CapitalIQ	US, EU, LatAm&Caribbean, Africa&Middle East
Number of investments by industry	CapitalIQ	Consumer Discretionary, Industrial, Healthcare, Materials, Telecom Services, Energy, Information Technology, Consumer Staples, Financials, Utilities and Others
Previous fund's IRR	Preqin	%
Second previous fund's IRR	Preqin	%
Previous fund's quartile	Preqin	Quartiles
S&P500 yearly return	Bloomberg	%

Table III
Preqin restricted Universe

The table shows how we go form 6,224 observations in the Preqin's universe to a smaller sample of 2,405 funds by considering only BO and VC and eliminating funds for which the performance measure was not available, which had a size smaller of $5M and vintages outside the range 1980-2009.

Preqin's restricted universe		
Sample	**Lost observations**	**Total observations**
Total Preqin's universe	-	6,224
Funds for which IRR is reported	1,273	4,951
Considering only BO and VC	2,307	2,644
Funds with reported size (>$5M)	161	2,483
Only vintages 1980-2009	78	2,405

Table IV
Number of investments and percentages by Region

The table illustrates the number (percentage) of investments by region and by fund's type. We recorded a total number of investments of 6,624, of which 78% were US-based. The US-bias is even stronger for VC, for which, 93% of the investments is in the USA.

Region	**BO**	**VC**	**All**
North America	2,967 (70%)	2,231 (93%)	5,198 (78%)
European Union	927 (22%)	38 (2%)	965 (15%)
Asia	212 (5%)	107 (4%)	319 (5%)
Latin America and Caribb	106 (3%)	1 (0%)	107 (2%)
Africa/Middle East	17 (0%)	18 (1%)	35 (1%)
Total	4,229 (100%)	2,395 (100%)	6,624 (100%)

Table VI
Descriptive Statistics for number of investments and number of industries

The table shows the descriptive statistics for the number of investments and the number of industries in which the PE firms invested. We can see that, on average, VC have a larger number of investments in their portfolios than BO. Overall the average number of investments is 11.62. On the other hand, VC investments are much more focused in fewer industries, with an average number of industries of 2.7, while BO have an average number of industries of 4.32. Overall the average PE firm invests in 3.83 industries.

Number of Investments	**BO**	**VC**	**All**
Average	10.96	13.02	11.62
1st Quartile	14	18	15
Median	9	11	9
3rd Quartile	6	6	6
Stand. Deviation	7.97	8.95	8.35
Mode	5	4	5
Number of Industries	**BO**	**VC**	**All**
Average	4.32	2.79	3.83
1st Quartile	5	3.25	5
Median	4	3	4
3rd Quartile	3	2	2
Stand. Deviation	1.81	1.46	1.84
Mode	4	2	3

Table VII
Descriptive Statistics for Fund's Size

The table shows the descriptive statistics for size by type of investments. It also compares the figures of our sample with that of Preqin's restricted universe. We can see that the average size for BO is $2.3B and $494M for VC. Overall, the average size is $1.77B. This number is higher when compared with Preqin. However, looking at median numbers, our sample is more similar to Preqin. Finally, we can see that the aggregated investments in our sample is $1.01 trillion, only $600M lower than the aggregated amount invested recorded by Preqin.

Size Descriptive Statistics	BO	VC	All	Preqin
Average	2,382	494	1,772	608
Minimum	27	19	19	6
Maximum	21,700	3,000	21,700	21,700
Stand.Dev.	3,022	527	2,655	1,462
Median	1,300	304	800	505
1st Quartile	3,100	610	2,000	205
3rd Quartile	582	163	320	81
Mode	1,100	150	1,000	100
Obs.	386	184	570	2,405
Aggregation	919,396	90,882	1,010,278	1,637,904

Table VIII
Size comparison by vintage (Preqin vs. Sample)

The table shows the average size by vintage year for VC and BO. It also compares our sample with Preqin's restricted universe. We can clearly see that the average size has increased over time for both BO and VC and this feature is present in our sample as well as in Preqin's. We can also notice that the average of our sample is larger than that of Preqin. Note that we cannot rely on the first vintages because we have too little observations.

Vintage	Preqin			Sample		
	VC	BO	All	VC	BO	All
1981	44	-	44	-	101	101
1982	42	328	74	-	150	150
1983	70	98	74	81	246	191
1984	57	249	99	100	160	130
1985	46	138	56	178	65	121
1986	59	160	103		663	663
1987	102	887	338	235	136	186
1988	97	475	271	59	149	113
1989	59	414	175	761	95	317
1990	75	225	145	606	135	404
1991	91	232	150	877	160	339
1992	82	397	211	172	162	167
1993	81	296	160	479	145	327
1994	82	605	389	1319	156	829
1995	95	437	268	826	320	688
1996	141	429	276	867	165	612
1997	123	697	385	1355	181	910
1998	144	799	489	1627	396	1161
1999	282	725	480	1377	399	942
2000	316	964	560	1813	768	1479
2001	274	783	449	1797	732	1401
2002	155	756	414	1018	456	878
2003	150	945	544	2325	398	1919
2004	175	818	488	1677	558	1304
2005	234	1102	734	2604	455	2150
2006	300	1919	1124	4531	835	3299
2007	316	1891	1094	4250	996	3806
2008	319	1682	997	4089	949	3553
2009	370	1172	798	2226	930	1902
1980-2009	**217**	**1061**	**607**	**2382**	**494**	**1772**

Table IX
Descriptive Statistics for IRR

The table shows the descriptive statistics for IRR by fund's type and compares it with Preqin's restricted universe. We can notice that our sample's average is slightly higher than that of Preqin. However, the observations of the sample are much less disperse, with smaller standard deviation. We can also notice that the average IRR for VC is higher than that for BO. However, the reverse is true in terms of median IRR and 1st quartile.

IRR Descriptive Statistics	BO	VC	All	Preqin
Average	14.47	16.63	15.16	14.07
Minimum	(30.50)	(18.60)	(30.50)	(100.00)
Maximum	94.00	188.40	188.40	1,015.70
Stand.Dev.	15.41	29.30	20.92	35.41
1st Quartile	20.63	20.05	20.48	20.00
Median	11.85	8.55	10.75	9.65
3rd Quartile	6.33	(0.93)	4.73	1.20
Mode	6.00	(6.60)	10.00	11.00
Obs.	386	184	570	2,405

Table X
Descriptive Statistics for TVPI multiple

The table shows the descriptive statistics for TVPI by fund's type and compares it with Preqin's restricted universe. We can notice that our sample's average is slightly higher than that of Preqin. However, the observations of the sample are much less dispersed and have a much lower standard deviation than in Preqin. We also notice that the average TVPI is higher for VC. However, the reverse is true in terms of the median.

TVPI Descriptive Statistics	BO	VC	All	Preqin
Average	1.71	1.99	1.80	1.72
Minimum	0.29	0.27	0.27	-
Maximum	8.29	19.62	19.62	42.45
Stand.Dev.	0.81	2.06	1.35	1.82
1st Quartile	2.01	2.11	2.06	1.95
Median	1.51	1.39	1.48	1.36
3rd Quartile	1.22	0.98	1.17	1.00
Mode	1.70	0.69	1.09	1.09
Obs.	386	184	570	2,405

Table XI
Description of the variables used in the regressions

The table reports the description of the additional variables used in the analysis and not described in the text.

Variable	Description
Experience (1st/2nd fund)	a dummy variable, which takes value zero if the fund is either a first- or second-time fund, one otherwise.
Experience (years)	a dummy variable, which takes value one if the fund has been active in the market for more than 10 years, zero otherwise.
Fundraising	the natural logarithm of the cumulative fundraising in $M
Experience level dummy variables	4 dummy variables, which distinguishes between 4 levels of experience according to the fund sequence number: 1) fewer than or equal to 3 funds opened before; 2) more than 3 and fewer than or equal to 8 funds opened before;3) more than 8 and fewer than or equal to 14 funds opened before; 4) more than 14 funds opened before.
Size level dummy variables	3 dummy variables, which take value one respectively for 1) size < $400M; 2) $400 < = size < 800M, 3) size > $800M.
Size dummy	a dummy variable, which takes value one if the fund's size is larger than $500M, zero otherwise.
Industry concentration (>2/3	a dummy variable, which takes value one if at least 2/3 of the investments are in one industry, zero otherwise.
Investment variation by industry	Standard deviation of the number of industries in each fund.
Regional Concentration (100%)	a dummy variable, which takes value one if all the investments are in one region only, zero otherwise.
Regional concentration (2/3	a dummy variable which takes value one if the number of investments into the dominant geographical area, over the total number of investments is in excess of 2/3, zero otherwise.

Table XII
Regression Model: Performance and fund's characteristics

The table reports the regression analysis for fund's characteristics. In panel 1 we employ previous performance, size, experience (measured in sequence number) and fund's type. Firstly, the coefficient of Log (1+ Previous fund's IRR) is 0.115 and it is significant at 1% confident level. Secondly, size has a positive and concave effect on performance. Thirdly, experience is a very important driver of performance, second after size in terms of magnitude. In panel 2 we extend our regression model by inserting variables in order to account for the effect of industry concentration. The effect of this variable is positive but small. In panel 3 we employ a variable for regional concentration but it was found to be not significant at any reasonable confidence level. In panel 4 we put both industry and geographical concentration together. In panel 5 we employ the average S&P500 return for the first 3 years after fundraising, which has been found to have a positive effect on performance. Finally the last two panels take the specification 1 and 5 respectively and use the heteroscedastic standard errors.

Dependent Variable: Log (IRR-benchmark)							
Specification (n)	(1)	(2)	(3)	(4)	(5)	(1-HR)	(5-HR)
(Constant)	-0.19***	-0.199***	-0.188***	-0.163**	-0.126*	-0.1283*	-0.1259*
IRR previous fund	0.155***	0.163***	0.154***	0.162***	0.168***	0.1858***	0.17
	(0.04) [0.17]	(0.04) [0.18]	(0.04) [0.17]	(0.04) [0.18]	(0.04) [0.19]	(0.07)	(0.07)
Log (Size)	0.088**	0.081*	0.089*	0.08*	0.06	0.06	0.06
	(0.05) [0.74]	(0.05) [0.68]	(0.05) [0.75]	(0.05) [0.67]	(0.04) [0.52]	(0.04)	(0.04)
Log (Size)^2	-0.015**	-0.013*	-0.016**	-0.013*	(0.01)	-0.0124*	-0.011
	(0.01) [-0.76]	(0.01) [-0.67]	(0.01) [-0.77]	(0.01) [-0.67]	(0.01) [-0.55]	(0.01)	(0.01)
Log (Fund sequence)	0.131***	0.13***	0.131***	0.13***	0.134***	0.1353***	0.1339***
	(0.04) [0.62]	(0.04) [0.61]	(0.04) [0.62]	(0.04) [0.62]	(0.04) [0.63]	(0.04)	(0.04)
Log (Fund sequence)^2	-0.073***	-0.072***	-0.073***	-0.072***	-0.076***	-0.0781***	-0.0756***
	(0.03) [-0.57]	(0.03) [-0.57]	(0.03) [-0.58]	(0.03) [-0.57]	(0.03) [-0.6]	(0.03)	(0.02)
Industry Concentration		0.032**		0.045**	0.04**		0.0402**
		(0.02) [0.11]		(0.02) [0.12]	(0.02) [0.11]		(0.01)
Regional Concentration (>90%)			(0.00)	(0.00)			
				(0.01) [-0.02]			
Venture Capital Dummy	0.017**	0.01	0.017**	0.01**	0.01	0.0124*	0.01
	(0.01) [0.12]	(0.01) [0.07]	(0.01) [0.12]	(0.01) [0.07]	(0.01) [0.06]	(0.01)	(0.01)
Average 3-year S&P500					0.16***		0.1601**
					(0.06) [0.12]		(0.07)
Adjusted R^2	9.4%	10.1%	9.3%	10.2%	9.7%	9.1%	11.1%
Vintage Fixed Effect	Yes	Yes	Yes	Yes	No	No	No
Number of Obs.	514	514	514	514	514	514	514

(Standard Error); [Standardized Beta]; * significant at 10% confidence; ** significant at 5% confidence; *** significant at 1% confidence

