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Private Equity Zombie Funds: Performance and Fund Characteristics

An empirical analysis of the global private equity market

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Abstract

This thesis investigates performance and other characteristics of zombie funds in the global private equity market using a dataset from Preqin. Our sample comprises a total of 4 204 private equity funds with vintage years from 2003 to 2008. We find that zombie funds constitute a substantial part of the global private equity market as we identify 1 274 zombie funds in our sample. Using IRR and TVPI to measure performance, we find that zombie funds underperform other private equity funds. Furthermore, by looking at DPI, we find that zombie funds distribute less capital back to investors than non-zombie funds. This thesis is based on interim performance measures. We moreover examine whether different fund characteristics display significant relationships to zombie funds. We find that zombie funds tend to be small and report performance data less frequently compared to other private equity funds.

Preface

This thesis is written as part of a Major in Finance, and marks the end of two-year master study of economics and business administration at the Norwegian School of Economics in Bergen. Through the course of our study, we have developed a great interest in private equity as an investment vehicle and were motivated to explore the topic further. It has been a time-consuming, yet a very exciting and rewarding process. We have gained valuable knowledge about the private equity industry and how to conduct empirical research throughout this period.

There are several people we wish to thank for advice and assistance during this research. First, we would like to thank our supervisor, Associate Professor Tommy Stamland, for constructive criticism and guidance along the way. Furthermore, we would like to thank Associate Professor Carsten Bienz for assistance in obtaining data on the private equity industry. We would also like to thank Account Manager at Preqin, Justin Kimble, who provided us with data and guidance on its usage. Last, we thank Investor Relations Director at Verdane Capital, Frida Einarson, for sharing her industry knowledge with us.

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1. Introduction

We will begin by presenting the background and motivation of this thesis, before we explain the topic and research question. The last part of this section will provide an overview of the thesis structure.

1.1 Topic and Research Question

Recent news articles and industry research highlights a dark side of the private equity industry, where funds raised several years ago are slowly becoming the 'living dead'. Having no clear plans for raising a successor fund, these zombie funds hold on to assets to keep the funds alive. Even with low hopes of profiting from the remaining assets, they hold on to investments simply to collect management fees. These funds might end up destroying value and create problems for all parties involved. In 2013, Preqin (2013a) identified about 1 200 potential zombie funds and reported that as much as $ 116 bn could be trapped in such funds globally. Furthermore, these funds are growing in numbers following the financial crisis of 2007-2008. Consequently, both the private equity industry and the authorities have become aware of the potential problems posed by zombie funds. Financial authorities in the U.K. and the Securities and Exchange Commission of the U.S. have launched investigations of such funds. Despite the increased awareness of private equity zombie funds, research on this topic is limited.

Based on the growing concern for and lack of empirical research on zombie funds, we wish to provide some insight on this topic. Specifically, we wish to test whether zombie funds underperform other private equity funds and if they display different fund characteristics. We will explore the global private equity market, which gives us the following research question:

"Do zombie fund performance and characteristics differ from those of other private equity funds globally?"

1.2 Thesis Structure

In the first and introductory chapter we explain the choice of topic, the motivation for the thesis and the research question, before we present the thesis structure. In **chapter**

2, we give a general description of private equity, the development of this market's history, private equity fund types, and zombie funds. **Chapter 3** looks at agency theory in private equity. This section lists potential agency problems within private equity and zombie funds, and gives possible solutions for investors and investees. **Chapter 4** presents theory on diversification and performance in private equity. We here explain the most common return measures used for this industry, and the possible strengths and weaknesses linked to each measure. **Chapter 5** outlines previous research related to our topic. In **chapter 6** we present the methodology of the thesis where research design, data, reliability and validity, potential biases and methods of analysis are explained. Characteristics and returns of zombie funds are examined in **chapter 7**, which are further compared to those of other private equity funds. **Chapter 8** covers the empirical analysis where we test for the significance of characteristics and performance of zombie funds in comparison to non-zombie funds. Finally, **chapter 9** summarizes the thesis with a conclusion and suggestions for further research.

2. What is Private Equity?

Private Equity (PE) is a form of equity consisting of investors and funds that make investments directly into private portfolio companies not listed on a stock exchange. These types of investments are characterized especially by active ownership. Active ownership entails that the private equity companies work closely with the management of the acquired portfolio companies to create value by contributing capital and complementary expertise. Private equity funds invest in companies that cover the entire spectrum from startups to mature businesses, and the type of expertise provided depends on what stage and industry the acquired company operates in. There are two broad categories of private equity funds: buyout funds (BO) and venture-capital funds (VC). A buyout fund acquires shares in an established company, whereas a venture-capital fund will co-invest with the entrepreneur in a company at an early stage or in a company seeking to expand.

The private equity funds often obtain a majority stake in the portfolio company to ensure influence on the board and thus active ownership (Isaksen and Biørnstad, 2006). This control is achieved so that the strategic measures needed to assure value creation can be implemented. Active ownership means that the fund, in addition to contributing capital, actively collaborates with the company's board and management on its development. The private equity fund will assist the company in strengthening management expertise, delivering operational improvements and accessing new markets. This participation, however, consumes a lot of time and resources, and so private equity funds will usually not have more than 3-5 portfolio companies per employee (Nygård and Normann, 2008). To be able to drive this kind of value growth, specialized expertise is a prerequisite. BO requires skills in the fields of restructuring, strategizing and growth, while for VC abilities within marketing, product development and research are of higher priority.

PE funds invest in portfolio companies with high growth and development potential. The acquisitions are primarily directed at small to mid-size companies. 80 % of companies receiving PE investment in Europe in 2013 had less than 250 employees. Even though larger businesses are potential portfolio companies, some are just too large to be considered for acquisitions.

The aspiration of PE funds is to achieve a positive economic development and cash flow growth for their portfolio companies. This is often accomplished through four value increasing roles (Jakobsen, 2006):

1. The funds contribute to economic development through *selection* of the companies that will be invested in.
2. By *supplying capital* to the acquired companies, funds provide an opportunity for further growth and development.
3. PE funds can contribute *complementary resources and expertise* that the portfolio company does not already possess, through networks and advisory services.
4. The advisory process materializes through *active participation* in the portfolio company's board and through other contact with its management. Strategic consultation related to the company's further development might include recruitment of key employees and establishing contact with new customers and partners. Other examples of management tasks private equity funds may perform are raising additional capital and creating good internal routines and practices to ensure cooperation at all company levels.

The most widespread organizational structure in the PE industry today is the limited partnership, which has grown from accounting for only 40 % of the venture pool of capital in 1980 to constitute 80 % of the same pool by 1992 (Mehta, 2004; Gompers and Lerner, 1999). PE funds are regularly organized as limited partnerships (LLPs) or limited liability companies (LLCs), and not as corporations. The limited partners (LPs) passively invest money in PE funds that are actively managed by general partners (GPs). The LPs do not participate in the daily operations of the fund, and therefore relies on the GPs to make a satisfactory return on investment. Complications can emerge as a result of the fact that LPs cannot actively observe the actions of the GPs. In order to protect the interests of the LPs and minimize the information asymmetry problems that can arise between LPs and GPs, a contract concerning compensation and other terms is usually created between the two parties (Mehta, 2004).

The lifespan of a PE fund depends on the purpose of the fund and the type of companies it will invest in. A VC fund will consistently have a longer lifetime than a BO fund (Nygård and Normann, 2008). Generally, PE funds are ten-year limited partnerships (EVCA, 2012). These ten years plus a two-year potential extension period is the usual maximum fund lifespan. This means that LPs commit their capital for a long time, thus PE investments are considered to be illiquid. What distinguish a PE investment from other equity investments are the opportunities for committing additional capital and exit. In mutual open-end funds investors have a continuing opportunity for committing more capital and for exiting the investment. In a PE fund, however, the fund will close for further committed capital once the target capital is raised, as these are closed-end funds. The investor has the option to trade his shares in a secondary market during the life of the fund. However, estimating the value of this share is difficult, and so investors cannot trade in and out easily. The long commitment of high volumes of capital results in institutional investors being the primary investor in PE. In 2013, pension funds provided almost 40 % of the total global fundraising of the industry. Funds of funds contributed 16 %, while sovereign wealth funds and insurance companies both provided 11 % the same year (EVCA, 2013).

Various exit strategies are present at the end of the fund investment period. The most widely used exit routes are initial public offerings (IPOs), trade sales or mergers, secondary sales to another GP, restructuring, recapitalization and sales directly to the management of the portfolio company (Preqin, 2011). In an IPO, the company's shares are listed on a stock exchange for the first time, and the investor will be able to sell shares to the public. A trade sale involves selling all shares of the company to a third party where said party often is a firm operating in the same industry as the company sold. In a secondary sale a PE investor sells the company to another PE firm. Recapitalization entails re-leveraging the company and using the proceeds to repurchase the company's own shares from the investor. In 2011, the most frequently observed exit type was trade sales, followed by IPOs (Preqin, 2011).

PE managers are compensated through four main sources of revenue, namely management fees, carried interest, deal fees and monitoring fees (Migliorini, 2014).

Management fees cover all expenses incurred by the PE fund and include salaries, operating costs and the cost of monitoring portfolio companies. This fee is the GPs primary source of income and usually range from 1,3 % to 2,5 % of committed capital during the investment period. Carried interest serve as a performance fee, and is generally equal to 20 % of the capital gains realized from the investments of the fund. A hurdle rate, of typically 8 %, must be reached before the carried interest is paid the to GPs. Every time a GP executes an acquisition or exit it may charge a deal fee. This fee is typically between 0,5 % and 1,5 % of the deal's equity or enterprise value. A few years ago, LPs started to put more pressure on GPs to improve their fee structure, thus deal fees are not common practice today. Many GPs charge a monitoring fee once an investment is made. The portfolio company pays this fee to the GPs for consulting and advisory services (Migliorini, 2014).

2.1 Private Equity History

Historically, the U.S. has been the largest PE market worldwide and is usually viewed as the founder of the modern PE. Several early establishments helped the development of the U.S. as the PE industry leader. The War Finance Corporation was established in 1918, initially to support war-related industries, but later moved on to focus on financial backing of agricultural and railroad companies. In 1946, the French general Georges Doriot established the American Research and Development Corporation (ARD) at Harvard. Since this event, VC has had strong relationships with universities in the U.S. A symbol of ARDs several successful investments is the IPO of the Digital Equipment Corporation in 1970 - a company later to be a part of the merger to form Compaq. With the goal of supporting small businesses, the Small Business Administration (SBA) was founded in 1953. Five years later, in 1958, Small Businesses Investment Companies (SBIC) was established, which may be regarded as the event where modern VC industry was born (Demaria, 2010).

The boom in the stock market during the 1960s gave an additional strength to the growth in the VC industry, but PE experienced a slight setback as a consequence of the Employee Retirement Income Security Act (ERISA) in the following decade. The government restricted pension funds from taking excessive risk, having an effect on PE, which is considered a high-risk investment. However, during the 70s and early

80s VC, measured in million dollars invested, was once again larger than BO. Nevertheless, in the late 80s BO experienced a significant growth and eventually surpassed VC.

Europeans have tried to copy the U.S. PE model, although with some challenges as the culture for entrepreneurship is somewhat different. One obstacle is the fragmentation the European market. There may be significant differences in laws (e.g. taxes) as well as cultural characteristics that bring along these challenges. Historically being risk-averse, there has been a careful approach to entrepreneurship in Europe and possibly to the idea of investing in PE funds (Demaria, 2010). A third challenge is related to immigration and education. Looking to the U.S., a significant part of the startups have been founded by immigrants. For example, 52% of the startups in Silicon Valley in 2009 were founded by immigrants (The Economist, 2009b). Attracting foreigners to the universities, the U.S. has enhanced the number and quality of the startups and thus improved the market conditions for PE.

The U.K. has for a long time been the financial center of Europe and has shown tradition for innovation. Building on this and establishing VC vehicles, the U.K. grew to be the leading PE market in Europe during the 90s, a position it still holds today (Demaria, 2010). Another important effect was the country's similarity to the U.S. in terms of language and culture, which made it an attractive position for regional and pan-European LBO funds.

Through the tax framework for capital gains, European countries have encouraged investors to invest in PE firms. Furthermore, U.K. and France enabled retail investors to participate by creating venture capital trusts. Taking the IT crash in the U.S. in 2000 into consideration, the possibilities of an attractive return over risk significantly increased in this period. (Demaria, 2010)

2.2 Different Types of Private Equity Investment

There are four fundamental types of PE investment at the company level: buyout, development capital, growth capital and venture capital (Fraser-Sampson, 2011). Which of these groups a PE fund belongs to depends on the type of company in which it invests and at what stage in the product life cycle the company operates. Within these main groups, different strategies are used to achieve given targets. In the following section, we will give a brief description of the most common fund types, namely buyout, venture capital, growth, real estate, infrastructure and fund of funds (Preqin, 2015a). In addition, we will look to mezzanine.

2.2.1 Leveraged Buyout

A buyout fund is a fund with a predominant strategy to acquire controlling stakes in an established company. The portfolio companies of a buyout fund are typically mature companies exhibiting growth or companies in a restructuring process, who generate cash flows from operations on their own. The strategy builds on making investments through acquisitions of a company's assets from its current owners by the use of interest bearing instruments, such as loans and bonds - hence the name leveraged buyout (LBO) (Blaydon and Wainwright, 2006). The ratio of debt to equity in an LBO ranges from 60 % to 90 % debt, where the payments of interest and loan principal on said debt are secured by the cash flows of the acquired company (Kaplan and Strömberg, 2008).

The value creation in an LBO is not necessarily aimed at creating growth, but rather at maximizing the cash flows of the acquired company (Reiten and Sundstrøm, 2001). LBOs involve considerable effort by the GPs that goes beyond the completion of the acquisition. Once the acquisition is completed, the company must be operated optimally to maximize the cash flows of the company's debt and equity.

The following figure illustrates the general capital structure of an LBO.

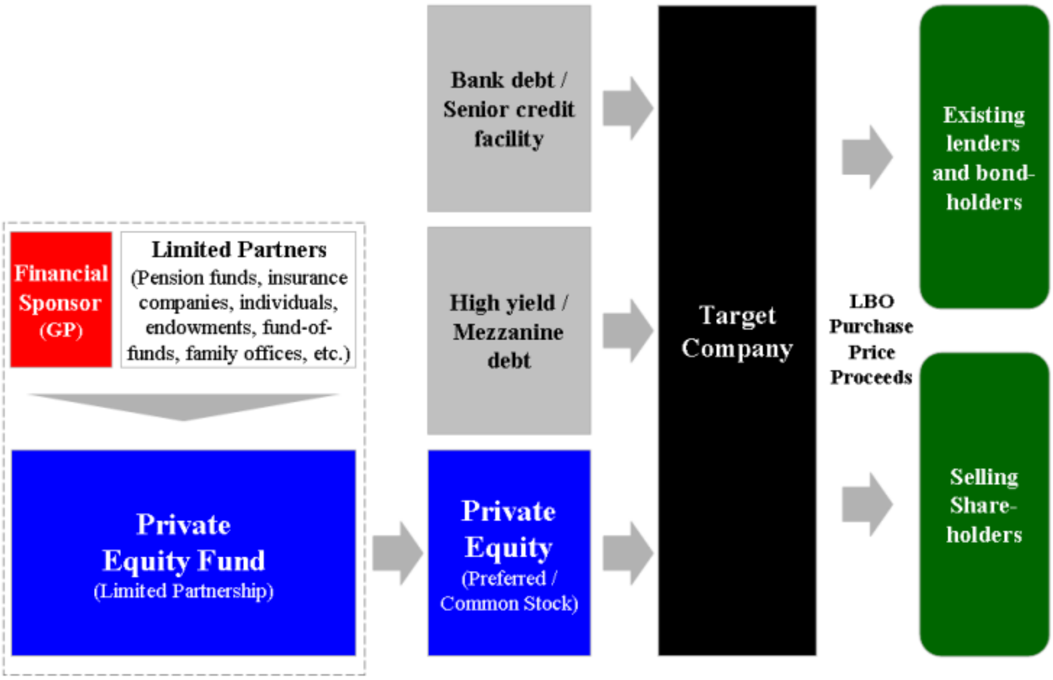

Figure 1: Diagram showing the basic structure of a generic LBO transaction (Wikipedia, 2015)

The capital structure of an LBO usually consists of four types of capital; bank loans, which typically accounts for 50 %, high-yield debt, often at 10 %, mezzanine debt at about 10 %, and PE, which serve as the remaining 30 % (Blaydon and Wainwright, 2006). Bank debt involves a revolving credit facility that can be paid back and drawn down as desired by the company, in addition to several tranches that differs in seniority, maturity and cost. High yield debt is used to compensate for debt levels that banks are not willing to provide. This debt has a subordinate position to bank debt, and thus a higher interest rate. Mezzanine debt has an even lower position than high yield debt, and is therefore provided by lenders who require an even higher interest rate and warrants as compensation. In the case of a bankruptcy, the different debt holders have priority over equity holders in receiving the proceeds from any sale of company assets. Therefore, PE is perceived to be the more risky form of capital (Blaydon and Wainwright, 2006).

The Federal Reserve has issued guidance persuading market participants to avoid debt levels of higher than six times company EBITDA (earnings before interest, tax, depreciation and amortization) in LBOs. Still, according to S&P Capital IQ LCD, 40 % of all U.S. LBO deals display leverage above this ratio (Tan, 2014). A concern regarding this high use of leverage is if the acquired company runs into trouble and paying off debt becomes difficult. The debt-investors will then suffer. Companies with higher debt ratios are considered more likely to run into financial difficulties.

2.2.2 Venture Capital

Venture capital is investments in companies at an early stage or companies seeking to expand (Argentum Glossary, 2015). Entrepreneurs often lack the financial means to fund their projects themselves, and are therefore looking for alternative sources of financing. These types of companies are often developing new technologies, new market-concepts and further developing existing products into new fields and areas of usage (Kintel and Knutsen, 2014). It is common to classify venture capital in two categories: sector and stage. The three most important sectors according to Fraser-Sampson (2011) is IT, Telecom and Life Science, while stages can be separated into seed, early, mid and late stages.

The seed stage is the earliest stage in which the company has yet to earn its first stream of revenue. Worth mentioning though, is that some investors tend to interpret the first venture capital financing round as a seed stage even though the portfolio company might have been around for a while, already earning revenues. The early stages will naturally be the stages following the seed stages, but where the company still is small and/or young. At the early stages, technological and market competence is of high importance as the GP seeks to help the portfolio company develop. In the mid- and late stages, financial competence is of high importance as the company at that stage is more mature with a developed product and market. At this point, the company might have turned profitable and is therefore seeking financing for further expansion. (Fraser-Sampson, 2011)

In terms of amount invested, the seed stage only accounts for a small percentage of total VC. Seed investments are defined as small capital amounts invested in contractors to examine if an idea or a product qualifies for further investment. In 2014, only 1.5% of the total VC amount invested in the U.S. was invested in seed capital, while the remaining 32.7%, 40.9% and 24.9% were invested in the three succeeding stages (PWC MoneyTree Report, 2015). Note, however, that PWC in their report refers to the stages as seed, early, *expansion* and later stages.

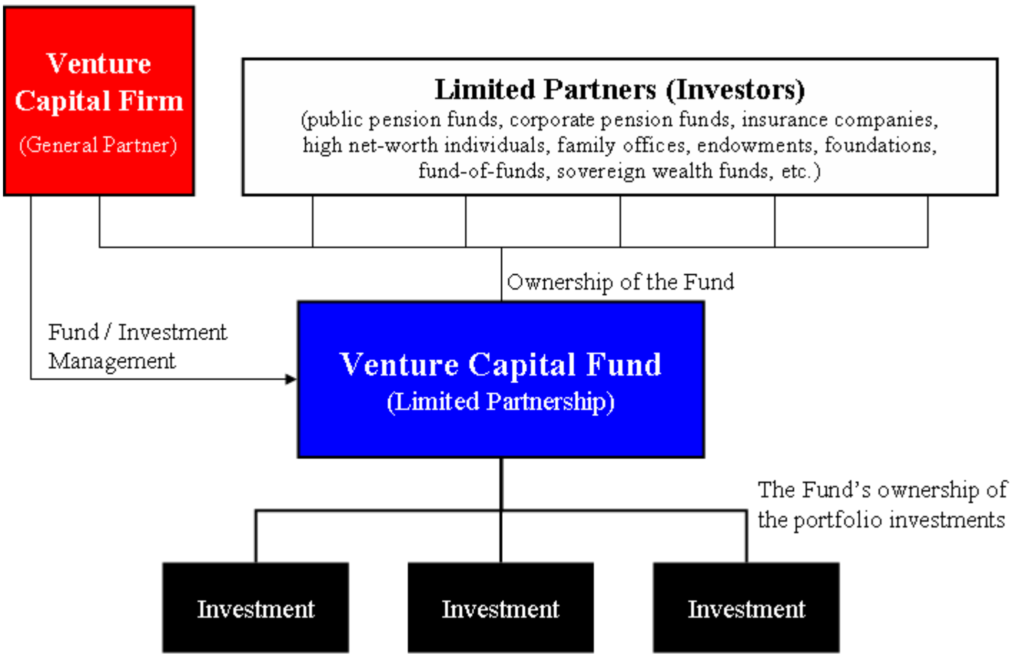

Figure 2: Diagram showing the basic structure of a generic Venture Capital Fund. (Wikipedia, 2015)

2.2.3 Development Capital and Growth Capital

Development Capital (DC) and Growth Capital (GC) are similar in several ways according to Fraser-Sampson (2011). In terms of size, the two categories are small compared to, for example, BO, but measured in number of deals they are quite significant. Furthermore, in DC and GC the investors usually take minority stakes in the companies. A third similarity is that neither makes use of acquisition debt, as opposed to BO.

Investors in DC target companies at a late phase in their lifecycle, either at mature or declining stages, seeking to improve their earnings. These types of firms often need capital for growth or development, in which case DC provides capital in exchange for a stake in the company or the transaction might be treated as a convertible bond. A convertible bond is a bond that can be converted into a prearranged amount of company shares at certain times of the bond's life. This type of transaction can be regarded a “money-in” transaction as the capital of the company increases. A so called money-out transaction occurs if some of the company's existing owners wish to pull out or in the case of consolidation of shares, in which case the DC fund might buy the existing shares.

In GC the investors target companies at an earlier stage than DC. The fund acquires companies in growth and if not already profitable, than at least with good prospects. This is why, according to Demaria (2010), GC can be considered one of the least risky investments within the universe of PE. It follows that, for the same reason, the potential reward is lower as the company already is valued quite high. Where the focus of DC is to improve the bottom line, the main focus for GC is to improve the top line (Fraser-Sampson, 2011). Increasing sales is considered crucial to keep up with the growing market.

2.2.4 Real Estate

Real estate PE is an asset class, which contains investments in real estate property. The capital of all LPs committing funds is pooled together, and the GPs select what types of real estate that will be included in the fund's portfolio. GPs will typically construct their investment portfolios to obtain diversification, i.e. the use of a mixed variety of investments to achieve higher return and lower risk. According to Cyril (2010), there are several reasons why large buyout operators diversify into real estate. One rationale is that the skills needed for real estate investment and large buyout investment are basically the same. The GPs have gathered this competence through experience and started to offer it in other parts of the market as well. Another reason is the extensive evolvement seen in GPs. PE funds have grown to conform legal capabilities, a secretary general to coordinate the multiple funds and manage the GP structures, and investor relation capabilities.

Broadly speaking, there are three types of investment strategies involved in PE real estate: core, value-add and opportunistic funds. The core strategy entails investing in stable, fully leased, multi-tenant property in big metropolitan areas. This investment is unleveraged, and has a steady and predictable cash flow, which makes it low in risk, but also low in potential return. Value added investments involve acquiring property, improving it or its management, and then selling it when the value has increased due to the changes made. Both the risk and return profiles of this investment type is medium to high. Opportunistic funds invest in property that require a high degree of enhancement. This is typically real estate under development and raw land. This type of investment displays a high risk and high return profile (Tradespoke, 2015).

2.2.5 Infrastructure

This asset class includes PE funds that invest in infrastructure assets. Infrastructure assets can be defined as the physical structures and networks that provide fundamental services to the public and community (Macquarie, 2009). Infrastructure is typically divided into two broad categories: economic and social infrastructure. The economic sector includes transport, utilities, communication and renewable energy. Social infrastructure consists of schools, hospitals and defense buildings, prisons and stadiums (OECD, 2014). This suggests that there are a number of different investment vehicles available to private investors of infrastructure. Both debt and equity vehicles are used in this category. As a result of the many investment vehicles available, not all investments within this asset class display the same risk and return characteristics. The elected investment will therefore depend on the nature of the asset and overall asset allocation of the investor's portfolio.

The different forms of infrastructure investment have different risk, return and time horizon profiles. We will now give a brief description of the most common forms of infrastructure investments. Direct investments into infrastructure assets such as toll roads typically require the longest time horizon, given the long lives of such assets. These investments often require large capital outlays and cannot easily be sold due to the physical nature of the assets. Direct investments may also expose the investor to great political and regulatory risk. An investor can additionally invest indirectly in infrastructure by acquiring listed securities of companies that operate in infrastructure sectors. This can eliminate the large capital outlay requirement, make it easier for the investor to diversify, reduce exposure to liquidity risk and shorten the time horizon. Unlisted infrastructure funds enable smaller investors to participate through relatively smaller capital requirements and provides diversified exposure (Bitsch et al., 2015). PE infrastructure falls within the last category.

2.2.6 Fund of Funds

As the name suggests, a fund of funds does not invest directly in companies, but holds a portfolio of several private equity funds. Therefore, rather than investing in one specific fund, an investor might invest in a so-called fund of funds. This might be an attractive opportunity for an investor seeking the potential returns in the PE market, but lacking necessary knowledge and/or resources for investing in specific PE-funds or for investors seeking larger diversification (Kocis et al., 2010). The diversification however, might differ between funds of funds, as some will target a wide spread of different PE funds across the globe, while others might specialize in more specific types such as U.S. venture funds etc. (Fraser-Sampson, 2011). A fund targeting mainly new funds can be called a Primary (or Primaries) fund of funds, whereas a Secondary fund of funds will generally invest in existing funds (Argentum Glossary, 2015). Where a typical PE fund holds about 20 direct investments, a fund of funds has a portfolio of about 20 funds, spreading the investor's risk over as much as 400 direct investments (Weidig, Kemmerer and Born, 2005). Even though the focus lies on investing in funds, funds of funds might in some cases also invest in companies (Kocis et al., 2010).

Funds of funds are not included in the potential zombie fund category. This is due to the nature of these funds, which does not meet the criteria for our chosen zombie fund definition. Only direct PE funds types can be classified as zombie funds. This will be discussed in more detail later in this thesis.

2.2.7 Mezzanine

Mezzanine is another type of PE investment. More specifically, it is the use of mezzanine debt to finance buyout transactions. A mezzanine investor lends capital in a buyout transaction, but has, through a warrant, the right to convert all or part of it into shares in the acquired company. According to Silbernagel and Vaitkunas (2003), mezzanine is a collective term for loan instruments with return and risk profiles that lie between senior debt and private equity. “Junk bonds” may also be included in this term. Mezzanine debt is usually unsecured, or has security rights that rank below that of senior debt. This makes the lender able to charge a higher interest rate as compensation for additional liquidation risk (Fraser-Sampson, 2011).

Mezzanine can generate several benefits for both the borrower and the investor. The use of mezzanine financing can provide benefits to the company as a source of capital when bank debt is unavailable or unsuitable. In addition, mezzanine debt is more flexible than bank debt. Mezzanine can be a cheaper source of capital, and it is proven to increase return on equity. Furthermore, it will reduce the equity requirement for the investor, and its interest is generally tax-deductible. It also enables a higher number of or larger transactions (Mezzmanagement, 2015).

2.3 Zombie Funds

Zombie funds are funds that meet the following criteria:

1. Closed-end with-profits funds that are close to or beyond their pre-agreed lifespan
2. Funds with managers that have not successfully raised follow-on capital and have no clear plans of liquidation

The fund's duration and the GP's ability to raise a follow-on fund are two crucial aspects of the zombie fund interpretation (Pedersen and Sand, 2014). Zombie funds are funds close to or beyond their pre-agreed lifespan with managers who have not successfully raised follow-on capital. The potential harm of zombie funds is of growing concern to investors and has received a lot of attention in the PE industry lately.

For the purpose of this thesis, zombie funds are funds with vintage years from 2003 to 2008, managed by GPs that have not successfully raised a follow-on fund since 2008. These funds are retained beyond or approaching the end of their planned lifetime and the industry average of ten years. This walk towards a far extended lifespan leads such funds to slowly becoming the “living dead” - hence the name zombie funds. These are near-dead funds that tie up the investor's money while continuing to charge fees even though hopes of profiting from the remaining assets have faded. The GPs sit on the fund assets past the expected holding period, with no plans of liquidation or of raising an additional fund.

Succeeding the global financial crisis of 2007-2008, increased political and economic uncertainty, greater sovereign risks, and less available bank financing caused a fall in the overall performance of the PE industry. This is demonstrated by a reduction in median internal rate of return (IRR) for global buyout funds from 19,5 % to 10,5 % (Migliorini, 2014). This poorer performance decreased many LPs willingness to allocate capital to this market. PE fundraising suffered as a result of the recession, both in terms of the amount of capital raised and the number of GPs able to raise funds. From 2008 to 2009 the amount raised by PE funds fell from $688 bn to $319 bn, while the number of GPs raising funds declined from 1 146 to 751. Consequently, many GPs had to delay their plans of raising follow-on funds and cut down fundraising targets. Current figures show that PE fundraising has not yet reached the record high levels of the PE golden age experienced in the years leading up to the crisis (Migliorini, 2014).

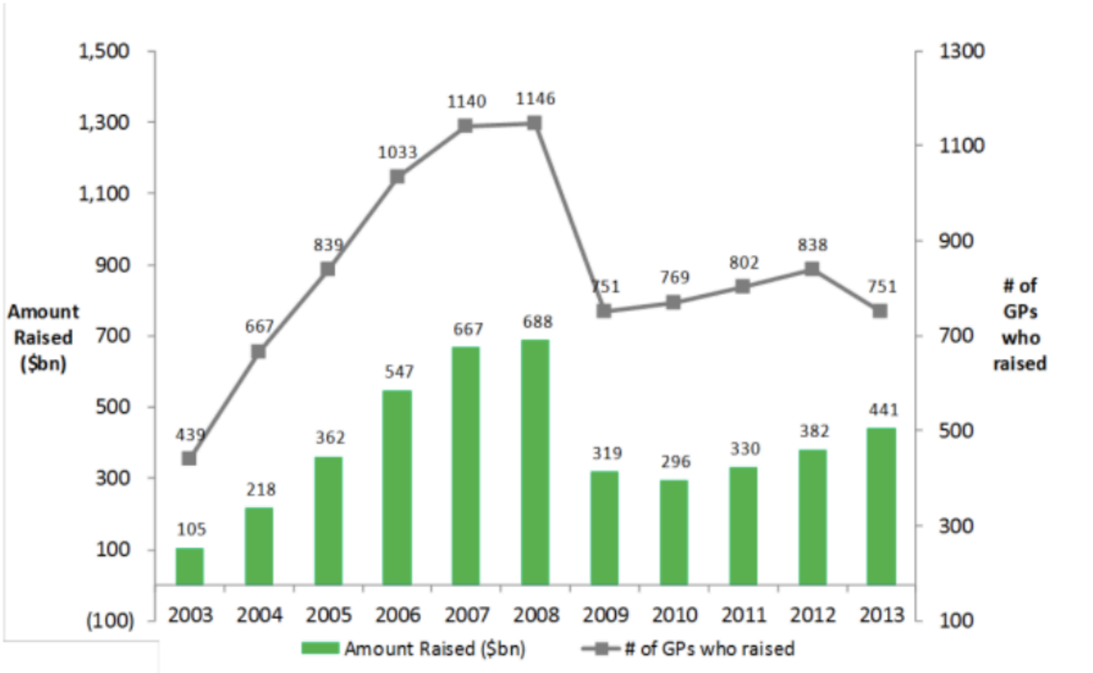

Figure 3: Total amount raised by general partners over the period 2003-2013 (Migliorini, 2014)

As a result of the difficulties following the financial crisis the number of zombie funds rose dramatically. These funds exhibit significant remaining unrealized values (Preqin, 2014). Preqin (2014) defines zombie funds as seven to twelve year old active funds, managed by GPs that have failed to raise capital within the past seven years. Our definition conforms to the one applied by Preqin.

Preqin (2013b) reported the identification of approximately 1 200 zombie funds in 2013, and that as much as $116 bn of PE assets might be trapped in such funds. Using their updated database (2015), we identify 1 274 zombie funds, which indicates that the problem is not going away. Furthermore, Preqin's findings suggest that the median distributions to paid-in capital are much lower for zombie funds than for their peers.

3. Agency Theory and Asymmetric Information

Agency theory highlights possible incentive and monitoring problems between a principal and an agent. A principal-agent relationship occurs when one party is dependent upon the actions of another party. The principal is the party that delegates property rights, while the agent is the delegated party (Duffner, 2003). In a financial environment, the principal is typically the investor while the investee acts as the agent. The agent (company management) is closer to the company's operation and therefore better informed than the principal. Problems can arise if agents behave opportunistically, i.e. exploits this superior information to maximize their own utility, often at the expense of the principal. The focus of agency theory is the search for relationship designs that align the interests of the two parties (Duffner, 2003).

Previous papers by Duffner (2003) and Mehta (2004) suggest that agency problems can be broadly divided into three large categories, namely adverse selection, holdup and moral hazard. Adverse selection is typically associated with asymmetric information and concerns information bias on the investment date. This problem can occur in markets where one party cannot discriminate between good and bad quality of the other party or investment opportunities. The agent will have an information advantage. The principal will face difficulties in choosing the good investment opportunities over the bad ones, and risks being forced out of the market due to this uncertainty (Brickley et al., 2008). Holdup describes situations in which the agent systematically uses gaps in incomplete contracts to his own advantage. After investments have been made and sunk costs incurred by the principal, the agent reveals his hidden intention, forcing the principal to renegotiate the terms of the contract. In such cases, the agent will have the upper hand in the negotiations (Duffner, 2003). Moral hazard concerns information bias after the investment is made (Fossen et al., 1999). Moral hazard occurs when the agent either uses information not observable by the principal or performs actions not observable by the principal to promote self-interests at the expense of the principal's utility. The main issue lies in the contractility of actions of the agent. The investor can typically only observe the company's final output or success, and not the actions taken by the company. It is therefore difficult to distinguish the results from chance or bad behavior (Duffner, 2003).

Theory suggests the following solutions and mitigations to agency problems: aligning interests, monitoring, bonding, vertical integration, signaling, information disclosure and creating a dynamic relationship (Duffner, 2003).

- *Aligning interests* of the principal and agent address the problems of adverse selection, holdup and moral hazard. This refers to different measures that can be applied to assimilate the agent's personal utility maximization and the principal's interest. Examples of measures used are sanctions, convertible debt and collateral.
- *Monitoring* is a measure aimed at solving moral hazard and holdup problems. Monitoring means that the actions expected from the agent is put down in a contract, and that the principal later can control for compliance. Sanctions are very important in this context.
- *Bonding* also targets moral hazard and holdup problems. Bonding entails the agent to prove, at his own cost, that his behavior is in compliance with the interests of the principal. Bonding can be achieved through voluntary reporting to the investor and third party auditing.
- *Vertical integration* is a technique used against holdup that tries to integrate the invested company into a hierarchical structure with authority.
- *Signaling* is a measure against adverse selection, and involves obtaining credible information regarding the investment quality, risk and expected return for the investor. This information would otherwise be very costly for the investor to retrieve.
- *Information disclosure* concerns the adverse selection problem, where the market participants try to make themselves more transparent before a contract is entered into. Measures to aid information disclosure involve screening, third party auditing and information exchanges.
- *Creating a dynamic relationship* focuses on solving problems of adverse selection, holdup and moral hazard. This process aims at creating a relationship between the participants over time that will benefit both sides of the repeated transactions.

In addition to the solutions listed above, we wish to highlight reputation as an important mechanism in agency relationships. Having a good reputation is crucial in any voluntary market and provides incentives for the agent to align his actions with those in the best interest of the principal.

3.1 Agency theory in Private Equity

PE firms act as a financial intermediary in the market. On the one hand there are investors seeking return on their money, and on the other there are portfolio companies seeking capital and competence. As an intermediary, the PE firm will both hold the role as an agent, in the relationship with the investors, and as a principal, in the relationship with the portfolio companies. We can therefore separate the agency problem in two main categories, the relationship PE fund - Portfolio Company, and Investor – PE fund.

In the relationship between the PE firm and the portfolio company, the PE fund will have certain expectations of the portfolio company management, thus taking on the role as the principal. The portfolio company, as the party seeking capital, will have an information advantage. To solve this issue, the PE firm will thoroughly analyze potential investments using due diligence and valuation upfront (Duffner, 2003). The moral hazard aspect of the PE fund - portfolio company relationship is not critical due to the GPs active participation in company operations and the resulting monitoring ability.

Adverse selection may occur in the relationship between the GPs and the LPs, as the LPs do not have complete information regarding the GPs talent or investment skills. Mehta (2014) list two main solutions to this problem. Profit sharing is an opportunity for GP to signal their skills and talents. A confident GP will more often accept a more uncertain and performance based compensation scheme than will a less confident GP. In essence, a compensation scheme that relies more on performance (carried interest) than fixed fees (management fees) may signal a high quality investment-team. This way the LPs may seek the seemingly better GPs by considering how the compensation is designed. Covenants may be included in the limited partnership both for reducing adverse selection and moral hazard, and are explained below.

As investors during the fund's lifetime learn more about the GPs' investment skills and abilities to produce high returns, their willingness to invest in the same PE firm in the future is affected. In the case of a GP that has performed poorly, and therefore might have difficulties raising another fund, the GP might be incentivized to charge high fees and postpone the liquidation of the fund at the expense of the LP, as in the case of a zombie fund. This might be seen as a hold-up problem in PE (Phalippou, 2010).

Moral hazard is also an important aspect in private equity relations where the LPs cannot perfectly monitor the GP's effort. Again, both profit sharing and covenants are listed as the two most important ways to reduce the moral hazard problem. With a performance-based compensation, such as carried interest, the agent (GP) is incentivized to exert high effort. When GPs are able to produce high returns by quality investments and work, they will increase their wages as they receive an agreed upon part of the fund's return. Covenants will also effectively reduce moral hazard, as they directly restrict the GP's behavior after the point where the LPs have committed capital. Gompers and Lerner (1996) divide these types of covenants into three primary categories; covenants related to the overall management of the fund, the activities of the GP, and the permissible types of investments. Those related to overall management work to restrict the structure of the funds. Usage of debt might, for example, be extensive if the GP want to increase risk, considering his own position as a sort of option (high upside, but limited downside). The GP might also wish to influence the performance of other funds through co-investments or boosting the performance of underperforming firms by increasing funding. The second main group of covenants relates to the GP's behavior, both associated with its relationship with portfolio companies and the fund itself, and outside the fund. As an example, risk-averse GPs might want to sell their partnership interest, reducing the risk related to performance, an action not in the LPs best interest. Outside the fund, GPs might take on other roles, for example in the boards of other firms. If the amount of time spent on such activities becomes too high, it might reduce the GPs focus on the fund and thus its performance. The third group is as implied, types of investments the GP is allowed or encouraged to do. This might be related to sectors, markets, firm-sizes etc.