Table XIII
Test of Normality

The table reports the test of normality of standardized residuals for specification 1 and 5 respectively. It shows both Kolmogorov-Smirnova and Shapiro-Wilk tests. However, the former is not reliable and we focus on the latter. Overall, we can detect strong department from normality

	Kolmogorov-Smirnova			**Shapiro-Wilk**		
Specification	Statistic	df	Sig.	Statistic	df	Sig.
1	0.103	514	0.000	0.923	514	0.000
5	0.099	514	0.000	0.919	514	0.000

Table XIV

Robustness test on the dependent variable

The table reports the regression analysis to test the robustness of the dependent variable and we showed that most of our findings are valid independently from how we measure fund's performance. In panel 6 we replace the Log (1 + IRR - benchmark) with the TVPI multiple and we can see that the relevance and the signs of almost all the variables' coefficients remained unchanged. The most striking feature of the new regression was the impressive increase of the goodness of fit of the model (i.e., the adjusted-R2 went from 10.2% to 33.9%). Contrarily to previous specifications, however, the industry concentration lost its significance. Finally, the dummy distinguishing between fund's types changed its sign, indicating that, ceteris paribus, VC performed, on average, poorly in terms of TVPI. This finding is interesting and indicates that VC IRRs are mostly driven by short holding periods. In panel 7, we used as dependent variable a dummy, which takes value one if the fund performance ranked in the top 25%, zero otherwise. However, being this variable binomial, we have performed a binomial logistic regression and noticed that most of the coefficients maintained the same signs and remained significant, with the exception of experience. In panel 8 we used as dependent variable, a discrete variable, taking the number of the fund's quartile (i.e., 1= top 25%, 2, 3 and 4= worst 25%) and exploited a multinomial logistic regression to understand whether, also in this case, our explanatory variables were significant determinants of performance. The coefficients in the model had the worst 25% of the funds as reference case. The variables, which drive top-quartile funds' performance, are the same as in specification 7 and, again, the experience is not significant. However, we can see that experience is important to be classified in the second quartile with respect to the worst 25%. On the other hand, for the second-best 25%, size does not matter anymore.

Robustness Test on Dependent Variable

	(6)	(7)	(8)		
			1st	**2nd**	**3rd**
(Constant)	0.035	-4.528	-8.921**	-7.31**	-7.852**
IRR previous fund	0.279***	3.956**	7.864***	5.555**	3.508
	(0.075) [0.15]	(1.57)	(2.536)	(2.527)	(2.628)
Log (Size)	0.142*	4.02**	5.543**	2.803	4.666**
	(0.083) [0.569]	(1.978)	(2.2)	(1.939)	(2.198)
Log (Size)^2	-0.023*	-0.636*	-0.899**	-0.44	-0.69*
	(0.014) [-0.535]	(0.332)	(0.373)	(0.326)	(0.365)
Log (Fund sequence)	0.232***	-0.552	2.141	6.67***	-0.318
	(0.078) [0.521]	(1.662)	(2.205)	(2.219)	(2.141)
Log (Fund sequence)^2	-0.122***	0.245	-1.569	-4.04***	-0.092
	(0.046) [-0.46]	(1.007)	(1.299)	(1.294)	(1.239)
Industry Concentration	0.03	1.465**	1.813*	0.564	1.118
	(0.033) [0.04]	(0.703)	(0.968)	(0.933)	(0.958)
Regional Concentration (>90%)	0.001	0.089	0.047	0.041	-0.126
	(0.012) [0.004]	(0.254)	(0.352)	(0.342)	(0.351)
Venture Capital Dummy	-0.029**	-0.417	-0.197	0.028	0.232
	(0.014) [-0.098]	(0.295)	(0.414)	(0.406)	(0.429)
Dependent Variable	**Log (TVPI)**	**First Quartile (dummy)**	**Quartile (i.e. 1st, 2nd, 3rd vs 4th)**		
Regression method	Linear	Binomial Logistic	Multinominal Logistic		
Adjusted R^2	33.9%				
Nagelkerke R Square		13.9%	11.5%		
Vintage Fixed Effect	Yes	Yes	Yes		
Number of Obs.	514	514	514		

(Standard Error); [Standardized Beta]; * significant at 10% level, ** significant at 5% level, *** significant at 1% level

Table XV
Subgroup analysis (fund's type and vintage)

The table reports the regression for fund's type and vintage subsamples. In panel 9, we can see that size effect is not significant for BO, because this business is much more scalable when compared with VC. On the other hand, past performance and industry concentration have a strong positive effect. Moreover, experience has the positive and concave relation with current performance. Our model fits better for VC (panel 10), for which we find a strong positive and concave effect of size. Moreover, differently from BO funds, the effect of industry concentration is not very significant but still positive. This lack of significance may be due to the fact that VC are much more industry focused than BO and 82% of their investments is in Technology and Healthcare. Panel 11 to 13 look at the vintage subsample for the three last decades respectively. Panel 14 shows the regression performed for the liquidated funds (1980-2003). Note that for the period 1981-1990 we have only 26 observations and therefore, being the statistical significance of the model rather low, it is useless to make any sort of inference. For the decade 1991-2000, we have 192 observations (78 VC and 114 BO) and, therefore, we can make more confident statements. The effect of size is still positive, concave and significant. Moreover, we found the usual concave relationship between performance and experience measured as a Log (Sequence number). For the period 2001-2009 we recorded 296 funds (74 VC and 222 BO). For this decade, we documented three important pieces of evidence. Firstly, size does not play an important role anymore, with both the Log (Size) and its quadratic form being not significant at any reasonable level. Secondly, in contrast to the past decade, industry concentration matters. Finally, we find a strong and significant effect of experience. As a final step, considering only liquidated funds, we are confident that the NAV appraisal has not influenced our regression analysis.

Dependent Variable: Log (IRR-benchmark)						
	(9)	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**
(Constant)	-0.009	-0.515***	-0.512**	-0.359**	-0.082	-0.253**
IRR previous fund	0.146**	0.122*	-0.74	0.14**	0.173***	0.161***
	(0.06) [0.15]	(0.07) [0.16]	(0.6) [-0.64]	(0.06) [0.17]	(0.07) [0.17]	(0.06) [0.18]
Log (Size)	0.006	0.305**	0.292	0.21**	0.034	0.141*
	(0.06) [0.05]	(0.14) [1.54]	(0.2) [3.2]	(0.11) [1.32]	(0.06) [0.3]	(0.08) [0.93]
Log (Size)^2	-0.002	-0.053**	-0.057	-0.039**	-0.005	-0.026*
	(0.01) [-0.11]	(0.03) [-1.36]	(0.05) [-2.96]	(0.02) [-1.35]	(0.01) [-0.3]	(0.02) [-0.94]
Log (Fund sequence)	0.078*	0.235**	0.708	0.173*	0.113**	0.191**
	(0.05) [0.47]	(0.12) [0.71]	(0.46) [3.11]	(0.1) [0.57]	(0.05) [0.66]	(0.08) [0.66]
Log (Fund sequence)^2	-0.046*	-0.14*	-0.612	-0.098	-0.064**	-0.102*
	(0.03) [-0.47]	(0.08) [-0.62]	(0.4) [-2.97]	(0.06) [-0.49]	(0.03) [-0.64]	(0.05) [-0.53]
Industry Concentration	0.052***	0.032	-0.011	-0.007	0.073***	0.018
	(0.02) [0.15]	(0.05) [0.06]	(0.09) [-0.05]	(0.04) [-0.02]	(0.02) [0.24]	(0.03) [0.04]
Regional Concentration (>90%)	-0.007	-0.001	0.012	-0.004	-0.005	-0.01
	(0.01) [-0.06]	(0.02) [-0.01]	(0.07) [0.08]	(0.01) [-0.02]	(0.01) [-0.04]	(0.01) [-0.06]
Venture Capital Dummy			0.004	0.021	0.001	0.017
			(0.03) [0.05]	(0.02) [0.14]	(0.01) [0.01]	(0.01) [0.11]
Subsample	**BO**	**VC**	**1980-1990**	**1991-2000**	**2001-2009**	**1980-2003**
Adjusted R^2	3.9%	19.0%	NM	10.9%	5.2%	7.0%
Vintage Fixed Effect	Yes	Yes	yes	yes	yes	yes
Number of Obs.	344	170	26	192	296	286

(Standard Error); [Standardized Beta]; * significant at 10% level; ** significant at 5% level; *** significant at 1% level

Table XVI
Subgroup analysis (size and geography)

The table reports the regression subsample analysis by size and geography. In panel 15 to 18, we have analyzed funds smaller than $500M, smaller than $1B, larger than or equal to $1B, and larger than $3B respectively. Firstly, our model fits best funds smaller than $1B. As a consequence, in panel 15, we can see that almost all the variables are significant, with size playing the most important role. Second and third places are, respectively, for experience and past performance. For funds larger than $1B experience and industry concentration were the most relevant performance drivers. Moreover, regional concentration seems to have a negative effect on performance for funds smaller than $500M. The effect is rather small but significant at 5% confidence level. Therefore, for smaller funds, it seems better to diversify geographically. For funds with size larger than $3B, the only significant variable is past performance. Panel 19 and 20 show the regression by geography comparing US with Non-US. Leaving aside the fact that the strong US bias may affect the analysis, we can see that, while the findings outlined above remain true and sometimes coefficients have an even larger magnitude for the US subsample, the same cannot be said for the Non-US funds. While the sign of the majority of the coefficients did not change, their significance was either very low or null.

Dependent Variable: Log (IRR-benchmark)						
	(15)	**(16)**	**(17)**	**(18)**	**(19)**	**(20)**
(Constant)	-0.535***	-0.163	-0.387	-0.145	-0.18**	-0.083
IRR previous fund	0.184***	0.073	0.104	0.192**	0.189***	-0.166
	(0.06) [0.21]	(0.06) [0.08]	(0.08) [0.12]	(0.09) [0.24]	(0.05) [0.21]	(0.14) [-0.2]
Log (Size)	0.406***	0.079	0.272	0.094	0.087*	0.038
	(0.15) [1.76]	(0.21) [0.49]	(0.26) [0.91]	(0.68) [-1.58]	(0.05) [0.7]	(0.14) [0.39]
Log (Size)^2	-0.083***	-0.013	-0.049	-0.017	-0.015*	-0.005
	(0.03) [-1.73]	(0.03) [-0.56]	(0.06) [-0.73]	(0.09) [1.45]	(0.01) [-0.7]	(0.02) [-0.34]
Log (Fund sequence)	0.136*	0.153***	0.108	0.089	0.134***	0.072
	(0.07) [0.48]	(0.05) [1]	(0.11) [0.33]	(0.07) [0.46]	(0.05) [0.6]	(0.1) [0.53]
Log (Fund sequence)^2	-0.087*	-0.081***	-0.061	-0.049	-0.074***	-0.036
	(0.05) [-0.48]	(0.03) [-0.94]	(0.08) [-0.28]	(0.04) [-0.5]	(0.03) [-0.55]	(0.06) [-0.47]
Industry Concentration	0.018	0.058***	-0.006	0.038	0.04**	0.034
	(0.03) [0.04]	(0.02) [0.2]	(0.04) [-0.01]	(0.03) [0.17]	(0.02) [0.11]	(0.06) [0.11]
Regional Concentration (>90%)	-0.014	0.001	-0.046**	-0.009	-0.004	0
	(0.01) [-0.07]	(0.01) [0.01]	(0.02) [-0.2]	(0.01) [-0.08]	(0.01) [-0.03]	(0.02) [0]
Venture Capital Dummy	0.015	-0.009	0.013	-0.016	0.011	0.035
	(0.01) [0.1]	(0.01) [-0.06]	(0.02) [0.07]	(0.04) [-0.05]	(0.01) [0.08]	(0.03) [0.21]
Subsample	Size < $1000M	Size >= $1000M	Size <= $500M	Size >= $3000M	**US**	**Non-US**
Adjusted R^2	9.5%	8.3%	8.5%	3.1%	9.7%	17.8%
Vintage Fixed Effect	yes	yes	yes	no	Yes	Yes
Number of Obs.	277	237	181	102	451	63

(Standard Error); [Standardized Beta]; * significant at 10% level; ** significant at 5% level; *** significant at 1% level

Table XVII
Subgroup Analysis (Industries)

The table reports the regression subsample analysis by industry. In panel 21 we used 10 dummy variables (i.e. one less than the number of industries), which take value one if at least on investments in that industry was made, zero otherwise. The industry classification comes from CapitalIQ, and we can distinguish eleven industries (i.e., Consumer Discretionary, Industrial, Healthcare, Materials, Telecom Services, Energy, Information Technology, Consumer Staples, Financials, Utilities and Others). We need to be aware of the fact that each performance observation is associated, at the same time, with more than one industry, because we do not have IRRs for the investments but only at fund's level. Therefore, this analysis, even if sound in theory, has some drawbacks in practice, and is not very precise. From this regression, we can see that when we enter these new dummies, the magnitude and significance of the other coefficients are only slightly affected. Moreover, we can notice that the only three industries that seem to have a significant effect on performance are Energy, Information Technology and Consumer Staples. In panel 21, we regressed current performance against variables that count the number of investments in that particular industry. Firstly, size loses its significance. Secondly, only Information Technology and Consumer Staples seem to have a relevant impact on performance. Their coefficients are positive and significant at 1% confidence level. Moreover, also in this case, the magnitudes of these variables are comparable to that of the past fund's performance.

Dependent Variable: Log (IRR-benchmark)			
	(21)		**(22)**
(Constant)	-0.168**	(Constant)	-0.132*
IRR previous fund	0.147***	IRR previous fund	0.131***
	(0.042) [0.166]		(0.041) [0.148]
Log (Size)	0.08*	Log (Size)	0.063
	(0.046) [0.674]		(0.045) [0.531]
Log (Size)^2	-0.014*	Log (Size)^2	-0.011
	(0.008) [-0.691]		(0.008) [-0.543]
Log (Fund sequence)	0.125***	Log (Fund sequence)	0.114***
	(0.043) [0.591]		(0.043) [0.536]
Log (Fund sequence)^2	-0.071***	Log (Fund sequence)^2	-0.065**
	(0.026) [-0.562]		(0.025) [-0.517]
Industry Concentration	0.085***	Industry Concentration	0.038*
	(0.026) [0.238]		(0.02) [0.105]
Regional Concentration (>90%)	0.002	Regional Concentration (>90%)	-0.001
	(0.007) [0.014]		(0.007) [-0.006]
Venture Capital	0.008	Venture Capital	0.006
	(0.009) [0.06]		(0.009) [0.046]
Consumer Discretionary dummy	0.007	Consumer Discretionary	-0.001
	(0.007) [0.05]		(0.001) [-0.023]
Industrial dummy	0.009	Industrial	0.002
	(0.007) [0.065]		(0.002) [0.068]
Healthcare dummy	-0.007	Healthcare	-0.001
	(0.006) [-0.05]		(0.001) [-0.066]
Materials dummy	0.006	Materials	0.002
	(0.008) [0.039]		(0.004) [0.03]
Telecom Services dummy	0.013*	Telecom Services	0.002
	(0.007) [0.087]		(0.003) [0.035]
Energy dummy	0.018**	Energy	0.006***
	(0.008) [0.103]		(0.002) [0.146]
Information Technology dummy	0.014**	Information Technology	0.002***
	(0.007) [0.103]		(0.001) [0.175]
Consumer Staples dummy	-0.003	Consumer Sample	-0.001
	(0.007) [-0.019]		(0.004) [-0.014]
Financials dummy	0.002	Financials	-0.003
	(0.006) [0.011]		(0.002) [-0.064]
Utilities dummy	0.004	Utilities	-0.002
	(0.012) [0.015]		(0.004) [-0.025]
		Others	-0.015**
			(0.007) [-0.092]
Adjusted R^2	11.7%	Adjusted R^2	14.3%
Vintage Fixed Effect	Yes	Vintage Fixed Effect	Yes
Number of Obs.	514	Number of Obs.	514

(Standard Error); [Standardized Beta]; * significant at 10% level; ** significant at 5% level; *** significant at 1% level

Table XVIII
Robustness test on Size

The table reports the regression analysis to test the robustness of size. Panel 23 uses as only explanatory variable the Log (Size) and panel 24 uses this last variable together with its quadratic term. The coefficients of these regressions are not significant. This could be explained by the large number of omitted variables, such past performance, which make the model highly unreliable. Panel 25 introduces also past performance and we can see that both coefficients of size are again significant. In panel 26, we replace the variable Log (Size) and Log $(Size)^2$ with a dummy variable, which takes value one in case the fund's size was larger than $500M, zero otherwise. By doing so, we observe that the coefficient for size is negative, as in the case where only the Log (Size) without its quadratic term was exploited, and significant at 10% confidence level.

Dependent Variable: Log (IRR-benchmark)				
	(23)	**(24)**	**(25)**	**(26)**
(Constant)	0.026	-0.021	-0.103	-0.038*
IRR previous fund			0.141	0.166***
			(0.04) [0.16]	(0.04) [0.19]
Log (Size)	-0.009	0.024	0.075*	
	(0.01) [-0.08]	(0.04) [0.2]	(0.05) [0.63]	
Log (Size)^2		-0.006	-0.014*	
		(0.01) [-0.28]	(0.01) [-0.69]	
Log (Fund sequence)				0.131***
				(0.04) [0.62]
Log (Fund sequence)^2				-0.075***
				(0.03) [-0.59]
Industry Concentration				0.048
				(0.02) [0.13]
Size Dummy				-0.013*
				(0.01) [-0.09]
Adjusted R^2	3.4%	3.3%	6.5%	9.5%
Vintage Fixed Effect	Yes	Yes	Yes	Yes (decades)
Number of Obs.	570	570	514	514

(Standard Error); [Standardized Beta]; * significant at 10% level; ** significant at 5% level; *** significant at 1% level

Table XIX
Robustness test on Experience

The table reports the analysis to test the robustness of experience. In panel 27 we regressed current performance over previous performance and the Log (Sequence number) only, while in panel 28 we added its quadratic term. In the former case the coefficient for experience is positive but not significant, while, in the latter case, both coefficients are significant at 1% confidence level. In panel 30-32, we replace the Log (Sequence number) with variables that measure experience but have a different form. Firstly, in panel 30, we used as a dependent variable a dummy variable, which takes value one if the PE firm has already opened at least 2 funds before the current one and zero otherwise. In panel 31 we measure experience in term of years the PE firm is active on the market via a dummy variable, which takes value one if the PE firm has been for more than 10 years in the business (i.e. the time between the PE firm foundation and the vintage year of the fund), zero otherwise. Finally in panel 32 we measure experience through the natural logarithm of the cumulative fundraising (in $M) of the PE firm excluding the current fund. To sum up, experience has a positive effect on performance independently from how it is measured. Moreover, when a quadratic term is added to the regression, the concavity of the relation emerges.

	Dependent Variable: Log (IRR-benchmark)					
	(27)	**(28)**	**(29)**	**(30)**	**(31)**	**(32)**
(Constant)	-0.017	-0.065***	-0.139*	-0.133*	-0.14**	-0.143**
IRR previous fund	0.131***	0.142***	0.155***	0.154***	0.153***	0.157***
	(0.042) [0.148]	(0.042) [0.159]	(0.042) [0.175]	(0.042) [0.174]	(0.042) [0.172]	(0.042) [0.177]
Log (Size)			0.086*	0.083*	0.088*	0.076*
			(0.046) [0.726]	(0.046) [0.696]	(0.046) [0.735]	(0.046) [0.634]
Log (Size)^2			-0.014*	-0.014*	-0.014*	-0.013*
			(0.008) [-0.694]	(0.008) [-0.683]	(0.008) [-0.708]	(0.008) [-0.657]
Log (Fund sequence)	0.009	0.146***	0.012			
	(0.01) [0.041]	(0.043) [0.69]	(0.01) [0.055]			
Log (Fund sequence)^2		-0.084***				
		(0.025) [-0.665]				
Industry Concentration			0.045**	0.046**	0.048***	0.047**
			(0.019) [0.126]	(0.018) [0.127]	(0.019) [0.132]	(0.019) [0.131]
Regional Concentration (>90%)			-0.002	-0.002	-0.003	-0.001
			(0.007) [-0.014]	(0.007) [-0.014]		(0.007) [-0.007]
Venture Capital Dummy			0.014*	0.012	0.013*	0.015*
			(0.008) [0.099]	(0.008) [0.083]	(0.008) [0.095]	(0.008) [0.108]
Experience (>2 funds)				0.019***		
				(0.006) [0.13]		
Experience (>10 years)					0.014**	
					(0.006) [0.097]	
Log (cumulative fundraising)						0.012*
						(0.006) [0.127]
Adjusted R^2	5.9%	7.8%	8.9%	10.2%	9.5%	9.3%
Vintage Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs.	514	514	514	514	514	514

(Standard Error); [Standardized Beta]; * significant at 10% level; ** significant at 5% level; *** significant at 1% level

Table XX
Robustness (Industry and Geographical concentration and Persistence)

The table reports the robustness analysis for industry and regional concentration and for persistence. In panel 33, we measure industry concentration via a dummy variable, which takes value one if at least 2/3 of the portfolio is concentrated in one industry, zero otherwise. In panel 24, instead, we use the standard deviation of the number of investments in each industry. To sum up, industry concentration is an important driver of performance. However, both its significance and its magnitude vary according to the variables used to measure it. Panel 35 shows a regression in which previous fund's IRR is the unique explanatory variable and it still remains an important and significant variable. In panel 36 we measure persistence with the previous fund's quartile and also in this case, the coefficient for persistence is very important and significant at 1% confidence level. Moreover, the goodness of fit of the model improves slightly and all the other relations remain almost untouched in terms of magnitude and significance. In panel 37-38 we measure the robustness of regional concentration. In panel 37 we measure geographical concentration with a dummy variable, which takes value one if the PE firm invests only in one industry, zero otherwise. In Panel 38 we measure geographical concentration with a dummy variable, which takes value one if more than 2/3 of the investments are focused in one region only, zero otherwise. Both coefficients for these two variables are small, negative and not significant. Therefore, we can conclude that, in our sample, geographical concentration is not an important driver of performance. However, it is difficult to make generalization out of this finding because our sample is strongly US-biased and, therefore, geographical analysis may be not totally relevant given the characteristics of our sample.

	Dependent Variable: Log (IRR-benchmark)					
	(33)	**(34)**	**(35)**	**(36)**	**(37)**	**(38)**
(Constant)	-0.185***	-0.177**	-0.01	-0.125*	-0.161**	-0.155**
IRR previous fund	0.162***	0.156***	0.133***		0.162***	0.161***
	(0.042) [0.182]	(0.042) [0.175]	(0.042) [0.15]		(0.042) [0.182]	(0.042) [0.182]
Log (Size)	0.082*	0.082*		0.082*	0.079*	0.078*
	(0.046) [0.686]	(0.046) [0.687]		(0.047) [0.683]	(0.046) [0.665]	(0.046) [0.656]
Log (Size)^2	-0.014*	-0.015*		-0.014*	-0.013*	-0.013*
	(0.008) [-0.686]	(0.008) [-0.723]		(0.008) [-0.675]	(0.008) [-0.665]	(0.008) [-0.649]
Log (Fund sequence)	0.131***	0.126***		0.112***	0.131***	0.131***
	(0.043) [0.617]	(0.044) [0.592]		(0.044) [0.529]	(0.043) [0.618]	(0.043) [0.618]
Log (Fund sequence)^2	-0.072***	-0.071***		-0.062**	-0.073***	-0.072***
	(0.026) [-0.571]	(0.026) [-0.559]		(0.026) [-0.492]	(0.026) [-0.577]	(0.026) [-0.572]
Industry Concentration				0.049***	0.045**	0.044**
				(0.019) [0.136]	(0.018) [0.126]	(0.018) [0.123]
Regional Concentration (>90%)	-0.003	-0.002		-0.003		
	(0.007) [-0.02]	(0.007) [-0.013]		(0.007) [-0.018]		
Venture Capital Dummy	0.01	0.011		0.007	0.01	0.01
	(0.008) [0.07]	(0.008) [0.081]		(0.008) [0.053]	(0.008) [0.068]	(0.008) [0.071]
Idustry Concentration (>2/3)	0.02***					
	(0.007) [0.132]					
Stand.Dev. Of n. of industries		0.004*				
		(0.002) [0.091]				
Previous fund's quartile				-0.011***		
				(0.003) [-0.174]		
Regional Concentration (100%)					-0.004	
					(0.006) [-0.032]	
Regional Concentration (>2/3)						-0.01
						(0.011) [-0.041]
Adjusted R^2	10.4%	9.7%	5.9%	10.4%	10.2%	10.3%
Vintage Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs.	514	514	514	514	514	514

(Standard Error); [Standardized Beta]; * significant at 10% level; ** significant at 5% level; *** significant at 1% level

Figures

Figure B

J-curve effect illustration

The graph illustrates the J-curve effect. We can see that the IRR is negative for the first few years. This effect is the consequence of the structure of cash inflows and outflows typical of PE funds. If we measure cumulative returns over time via IRR since inception till a given year X, we can see that the IRR is negative at the early stages of the fund's life. The IRR will be virtually negative till when the distributions to LPs match at least the contributions they did and this moment is called payback point.