However, it should be noted that including such covenants significantly increases the need for monitoring, and might be difficult to enforce. (Gompers and Lerner, 1996)

In some cases, large LPs may be given the opportunity to sit on advisory boards. Participating in these boards may enhance their ability for monitoring decision-making and exert an advisory role, for example related to hiring and dismissing GPs. (Mehta, 2004)

The PE incentive structure (GPs sources of revenue) can create conflicts of interest between GPs and LPs. After the global financial crisis and the fall in the performance of the PE industry, the number of GPs able to raise a follow-on fund decreased. Migliorini (2014) concluded, based on interviews with LPs, that LPs loss of faith in the GP, underperformance, significant changes in the investment team and unclear succession plans are the most prevalent reasons why GPs fail to raise subsequent funds. Once any of these factors are present, the chances of successfully raising a follow-on fund are small. The PE fund will then be on its way to becoming a zombie fund, and several potential conflicts of interests can arise between LPs and GPs.

In the case of a fund whose GPs are confident of raising a successive fund, the revenue structure will align the interests of the LPs and GPs. The need to show strong early realizations and robust IRRs to ensure the raising of a follow-on fund will induce PE firms to exit in a timely manner. Thus the importance of a dynamic relationship and reputational effects becomes apparent. The promise of raising a new fund will increases chances of earning future regular income (through management fees) with carried interest opportunities from prior funds giving an opportunity for performance driven revenue.

Conflicts of interest can arise when the fund suffers from poor performance so the hurdle rate is out of reach and carried interest revenues are off the table, and when the fund is unable to raise follow-on capital. If carried interest from the existing funds is unlikely and no management fees from new funds are in sight, the GPs must rely on current management fees as the main source of income. In effect, there are no incentives for the PE fund to exit investments in a proper time fashion as this would reduce their fee-based income and possibly result in internal restructuring (Migliorini, 2014). The GPs will then keep the fund artificially alive, as this is their most lucrative option. Management fees can still be charged and some GPs even charge their own "consulting fee" as to collect as much money from the fund as possible (Pedersen and Sand, 2014).

Furthermore, zombie funds can hurt the quality of the GP team and investments, thus negatively affecting the return to LPs (Migliorini, 2014). As soon as investment professionals become aware of the dark future awaiting the GP, the investment team can quickly evaporate. There may be personal reputational effects of participating in running a zombie fund, which might influence one's entire career. The best typically leave first, thus reducing the quality of the team. Moreover, the management of the portfolio company may lose confidence in the GP. As a result of these adverse events, several scenarios can arise that will hurt the LP's return:

- The commitment and attention to the portfolio company may decrease
- Higher management fees paid to GPs by LPs
- Capital distributions to LPs may be delayed, which reduce the time value of the investment
- Delayed exit may cause lower exit values as forced or semi-forced exits contain lower bids

3.1.1 LP Solutions

As indicated by Migliorini's (2004) findings, it is crucial for investors to address the problems of zombie funds to safeguard returns. Both short term and long term actions can help solve these potential problems. The short-term actions propose solutions for investors currently invested in zombie funds, while the long-term actions serve as guidelines for avoiding investment in potential zombie funds.

There are four short-term responses for investors currently invested in zombie funds: restructuring the terms of the fund, selling a majority of the portfolio to a secondary investor, sale of the GP and removal of the GP (Migliorini, 2014).

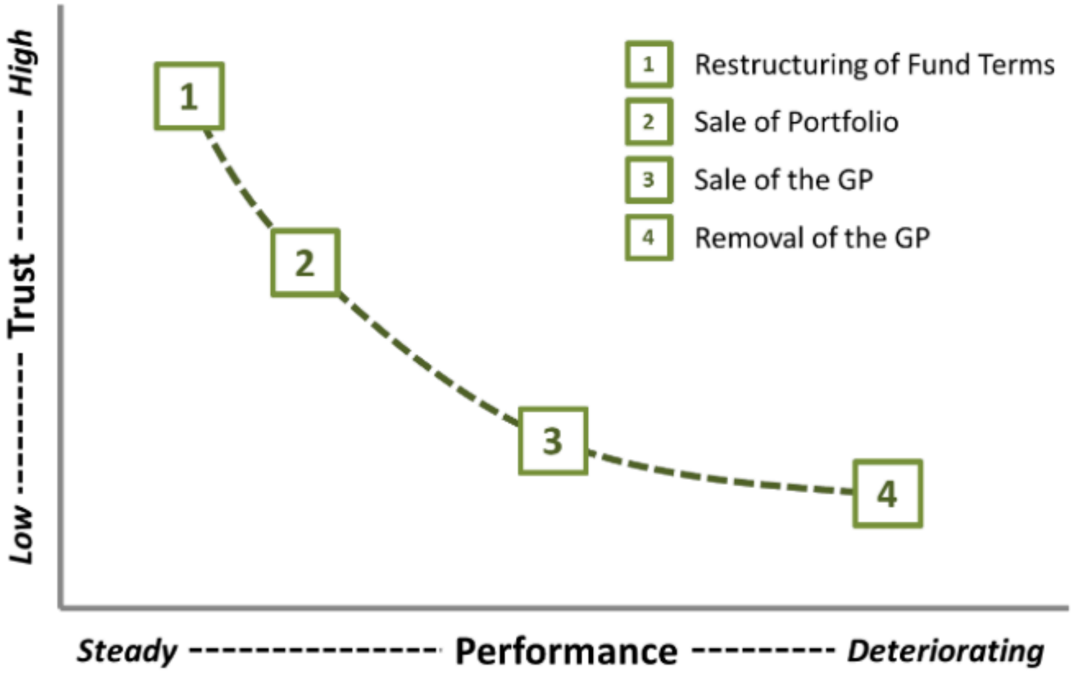

Figure 4: Short term actions for LPs to address zombie funds (Migliorini, 2014)

Restructuring the fund terms concerns alteration of given terms of the limited partnership agreement to further align GP and LP interests. Frequently used measures are reduction of carried interest, management fee review, fund extensions and team restructuring. These techniques will align the interests of the GP with those of the LPs, while simultaneously benefit the LPs as the cost of reviewing the terms often is lower than potential losses resulting from uncommitted GPs. Nevertheless, Migliorini (2014) finds that LPs are typically reluctant to agree to alteration of fund terms as they feel that this would reward perceived adversarial behavior.

The second cited option for an investor involves the sale of a majority of the fund's LP interests to an independent buyer. The secondary buyer becomes the main, if not the sole, LP in the fund. This technique is commonly used when one or more of the following scenarios are present:

- LPs disagree on what to do with the fund's GP
- Most LPs want or need liquidity
- The GP has the credibility to keep managing the fund, as could be the case when GP mistakes are amplified by external factors

Sale of the GP involves LPs to actively encourage the GP to merge with another established GP in hope of improving the quality of the investment team. This may also increase the chances of successfully raising a follow-on fund.

Removal of the GP by the fund's LPs is the most extreme measure LPs can undertake. The limited partnership agreement commonly includes a no-fault removal clause that permits LPs to terminate GP management of the fund at any time, subject to the payment of a predetermined fine. Migliorini (2004) suggests that this option is rarely, if ever, used. The rationale supporting this finding is that removal of the GP can be more risky and expensive than maintaining the current position. If the removal right is exercised, LPs will have to pay the penalty in addition to hiring a new GP, unless they sell their share of the fund in the secondary market. The risk is based on the fact that this new GP will know less about the portfolio than the previous GP.

The long term solutions available to LPs builds on strengthening the screening process of potential investment funds as to avoid allocating capital to weak GPs, in effect, reducing the chances of having zombie funds in one's portfolio. The investor can review the fund structure/ limited partnership agreement for new commitments, strengthen monitoring to detect weak GPs early and commit capital to GPs managing multiple funds (Migliorini, 2014).

Review of the fund structure can help mitigate the strongest conflict of interest after the expiration of the investment period, namely the link between committed capital and management fees. One technique to achieve this goal is to review the fund structure up front. It may, for instance, be an option to include a provision stating that management fees will be reduced after the expiration of the fund, effectively reducing GPs incentive to postpone the sale of existing assets. Another technique is to reduce the threshold and penalty for GP removal. If lowered, these terms will provide LPs with greater bargaining power and increase GP incentive for proper exit. An additional measure LPs can take on is to reduce the right to automatic extension. Currently, GPs can ask for an automatic one-year fund extension. LPs could, for instance, push for board approval for determining this matter. Finally, LPs can review the Key Man Clause. This clause allows GPs to replace other key GPs subject to certain conditions. By removing or altering this clause, the LPs can enhance the possibility of keeping the investment team close to the original one.

LPs can detect risky and weak investments early by strengthening their monitoring skills. The intention is to be able to sell the stakes of risky investments early on at a higher price and avoid handling possible complex situations for those investments at a risk of becoming zombie funds.

The issues of zombie funds typically emerge in standalone funds (Migliorini, 2004). LPs can therefore benefit from investing in GPs that manage multiple funds across investment strategies and geographies, compared to GPs operating a single fund. The risk and potential losses from an underperforming fund is reduced when there are several streams of revenue. Furthermore, GPs managing more than one fund will have a broader reputation to uphold in the LP community which gives incentives for compliance with what is expected by LPs.

3.1.2 GP Solutions

Migliorini (2014) suggests three critical areas on which GPs of zombie funds should focus in order to be in a better position with respect to future fund-raising. The most obvious aspect is deliverance of positive performance on the existing portfolio. Continuous improvement of the portfolio companies is important if they are to seek future funding. After all, investors in the fund are expecting good returns even though the funds' lifetime is exceeding the market standards, and GPs with better performing funds are generally more likely to raise follow-on funds and larger funds (Kaplan and Schoar, 2005).

More crucial however, is the GPs ability to maintain investors' trust, i.e. to preserve a good reputation among investors. The LPs might accept relatively poor performance if they have trust in how the GPs are managing the fund. Disclosing useful information may help both current investors, but also potential external investors, in evaluating how the GP is in fact creating value in the portfolio. As the GP itself is the main source of information for the LPs, transparency is crucial for maintaining trust (Ghani, 2011). As in the entire finance industry and most businesses, professional conduct is of high importance and essential in order to uphold trust from investors and other stakeholders. The EVCA Handbook (2014) lists six codes of conduct, all mandatory for EVCA members:

1. Act with integrity
2. Keep your promises
3. Disclose conflicts of interests
4. Act in fairness
5. Maintain confidentiality
6. Do no harm to the industry

Acting with professional conduct and transparency, as well as managing the fund with the LPs best interests in mind, is expected.

A third element is the reframing of the GP's equity story. Essentially, this means staying consistent with respect to investment strategy and maintaining a relevant and skilled team in order to signal what the investors can expect from a potential follow-on fund. In the end, the exits of the portfolio companies need to be successful, particularly on the deals most related to future follow-on funds. (Migliorini, 2014)

3.2 Zombie Funds and the Secondary Market

In 2013, Preqin identified 1 732 portfolio companies held by zombie funds and correspondingly $ 116 bn worth of assets trapped under their management (Preqin, 2013b). However destructive for the current investor, such portfolio companies may provide investment opportunities for fund managers and other potential acquirers on the search for assets at discounted prices. The secondary market can as such serve as an interesting investment for potential investors, while offer some solution to GPs with zombie funds and LPs invested in them. A fund manager can, for instance, take over the assets of a zombie fund through a secondary buyout, thereby generating an exit and liquidity for the primary investor (Preqin, 2013b).

A large part of the PE secondary market is the involvement of secondary buyers in GP-led transactions and fund restructurings. Zombie funds are typically funds close to or past their pre-agreed lifespan with significant unrealized values. Furthermore, it is uncertainty related to what part of this remaining value that can be realized. Investors in these funds are often unwilling to back new funds by the same managers, and the investments in existing funds may be deprived of the capital required for value creation. According to Preqin (2014), LPs are increasingly considering investment opportunities in the secondary market. This serves, to some degree, as a solution as willing sellers are bought out while GPs get a new injection of capital to the fund.

As a consequence of the uncertainty relating to the realization of remaining assets, zombie funds are hard to price in a secondary market. The problem is the clear incentive for the GPs to hold on to investments to collect management fees, which may give the incentive to overstate the value of their assets. It has been argued that zombie fund managers state unrealistic high values on their remaining assets (Pulliam and Eaglesham, 2012). This can make it hard for an LP invested in a zombie fund to trade his stakes. Furthermore, secondary trades of stakes in zombie funds tend to sell for 30 - 40 % less than what the GP team valued the assets at (Pulliam and Eaglesham, 2012).

The secondary PE market still has some limitations that may contribute to the challenges of secondary zombie trades. However, 15 % of LPs interviewed by Preqin (2014) considered this secondary market to be of core importance in their PE portfolios. 33 % of these respondents also stated that investments in the PE secondary market are of increasing importance in their portfolios. This may be an indication that more and more LPs view secondary PE transactions as part of their investment strategy.

4. Theory on Diversification and Performance in Private Equity

In this section we will look at theory behind diversification and return in PE.

4.1 Diversification

A portfolio is a grouping of investment vehicles owned and controlled by an investor or organization. Diversification is a risk management technique that involves infusing a variety of different investment classes within a portfolio. Different asset classes have different risk and return profiles, and thus perform differently under various economic circumstances. The rationale behind diversification is to adapt and optimize the relationship between risk and return, thus improving investment results. A portfolio of different kinds of investments will, on average, yield a higher return and expose the investor to less risk than any of the individual investments held in a portfolio. There are several factors to consider when trying to achieve the desired effect of diversification within PE. Two of the most crucial factors are GPs ability to select the appropriate portfolio companies and investors accessibility to the best funds. Previous research suggests that successful manager selection is the strongest contributing factor to above-industry returns (Nygård and Normann, 2008).

4.1.1 Diversification and Private Equity

One should differentiate diversification with PE as part of a broad portfolio of many asset classes from diversification within PE funds. Both of these techniques are discussed below.

An investor who includes a portion of PE in an otherwise well-diversified portfolio does so to move closer to the efficient frontier of risky assets, i.e. the graphical representation of the risk-return tradeoffs for different portfolio compositions. PE seems to display a modest correlation to public equities, which would imply a diversification benefit by allocating a portion of one's portfolio to PE (Fort Washington, 2006). Meyer and Mathonet (2011), on the other hand, argue that this is not necessarily the case as data for PE investments is relatively deficient because of their private nature. They suggest that conservative valuations, the scarcity of available data (due to the lack of transparency) and a rather inefficient secondary market make such correlation calculations imprecise. Investments in portfolio companies will in principle depend on general market conditions such as economic cycles, regulations, trading regimes, whether the timing is good for IPOs etc. These conditions point to at least some degree of correlation between PE and public equities (Nygård and Normann, 2008).

Gompers and Lerner (2001) find that adding PE to a portfolio shifts the efficient frontier towards higher return accompanied by lower risk. Fort Washington (2006) further demonstrates that adding 5% to 10% PE exposure to a portfolio will increase expected return while reducing the risk exposure. There are, however, several factors to consider in this diversification decision. The part of a total portfolio allocated to PE should not be too big as one risks becoming under-diversified and exposing oneself to great liquidity risk. The absolute size of the PE part of the portfolio must also be taken into account as too large or too small amounts may have advantages and disadvantages. Furthermore, it is crucial to consider what a PE investment will contribute to a current portfolio. If, for instance, the investor does not have enough capital to invest in PE without it affecting the rest of the portfolio, adding a portion of PE may not lead to the desired effects. PE investments require large capital outlays, a relatively long time horizon and access to the top quartile funds and GPs. Investments in PE may thus be demanding for a private investor. A solution for private investors is to invest in funds of funds (Fort Washington, 2006).

One way a PE fund can diversify its portfolio is by including several portfolio companies. Merely adding companies to the portfolio, not necessarily from different industries, can be considered the most primitive way of diversifying. This is called “naive diversification” (Lossen, 2006). The fund can increase its diversification further by spreading the investments over a time dimension, called dynamic diversification. Moreover, Lossen (2006) mentions three ways the PE fund can reduce risk while taking company characteristics into consideration (systematic diversification): by diversifying across financing stages, industries and/or countries.

According to Ljungqvist and Richardson (2003) PE funds only diversify to a limited extent with respect to the number of portfolio companies held in their portfolios. The average number of portfolio companies is found to be 16.1 for BO and 37.3 for VC.

This is a seemingly large difference, but could be explained by the considerably higher risk of investing in VC compared to BO and the fact that a BO investment usually consists of a substantially larger capital amount than VC. Furthermore, diversification with respect to different industries is found to be low compared to public equity funds. PE funds have, to a great extent, a tendency to give more weight to one dominant industry in their portfolio. Ljungqvist and Richardson (2003) find that the average PE fund invest close to 40% in one specific industry.

Considering the fact that PE funds are acting as active owners in their investments, high expertise and competence is required within the markets and businesses in which the portfolio companies operate. Seeking to add as much value to their portfolio companies as possible, and in this way providing high returns to the investors, PE funds often specialize with respect to certain financing stages, industries and geographic areas. Therefore, achieving a high degree of diversification is problematic for these types of funds (Lossen, 2006).

4.2 Performance in Private Equity

Financial assets are typically divided in two groups; listed securities and unlisted securities. Listed securities, such as stocks and bonds, are instruments listed on a public exchange. As listed securities are constantly traded in the market, measuring performance is a relatively simple matter. Assuming efficient markets, observed market prices represent the market's perceived underlying value of the given asset. Therefore, the historical return of listed securities can be measured based on observed market prices over a certain time period. The risk of the same instruments can be measured as the standard deviation of such a series of observations based on the same time period. In short, returns are calculated as the ratio between the price at the beginning of the investment period and the price at the end of the investment period. It is also possible for investors still holding securities to calculate unrealized returns using the same method. Investors may also view the returns as average periodical returns, e.g. yearly returns. These averages can be calculated both as an arithmetic average and as a geometric average, the latter usually being preferred as it takes into account the compounded interest effect.

Unlisted securities, such as PE and real estate, are instruments not listed on a public exchange. Unlike stocks and bonds, PE investments extend over a long time horizon, with the typical fund lifetime of ten years and possible extension of two years (Phalippou and Gottschalg, 2005). Furthermore, PE investments have low transaction volumes due to the lack of a well-established and functioning secondary market. Given that PE portfolios are not frequently traded, market prices to appropriately calculate periodic returns do not exist (Kothari et al., 2012). It is therefore not possible to use the most common methods as described by standard financial theory to measure PE risk and return. We will now describe the most common techniques used to measure the performance of PE funds.

4.2.1 Performance Measurement in Private Equity

There are three common performance measures used in the PE industry: internal rate of return (IRR), public market equivalent (PME) and multiple values (Kintel and Knudsen, 2014).

4.2.2 Internal Rate of Return (IRR)

IRR is the discount rate that gives a net present value (NPV) of a series of (positive and negative) cash flows equal to zero (Ellis et al., 2012). IRR is the most commonly used performance measure for PE and is mathematically represented by:

$$NPV = 0 = \sum \frac{C_i}{(1+r)^i}$$

Where NPV is net present value, C_i is net cash flow in the period, and r is the calculated internal rate of return

The internal rate of return represents the average return on invested capital, given all cash inflows and outflows. IRR is normally measured as a net of fees or gross of fees rate. Gross IRR is calculated using cash flows between investors and funds before the deduction of management fees, carried interest and other fixed costs. For net IRR calculations, the same cash flows are used, but management fees, carried interest and other fixed costs are subtracted. Net IRR provides a better measure of the investment return as it represent the actual cash flows taken place between the fund and the investor. Realized IRR is calculated after the liquidation of the fund and is the most credible measure as it is based on historic figures.

According to Clausen (2007) there are four main reasons why IRR is well suited to measure performance within PE. First is the lack of an efficient secondary market for PE fund units. PE fund investments are less frequently traded in the secondary market than listed securities. The lack of continuous transactional market information makes periodic returns unavailable as a measure of performance. Second, IRR takes into account the cash flow profile of PE. Investors will experience a varied cash outflow as the fund draws in capital and a stream of inflowing capital as the fund realizes its investments. These cash flows are not known ex ante. Third, IRR accounts for the reinvestment effect and the time value of money. In order to provide a sensible picture of fund performance one needs a measure that, given all disbursements and receipts, calculates reinvested average returns (per period) over the total lifetime. The time value of money is included since IRR, by definition, is the discount rate that gives a net present value of zero. Last, contributed capital is considered fixed. The GPs will have total control over the capital amount injected into portfolio companies at any time. Committed capital is thus considered as fixed even though it in practice is paid in tranches. It is therefore recommended to use a cash-weighted return as performance measure for closed PE funds, a requirement satisfied by IRR (Clausen, 2007).

4.2.3 Interim IRR

PE funds are usually long-lived and interim IRR is used as a performance measure for non-liquidated funds. Interim estimates of return are based on an appraisal of expected future cash flows. As such, interim IRR represents an estimate and not actual realized return (Ellis and Steer, 2011). To calculate interim IRR, the portfolio's net asset value (NAV) must be assessed:

$$NPV = 0 = \sum_{i=0}^{I} \frac{C_i}{(1+r)^i} + NAV_I$$

Where NPV is net present value, C_i is net cash flow in the period, r is the calculated internal rate of return, and NAV_I is the estimated net asset value.

NAV is based on the expected present discounted sum of future cash flows, and is such a subjective value, making interim IRR an uncertain estimate during the first years of the fund's life. Once funds are sufficiently mature, usually after four to six years, no evidence of systematic over- or under-valuation across a sample of UK funds can be found (Ellis and Steer, 2011). Interim IRR typically approaches actual IRR at the end of the fund's life because the subjective value of future expected cash flows then constitutes a smaller part of the IRR.

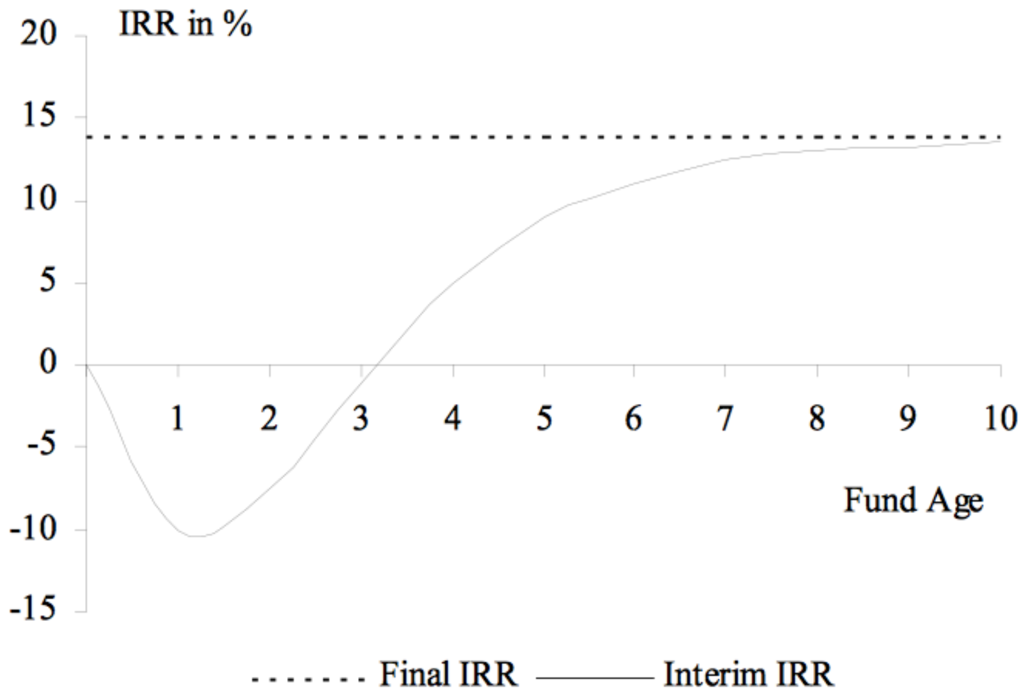

Figure 5: Typical evolution of realized IRR and interim IRR (Burgel, 2000)

An alternative is to use the price of a recent investment to calculate NAV. This method can be used when the investment being valued was itself made recently. The cost of the recent investment will usually provide a good estimate for the fair value of the investment. Contrary to NAVs calculated using expected future cash flows, the validity of this estimate will decrease over time (IPEV, 2009).

4.2.4 The J-curve

As already suggested, one must distinguish realized IRR and interim IRR. Previous research tries to eliminate data from unrealized funds, or at least the data from sufficiently young funds, when analyzing PE historical returns (Clausen, 2007). This is particularly important since the majority of fund earnings are realized in the last part of the fund's life. The early stages of any investment period will be characterized by cash outflows, thus the low interim IRR of young PE funds will unjustly lower the average return of the industry. The problem is that the residual value used in the interim IRR calculation does not necessarily reflect the actual values in the fund, and may give a false expectation of the future.

PE investments show particular cash flow and return attributes known as the J-curve. Every stage of a PE investment will have an effect on the fund's cash flow. The investment phase is characterized by negative cash flows, but as soon as the fund starts to generate earnings and distribute capital to investors, positive cash flows are obtained. This pattern is illustrated by J-curve, named after the graphical representation of interim IRR from fund inception to termination. An important factor to consider is that the curve shows cumulative interim IRR and not interim IRR for any specific year.

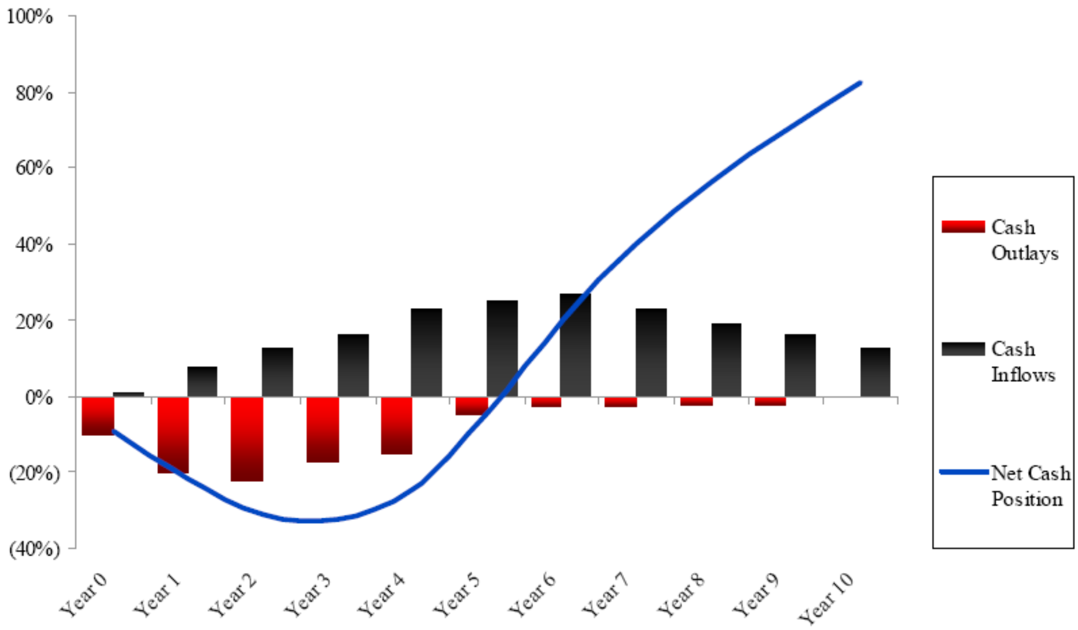

Figure 6: The J-curve effect of PE (Wikipedia, 2015)

The NAV will initially be valued at the cost of the investments made by the fund, while advisory fees, start-up and other fixed costs are paid continuously. Additionally, loss-bearing investments, especially in the VC area, will be recognized as an impairment loss. The first years of a fund will thus be characterized by negative interim IRRs. This negative pattern will be present until the fund starts to realize investments and the return increases. According to Burgel (2000), it is only after three to five years that interim IRR can provide a reasonable indication for the final IRR. After seven to eight years it is unlikely that significant changes in interim IRR will materialize. Towards fund termination, the interim IRR has a tendency to converge toward the finally realized IRR.

4.2.5 Advantages and Drawbacks of IRR

The advantage of IRR, and the main reason why it is normally used as a performance measure in the PE market today, is that it somewhat solves the issue of the cash flow structure in a PE fund. As the GP calls capital when it is needed and 'randomly' distributes it, other performance measurements used in other financial assets, such as stocks, become troublesome to apply.

Berk and DeMarzo (2013) list three general pitfalls one should beware of when evaluating IRR as a performance measure; delayed investments, multiple IRRs and nonexistent IRR. Delayed investments are investments represented by a positive cash flow first, followed by negative cash flows. This is not relevant for PE funds as it is necessary with a cash outflow in the beginning of the funds lifetime for investing in companies. In some cases a project might have more than one IRR, i.e. the project's NPV is 0 for more than one discount rate. It is difficult to evaluate performance in these cases, especially if the cost of capital lies between the given IRRs. The third pitfall is the case of nonexistent IRR. The project might simply not have any discount rates for which the NPV is zero, thus NPV will always be either negative or positive.

In addition to these pitfalls, Phalippou (2008) points to four issues with IRR in a PE context. First, as timing of the cash flows can significantly influence the IRR, the GP can use this to their advantage, for example earlier exits at the expense of total return for the investors. Additionally, by pooling funds together the GP is able to 'hide' poor performing funds (with negative IRR) as the pooled group may present a good IRR even though, if separated, only one of them has a positive IRR. A third issue is related to the reinvestment assumption. For IRR to be a proper performance measure, the intermediary dividends must be reinvested at the IRR rate. If not, the IRR will overstate (if positive) or understate (if negative) the effective return, thus give an exaggerated picture of the volatility of performance. Furthermore, using IRR will lead to upward-biased average performance measures. Last, GPs, incentivized by 'kick-backs', will be tempted to adjust cash flow amounts.

4.2.6 Modified IRR

Phalippou (2008) argues that using modified IRR (MIRR) is a better solution than the simple IRR. In calculating MIRR the cash flows are broken down to distributions (positive cash flows) and contributions (negative cash flows). All the contributions are discounted to a single present value with a given discount factor and all cash distributions are assumed to grow to a single future value at a given reinvestment rate (Kocis et al., 2010). Calculating the MIRR will then be an easy matter using the following formula:

$$MIRR = \sqrt[i]{\frac{\left(FV(Positive\ cash\ flows, reinvestment\ rate)\right)}{-PV(negative\ cash\ flows, finance\ rate)}} - 1$$

Where MIRR is modified IRR, i is number of periods, FV is future value, and PV is present value.

Assuming a reinvestment rate or looking at how the cash is actually invested by the investor will in most cases lead to a more conservative and correct picture of the actual return.

An argument against using MIRR is often that knowing which funds are performing well, the investors can reinvest the dividends in these funds, in which case the IRR will provide a correct image of the return. However, Phalippou (2008) argues that, for high performing IRR-funds, picking and reinvesting in equally good funds is simply unrealistic. Furthermore, computing MIRR on the investors track record, will take this ability into account.

Another valid argument against MIRR as a performance measure for PE funds is the fact that the reinvestment rate is not within the GPs reach. Therefore one can argue that it is not a good measure of the fund's performance, even though it might provide a good picture of the investor's return. Another drawback is that MIRR assumes that the cash is invested at the reinvestment rate during the expected lifetime of the fund, even after all portfolio investments are liquidated. This can be solved by using isolated MIRR (IMIRR), similar to MIRR but calculated only over the funds ‘active’ lifetime. (Ellis et al., 2012)

4.2.7 Average IRR, Weighted IRR and Pooled IRR

Several methods exist for calculating the return of the PE industry as a whole, with the average IRR being one. This measure assumes an equal weight of all funds regardless of fund size and capital amount, and will therefore not give an accurate impression of the overall industry performance. In order to solve this challenge, a weighted IRR could be used. Weighted IRR, on the other hand, does not account for the different time periods of the money at work. A solution could be the use of an overall IRR, called pooled IRR, constructed by collecting monthly cash flows of all funds and calculating the IRR based on the industry net cash flow. This method entails perceiving each individual fund's cash flows as part of one large entity (Kintel and Knudsen, 2014).

4.2.8 Multiples

The use of multiples is a completely different way of looking at PE returns than the IRR. It should be used as a supplement to IRR. This method consists of creating ratios between different values and provides insight to a fund's development. Multiples used for PE fund returns are Distributed over Paid In (DPI), Paid In to Committed Capital (PICC), Residual Value to Paid In (RVPI) and Total Value to Paid In (TVPI) (Fraser-Sampson, 2011). It is important to note that these multiples are restricted to analyzing fund returns and not the returns of individual transactions.

4.2.9 Distributions over Paid In (DPI)

Distributed over paid in (DPI) is a ratio of cash distributed back to the investor over cash paid in from the investor. This is usually a good measure towards the end of the fund's life, as most of the values at this point should be realized (Fraser-Sampson, 2011). This ratio is also called the realization multiple (Kocis et al, 2010).

$$DPI = \frac{Cumulative\ distributions}{Cumulative\ paid\ in\ capital}$$

4.2.10 Paid In to Committed Capital (PICC)

PICC is not a measurement of the funds performance but rather a multiple describing how much the LP's have paid in, i.e. how much the GP has invested, relative to how much is committed. This can be useful in considering whether the fund is having trouble putting all committed capital to good use. (Fraser-Sampson, 2011)

$$PICC = \frac{Cumulative\ paid\ in\ capital}{Committed\ Capital}$$

4.2.11 Residual Value to Paid In (RVPI)

RVPI measures the unrealized values in the fund compared to the paid-in capital and is therefore often referred to as the unrealized multiple. This provides insight to how the fund has created value before liquidating their investments and distributing the cash to the investors. (Kocis et. al, 2010, Fraser-Sampson, 2011)

$$RVPI = \frac{Valuation}{Cumulative\ paid\ in\ capital}$$

Where Valuation is the value of the fund's remaining investments.

4.2.12 Total Value to Paid In (TVPI)

By combining DPI and RVPI as described above, we get TVPI. TVPI is a measure that considers both the distributions and the residual values in the fund over paid in capital by the investor. This multiple is the most common to look at in the PE market as it provides the better picture of the funds total performance during its life. (Kocis et. al, 2010, Fraser-Sampson, 2011)

$$TVPI = DPI + RVPI = \frac{Cumulative\ distributions + Valuation}{Cumulative\ paid\ in\ capital}$$

4.2.13 Advantages and Drawbacks of Multiple Values

The essential advantage of multiples is that they are uncomplicated and easy to use. PE funds will typically use multiples to give investors an indication of the returns of individual investments. A multiple value greater than one signals value creation. For instance, a multiple of 1,5 means a 50 % return on investment (Ellis et al., 2012). Another advantage is that multiples can be a good measurement of total value creation before final liquidation, especially through TVPI (Kocis et al., 2010).

The most distinct drawback of the multiple method is that it takes no account of the timing of drawdowns and distributions over the fund's lifetime, thus neglecting the time value of money. A multiple will not provide an indication of how time effective investments were made. For example, a multiple of 1,5 delivered over a ten-year span does not demonstrate an especially strong achievement, in terms of the implied geometric annual return (Ellis et al., 2012). Therefore, an investor should know the investment duration when analyzing fund performance using multiples. Another critique concerning this method is the fact that little information about the underlying risk profile is provided to investors. However, this challenge applies to other measures of return for PE funds and other non-traded assets as well.

4.2.14 Public Market Equivalent (PME)

The public market equivalent (PME) is a measure that helps investors compare returns across different asset classes. Given the nature of the IRR, it is not convenient to match it to more standard measures of return used for stocks and bonds. PME is a measure that makes it appropriate to compare IRRs to public markets. This technique allows investors to match IRRs with returns yielded by public markets over the same timing of cash flows.

Kaplan and Schoar (2005) introduced PME, which is an alternative measure of return based solely on cash flows. The method is an expanded version of TVPI where the fund is compared to a market index. An earlier, but slightly different measurement method that also used to be called public market equivalent, was introduced by Long and Nickels (1996). As proposed by Long (2008), this method now goes by the name ACG Index Comparison Method.

By discounting the cash flows with public market returns, e.g. S&P 500, across the same time period, we can find the PME, reflecting the PE return relative to other investment vehicles (Kaplan and Schoar, 2005). PME estimates the cash flows between the fund and LPs. These cash flows are separated into positive and negative cash flows, called distributions and capital calls. Distributions are cash flows, net of fees, returned to the LPs by the fund. Capital calls are LPs investments into the fund, including management fees. Distributions and capital calls are then discounted by the realized market return over the equivalent time period, and PME is the ratio between these two figures:

$$PME = \sum\nolimits_t \frac{\frac{dist(t)}{1 + r_M(t)}}{\frac{calls(t)}{1 + r_M(t)}}$$

Where dist is distributions, r_M is the realized market return from fund inception (t=0), and calls is called capital.

This way LPs can easily see how their funds would have performed if they had invested differently. The two main asset classes that PE fund performance is compared to are fixed income securities and public equities (Ellis et al., 2012). It should be put some thought into deciding which index to use in the PME calculation as different funds are comparable to different indices. It might, for example, be natural to use S&P500 as a benchmark for some funds, but NASDAQ or OSEBX for other funds. Using an inappropriate index as comparable might give a misleading picture of a fund's performance (Kocis et al., 2010). For the two most essential asset classes it is usually appropriate to use ‘total return’ indices, which accounts for coupon payments and dividends. Previous research by Gottschalg et al. (2010) suggests, however, that PE fund performance can be driven by sector selection. If this is the case, the investor may wish to use the PME method not based on an index as a whole, but compose a specific and representative index of the related industry mix.

A prerequisite for the PME to measure the true risk-adjusted return has been that the β must be equal to 1. Specifically, it will be overstated if the beta is higher than 1, i.e. higher risk compared to the market, or understated with a beta lower than 1 (Kaplan and Schoar, 2005). According to Sorensen and Jagannathan (2013) however, given three assumptions, it is not necessary with a beta equal to 1. These assumptions are frictionless market and the ”law-of-one-price,” that the LP has a log-utility, and that the LP's wealth portfolio grows at the public market return. Hence, they argue that with these neither very controversial nor restrictive assumptions, PME can be considered a good performance measure independent of the risk.

4.2.15 Advantages and Drawbacks of PME

Unlike IRR, the PME does not include an underlying assumption that distributions are reinvested in any particular way. Another advantage is that PME is robust to the timing of cash flows. With IRR, the GP can manipulate the performance figure by the timing of cash flows, but this type of behavior will not affect the PME. (Sorensen and Jagannathan, 2013). Additionally, it is a measure easy to interpret. A PME greater than 1 tells us that the PE fund has achieved good returns relative to the comparable index, whereas a PME lower than 1 indicates a poor performance relative to the index (Kaplan and Schoar, 2005). However, this interpretation may not always be accurate, due to the interaction between the timing of the cash flows and the timing of the market returns.

There are several drawbacks related to the PME method. A potential problem in the calculation of PME is caused by the usage of realized returns. The amount of noise of these returns can be significant and may lead to highly misleading PME figures. As such, PME can be subject to manipulation. Furthermore, while IRR and PME are comparable, the two measures still contain different characteristics. For example, PME makes no adjustment for the illiquid nature of PE investments. Moreover, these are absolute measures of performance, and do not advise the investor on how to allocate capital among different asset classes (Ellis et al., 2012).

5. Previous Research

There are certain factors that must be highlighted when evaluating previous research. It is, for instance, important to be aware of the kind of data the results are based on and what strengths and weaknesses this data contains. A predominant challenge when analyzing PE performance is the limited availability of data. Unlisted companies are not legally obligated to report performance data, thus research must be based on voluntary reporting by PE funds.

A potential weakness of research based on databases with voluntary reporting (such as Preqin and Thomson Reuters) is the lack of ability to check whether the reported figures are correct. Many of these databases do, however, require performance reporting by both GPs and LPs, to facilitate detection of any manipulation.