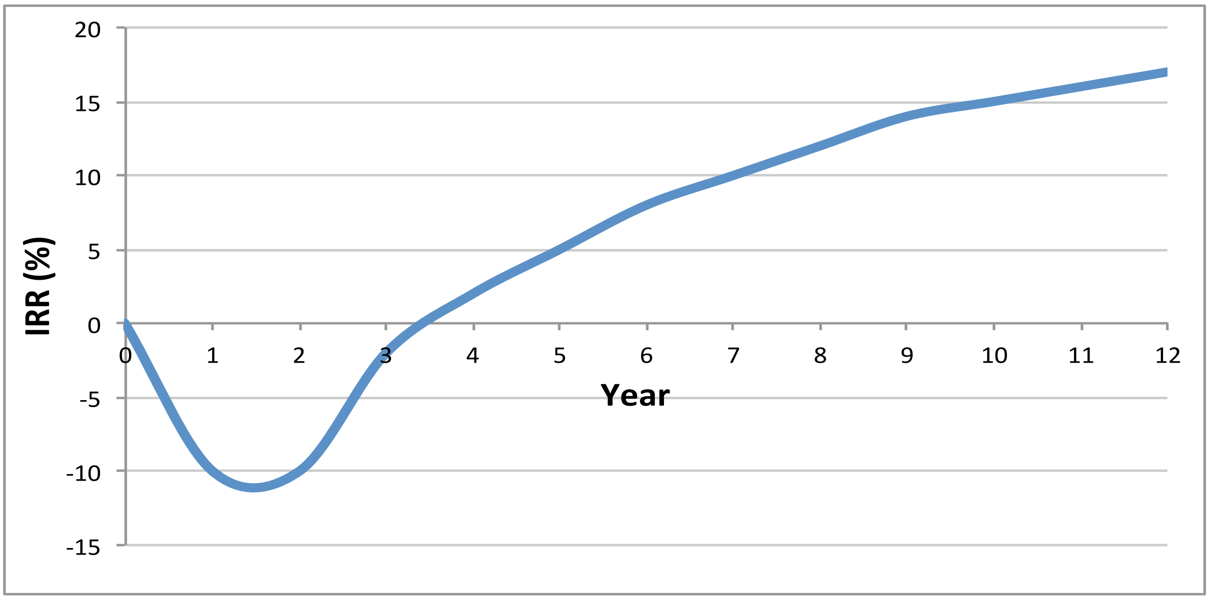


Figure C

Size distribution: Preqin's universe vs. Sample

The bar chart compares the distribution for the variable size in $M by vintage year of our sample with that of Preqin's universe. We can see that our sample has a much larger average size for almost all the vintages. Note that we cannot trust the average for the first 10 years because the number of observations is rather low. However, it is clear that the size has increased over time and in our sample this effect s much stronger.

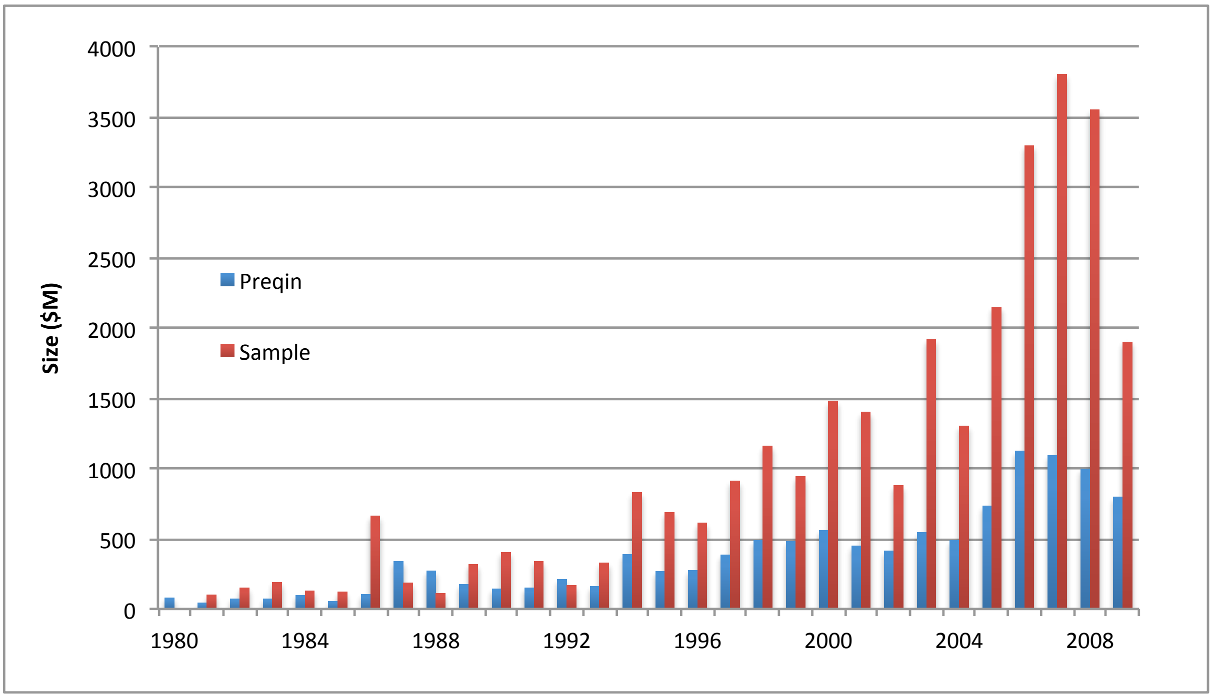


Figure E
IRR minus 6-year rolling average S&P500 between 1990 and 2007

The graph shows the spread between the vintage year IRR and the 6-year rolling average S&P500 between 1990 and 2007. We can notice that the excess IRR was positive for all the vintages. Moreover, we notice some cyclicality and a high peck at the end of the 1990s.

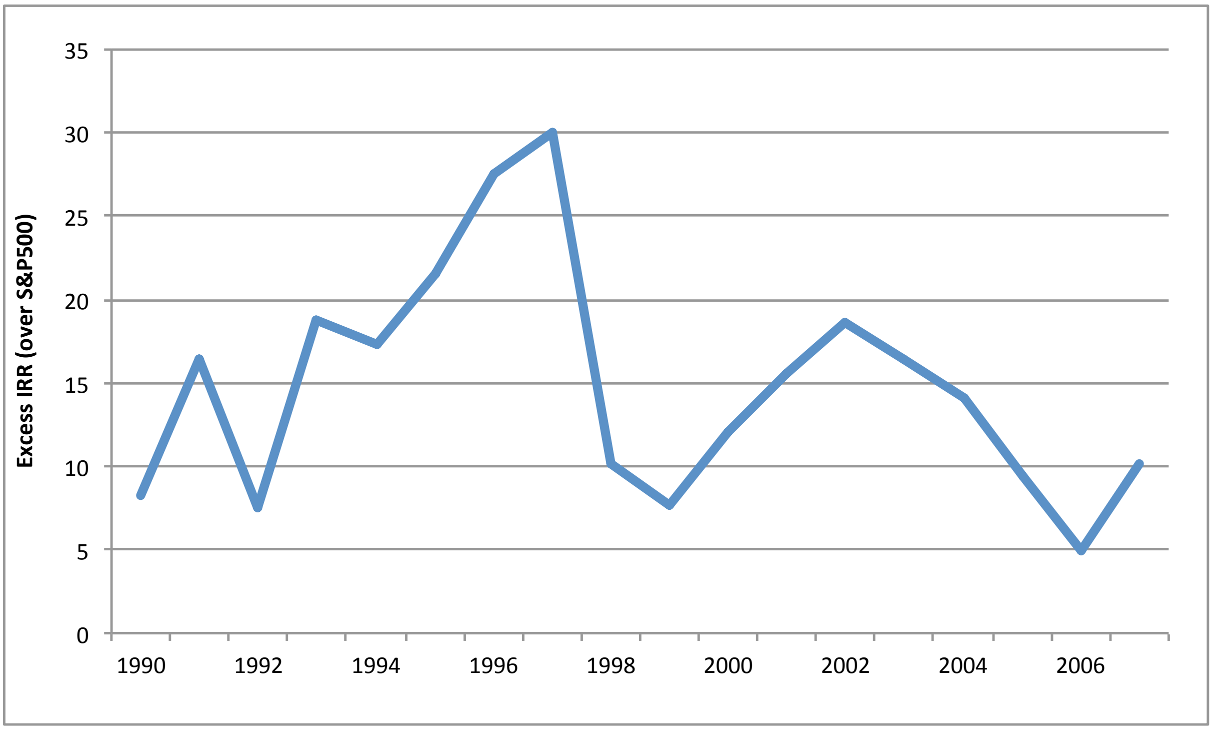


Figure F
Median IRR and TVPI by fund type

The graph compares the median IRR and TVPI by fund's type over time between 1990 and 2009. BO and VC follows the same pattern with some exceptional years (i.e. last 6 vintages of 1990s). Moreover, in the 1990s, the TVPI of VC was, on average, higher than that of BO, but the reverse was true in 2000s. Also in terms of IRR, we can see the same pattern, with VC outperforming BO in 1990s and underperforming in 2000s. Note, however, that also in this case the last few vintages are not fully reliable because of unrealized investments.