We will now give a brief description of some previous studies on zombie funds.

5.1 Robinson and Sensoy, 2012

Robinson and Sensoy (2012) (hereafter R&S) use a proprietary, confidential dataset gathered from a large, institutional LP with extensive investments in PE. Their sample consists of 837 PE funds with vintage years ranging from 1984 to 2009. The funds included are U.S. located funds. They represent 34,4 % of the VC pool and 55,7 % of the BO pool over this time period, and can thus be said to account for a significant portion of the documented PE-universe. The representativeness of this sample can be a concern as the information is obtained from one single LP. R&S compared the data to that of commercially available databases (such as Preqin and Cambridge Associates), without finding evidence that the performance of BO funds differ significantly. However, the performance of VC funds is somewhat below that reported in commercially available databases.

R&S investigate if there is a connection between the fee structure of PE funds and the incentive to exit investments late. They find that incentives for delayed exit arise when the basis for the management fee changes to be based on net invested capital at some point during the fund duration, which it does for a third of the funds included in their dataset. This means that management fees are calculated on the ground of total equity investments minus the cost basis of realized, exited investments. One rationale behind this fee basis is for LPs to avoid paying fees for investments that are no longer managed by the GPs. However, this fee structure means that exiting investments will reduce the base of capital on which GPs earn management fees, giving incentives for delaying liquidation and holding on to zombie investments. According to R&S, no systematic evidence exists on whether GPs actually behave this way. They find evidence that funds whose fee basis changes from committed capital to net invested capital are indeed more likely to exit investments later.

5.2 Migliorini, 2014

Migliorini (2014) (hereafter M) used data from Preqin and further drew on insights from interviews with LPs and service providers such as lawyers and placement agents for his research. Unfortunately, M does not state the number of interviews conducted, so little can be said about the strengths and weaknesses of this information. A possible validity problem can arise if too few interviews were included, and if these were influenced by highly subjective opinions.

M's research is aimed at providing an overview to be used by both GPs and LPs facing the issues of zombie funds. M finds that zombie funds are a sharply increasing phenomenon that brings along a number of problems. Chief among these issues, M states the lack of resources to execute a fund's mandate, misalignment of interests between GPs and LPs, and capital trapped in non-performing funds. He further goes on to list possible long- and short-term solutions to the misalignment of interest problem, which is discussed in detail in the previous ‘agency problems in PE’ section.

M found the financial crisis of 2007-2008, in addition to the record fundraising in the GP community leading up to the crisis paired with reduced capital allocation following the crisis, to exacerbate the zombie fund issue.

According to M, the main issue brought about by zombie funds is the GP incentive to keep non-performing funds alive to squeeze as much money out of it as possible. This is achieved through the continuance of charged management fees, and may not be in the best interest of the LP. The short term solutions discussed in the ‘agency problems in PE' section is aimed at resolving conflicts of interest once a zombie situation has materialized. M lists the long-term solutions as a guide for avoiding investing in a potential zombie fund. Interestingly, the interviews conducted by M showed that LPs do not necessarily show more involvement despite the sharp rise in the number of zombie funds for the last five/six years. The stated reason being that LPs do not have the time and resources to deal with zombie funds given the relative size of their exposure and the reputational damages that may follow an intervention.

5.3 Pedersen and Sand, 2014

Pedersen and Sand (2014) (hereafter P&S) base their research on two databases of PE funds with vintage years from 1998 to 2007 and from 2008 to 2014, both extracted from Preqin. Their data is restricted to only include Nordic private equity funds. More specifically, funds with headquarters in the Nordic region are included, regardless of where their investment focus lies. P&S state that well performing funds will have incentives to report performance data, while poor performing funds will not. To prevent any consequently bias in their research, they use different exit types as a measure of a fund's success (e.g. IPO or trade sale etc.). They claim that this prevents any violation of the random sampling assumption in their regression analysis.

266 Nordic PE funds are included in P&S's research. They apply the same zombie fund definition as Preqin to identify 80 potential zombie funds in the included sample. This constitutes a 30,1 % of the included funds.

The 80 identified potential zombie funds amounts to $4 365 bn worth of PE assets in terms of committed capital. P&S further observed two periods, in terms of vintage distributions, with a significant increase in the number of zombie funds. These periods were the leads up to the dot-com bubble of 2000 and the financial crisis of 2007-2008. Another finding was that the majority of the identified zombie funds were VC funds, but also a significant amount was BO funds. Moreover, P&S found that Iceland and Denmark are small players regarding the number funds raised between 1998 and 2007 that later turned zombie, while zombie funds are evenly distributed in Norway, Sweden and Finland.

P&S further found that zombie funds are a significant and increasing problem in the PE industry. They are characterized by inferior performance and most frequently strikes funds with a small amount of committed capital.

5.4 Summary

Empirical research on zombie funds is limited. Literature and empirical research focusing explicitly on zombie funds is scarce at best. What can be agreed upon is that zombie funds have emerged as a PE industry problem with great potential ramifications. We therefore wish to provide insight into this field by providing descriptive statistics on global zombie fund effects.

6. Methodology

Research builds on curiosity and the search for further knowledge on a given topic. Scientific research is the method of collecting data to derive information, for the purpose of using this information to aid rational decision-making. The research process typically consists of four steps: planning, acquiring, analyzing and disseminating relevant data (Sachdeva, 2009). This section elaborates on the tools we have used to describe and analyze the relevant data. We will now describe the preparation and data collection phase, as well as an analysis of the included dataset. Furthermore, we will present reliability and validity, in addition to some potential biases of the research. Lastly, the methods used for analysis will be defined.

6.1 Research Design

It is important to clarify the purpose of the study before preparing the research design. This research is mainly related to personal goals as we have developed a great interest in the field and want to learn more about PE zombie funds. There is limited empirical research on this phenomenon and we wish to investigate the global PE zombie fund market. Recent interviews show an increased awareness among institutional investors related to zombie fund problems, a problem that has seen a rapid growth since the in the recent years (Pedersen and Sand, 2014). Despite this growing attention, research that mainly focuses on zombie funds is scarce. We therefore wish to complement the existing literature on this exciting subject.

This study will focus on the hypothetico-deductive model where research proceeds by formulating a hypothesis that can be falsified by a test on observable data. The hypotheses can be based on assumptions, calculations and intuition. We will use calculations based on market data and intuition to established hypotheses. The issues will then be tested with empirical data to either refute the original hypothesis or strengthen it. It should be noted that this method cannot confirm any hypotheses, only enhance them. As it proves difficult to confirm a scientific theory no matter how large amounts of data one has (Popper, 2012), these tests will focus on finding debilitating evidence. It is desirable to be able to generalize any potential findings.

We wish to examine the performance of zombie funds based on historical data. We will use both cross-sectional surveys and panel data. Cross-sectional studies are used to compare differences among subjects at a given point in time, and can provide information on variations between zombie funds distinguished by different characteristics such as fund type and size. Analysis with panel data deals with cross-sectional time series. Data is collected over time and on the same subjects before a regression model is run over both dimensions, which can provide insight on zombie fund performance.

6.2 Data

There are two main sources of data for quantitative research, primary sources and secondary sources. The researcher collects primary data through methods such as surveys, direct observations, interviews and logs. Obtaining primary data may yield more reliable results, as the researcher has obtained and analyzed the data himself, securing quality. Secondary data is edited primary data, which is already available in journals, books and databases. Secondary sources can contain valuable information, but one should think carefully about what information one is looking for before starting the actual query as this data was collected for another purpose than the problem at hand (Sachdeva, 2009).

We have chosen to use secondary data from the Preqin database. More specifically, data is obtained from four databases within Preqin: Funds in Market, Fund Manager Profile, Performance Analyst and Investor Intelligence. Our population represents all zombie funds globally, of which our sample is limited to the data reported to Preqin. The ideal criterion for sample selection is to reflect the total population in a correct manner, so that the results found from the sample can be inferred to represent the entire population (Lewis et al., 2012).

Preqin has since its founding in 2003 been the leading source of data and intelligence for the alternative asset classes industry (Preqin, 2015b). More than 24 000 professionals in over 94 countries use their products and services. PE is one of the asset classes that Preqin provides data and information on, with said data encompassing the following areas: fund and fundraising, performance, fund managers, institutional investors, deals and fund terms. We chose Preqin as its data reaches back to 1980 and contains information on over 20 000 of PE funds worldwide. Preqin has, compared to competitor benchmarks, more than 1 000 additional funds reporting data (Preqin, 2013c).

Preqin gathers performance data through two methods; directly from GPs and through the Freedom of Information Act - which allows data collection directly from LPs. Each of these methods accounts for 50 % of the gathered data (Preqin, 2013c). Since reporting is done on a voluntary basis, the data material may contain biases. GPs will not have incentives to report results when funds perform poor. LPs, on the other hand, are not subject to the same incentive and their reporting may to some degree neutralize this effect. This will be discussed in more detail in the reliability section.

6.3 Reliability and Validity

It is important that published results from any research can sustain investigation and verification. This applies to all aspects of the research, including sources used, methods used and conclusions reached. Reliability and validity are two concepts with the aim of ensuring quality and accuracy of the research. These two concepts will be examined below:

6.3.1 Reliability

Reliability is critical in quantitative research, and provides an indication of how reliable and accurate the data is in relation to collection and processing. Reliability is thus based on measurement precision or measurement error - which should be minimized to the highest degree possible. This concept refers to whether your findings are consistent if the same collection techniques and analytic process is repeated or replicated by another researcher (Lewis et al., 2012). Good reliability is present if the research yields the same findings each time it is used, regardless of who performs it. Information about reliability is important because it indirectly indicates what weight can be attributed to the results (Nygaard and Normann, 2008).

According to Preqin, there is no selection bias in the reported data as it is gathered from both GPs and LPs, to make sure the benchmark will not be too heavily influenced by either request. It has been suggested that the requirement of reliability can, to some extent, be difficult to satisfy with respect to databases containing selection bias. Kaplan and Schoar (2005) believe that funds performing extraordinary good or bad will have little motivation to report their results. They do, however, fail to confirm these hypotheses through research and cannot conclude whether GPs actually behave this way. Funds with low or negative returns will not wish to report results as this may lower the chances for collecting follow-on funds. If this is indeed the case, it will create a positive or negative bias in average returns. Kaplan and Schoar (2005) believe that if there is a bias, it would most likely take the form of underreporting by the worse performing funds. Given the relationship between zombie funds and performance, which we will address later in this thesis, it is reasonable to assume that most zombie funds are among the poor performers. According to the previous rationale, this suggests that GPs operating zombie funds have little incentive to report performance data. LPs, on the contrary, do not share this view, as they are not concerned with raising additional funds.

6.3.2 Validity

Validity indicates the extent to which the data represents the phenomenon one wants to measure. It is the degree to which the data measures what it claims to measure. Three forms of validity have been identified to secure the quality of research: construct validity, internal validity and external validity (Lewis et al., 2012).

Construct validity regards the extent to which research measures actually measure what they intend to estimate. This is a highly relevant concern regarding empirical research. An important question is therefore whether the data obtained from Preqin can be used to evaluate zombie fund performance. Construct validity is a typical measure phenomenon and can therefore not be viewed as absolute, but rather as a quality requirement approximately fulfilled (Kintel and Knudsen, 2014). More precisely, we never know whether this validity is obtained and how big a problem it poses. The assessment is in some instances done using common sense, which is referred to as 'face validity'. We have obtained performance data on zombie funds from the global market set up against hypotheses concerning performance of zombie funds in the same market.

Harris et al. (2013) suggest that when data is obtained from GPs, or at least in part from GPs, it is possible for GPs to strategically stop reporting and cause the results to be out of date. It would be optimal with performance information on more of the zombie funds found in Preqin. Of 1 274 identified zombie funds, recent performance data is found for only a part of them. Some funds do not report at all, while other funds have not reported for several years. Furthermore, although Preqin has summary performance data (IRR and multiples), cash flow data can only be found for a subset of these funds. This is mainly obtained from public investors subject to the Freedom of Information Act (Harris et al., 2013). Access to cash flow information might provide higher quality data. Another possible negative aspect of the data may be that the results and characteristics of the reporting fund investors might deviate from the average investor, thus giving a false image of the industry (Kintel and Knudsen, 2014).

Internal validity, or measurement validity, is related to the causality between our variables, i.e. if we observe causal relationship between our variables. As this is a descriptive study, a causal conclusion cannot be warranted (Lewis et al., 2012).
External validity regards the extent to which the results can be generalized across time and space to relevant contexts (Lewis et al., 2012). Preqin's database is large and consists of funds from all over the world. Fund characteristics from other databases are similar across the world (Kintel and Knutsen, 2014), thus it is reasonable to assume that findings obtained from similar databases would provide comparable results.

6.4 Potential Biases

We will now discuss some potential biases of the data.

6.4.1 Omitted Variable Bias

This bias occurs when a relevant variable is omitted from a model. The model outcome can be biased if the omitted variable is correlated with the included independent variables, and if the omitted variable is a determinant of the dependent variable. This is typically a possible issue with any analytical model.

6.4.2 Sample Selection Bias

Sample selection bias occurs when one applies a non-randomly selected data for statistical analysis. This could be the case if only GPs reported data based on the reporting incentives discussed above. The result would lead to the use of a non-random sample that might not be representative of the entire population. As already mentioned, no research has been able prove that GPs act in a way to omit reporting for poor performing funds, and our dataset is collected from both GPs and LPs.

6.4.3 Survivorship Bias

Survivorship bias (also called survival bias) is the logical error that occurs when concentration is focused on the people or things that "survived" a process and overlooking those that did not due to their lack of visibility. This bias can lead to false results if those observations that did not "survive" are systematically excluded from the sample.

6.5 Methods of Analysis

We will now review the methods we have chosen for the analysis of zombie funds. The purpose is to provide an overview of what the various methods express and what assumptions underlie the use of them.

6.5.1 Multiple Regression

Regression is a dependency model, with the aim of explaining the variation in a certain variable as a function of explanatory variables. It is a statistical technique that attempts to explain the change in one variable, called the dependent variable, as a function of a set of variables called independent variables. An ordinary least squares (OLS) regression model can be written as:

$$Y_i = ß_0 + ß_1 X_{1i} + ß_2 X_{2i} + \cdots + ß_K X_{Ki} + \varepsilon_i$$

Y_i is here the dependent variable that we want to explain, and Y_i is supposed to be explained by the explanatory variables X_{1i} through X_{Ki}. ε_i express the stochastic error term. A regression model uses the variation in the independent variables to explain variation in Y_i. Any variation that is not explained by the independent variables is captured by the stochastic error term. The terms β_0, β_1, β_2 and β_K are called regression coefficients, and attempts to isolate the effect on Y_i of a change in one variable from the effect on Y_i of changes in other variables. β_1 will, for example, give the change in Y_i as X_{1i} increased by one unit. A major advantage of multiple regression is its ability to measure the effect a single variable has on Y_i when all other variables are held constant. The parameters of this model are based on the ceteris paribus assumption, to indicate that influence from other variables cannot be excluded (Aassve, 2011; Stock and Watson, 2012).

A regression analysis will not say anything about causality between two or more variables, it will only test the strength and direction of the quantitative relationship. Demonstration of causality is a logical and experimental problem, not a statistical one. It is thus important to be aware of the fact that even if regression techniques are employed, one will not necessarily get causal effects (Aassve, 2011). It is important to note that the result of a multiple regression is extremely sensitive to the combination of independent variables included in the analysis. A very important explanatory variable in regression estimation will depend on other explanatory variables chosen for the analysis. If the interesting variable is the only one explaining something important about the dependent variable, it will appear as crucial. If, on the other hand, the interesting variable is one of several variables with explanatory power, it will usually be perceived as less important (Pallant, 2005; Kintel and Knudsen, 2014).

6.5.2 Assumptions Underlying Multiple Regression

Gujarati (2003) gives ten underlying assumptions for the classical linear regression model (CLRM): the regression model in linear in the parameters, X_i is assumed to be non stochastic, zero mean value of disturbance, ε_i, homoscedasticity or equal variance of ε_i, no autocorrelation between the disturbances, zero covariance between the residual, ε_i, and the independent variable, X_i, the number of observations n must be greater than the number of parameters to be estimated, variability in X_i values, the regression model is correctly specified and there is no perfect multicollinearity. However, all these assumptions are not strictly necessary for consistent estimation of parameters. CLMR (OLS) needs one thing and that is orthogonality of residuals and regressors. The residuals serve as the unexplained variation in Y_i, and if they are not orthogonal to X_i more explanation can be extracted from X_i by a different choice of coefficients (Cottrell, 2011). One can never be certain whether this assumption is satisfied, however, it is assumed when running OLS regressions.

6.5.3 Generalized Least Squares Regression

Generalized least squares (GLS) regression is a technique used to estimate the unknown parameters in a linear regression model. If the variances of the observations are unequal (display heteroscedasticity) or if a certain degree of correlation is present between the observations, ordinary least squares (OLS) can yield inaccurate inferences. The move from OLS to GLS is thus a way to correct for autocorrelation (McGill, 2012). The difference of the two models is in the error term. More specifically, it is expected that the assumptions about the residuals are different. OLS gives the maximum likelihood estimate for β_i when the parameters have equal variance and is uncorrelated, and the error term is white. GLS allows the same approach to be generalized to give the maximum likelihood estimate of β_i when the error term is colored (heteroscedasticity). The GLS equation is identical to the OLS equation with the exception of the error term (McGill, 2012).

6.5.4 Assumptions Underlying GLS Regression

The main difference separating GLS from OLS is the property that residuals need not follow the same assumptions as those required for OLS analysis. GLS is as such a generalization of the OLS model that relaxes the assumptions that the residuals are homoscedastic and uncorrelated. GLS assumes that $Var(\varepsilon) = \sigma 2\Omega$, where the last term represents an n*n symmetric and invertible matrix. The diagonal elements of this matrix indicate the error variances for each case while the off-diagonal elements specify the error correlations for each pair of cases. All the other classical assumptions hold while heteroscedasticity and/ or autocorrelation is allowed for. (McGill, 2012)

6.5.5 Logistic Regression

Logistic regression, also called logit regression, is a test for analyzing a dataset in which there are one or more independent variables that determine an outcome. The outcome is measured with a dichotomous variable, i.e. a variable that only has two possible outcomes. The test aims at finding the best fitting model to describe the relationship between the dichotomous dependent variable and a set of independent variables (MedCalc, 2015). Logit regression generates the coefficients of a formula to predict a logit transformation of the probability of presence of the dependent variable.

6.5.6 Assumptions Underlying Logistic Regression

Logit regression does not require many of the key assumptions of linear regression, particularly those regarding linearity, normality, homoscedasticity and measurement level. However, some other assumptions still apply.

Assumption 1 - The true conditional probabilities are a logistic function of the independent variables.

Assumption 2 - No important variables are omitted. No extraneous variables are included.

Assumption 3 - The independent variables are measured without error.

Assumption 4 - The observations are independent.

Assumption 5 - The independent variables are not linear combinations of each other.

6.5.7 Kruskal-Wallis H-Test

The Kruskal-Wallis H test is a rank based nonparametric test that is used to test for statistically significant differences between two or more groups of an independent variable (Lærd Statistics, 2015), and is such an extension of the Mann-Whitney U test to allow for comparison between more than two independent groups. This test can be applied when one wants to compare three or more data series coming from different groups. For instance, this test can be used investigate whether attitudes towards pay discrimination differ based on job position. Attitudes should then be measured on an ordinal scale.

It is important to note that the Kruskal-Wallis test is an omnibus test statistic and therefore cannot tell which specific groups are statistically significant from others. It only tells that at least two groups differ from each other. As more than two groups are typically included for this test, it is important to be able to determine which groups are different. If the Kruskal-Wallis test indicates a difference, one can carry out a post-hoc test (Lærd Statistics, 2015). A post-hoc test compares two and two groups to determine whether differences exist between these groups.