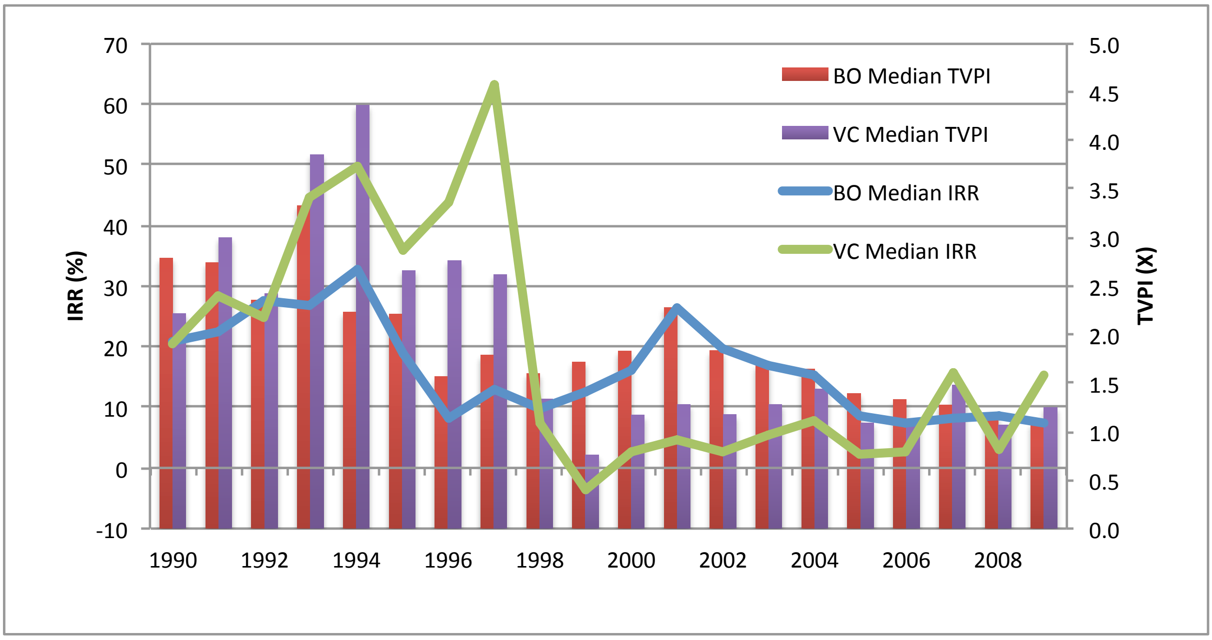
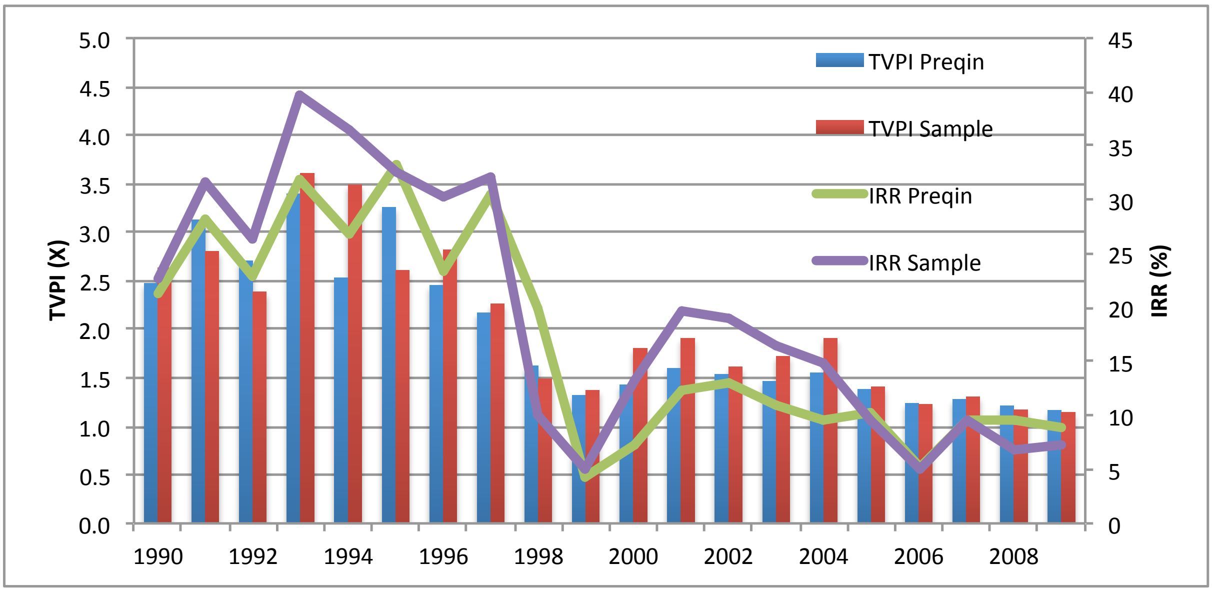


Figure G

IRR and TVPI by vintage (Sample vs. Preqin)

The graph compares the median IRR and TVPI for our sample and Preqin' s universe. We can see a quite homogenous pattern between our data and Preqin's with only few exceptional years (e.g., 1994). Moreover, we can see that our sample has, on average, performed better than Preqin's. We can attribute this fact to the presence in Preqin's of smaller funds, which we have not considered and whose performance was not excellent.



Appendix B

Tables

Table XXI
PE Firm considered in the sample

The table shows the names of the 151 PE firms in our sample with the related number of funds. We have a total of 570 funds with an average (median) number of 3.8 (3) funds per GP.

Firm	Funds	Firm	Funds	Firm	Funds	Firm	Funds
Accel	5	Charterhouse CP	3	Institutional Venture Partners	7	RRE Ventures	2
Accel-KKR	2	Cinven	3	Intersouth Partners	3	SAIF Partners	2
Aderdare	2	Clarus Ventures	2	InterWest Partners	8	Shasta Ventures	1
Advent International	7	Clayton Dubilier & Rice	5	J.H. Whitney & Co	2	Silver Lake Partners	4
Aisling	2	Clearstone Venture Partners	2	Kelso & Company	4	Sprout Group	5
Alta Communication	4	Clessidra	2	Kleiner Perkins Caufield & Byers	4	Summit Partners	11
American Securities Partners	1	Code Hennessy & Simmons	5	Kohlberg Kravis Roberts	6	TA Associates	7
Apax Partners	8	Cortec Group	4	Leonard Green & Partners	4	Tailwind Capital Partners	1
Apollo Global Management	5	CVC Capital Partners	9	Levine Leichtman CP	2	Technology Crossover Ventures	7
Aquiline Capital Partners	1	Cypress Group	2	Lime Rock Partners	2	Terra Firma Capital Partners	3
ARCH Venture	4	DCM	5	Lion Capital	2	The Blackstone Group	5
ArcLight Capital	4	Domain Associates	7	Littlejohn & Co.	3	The Riverside Company	11
Ares Management	3	Doughty Hanson & Co	2	Lone Star Funds	1	Thomas H Lee Partners	4
Arrowhead Mezzanine	2	EnCap	3	Madison Dearborn Partners	6	Thomas McNerney & Partners	2
Arsenal Capital	2	Endeavour Capital	2	Markstone Capital Partners	1	TowerBrook Investors	3
Aurora Capital	3	Energy Capital Partners	1	MatlinPatterson GA	3	TPG	13
Austin Ventures	8	Energy Spectrum Partners	2	Menlo Ventures	4	Trilantic Capital Partners	3
Avenue Capital Group	2	Essex Woodlands	6	MHR Fund Management	2	Trinity Ventures	4
Avista Capital Partner	2	Fenway Partners	3	New Enterprise Associates	9	Triton	2
AXA	4	First Reserve Corporation	6	New Mountain Capital	3	Union Square Ventures	1
Bain Capital	4	Francisco Partners	2	NGP Energy CM	6	US Venture Partners	5
Banc Fund Company	4	Frazier Healthcare	4	Nordic Capital	4	VantagePoint Capital Partners	3
Baring Private Equity Asia	1	Freeman Spogli	3	Oak Hill Capital Partners	3	Versant Ventures	2
BC Capital Partners	4	Genstar Capital Partners	2	Oak Investment Partners	10	Vestar Capital Partners	5
Berkshire Partners	5	GF Capital	1	Oaktree Capital Management	10	Vicente Capital Partners	1
Birch Hill Equity Partners	1	GGV Capital	3	Onex Corporation	3	Vista Equity Partners	2
BlueRun	1	GI Partners	3	OVP Venture Partners	5	W Capital Partners	1
Brentwood Associates	2	Giza Venture Capital	1	PAI Partners	4	Warburg Pincus	11
Bridgepoint	4	Glencoe Capital	2	Palamon Capital Partners	2	Wayzata Investment Partners	1
BV Investment Partners	3	Globespan Capital Partners	2	Palladium Equity Partners	1	Wellspring Capital Partners	3
Calera Capital	2	Gores Group	3	Parthenon Capital	3	Welsh, Carson, Anderson & Stowe	11
Canaan Equity Partner	2	Graham Partners	3	Permira	3	Wind Point Partners	4
Capital Resource	2	GTCR Golder Rauner	8	Perseus	2	WL Ross & Co	4
Carlyle Group	23	Health Evolution Partners	1	Polaris Venture Partners	5	Yucaipa Corporate	3
Castle Harlan	3	Hellman & Friedman	5	Prism Venture Partners	5		
Catterton Partners	4	Hicks, Muse, Tate & Furst	6	Prospect Venture Partners	3	**Total Number of Funds**	**570**
CCMP Capital Advisors	1	HM Capital Partners	2	Providence Equity Partners	5	**Total number of PE firms**	**151**
Cerberus CM	1	Huntsman Gay GC	1	Quadrangle Group	2	**Average Number of Funds per Firm**	**3.8**
Charlesbank CP	2	Insight Venture Partners	3	Ripplewood Holdings	2	**Median Number of Funds per Firm**	**3.0**

XXII
Descriptive Statistics for the variables used in the regressions

The table shows the descriptive statistics for the variables used in our analysis.

Descriptive Statistics								
	N	Range	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
Log (IRR-benchmark)	570	0.76	-0.33	0.42	0.01	0.07	0.88	6.44
Log (Previous fund's IRR)	514	0.88	-0.16	0.72	0.07	0.07	2.05	13.55
Log (Size)	570	3.07	1.27	4.34	2.91	0.56	-0.02	-0.32
Log (Size)^2	570	17.20	1.61	18.80	8.78	3.27	0.45	-0.22
Log (Fund Sequence Number)	570	1.52	0.00	1.52	0.66	0.37	0.11	-0.33
Log (Fund Sequence Number)^2	570	2.31	0.00	2.31	0.57	0.53	1.32	1.29
Log (Industry Concentration)	570	0.78	-0.78	0.00	-0.29	0.18	-0.15	-0.80
Regional Concentration (>90%)	570	1.00	0.00	1.00	0.70	0.46	-0.86	-1.27
Venture Capital	570	1.00	0.00	1.00	0.32	0.47	0.76	-1.43
Average 3-year S&P500	570	0.18	-0.07	0.11	0.01	0.05	0.11	-0.93
Size dummy	570	1.00	0.00	1.00	0.63	0.48	-0.53	-1.72
Experience (Years)	570	1.00	0.00	1.00	0.65	0.48	-0.63	-1.61
Experience (Funds Opened)	570	1.00	0.00	1.00	0.62	0.49	-0.52	-1.74
Log (Fundraising)	514	3.91	0.81	4.73	3.11	0.71	-0.05	-0.18
Industry Concentration (2/3)	570	1.00	0.00	1.00	0.28	0.45	1.01	-0.99
Stand. Dev. Number of investment	570	12.85	0.47	13.32	2.03	1.61	2.37	7.96
Regional Concentration (100%)	570	1.00	0.00	1.00	0.59	0.49	-0.36	-1.88
Regional Concentration (2/3)	570	1.00	0.00	1.00	0.93	0.26	-3.32	9.07
Quartile	570	3.00	1.00	4.00	2.25	1.03	0.28	-1.09
First quartile dummy	570	1.00	0.00	1.00	0.29	0.46	0.92	-1.16

Table XXIII
Bivariate Pearson Correlations

The table reports the bivariate correlation for the variable used in the regression. We can firmly state that there is no collinearity problem because the bivariate Pearson correlations are small. The only noteworthy correlations are, obviously, those between the Log (Size) and its quadratic transformation and those between Log (Sequence number) and Log (sequence number)^2. Moreover, the VC dummy has a modest correlation with size and industry concentration but the correlation is still lower than 60%. No other correlation is higher than 40%.

Correlations

	IRR previous fund	Log (Size)	Log (Size)^2	Log (Fund sequence)	Log (Fund sequence)^2	Venture Capital	Log (Industry Concentration)	Average 3-year S&P500	Regional Concentration (>90%)
IRR previous fund	**1**								
	514								
Log (Size)	**-0.082**	**1**							
	0.063								
	514	570							
Log (Size)^2	**-0.075**	**0.992****	**1**						
	0.088	0.000							
	514	570	570						
Log (Fund sequence)	**-0.048**	**0.368****	**0.369****	**1**					
	0.281	0.000	0.000						
	514	570	570	570					
Log (Fund sequence)^2	**-0.037**	**.354****	**.358****	**.945****	**1**				
	0.397	0.000	0.000	0.000					
	514	570	570	570	570				
Venture Capital	**-0.04**	**-0.497****	**-0.491****	**-0.06**	**-0.118****	**1**			
	0.364	0.000	0.000	0.150	0.005				
	514	570	570	570	570	570			
Log (Industry Concentration)	**-0.095***	**-0.359****	**-0.370****	**-0.108****	**-0.124****	**0.512****	**1**		
	0.032	0.000	0.000	0.010	0.003	0.000			
	514	570	570	570	570	570	570		
Average 3-year S&P500	**0.284****	**-0.338****	**-0.328****	**-0.198****	**-0.203****	**0.073**	**0.045**	**1**	
	0.000	0.000	0.000	0.000	0.000	0.081	0.280		
	514	570	570	570	570	570	570	570	
Regional Concentration (>90%)	**0.002**	**-0.370****	**-0.379****	**-0.149****	**-0.176****	**0.203****	**0.163****	**0.155****	**1**
	0.966	0.000	0.000	0.000	0.000	0.000	0.000	0.000	
	514	570	570	570	570	570	570	570	570

Pearson Correlation
Sig.(2-tailed)
N
*. Correlation is significant at the 0.05 level (2-tailed).
**. Correlation is significant at the 0.01 level (2-tailed).

Figures

Figure H
Size distribution

The histogram shows the distribution of size in $M. The average (median) size is $1.77B ($800M). Because average values are higher than median one, we observe a positive skewness driven by big outliers and deviation from normality. This last finding is obvious in light of the fact that data is coming from large LPs, which tend to invest in larger funds.

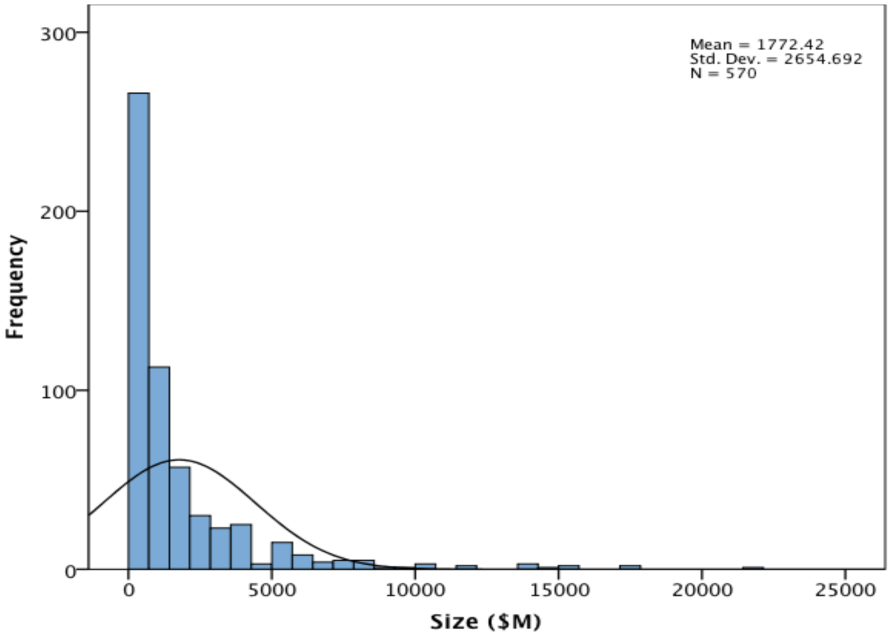


Figure I
IRR distribution

The histogram shows the distribution of IRR in percentages. It shows a positive (right) skewness and deviation from normality are rather acceptable.

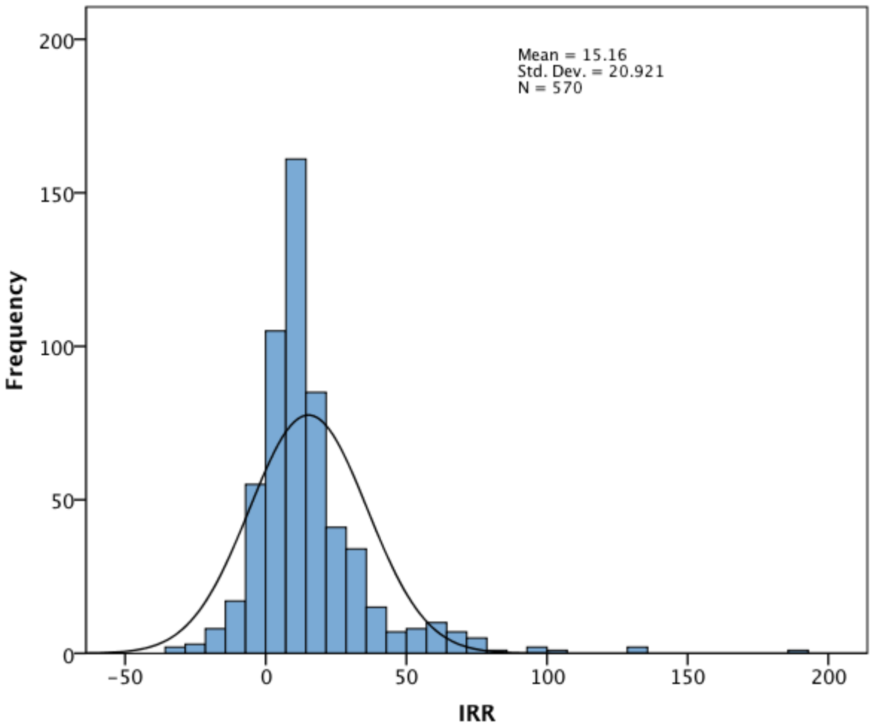


Figure L
TVPI distribution

The histogram shows the distribution of TVPI multiple. It shows a positive (right) skewness with a very big outlier.

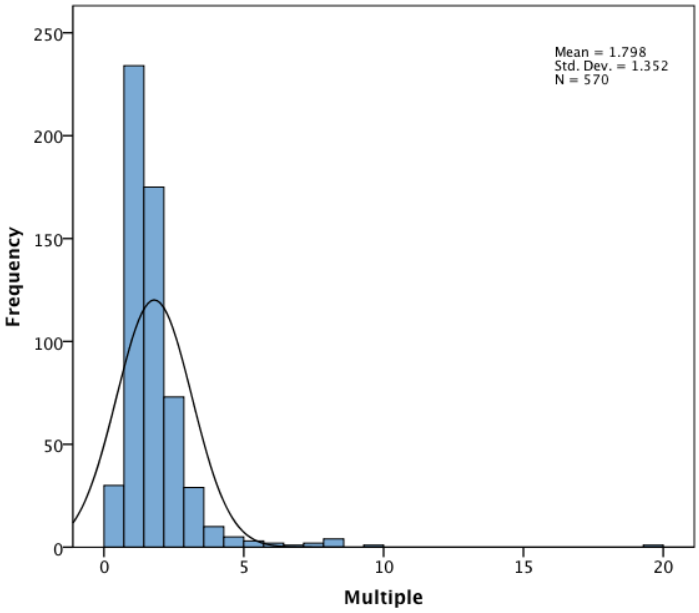
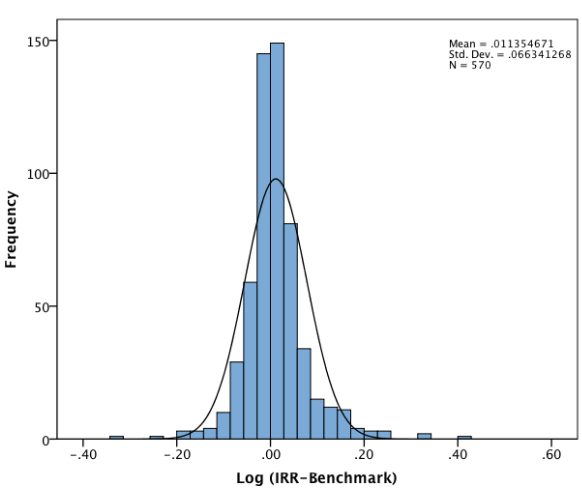


Figure M
Variable illustration

The histograms show the distribution of the variables used in the regressions. a) shows the Log (IRR-benchmark). This variable is rather robust normal but has some large peaks in the middle and smaller shoulders. b) shows previous fund's IRR. Also in this case the variable resembles a normal distribution even if with some deviations. c) and d) represents the Log (Size) and Log $(\text{Size})^2$ respectively and are rather normal. e) and f) are Log (Sequence number) and Log $(\text{Sequence number})^2$ respectively. These two variable deviate strongly from a normal distribution. g) shows the Log (industry concentration), while h) the Log (average 3-y S&P500). i) is a dummy variable for regional concentration, which can take value one (if the dominant region accounts for more than 90% of the investments) or zero. l) is a dummy variable for VC, which can take value one if the fund is a VC, zero if it is a BO. m) is the Log (Fundraising in $M) and we can see that this variable is rather normal. n) is the standard deviation of the number of investments in each industry. From o) to u), we have dummy variables which have been defined in **Table XI** above and can take value 1 or 0. Finally v) is a discrete variable that takes value 1 to 4 according to the quartile of the fund.

a)



b)

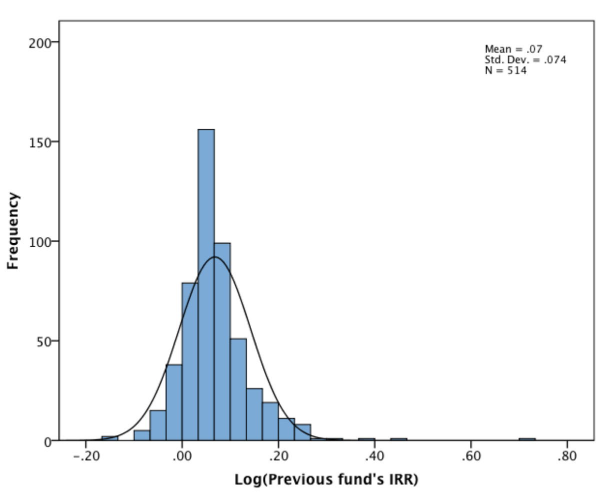
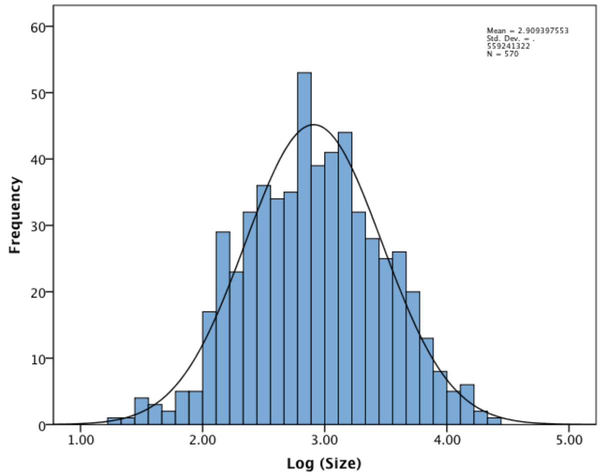
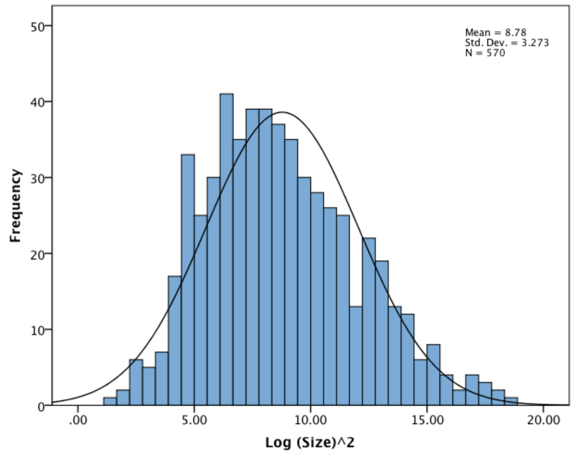


Figure M (continued)

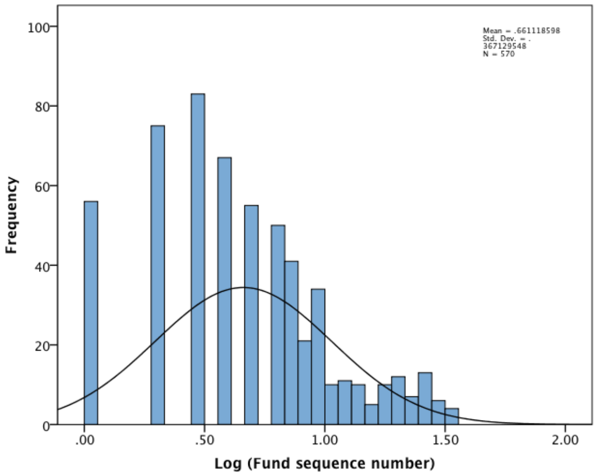
c)