6.5.8 Assumptions Underlying the Kruskal-Wallis Test

Assumption 1 - The dependent variable should be measured at the ordinal or continuous level, i.e. interval or ratio.

Assumption 2 - The independent variable should consist of two or more categorical, independent groups. The Kruskal-Wallis test is usually applied when one has three or more independent groups, but can also be used when one has two groups. However, the Mann-Whitney U test is more common to test for difference between two groups.

Assumption 3 - There should be independence of observations. This means that there should be no relationship between the observations in each group or between the groups themselves.

Assumption 4 - One must be able to determine whether the distributions in each group have the same shape (variability) in order to interpret the results.

6.5.9 Chi-square Test

A Chi-square test is applied when one has two categorical variables from a single population. The test is used to determine whether there is a significant association between these two variables. It could, for instance, be used to test for independence to determine whether gender is related to voting preferences. The Chi-square test is used to discover if there is a significant relationship between two categorical variables. The test compares the observed data to a model that distributes the data according to the expectation that the variables are independent.

6.5.10 Assumptions Underlying the Chi-square Test

Assumption 1 - The two variables should be measured at an ordinal or nominal level, i.e. categorical data.

Assumption 2 - The two variables should consist of two or more categorical, independent groups.

7. Characteristics and Returns of Zombie Funds

We will now look at different characteristics of zombie funds and how they perform. We first review zombie fund characteristics such as fund types, fund size, vintage years, region focus, fund location and industry focus. We then consider IRR and several multiples of zombie funds, before these measures are compared to those of PE non-zombie funds. Our data sample is collected from Preqin. As will be mentioned, not all identified zombie funds report performance. However, data concerning fund type, region focus, location and industry focus is disclosed for all zombies in our database and should not create the same potential for biasedness.

7.1 Zombie Funds

A total of 1 274 zombie funds were identified in the Preqin database. These are funds with vintage years ranging from 2003 to 2008 that have not successfully raised a follow on fund between 2009 and 2015. No liquidated funds are included in this sample. Liquidated funds are not active and thus fall outside the zombie fund definition. All the 1 274 funds are of status "closed", meaning that no further capital can be committed. Furthermore, funds in the categories Funds of Funds, Secondaries and Co-invest Multi-manager are excluded from the data set. This is because we only classify direct PE fund types as zombie funds. A PE fund of funds holds a portfolio of other PE funds rather than investing directly in portfolio companies. PE secondaries involve trading pre-existing investor commitments in PE. Co-investing means that one fund makes a minority investment directly into a company, alongside other PE funds. Multi-manager is another way of referring to funds of funds. Therefore, co-invest multi-manager cannot be included in the data set as a direct PE investment. These fund classes are clearly not direct PE fund types and are thus excluded from the zombie fund group.

A potential drawback of excluding funds that are liquidated within our sample period is the possibility of survivorship bias. It might be that by not including liquidated funds, we are not correctly tracking the performance of all funds. Instead, only those funds that remain active are tracked. In total, 93 funds are excluded as they are liquidated. Of these funds, we identify 26 funds that could be classified as potential zombie funds. However, we do not have information about the time of liquidation and cannot be certain as to whether these 26 funds should be included as zombies or if they are correctly excluded from the zombie group. Given the criteria of the zombie fund definition and above argument, we choose to include only active funds. This makes the presence of survivorship bias a possibility. Nevertheless, these funds represent only 2,00 % of our total sample of zombie funds. Note that this should be kept in mind when interpreting the results.

It should be pointed out that the identified zombie funds are more correctly classified as ´potential´ zombie funds. There is a possibility that some funds follow an abnormal strategic plan, e.g. an investment horizon exceeding the seven-year standard without plans of raising a successor fund. For convenience, we will simply label these funds as zombie funds throughout this thesis.

There is a range of different fund types found within the extracted zombie funds. The 1 274 funds can be distinguished into 18 different categories. The following table outlines the fund types and the number of zombie funds belonging to each of them. For convenience, we have chosen to gather similar fund types into larger groups. Early stage, early stage: seed and early stage: start-up are combined into one early stage group, consisting of 242 funds. Furthermore, venture (general) and venture debt is combined to represent 385 funds.

Fund Type	*Zombies*		*Non-Zombies*	
Balanced	33	2,59 %	68	2,32 %
Buyout	293	23,00 %	892	30,44 %
Co-investment	14	1,10 %	63	2,15 %
Distressed Debt	9	0,71 %	85	2,90 %
Early Stage	152	11,93 %	277	9,45 %
Early Stage: Seed	51	4,00 %	69	2,35 %
Early Stage: Start-up	39	3,06 %	69	2,35 %
Sum Early Stage	242	19,00 %	415	14,16 %
Expansion / Late Stage	70	5,49 %	94	3,21 %
Growth	120	9,42 %	297	10,14 %
Infrastructure	1	0,08 %	0	0,00 %
Mezzanine	52	4,08 %	181	6,18 %
Natural Resources	21	1,65 %	75	2,56 %
Real Estate	0	0,00 %	1	0,03 %
Special Situations	20	1,57 %	66	2,25 %
Timber	7	0,55 %	35	1,19 %
Turnaround	7	0,55 %	43	1,47 %
Venture (General)	380	29,83 %	594	20,27 %
Venture Debt	5	0,39 %	21	0,72 %
Sum Venture	385	30,22 %	615	20,99 %
Sum	**1274**		**2930**	

Table 1: Fund Types

As evident from the above table, the largest number of zombie funds can be found in the VC category. This type represents 385 funds, a figure amounting to 30,22 % of the identified zombie funds. This finding is true for the Nordic PE market as well, where a majority of identified zombie funds are VC funds (Pedersen and Sand, 2014). The second largest group of zombie funds is found within the BO type. 293 zombies are represented here, constituting 23,00 % of the total figure. The third largest category is the combined early stage group with 242 zombie funds, which is 19,00 % of the total figure. The last fund type containing a substantial number of zombie funds is growth. 120 zombie funds belong to this fund type, yielding 9,42 % of the total amount. For the rest of the fund types, the number of identified zombie funds is significantly lower. None of the remaining fund types show zombie funds exceeding 100. Mezzanine represents the largest number here, but its 52 zombie funds only amount to 4,08 % of all zombies. Infrastructure, timber, turnaround and distressed debt stand out as fund types where a particularly low number of zombie funds are represented.

The average zombie fund size is $233,75 mn, where BO funds are substantially larger (measured in committed capital) than VC funds with an average size of $403,12 mn compared to $123,42 mn. Early stage funds are on average smaller than BO and VC funds with mean committed capital of $80,03 mn. $181,69 mn is the average size of growth funds. It should be emphasized that fund size is a constant figure, i.e. it is based on final close of committed capital and is not affected by returns or distributions. Furthermore, paid-in capital does not affect our fund size variable.

Figure 7 shows the number of funds started in each of the included zombie fund required vintage years. The number of zombie fund start-ups is more modest in 2003, with a relatively stable increase in the years that follow until 2008. The global financial crisis of 2007-2008 represents the vintage years with the largest number of zombie fund start-ups, including 261 and 271 zombies respectively.

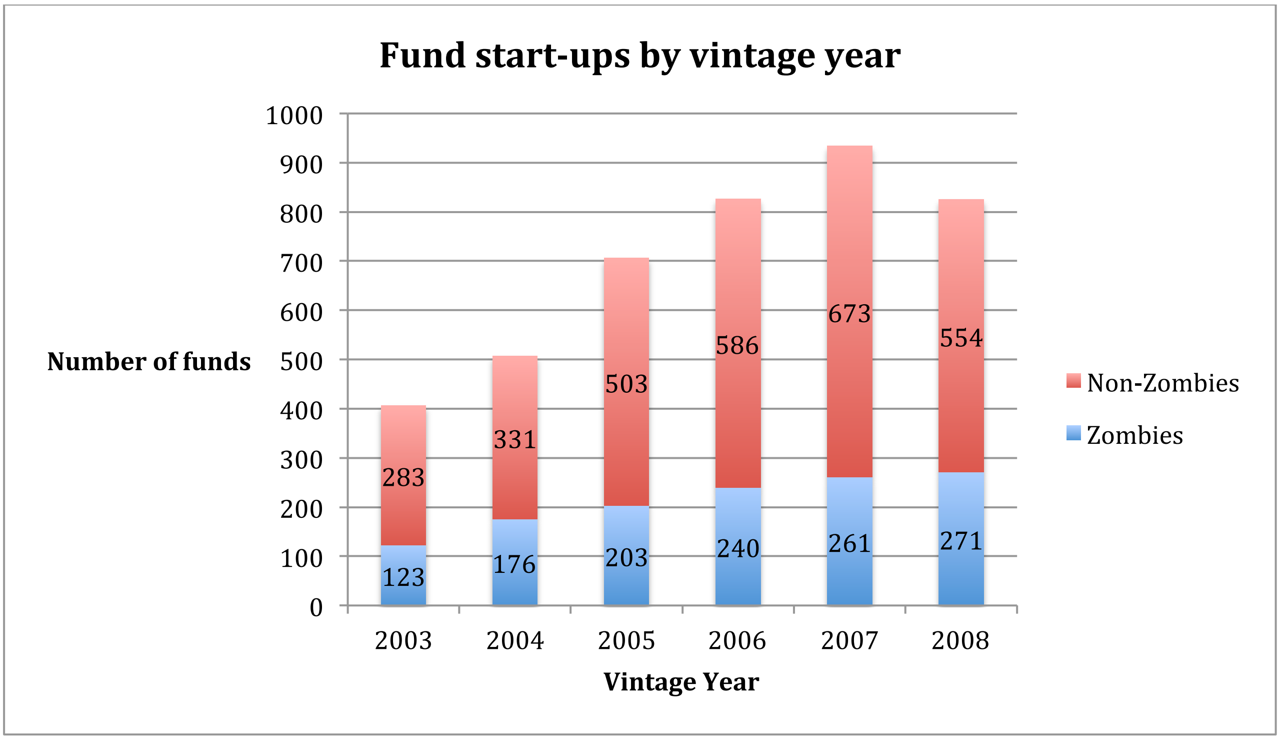

Figure 7: Overview of the number of fund start-ups from 2003-2008

The following table outlines the region focus of the 1 274 identified zombie funds. A fund's region focus is where its investment activity occurs and where its acquired portfolio companies reside. This table seems to suggest that the largest portion of zombie funds focus their investments in the U.S. 603 funds, which is equivalent to

47,33 % of the 1 274 zombie funds, target portfolio companies in the U.S. Furthermore, the table indicates that Europe is the second largest region of focus for zombie funds. 356 zombie funds base their investments in Europe, amounting to 27,94 % of the total figure. Additionally, a significant portion of zombie funds focus on the Asian market. This figure is 151 funds and constitutes 11,85 % of all zombies. The number of zombie funds focusing on the Americas, Australia, Middle East and Israel, and multi-regions is of less significance. This observation is as expected and conforms to the relative sizes of the PE markets in the different regions. The largest PE market in the world is found in the U.S., followed by Europe and then Asia.

Region Focus	***Zombies***		***Non-Zombies***	
Africa	45	3,53 %	71	2,42 %
Americas	23	1,81 %	71	2,42 %
Asia	151	11,85 %	553	18,87 %
Australasia	38	2,98 %	59	2,01 %
Diversified Multi-Regional	12	0,94 %	34	1,16 %
Europe	356	27,94 %	714	24,37 %
Middle East & Israel	46	3,61 %	77	2,63 %
US	603	47,33 %	1351	46,11 %
Sum	**1274**		**2930**	

Table 2: Region Focus

The location of the GP team may not always be the same as the fund's region focus. An investment team may be located in Asia while at the same time specialize and invest in U.S. companies. As one might expect, GPs of zombie funds are located in countries all over the world. The important extraction from the data is that the U.S. once again emerges with the highest frequency (see appendix 2). Out of the 1 274 zombie funds, 581 are located in the U.S. In effect, 45,60 % of all zombie funds are based there. Comparing this figure to the 603 zombie funds with investment focus in the U.S., it is evident that some funds invest in the U.S. while being based elsewhere. The second largest location of zombie fund GPs is the U.K., where 78 zombie funds can be found. Other European countries such as Finland, France, Germany, Italy, and the Netherlands also inhabit a relative large portion of zombie funds. Furthermore, worth mentioning is that Australia, Canada, China, and Japan are countries where respectively 33, 37, 30 and 29 zombie funds are located.

A substantial segment of the zombie funds are diversified funds (see appendix 3). A fund's industry focus concerns what market its portfolio companies operate in, and a diversified fund acquires portfolio companies engaging in several industries. 624 zombie funds are classified as diversified. Furthermore, a large portion of the zombie funds, 229 to be exact, focus on the IT and technology industry. 144 zombie funds invest in health and biotechnology businesses. The classification of the zombie fund industry focus is based on the market in which the fund's primary focus lies, and a fund may not be limited to exclusively invest in IT companies even though its main expertise is IT. Communication and telecom, consumer and retail, and industrial investments are also industries in which a relative large amount of zombie funds base their business, with 60, 58 and 47 funds respectively identified in each category.

We will mainly focus on IRR and multiples as determinants of performance. The lack of detailed cash flow data on individual funds limits the possibility to investigate PME and MIRR. As previously described, IRR represents the average return on invested capital, given all cash inflows and outflows. As such, an investor is better off as the IRR increases. The IRR values for zombie funds will be presented as both equally weighted and capital weighted averages. The figures used in this analysis are those directly reported to Preqin, as the underlying cash flows are not available to us. Kaplan and Schoar (2005) find that the IRR based on cash flows is strongly correlated with IRR reported by the Venture Economics database, with a correlation coefficient of 0,98. Furthermore, Harris et al. (2013) find that results based on data from Preqin and Venture Economics are generally consistent. Multiples also give insight into a fund's performance. The multiples in this analysis are those directly reported to Preqin. The ratios we will focus on are DPI, RVPI and TVPI.

When calculating IRR for a not yet liquidated fund, the net asset value/ residual value (NAV) must be estimated. The treatment of NAV is a widely debated topic in calculation of PE returns. In previous research, the treatment of NAV has largely been solved in two different ways. The first and most often observed method treats NAV as an incoming cash flow at the end of the fund duration and is based on the assumption that NAV represents the market value of the fund. The other method writes down the NAV. This method is applied by Phalippou and Gottschalg (2009) and Ljungqvist and

Richardson (2003). The first method has received critique as the lack of reliable market prices in the PE secondary market challenges whether NAV is a good measure of market value. Harris et al. (2013), on the other hand, argue that writing down NAV is the wrong procedure and will yield too low returns. As already mentioned, we use IRRs directly reported to and calculated by Preqin where IRR calculations are based on cash flows and valuation of unrealized assets.

As previously discussed, performance data is reported to Preqin on a voluntary basis. Only a portion of the 1 274 identified zombie funds has reported performance data in recent years. Preqin contains performance data on 210 zombie funds in 2013, while the equivalent figure from 2014 is 208. It may not be the same funds reporting each year. We will look at figures from 2013 in this part, as these are year-end figures, while numbers reported in 2014 are reported in different quarters.

Table 3 shows the performance based on IRR for the 210 zombie funds in our sample. The average return for all the funds as well as return for each fund type is presented. We display performance as equally weighted average, capital weighted average, median and upper and lower IRR.

	Net IRR (%)					
Zombie	**BO**	**VC**	**Early Stage**	**Growth**	**Others**	**All**
Average	6,09	-1,82	1,12	3,13	2,60	2,56
Capital Weighted Average	6,06	0,24	-2,02	3,31	8,28	5,62
Median	5,30	-1,35	-1,90	1,90	5,90	2,90
Min	-25,60	-61,60	-20,70	-17,90	-19,30	-61,60
Max	58,00	24,30	61,00	24,00	18,90	61,00
Observations	77	56	26	16	35	210

Table 3: Net IRR of zombie funds

We find that zombie funds on average deliver an IRR of 2,56 %. This rate of return to investor is low when considering the risk profile of PE. The performance will later on be compared to that of non-zombie PE funds in the same time period. Furthermore, it is evident from the table that BO zombie funds clearly outperform VC zombie funds with an IRR of 6,09 % compared to a negative VC return of 1,82 %. After BO funds, growth funds provide the best return with a rate of 3,13 %. Other fund types yield an IRR 2,60 %, which is almost the average of all zombie funds, while early stage funds provide an unsatisfactory IRR of 1,12 %. This information seems to support our suspicion that zombie funds underperform other PE funds, which will be explored later in this thesis.

If we look to capital weighted IRR, we notice that some IRR figures change. Returns for BO and growth funds remain the same, while they increase or decrease for the remaining fund types resulting in a change of the total average. When the average is capital weighted, larger funds (those with highest amounts of committed capital) will affect the mean value more than smaller funds. The capital weighted average for early stage funds is negative 2,02 %, a reduction of 3,14 percentage points from the equally weighted figure. This means that one or some of the larger funds in the sample have performed worse than the smaller funds. The capital weighted averages for VC and other funds, on the other hand, represent an increase from the equally weighted averages. IRR for VC funds rise to 0,24 % while IRR for other funds rise to 8,28 %. For these two categories, larger funds have performed better than smaller funds, leading to an alteration of the IRR figures. The result on total average is an increase to a return of 5,62 %, a jump of 3,06 percentage points. This return, even though larger than before, may still not be satisfactory when one considers the lifetime and risk profile of PE investments.

Zombie		DPI, RVPI and TVPI (%) BO	VC	Early Stage	Growth	Others	All
Average	**DPI**	54,81	32,98	21,40	33,60	45,54	41,69
	RVPI	65,21	69,80	100,47	78,96	70,60	72,40
	TVPI	122,18	102,78	120,03	112,55	116,14	114,80
Capital Weighted Average	**DPI**	58,39	29,34	24,38	40,26	67,29	55,48
	RVPI	67,87	73,80	71,08	73,56	78,88	72,50
	TVPI	127,02	103,14	95,00	113,82	146,17	128,48
Median	**DPI**	43,90	29,00	16,05	7,20	42,70	30,15
	RVPI	63,30	67,00	69,85	77,20	69,50	68,35
	TVPI	116,05	95,40	87,25	101,90	117,80	108,55
Min	**DPI**	0,00	0,00	0,00	0,00	0,00	0,00
	RVPI	0,50	1,90	1,30	0,00	17,00	0,00
	TVPI	18,80	8,20	3,80	38,90	44,00	3,80
Max	**DPI**	227,10	140,40	78,30	192,50	139,40	227,10
	RVPI	199,00	372,80	706,00	138,60	133,20	706,00
	TVPI	260,30	458,20	717,00	208,00	187,00	717,00
Observations	**DPI**	86	61	28	22	39	236
	RVPI	82	61	24	22	39	228
	TVPI	82	61	24	22	39	228

Table 4: DPI, RVPI and TVPI of zombie funds

If we look to the above table, we see equally weighted average and capital weighted average multiple values, in addition to median, upper and lower multiples. The multiples included are DPI, RVPI and TVPI, as these are indicators of a fund's performance. DPI is a ratio of cash distributed back to investors over cash paid in by investors. As a fund is closing in on the end of its life, most of the cash should be distributed back to investors. As evident from table 4, this is not the case for zombie funds. A DPI of, for instance, 50 % means that half of the capital paid in by investors has been returned. Ideally, DPI of liquidated funds should exceed 100 %, as positive returns should have been generated. The zombie funds have on average distributed 41,69 % of the cash committed by investors. This value is low as most of the zombies exceed their expected lifetime, and more capital should have been distributed back to investors. The largest DPI value is observed for BO funds with an average of 54,81 % distributed capital. This conforms to the above findings that BO funds are those generating the highest IRR value. VC funds, with a substantially lower return, have distributed on average 32,98 % of cash received from investors. However, the lowest distribution rate is found within early stage funds. These funds have only distributed 21,40 % of committed capital.