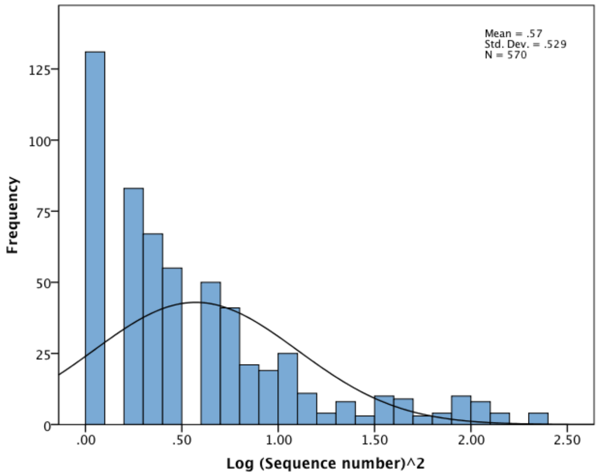
d)



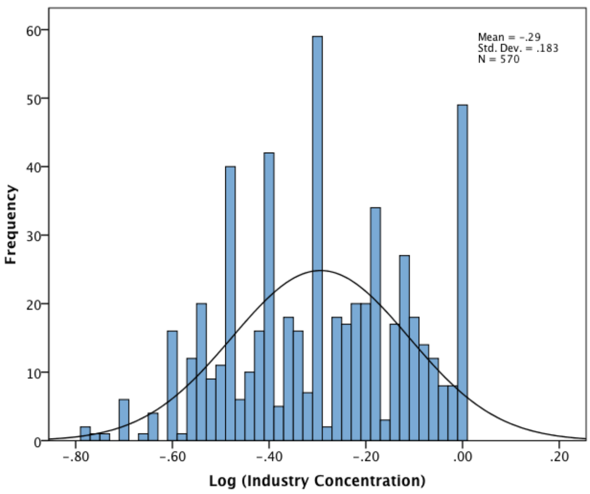
e)



f)



g)



h)

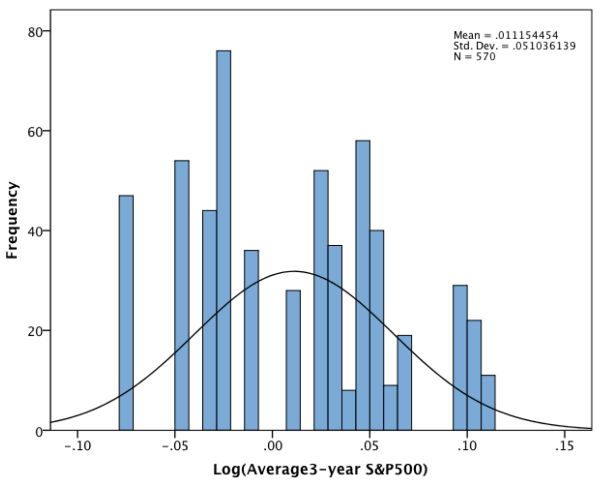
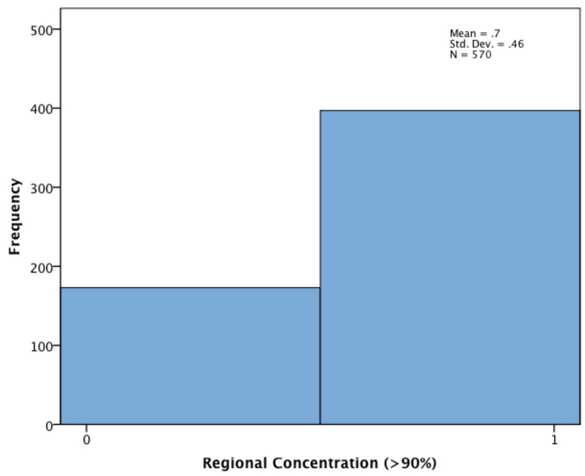
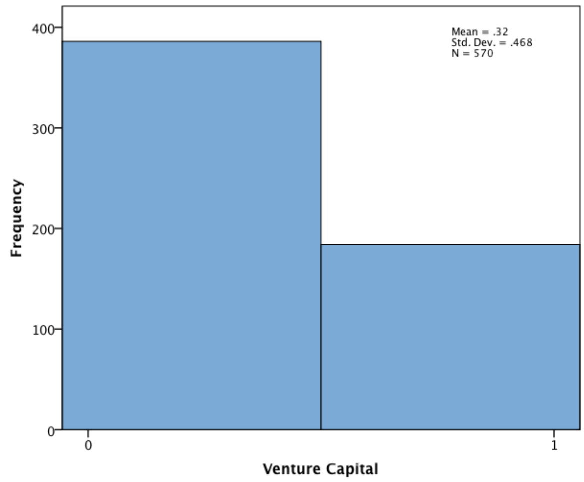


Figure M (continued)

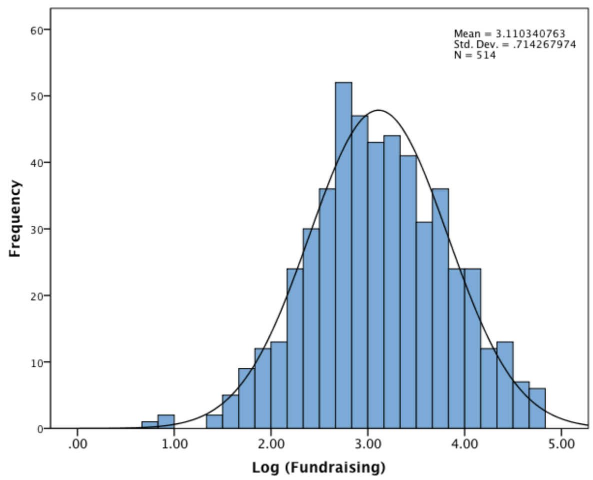
i)



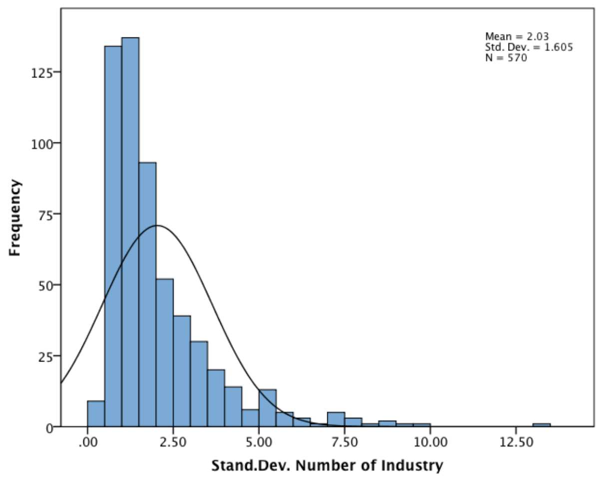
l)



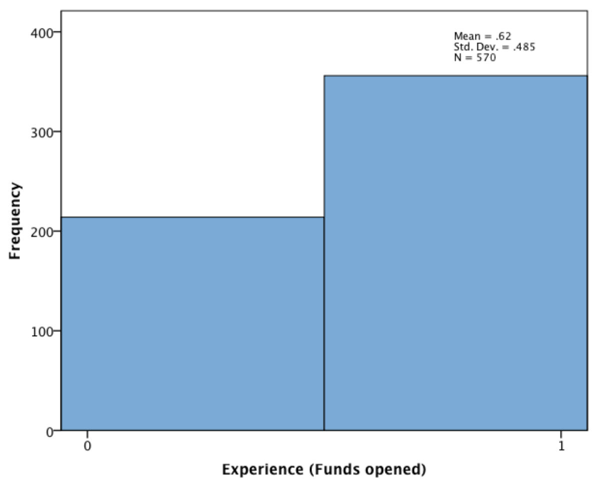
m)



n)



o)



p)

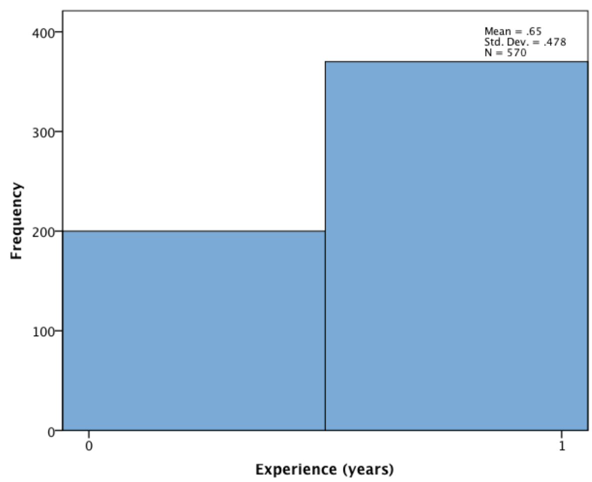
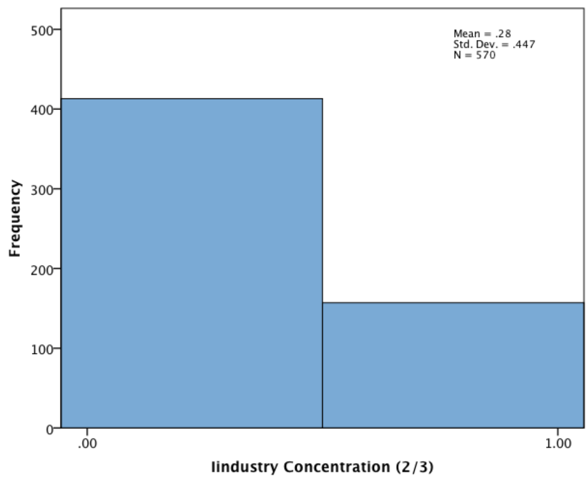
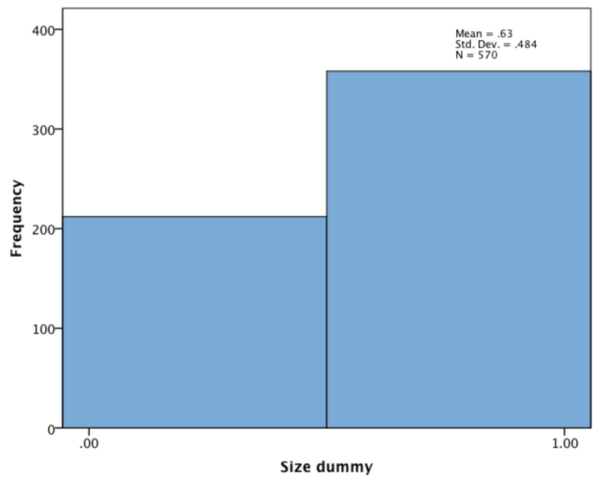


Figure M (continued)

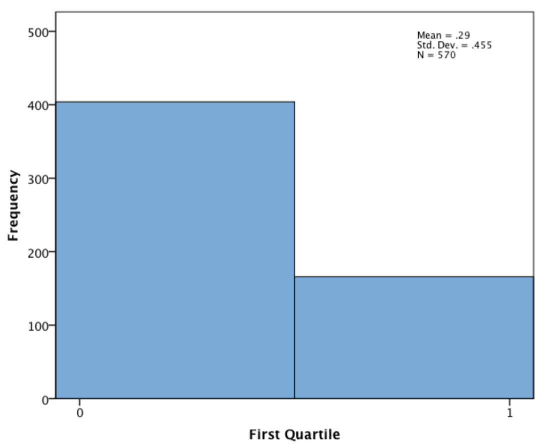
q)



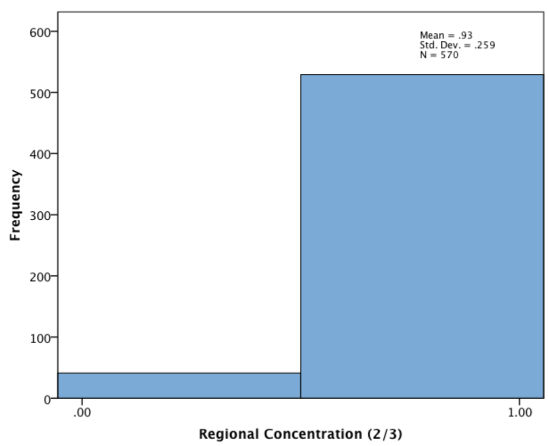
r)