RVPI provides insight on how a fund has created value before it is liquidated and cash is distributed to investors. It is a ratio that points to unrealized values of a fund. Average RVPI for the zombie funds in our dataset is 72,40 %. This means that 72,40 % of committed capital is currently held values in the funds. The highest RVPI is found for early stage funds, whose average rate is 100,47 %. The lowest rate is found in BO funds whose average RVPI is 65,21 %. However, this ratio must be analyzed together with the DPI value to provide a clear picture of performance. As such, TVPI is a superior measure of return.

TVPI combines DPI and RVPI to represent a measure of both the distributions and the residual values of a fund. This is the most common multiple to look at when determining total performance of PE funds (Fraser-Sampson, 2011). The average TVPI of all zombie funds is 114,80 %, indicating a slight increase in value. This figure will later be compared to an equivalent measure for non-zombie PE funds, to provide insight as to whether this TVPI is inferior to that achieved by other PE funds. The largest TVPI is of 122,18 % and represents the BO funds. Once again we see that the multiples and IRR values agree. The lowest TVPI is that of VC funds, with a rate of 102,78 %. As with equally weighted IRR, TVPI suggests that these funds are the worst performers.

If we consider capital weighted multiples, we see that the total DPI increases to 55,48 %. This indicates that some of the larger funds have distributed more cash to investors than some of the smaller funds in the sample. The largest capital weighted DPI is found for other funds and is 67,29 %. This is in accordance to the capital weighted IRR information as other funds provided the greatest return figure. The lowest DPI is found for the early stage funds, who have distributed 24,38 % on average. Once more, the multiples and IRR values tell the same story as early stage funds solely provided negative capital weighted returns.

The average TVPI for all fund types increases when one considers the capital weighted rate compared to the equally weighted one. TVPI for all zombie funds is 128,48 %, an increase of 11,91 percentage points. This is an indication that some large funds perform better than some of the small funds in the sample. The largest TVPI is found for other funds, and the lowest for early stage funds, again providing the same information as the capital weighted IRR figures.

The following table displays equivalent IRR information for non-zombie PE funds as table 5 outlines for zombie funds. The data is collected from Preqin and contains information on 2 930 funds. These funds have vintage years from 2003 to 2008, and represent the same fund types as those included in the zombie group.

	Net IRR (%)					
Non-zombie	**BO**	**VC**	**Early Stage**	**Growth**	**Others**	**All**
Average	14,43	8,12	10,86	11,38	9,77	11,84
Capital Weighted Average	10,84	8,47	10,10	10,88	9,86	10,51
Median	11,90	7,90	9,50	9,90	8,80	9,90
Min	-24,90	-14,50	-48,80	-25,30	-29,00	-48,80
Max	239,70	40,50	74,20	55,10	57,60	239,70
Observations	370	114	86	64	203	837

Table 5: Net IRR of non-zombie funds

This table seems to strengthen the perception that zombie funds underperform other PE funds. In 2013, zombie funds had provided an average IRR of 2,56 % while other PE funds brought a return of 11,84 % the same period. PE BO funds provided a 8,25 % better return than BO zombie funds, VC funds a 9,94 % better return than VC zombie funds, early stage funds a 9,74 % better return than zombie early stage funds, growth funds a 8,25 % better return than zombie growth funds and other funds a 7,01 % better return than other zombie fund types. Together PE funds provided a superior return of 9,28 % compared to its zombie counterpart. Albeit this large difference in performance, the same fund types range more or less the same for zombie funds and non-zombie funds. BO funds perform best, followed by the growth category. The worst performance is by VC funds in both instances, even though zombie VC funds are the only funds providing a negative average return when means are equally weighted. The only difference in the ranking of the best and worst performers is that of early stage and other funds.

The capital weighted IRR values for the non-zombie funds show a reduction of the rates for most of the fund types. BO fund return decreases by 3,52 percentage points, early stage return decreases by 0,76 percentage points and growth return decreases by 0,50 percentage points indicating an inferior performance by larger funds. VC fund return increases by 0,35 percentage points while other fund types increase their return by 0,09 percentage points. Together the effect is a 1,33 percentage points decrease in the overall IRR. The return gap is smaller between zombie funds and non-zombie funds when capital weighted IRRs are taken into account, yielding a reduced difference of 2,22 percentage points. Still, zombie funds are the worst performing funds. Comparing fund types, the capital weighted average IRRs of non-zombie funds are more persistent in value than those of the zombie funds who vary more. For the non-zombies, growth funds perform the best and VC funds the worst. This is not the same for the zombie funds where other fund types were found to exhibit the best returns and early stage funds the worst returns.

		DPI, RVPI and TVPI (%)					
Non-zombie		**BO**	**VC**	**Early Stage**	**Growth**	**Others**	**All**
Average	**DPI**	89,09	51,74	47,03	63,34	79,19	74,97
	RVPI	72,13	84,94	119,92	90,46	66,57	79,14
	TVPI	161,50	136,68	167,53	154,29	145,32	154,19
Capital Weighted Average	**DPI**	71,09	54,15	43,29	59,19	81,12	71,69
	RVPI	76,81	89,33	113,78	88,44	61,05	74,92
	TVPI	147,93	143,79	157,61	147,78	141,89	146,59
Median	**DPI**	73,50	40,00	31,70	51,80	73,60	62,05
	RVPI	72,00	81,20	96,15	85,95	60,35	76,10
	TVPI	151,50	134,80	139,50	142,95	138,95	143,70
Min	**DPI**	0,00	0,00	0,00	0,00	0,00	0,00
	RVPI	1,00	3,30	6,00	22,00	0,00	0,00
	TVPI	38,20	18,80	20,40	24,90	26,30	18,80
Max	**DPI**	467,50	194,30	614,80	437,10	270,30	614,80
	RVPI	210,30	420,00	1230,50	220,00	258,40	1230,50
	TVPI	548,00	460,00	1845,30	482,20	383,40	1845,30
Observations	**DPI**	391	128	94	69	208	890
	RVPI	385	128	92	68	204	877
	TVPI	385	128	92	68	204	877

Table 6: DPI, RVPI and TVPI of non-zombie funds

The performance of PE non-zombie funds is superior to that of zombie funds if one considers multiples as well as IRR figures. The above table shows that non-zombie funds have distributed an average of 74,97 % of committed capital back to the investors. This figure is substantially higher than the modest 41,69 % distributed by zombie funds. TVPI of non-zombie funds is also, as expected, larger than the equivalent zombie fund value. The non-zombies provided a TVPI of 154,19 % while the zombies gave a rate of 114,80 %. This difference of 39,39 % indicates that non-zombie funds performed significantly better than zombie funds in the period 2003-2013.

The capital weighted multiple values paint the same picture; non-zombie funds seem to perform better and distribute capital earlier on than zombie funds. As for the capital weighted IRR values, the gap between zombie fund and non-zombie fund performance decreases when capital weighted multiples are taken into account. The TVPI difference is now of 18,11 %. To sum up, both equally and capital weighted IRRs and multiples lead us to believe that zombie funds perform significantly worse than non-zombie PE funds.

IRR and TVPI by vintage year		
Vintage	**Net IRR(%)**	**TVPI**
2003	10,59	148,42
2004	-1,09	99,44
2005	2,83	114,96
2006	0,68	109,85
2007	1,70	107,04
2008	4,23	121,88

Table 7: Average IRR and TVPI for each vintage year

The above table displays net IRRs and TVPI values for zombies by the different vintage years ranging from 2003 to 2008. TVPI is the only multiple included as it represents the superior multiple for determining overall fund performance. As evident from the figures, TVPI and IRR agree. The best performance is reported by funds with vintage years in 2003, while the worst performance is observed for funds started in 2004. According to the IRR figures, the second worse return is delivered by funds with 2006 vintage, while the TVPI values rank 2007 as the second poorest performing vintage year. 2004 is the only year in which negative (average) returns are observed.

Another striking difference between zombie funds and non-zombie funds regards average fund size. The average size of the identified zombie funds is, as mentioned earlier, \$233,75 mn, while the average size of the non-zombie funds is \$534,38 mn. Non-zombie funds are thus on average 129 % larger than the zombie funds. We will later test for the significance of fund size as a determinant of a fund becoming a zombie.

The zombie funds described in this section represent a substantial part of the global PE market. Our sample contains 4 204 PE funds, of which 1 274 fulfill the zombie fund requirements. Thus, zombie funds constitute 30,30 % of PE funds started between 2003 and 2008. Pedersen and Sand (2014) found a similar figure for the Nordic PE market. They identified 80 zombie funds in the Nordic region, which translates to 30,10 % of the total Nordic market. This suggests that zombie funds represent a significant part of the PE market and is an issue where more insight is needed.

8. Empirical Analysis

The previous chapter provided a picture of the current zombie funds situation and highlighted differences between zombie and non-zombie funds. We will now test for significance and direction of the relationships between zombie fund characteristics and return. First, we will explore whether fund size, fund type and reaching target value impacts the likelihood of becoming a zombie fund. After that we examine whether zombie funds underperform other PE funds. The last section will look at reporting behavior, i.e. how frequently funds report performance data. Detailed results are listed in the appendix.

8.1 Do Zombie Funds Display a Relationship to Fund Size?

We earlier mentioned that the average size of zombie funds differs from that of non-zombie funds. Fund size is based on committed capital - which is a constant figure, i.e. it is measured by final close of committed capital and is not affected by returns or distributions. To determine whether fund size has an impact on the likelihood becoming a zombie fund, we look at the 4 204 PE funds included in our sample. 3 901 funds out of the total sample report size. The data is below divided into seven categories distinguished by size. We see that the largest part of zombie funds belong to the smallest size categories, as 82,20 % of the zombies are equal to or smaller than $300 mn. For the non-zombie funds, 67,20 % are equal to or smaller than $300 mn.

$ mn	***all funds***	***% of total***	***zombies***	***% of total***	***non-zombies***	***% of total***
0-30	696	17,84 %	247	21,74 %	449	16,24 %
30-50	343	8,79 %	109	9,60 %	234	8,46 %
50-100	624	16,00 %	214	18,84 %	410	14,83 %
100-300	1129	28,94 %	364	32,04 %	765	27,67 %
300-500	452	11,59 %	100	8,80 %	352	12,73 %
500-1000	337	8,64 %	62	5,46 %	275	9,95 %
>1000	320	8,20 %	40	3,52 %	280	10,13 %
Sum	**3901**	**100,00 %**	**1136**	**100,00 %**	**2765**	**100,00 %**
not reporting	303	7,77 %	138	12,15 %	165	5,97 %

Table 8: Fund size categories

A table displaying the different fund size categories by fund type is featured in appendix 4. It is evident that the largest parts of VC and early stage zombie funds are found in the smaller size categories. 33,33 % of VC zombies are equal to or smaller than $30 mn, while 38,86 % of early stage zombies are equal to or smaller than $30 mn. For BO funds, most zombies are between $100 and $300 mn in size. This is also true for growth zombie funds, where 38,18 % of the funds is found in this middle category. The aggregated other fund types also exhibit a size pattern of the majority distributed around the middle categories, displaying the same trend as BO and growth zombies. This may be an indication that small VC and early stage funds can be extra prone to becoming zombie funds. Nevertheless, the size patterns displayed above more or less match those for non-zombies and differences should be statistically tested for before drawing conclusions.

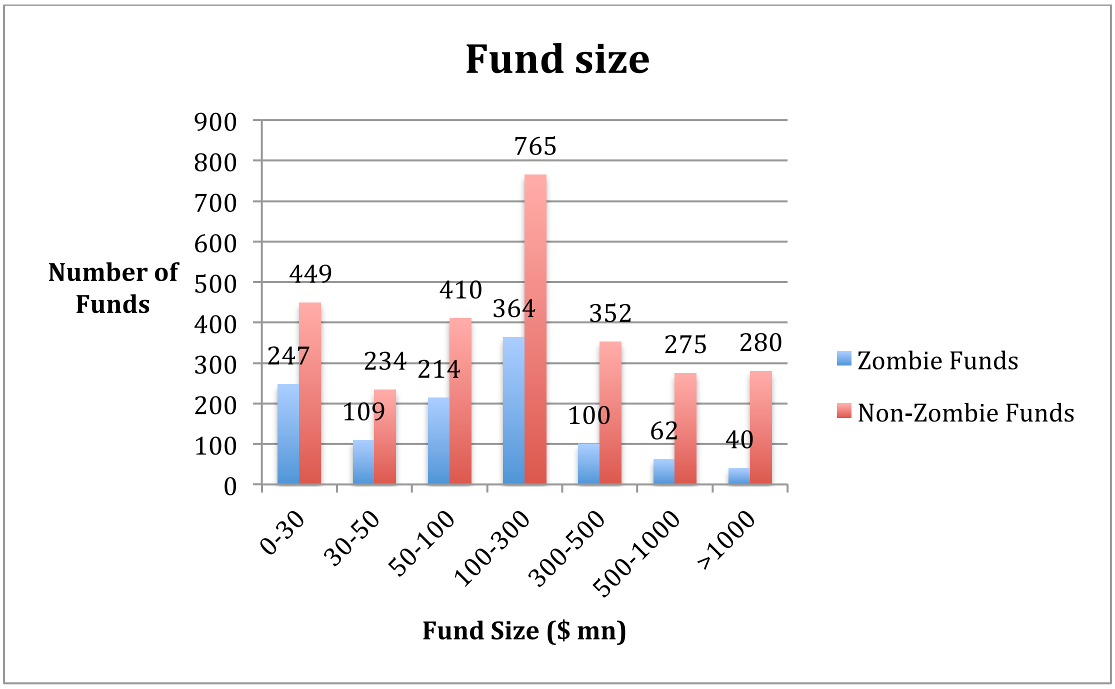

Figure 8: Number of funds in each fund size category

Based on the above diagram, we see that a large portion of the identified zombie funds figure on the left side. We label all funds with committed capital of $300 mn or less as "small" and funds with capital of $300 mn or more as "large". This diagram indicates that small funds more often turn into zombies than large funds do. Positioned on the above figure and the above standing argument, we put forth the hypothesis: "Zombie funds tend to be small".

H_0: None of the groups differ in regards to the ratio of zombie funds

H_1: At least one of the groups differ in regards to the ratio of zombie funds

To check for statistical significance, a Kruskal-Wallis test has been applied. From the test output (see appendix 5), we find that we can reject the null hypothesis that none of the groups differ at a 1 % significance level (p-value of 0,01 %). The Kruskal-Wallis test determines that there is a difference between at least two of the groups, but not the direction or size of these differences. An assumption behind this test is that the included dependent variable should be measured at the ordinal or continuous level. The dependent variable in this case is dichotomous, with one level for zombie funds and another for non-zombie funds. We will, therefore, apply a Chi-square test to confirm that there is a relationship between the dependent variable and fund size.

The test output of the Chi-square test (see appendix 6) tells us that there is a relationship between zombie funds and fund size. We can thus reject the null hypothesis of independence between the dependent and independent variable at a 1 % significance level (p-value of 0,00 %). The Chi-square test and the Kruskal-Wallis test yield the same result.

The next step is to find the direction of the evident differences between the groups, which will be done through a logistic regression analysis. A linear multiple regression model does not restrict the dependent variable to be between zero and one, and it assumes a constant partial effect of the explanatory variables. Therefore, a binary response model, such as a logistic regression, is more appropriate in this context (Wooldridge, 2009). An outlier is a value that is much smaller or larger than most other values in a dataset. Most parametric statistics are highly sensitive to outliers. To control for outliers in this model, we have left out all funds larger than $ 5 000 mn.

We expected to find a relationship between the “small” fund size and zombie funds. If one looks at figure 8, a ratio of zombie funds to non-zombie funds of approximately 50 % for the four smallest size categories becomes apparent. The regression analysis rendered these four independent variables statistically significant (see appendix 7). The regression outcome showed a significant positive relationship between “small” funds and zombies. Based on the analysis of this section, we conclude that there is indeed a relationship between fund size and zombie funds. More specifically, funds smaller than $300 mn display a positive relationship with the dependent variable.

8.2 Do Zombie Funds Display a Relationship to Fund Type?

Table 1 outlines the number of zombie funds and non-zombie funds within the different fund types existing in our zombie sample. The ratio of zombie funds and non-zombie funds to total funds in each category is also included. Data on fund type is reported for all the 4 204 PE funds included in this analysis. All early stage funds and VC funds are gathered to represent one group.

The interesting aspect to look at is what portion the zombie funds constitute within each category. To determine whether a significant relationship exists between fund type and zombie funds, one must consider the relative amount of such funds in each group. We see that some fund types are represented by a larger portion of zombie funds than other types. Overall, we see a considerable variety in the figures. This leads us to believe that fund type may be a contributing factor to the likelihood of a fund becoming a zombie. We must therefore test for the statistical significance of this relationship. Grounded in these findings we present the following hypothesis: “Zombie funds tend to display a relationship to fund type”.

We will first conduct a Kruskal-Wallis and Chi-square test, to see if any significant relationship exists between fund types and zombie funds.

H_0: None of the fund types differ in regards to the ratio of zombie funds
H_1: At least one of the fund types differ in regards to the ratio of zombie funds

The output of the Kruskal-Wallis test can be found in appendix 8. From the test results we can reject the null hypothesis that all categories are the same at a 1 % significance level (p-value of 0,01 %). It can thus be concluded that there is a statistical significant difference between two or more of the fund type groups.

The Chi-square test yields the same findings and the output can be seen in appendix 9. The null hypothesis of independence between the dependent and at least one independent variable can once again be rejected at a 1 % significance level (p-value of 0,01 %). Consequently, at least one fund type shows a significant relationship to zombie funds.

The nature of this relationship is further explored through a logistic regression model. In addition to prove that a relationship exists, it is important to understand the direction of it. We expected to find evidence of a relationship between zombie funds and fund type, however, none of the fund type variables turned out to be significant (see appendix 10). Thus, we do not find evidence regarding which fund types are more or less likely to become zombie funds.

8.3. Do Zombie Funds Display a Relationship to whether the Fund has Reached Target Value or Not?

Another aspect that might be interesting to gain insight on is whether it matters if a fund reaches its target value or not. A PE fund will have a target value for committed capital before cash is raised from investors. Thus, actual committed capital may deviate from target committed capital. 2 356 funds in our sample report data on both target value and realized capital, while the remaining funds only provide data on either committed capital or target capital, or neither. Both figures are required to determine if the target is reached. Out of these 2 356 funds, 1 464 actually did reach target value. We wish to investigate whether funds that have not reached their target value tend to become zombie funds.

H_0: $\beta_{targetvalue} = 0$

H_1: $\beta_{targetvalue} \neq 0$

A logistic regression is used for this purpose, as the dependent variable is a dichotomous variable that either takes the value one or zero, one for zombie and zero for non-zombie. An independent variable that represents whether target value is reached is included in the model. This independent variable is a dummy variable that is one if the target is not reached and zero otherwise.

The outcome of the regression model is displayed in appendix 11. We see that the 'not reached target value' variable has a positive coefficient of 0,15, but it is deemed not significant. Therefore, we cannot reject the null hypothesis that β is equal to zero. This means that we cannot make any conclusions as to whether not reaching target value makes a fund more likely to become a zombie.

R^2 is a statistical measure of how close that data are fitted to the regression line. As such, it indicates how much of the variability in the dependent variable that is explained by the independent variables in the regression. Stata reports pseudo R^2 for logit regression models, however, the interpretation is similar as for the ordinary R^2 measure. The R^2 figures for the above regression models are found in the respective appendices. They are found to be quite low which indicates that there are external factors missing from the model relating to the zombie variable.

8.4 Do Zombie Funds Underperform other Private Equity Funds?

This part is that of main focus in this thesis. We will look at two performance measures to determine whether zombie funds underperform other PE funds: IRR and TVPI. The multiple DPI will also be used to explore this phenomenon. DPI is not a direct measure of performance, but it provides information about cash flows and is therefore more tangible than IRR and TVPI. Furthermore, DPI demonstrates the return investors in these funds have received and is therefore of high interest in this context. Each of these measures will be discussed in a separate section before the findings are concluded in a brief summary.