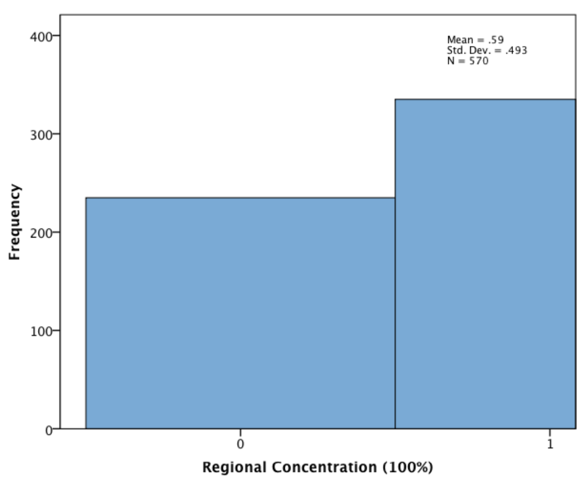
s)



t)



u)



v)

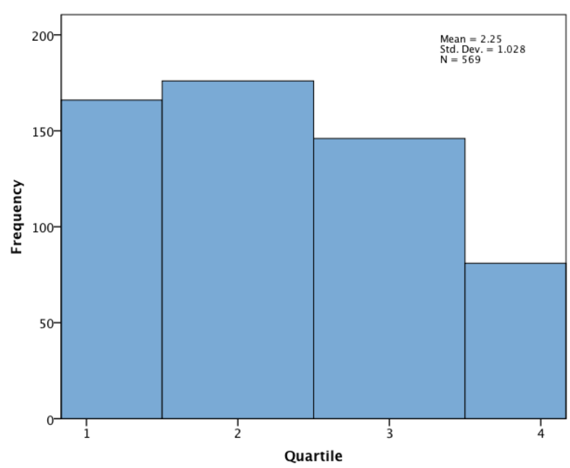


Figure N

Log (Industry concentration) by Fund's Type

The graph shows that VC are much more industry focused than BO (i.e., 82% of their investments is in Technology and Healthcare). The Log (Industry concentration) as defined above, shows strong deviations from normality with a long right tail for VC and many observations take value zero. This indicates that many VC funds are completely concentrated in one industry.

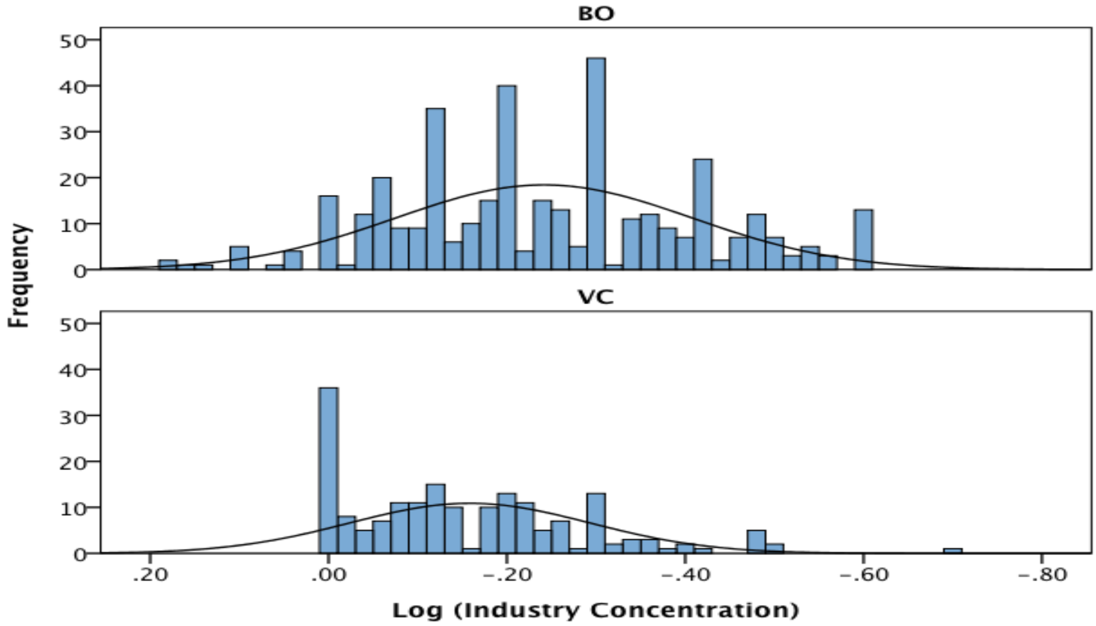
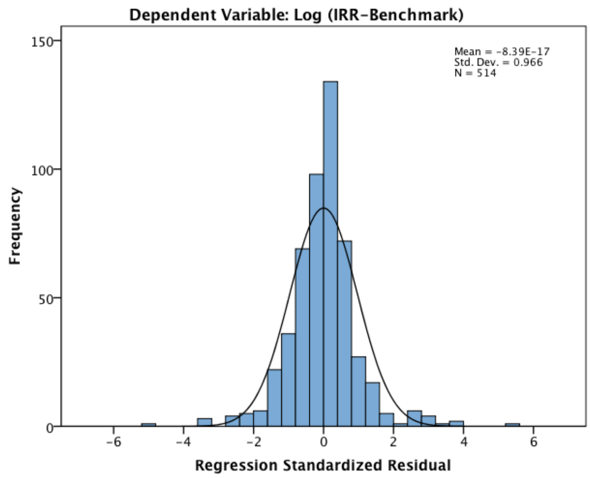


Figure O

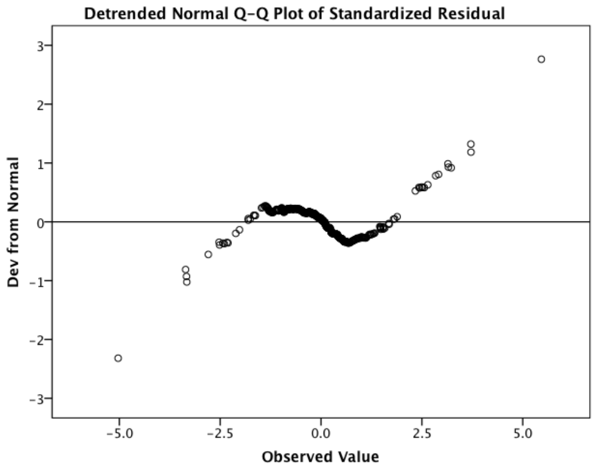
Normality assessment

The graphs assess the normality for the residuals of specification 1 as defined above. The panel a) shows a histogram and compare the residual distribution with that of a normal. Panel b) show a deferred Normal QQ-Plot for standardized residuals. Panel c) shows the QQ-Plot for standardized residuals. Panel d) shows a scatter plot, with regression standardized predicted value versus standardized residual. From all these figures, we can state that the residuals deviate from a normal distribution.

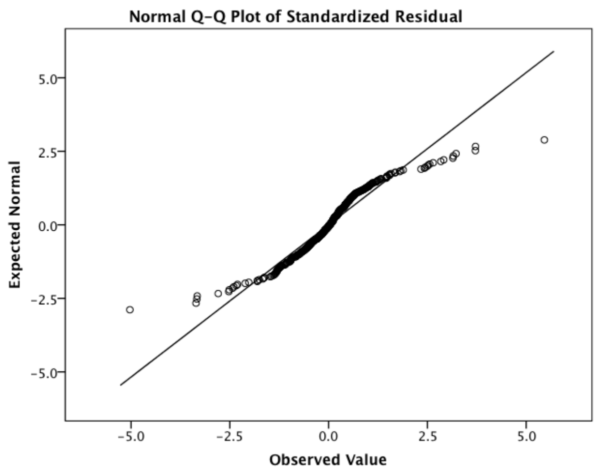
a)



b)



c)



d)

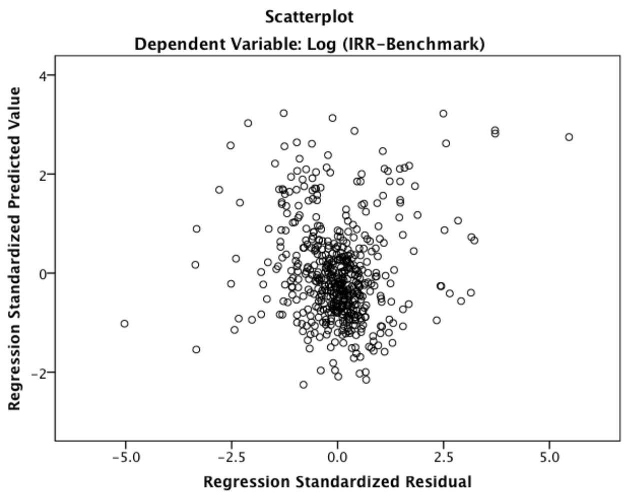
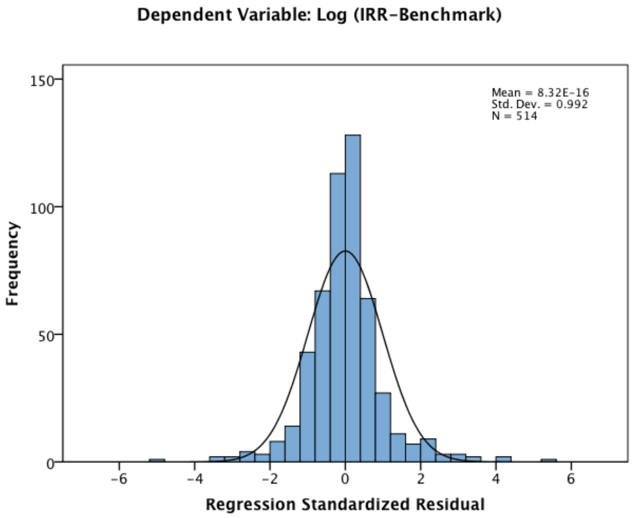


Figure P

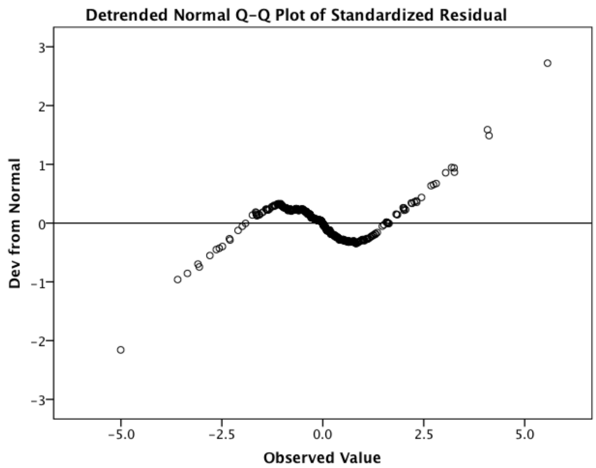
Normality assessment

The graphs assess the normality for the residuals of specification 5 as defined above. The panel a) shows a histogram and compare the residual distribution with that of a normal. Panel b) show a deferred Normal QQ-Plot for standardized residuals. Panel c) shows the QQ-Plot for standardized residuals. Panel d) shows a scatter plot, with regression standardized predicted value versus standardized residual. From all these figures, we can state that the residuals deviate from a normal distribution.

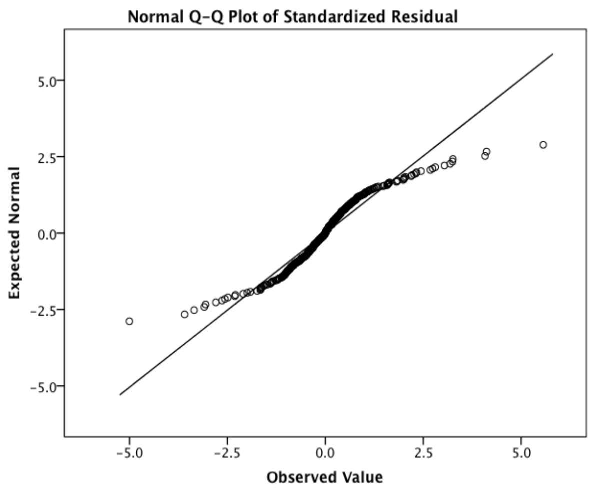
a)



b)



c)



d)