8.4.1 IRR

We earlier found that PE zombie funds recently provided investors with a substantially lower internal rate of return than non-zombie PE funds. Note that as our sample does not include liquidated funds, all IRR figures are interim. Realized IRR can only be calculated for liquidated funds and represents a more credible measure. Some concerns have been raised about interim IRR as it is based on an appraisal of expected future cash flow. However, research shows that interim IRR has a tendency to converge toward finally realized IRR towards fund termination (Burgel, 2000). All IRR figures are net of fees.

In 2013, zombie cumulative net IRR amounted to 2,56 % while other PE funds delivered a cumulative net IRR of 11,84 %. We therefore wish to test whether zombie funds are a statistically significant contributing factor to cumulative net IRR, and how strong this potential influence might be. We will also look at other significant variables affecting the IRR. Grounded in these IRR figures and above argument, we expect to find that zombie funds have a negative impact on return.

A generalized least squares (GLS) regression is used to explore this phenomenon. The dependent variable in this context is IRR, a continuous variable, making least squares regression the appropriate model for analysis. We use panel data for the purpose of examining performance. Panel data is a dataset in which variables are observed over several time periods, and is as such cross-sectional data measured over time. Ordinary least squares regression models, such as the linear multiple regression, ignore the panel data structure. A GLS model is thus more appropriate for this purpose as it takes into account the covariance matrix. The analysis includes 3 249 observations.

When performing a regression analysis, one should be aware that the constant term might vary over time. This is due to a phenomenon called fixed effects and may be brought about by instances such as legislative changes, tax changes, technological changes or other external influences such as wars or crises. These effects can be removed by adding dichotomous variables for time. By applying this technique, we have corrected the analysis for such fixed effects. To avoid the fixed effects trap, one must include one dichotomous variable less than the time units incorporated in the regression model. For example, for five units of time, four dichotomous variables must be included to avoid perfect collinearity (Kintel and Knudsen, 2014).

The zombie fund variable is represented by a dummy variable that takes the value one if the fund in question is a zombie fund and zero if the fund is not a zombie. The regression analysis yielded a zombie coefficient of negative 2,41. We can therefore reject the null hypothesis that β_{zombie} is zero at a 1 % significance level (p-value of 0,00 %). As expected, a strong negative relationship between zombie funds and performance emerged, and zombie funds are negatively related to IRR. This outcome is as we predicted and conforms to the IRR statistics earlier discussed in this paper.

We furthermore would like to explore whether poor performance, low IRR, is a contributing factor to funds turning zombie. More precisely, it would be interesting to test for the existence and strength of an endogenous relationship between these two variables. Unfortunately, this was not possible due to limited data. This test would require an instrumental variable that is correlated with the zombie variable but not correlated with the error term.

X	*Coeff. (ß)*	*Std. Err.*	*z-value*	*P>|z|*	*95% Confidence Interval*	
Zombie	-2,41	0,34	-7,16	0,00	-3,08	-1,75
IRR L1.	0,71	0,01	89,74	0,00	0,69	0,73
R^2	0,87					

Table 9: Results of GLS regression – IRR

The outcome of the analysis makes it clear that lagged IRR (L1.) is another factor contributing to the variability of the internal rate of return. Lagged IRR is the IRR from the previous period. As we are investigating cumulative IRR, it is not surprising that time t-1 IRR will influence time t IRR. The test shows a lagged IRR coefficient of 0,71 at a 1 % significance level (p-value of 0,00 %). As expected, a positive time t-1 IRR will have a positive impact on time t IRR.

The above table shows the R^2 figures of the regression model. The overall R^2 of our model is 0,87 meaning that 87,00 % of the variability in the IRR is described by the independent variables included. The R^2 measure will increase, as other significant explanatory variables are included in the model. However, 87,00 % explanatory power is very high. This high value might be explained by the inclusion of the lagged IRR value. As the IRR is cumulative, it naturally follows that the figure to a large degree is explained by values of previous years. Some funds in our sample do not update IRR each year, which might enhance this effect.

An additional regression analysis has been executed to further explore the relationship between IRR and zombie funds towards the end of their expected lifespan. In the context of this model, the dummy variable representing zombie funds only turns one after seven years from vintage. The variable will take the value zero for any year previous to this happening, meaning that we now investigate performance after the fund has, per definition, turned into a zombie. The same definition for zombie funds still apply, but the funds are only included as zombie funds after the passing of seven years. We use seven years as it represents the usual threshold for raising successor funds. We apply this technique as we wish to explore the isolated impact zombie funds have on IRR after they become zombie funds.

X	*Coeff (ß)*	*Std. Err.*	*z-value*	*P>|z|*	*95% Confidence Interval*	
Timezombie	-0,46	0,24	-1,86	0,06	-0,94	0,02
IRR L1.	0,93	0,01	130,37	0,00	0,92	0,95
R^2	0,96					

Table 10: Results of GLS regression – IRR and time zombie

Table 10 shows the regression result. The outcome is a negative coefficient of 0,46 at a 10 % significance level (p-value of 6,20 %). We once again find a negative regression coefficient, meaning that zombie funds tend to negatively impact IRR after they per definition can be categorized as zombie funds.

8.4.2 TVPI

The previous chapter suggested a large difference in the TVPI provided by zombie funds and non-zombie funds. We saw that zombie funds provided an average TVPI of 114,80 % in 2013, while non-zombie funds brought an equivalent rate of 154,19 %. These findings support our perception that zombie funds deliver a lower return than its non-zombie counterpart. A test will here be performed to check for the statistical significance of the relationship between zombie funds and cumulative TVPI, and we expect to find a negative relation between the two variables.

TVPI represents the continuous dependent variable in this model. As with IRR, a GLS regression model serves as the best fit for exploring the relationship of zombie funds and TVPI. We have once again corrected for potential fixed effects to ensure that the results are as accurate as possible. The regression includes 6 272 observations. We have excluded outliers, as the results are highly sensitive to such values. Therefore, funds that display a TVPI above 500 % are removed for the purpose of this analysis.

We wish to explore the relationship between the dependent variable TVPI and the independent variable zombie funds through this regression model. The zombie fund variable is represented by a dummy variable that is one in the case of a zombie and zero in the case of a non-zombie. As expected, the test outcome shows a strong negative relationship between the two variables (see table 11). We can reject the null hypothesis of a β_{zombie} equal to zero, as the zombie coefficient is negative 7,95 at a 1 % significance level (p-value of 0,00 %). The analysis therefore suggests that the zombie fund variable display a significant negative relation to TVPI.

X	*Coeff (β)*	*Std. Err.*	*z-value*	*P>|z|*	*95% Confidence Interval*	
Zombie	-7,95	0,94	-8,49	0,00	-9,79	-6,11
TVPI L1.	0,85	0,01	116,49	0,00	0,84	0,86
R^2	0,81					

Table 11: Results of GLS regression – TVPI

We furthermore find lagged TVPI to be a significant contributing factor to cumulative TVPI. Lagged TVPI measures TVPI of the previous period. The lagged TVPI coefficient is 0,85 at a 1 % significance level (p-value of 0,00 %), which indicates a positive relationship between cumulative TVPI and lagged TVPI.

The previous table shows an overall R^2 of 0,8135 for this model. This goes to show that 81,35 % of the variability in TVPI is explained by the included independent variables. Again, this high value might be explained by the inclusion of the lagged TVPI value. As the TVPI is cumulative, it naturally follows that the figure to a large degree is explained by values of previous years. Some funds in our sample do not update TVPI each year, which might enhance this effect.

A second regression has further been applied to investigate the relationship between TVPI and zombie funds towards the end of their expected lifespan. In this model, the zombie dummy variable will only take the value one if seven years has passed from a fund's creation. The results will shed light on the isolated effect zombie funds have on TVPI after they turn into zombies.

Table 12 displays the regression findings and we see a negative coefficient of 4,60 at a 5 % significance level (p-value of 1,10 %). Based on this outcome we conclude that there is indeed a negative relation between TVPI and zombie funds in this setting.

X	*Coeff (β)*	*Std. Err.*	*z-value*	*P>/z/*	*95% Confidence Interval*	
Timezombie	-4,60	1,8	-2,55	0,01	-8,13	-1,07
TVPI L1.	1,03	0,01	108,93	0,00	1,01	1,05
R^2	0,88					

Table 12: Results of GLS regression – TVPI and time zombie

8.4.3 DPI

It was previously shown that the identified zombie funds have distributed less capital to investors than corresponding non-zombie funds. Zombie funds had distributed an average of 41,69 % of capital in 2013, while their peers had disbursed 74,97 % of cash back to investors. Furthermore, Preqin's performance analyst shows that zombie funds have a much lower median distribution to paid-in capital compared to non-zombie funds (Preqin, 2013b). This leads us to believe that zombie funds may be a contributing factor to the amount of capital distributed to investors and we will now test for the statistical significance of this relationship. We expect to find a negative relationship between zombie funds and disbursed capital.

The dependent variable is represented by the continuous variable cumulative DPI. For the same reasons expressed with regards to IRR and TVPI as dependent variables, a GLS regression is used. The same technique as earlier is applied to correct for potential fixed effects. The number of observations for this model is 4 045. We have excluded outliers, as the results are highly sensitive to such values. Therefore, three funds are removed from the data as they provide a DPI above 500 %.

The explanatory variable of interest is once again a dummy variable taking the value one for zombie funds and zero for non-zombie funds. The results from the regression model are displayed in table 13. We find that our expectations are fulfilled as a strong negative relationship between DPI and zombies becomes apparent. The zombie coefficient turned out to be a negative 3,52. This indicates that the zombie fund variable is a negative predictor of the amount of capital distributed back to investors.

We therefore reject the null hypothesis that β_{zombie} is zero at a 1 % significance level (p-value of 0,00 %)

X	*Coeff (β)*	*Std. Err.*	*z-value*	*P>|z|*	*95% Confidence Interval*	
Zombie	-3,52	0,96	-3,67	0,00	-5,39	-1,63
DPI L1.	0,88	0,01	82,35	0,00	0,86	0,90
IRR L1.	0,53	0,03	17,21	0,00	0,47	0,59
R^2	0,88					

Table 13: Results of GLS regression – DPI

Another finding is the significant influence that lagged DPI has on the dependent variable. Lagged DPI represents last period's DPI. The regression shows a lagged DPI coefficient of 0,88 at a 1 % significance level (p-value of 0,00 %), meaning that previous distributions affects current cumulative distributions in a positive way. We furthermore find that lagged IRR shows a significant positive relationship to DPI. The analysis indicates a lagged IRR coefficient of 0,53 at a 1 % significance level (p-value of 0,00 %), meaning that last year's IRR affects the amount of cash distributed back to investors. We chose to include this last variable, as we believed previous return to affect distribution patterns.

Table 13 shows an overall R^2 of 0,8809 for this model. This goes to show that 88,09 % of the variability in DPI is explained by the included independent variables. This high value might be explained by the inclusion of the lagged DPI and IRR value. As both of these measures are cumulative, it naturally follows that the figures to a large degree is explained by values of previous years. Some funds in our sample do not update DPI or IRR each year, which might enhance this effect.

A second regression has further been applied to investigate what the relationship between DPI and zombie funds looks like after funds reach the end of their expected lifespan. The threshold we use to categorize a fund as a zombie is a seven-year passing from the fund's inception. Only when funds fulfill these criteria will the zombie dummy variable take the value one.

X	Coeff (ß)	Std. Err.	z-value	P>|z|	95% Confidence Interval	
Timezombie	-4,18	1,52	2,75	0,01	-7,16	-1,19
DPI L1.	1,11	0,01	96,12	0,00	1,09	1,14
R^2	0,88					

Table 14: Results of GLS regression – DPI and time zombie

The above table tells us that funds meeting the zombie fund definition tend to distribute less capital back to investors. We now see that this is also true for the time after a fund has turned into a zombie. The regression yields a negative coefficient of 4,18 at a 1 % significance level (p-value of 0,60 %). This latter coefficient is slightly larger than from the previous regression model, meaning that this effect is stronger after a fund has met the criteria described above. Since DPI represents actual cash outflows to investors, and is thus not subject to manipulation, this finding supports the perception that zombie funds provide lower returns than non-zombie funds. However, one should be aware that DPI does not consider values left in the fund that will be distributed at a potential liquidation.

We further want to investigate whether the relationship between DPI and zombie funds differ if we look at each vintage year separately. Longer-lived funds should have distributed more capital than shorter-lived funds. By comparing zombie and non-zombie funds of the same vintage, we only study funds of the same age. We run GLS regressions for each vintage year from 2003 to 2008, and the results are displayed in table 15 (The results of each regression model are also found in appendices 18 to 23):

Vintage	Coeff (ß)	Std. Err.	z-value	P>|z|	95% Confidence Interval		R^2
2003	-10,68	10,72	-1,00	0,32	-31,69	10,32	0,33
2004	-36,38	9,00	-4,04	0,00	-54,02	-18,75	0,30
2005	-18,12	6,17	-2,94	0,00	-30,22	-6,03	0,24
2006	-13,85	3,81	-3,64	0,00	-21,31	-6,40	0,30
2007	-19,89	3,76	-5,29	0,00	-27,26	-12,52	0,22
2008	-12,75	4,28	-2,98	0,00	-21,15	-4,36	0,17

Table 15: Results of GLS regression – DPI for each vintage year

We find zombie funds for all vintage years included in our sample to display a negative relation to DPI except for 2003. We now observe stronger negative relationships between zombie funds and DPI than in the previous models. The reason for this is that lagged values for DPI and IRR are excluded, and the effect of these lagged values may to some degree be incorporated in the zombie coefficients. Based on this analysis, we conclude that there is indeed a negative relation between zombie funds and DPI for each of the included vintage years, except for 2003 where the negative relationship is found to be insignificant.

We will now look at the development of DPI for possible patterns. None of the funds included in our sample are liquidated and so we cannot say whether zombie funds return less than was originally committed by the investor. We can, however, explore if DPI of zombie funds follow a different development than DPI of non-zombie funds. We expect the change in DPI to reflect the above found results. We forecast to find that zombie funds on average display a slower increase in DPI than non-zombie funds. Outliers are excluded for the purpose of this analysis, and all funds displaying a change in DPI above 200 % are removed.

Average change in DPI	
Zombies	19,94 %
Non-zombies	29,78 %

Table 16: Average change in DPI for zombie funds and non-zombie funds

Table 16 shows the mean increase in DPI each year for the funds included in our sample. Zombie funds display an average change in DPI of 19,94 % each year, while non-zombie funds show an average increase in DPI of 29,78 % each year. Based on these figures, we wish to test whether there exists a significant relationship between the development of DPI and zombie funds.

We test for the significance of this relationship by applying a regression analysis with change in DPI as the dependent variable. The model (see appendix 25) yields a regression coefficient of negative 0,10. We therefore reject the null hypothesis at a 1 % significance level (p-value of 0,00 %) and conclude that zombie funds deliver a slower growth in DPI than non-zombie funds. Appendix 26 shows the result for a similar regression but where the zombie dummy only takes value one once a fund is seven years old. The outcome provides comparable insight with a regression coefficient of negative 0,09 at a 1 % significance level (p-value of 0,20 %). Meaning that if we isolate the effect zombie funds have on the development of DPI after they turn into zombies, we observe the same inferior change.

We further wish to examine whether the relationship between zombie funds and the DPI development differ for each vintage year separately. Longer-lived funds will presumably have lower change in DPI per year. By comparing zombie funds and non-zombie funds of the same vintage years, we compare DPI development for funds of the same age. We run GLS regressions for each vintage year from 2003 to 2008, and the results are displayed in table 17 (The results of each regression model are also found in appendices 27 to 32):

Vintage	*Coeff (ß)*	*Std. Err.*	*z-value*	*P>|z|*	*95% Confidence Interval*		*R^2*
2003	-0,14	0,06	-2,33	0,02	-0,26	-0,02	0,11
2004	-0,11	0,04	-2,67	0,01	-0,19	-0,03	0,09
2005	-0,01	0,03	-0,35	0,72	-0,08	0,05	0,09
2006	-0,06	0,04	-1,33	0,19	-0,15	0,03	0,11
2007	-0,10	0,06	-1,66	0,10	-0,22	0,02	0,07
2008	-0,12	0,06	-1,91	0,06	-0,24	0,00	0,08

Table 17: Results of GLS regression – Change in DPI for each vintage year

We find negative relations between zombie funds and DPI development for all vintage years. However, 2005 and 2006 are found to be not significant. Based on this regression model, we conclude that zombie funds started in 2003, 2004, 2007 and 2008 deliver a slower growth in DPI than non-zombie funds with corresponding vintage years.

8.4.4 Summary

The main purpose of this section has been to investigate the relationship between zombie funds and return to investors. We have evaluated performance in the form of IRR, DPI and TVPI. Albeit DPI not being a direct performance measure, it is included as it provides insight on cash flows. Both IRR and TVPI are measures that can be manipulated. For this reason, and the fact that we do not have access to any of the underlying cash flows, we focus on DPI to gain as much information as possible. Our expectations were that zombie funds would display lower returns. The results of the several regression models show a similar result: zombie funds exhibit a strong negative relationship to all the return indicators included. The regression analysis applied to investigate the relationship between zombie funds and return indicators after funds turn into zombies also show negative relationships. Specifically, the DPI coefficient turned out to be more negative in this case, and so the negative impact that zombie funds have on DPI is stronger after a fund can be said to fulfill the zombie fund criteria. Furthermore, we found zombie funds to display a slower development of DPI than its non-zombie peers. Our findings are strengthened by tests yielding similar results for all vintage years.

It is important to emphasize that we cannot prove a causal relationships between any variables through a regression analysis. For instance, we cannot conclude that being a zombie fund will definitely lead to poor returns. It might be poor returns that lead a fund to becoming a zombie. However, what can be concluded from the regression is the strength and direction of the proven significant quantitative relationships. It would be interesting to explore the existence and strength of endogenous relationships between zombie funds and the different performance measures, i.e. if the performance affects the probability of becoming a zombie. As already mentioned, this could not be done in this thesis due to limited data.

As performance data is reported to Preqin on a voluntary basis, our dataset contains less information than optimal. This also explains the differences in the number of observations in each regression model. Furthermore, voluntary reporting leads to a non random-sample and measures such as IRR and TVPI have several drawbacks. One should thus be careful about inferring conclusions based on the previous analysis, although it provides a good overview of the current situation.

8.5 Do Zombie Funds Report Performance Data Less Frequently than Non-Zombie Funds?

It has earlier been discussed that poor performing funds have less incentive to report performance data than well performing funds. One reason for this is that reporting unsatisfactory returns can lower the changes for raising successor funds. As we found zombie funds to underperform other PE funds, it is reasonable to believe that zombie funds will have less incentive to report performance and thus report data less frequently to Preqin and other databases. We will now explore whether the identified zombie funds in our sample tend to report performance data less frequently than non-zombie funds.

We look at IRR and DPI, and the frequency to which these measures are reported to Preqin. The following table gives summary statistics of how often zombie funds and non-zombie funds on average reported IRR and DPI during the time-period of our sample.

Average times reported	**IRR**	**DPI**
All	1,36	2,05
Zombie	0,95	1,48
Non-zombie	1,54	2,29

Table 18: Average number of times performance data is reported

It is evident from table 18 that the zombie funds in our sample reported both IRR and DPI less frequently than non-zombie funds did. We will now test for statistical significance of the relation between reporting and zombie funds. OLS regression models are used for this purpose. Two models are applied, one with reported IRR as dependent variable and one with reported DPI as dependent variable. We have included dummy variables to control for the effects fund size, vintage year and fund types may have on the dependent variable. The results are summarized in table 19, and complete regression-outputs can be found in appendices 33 and 34.

Reported	*Coeff (ß)*	*Std. Err.*	*z-value*	*P>|z|*	*95% Confidence Interval*		*R^2*
IRR	-0,40	0,07	-5,71	0,00	-0,54	-0,27	0,15
DPI	-0,55	0,10	-5,53	0,00	-0,75	-0,36	0,16

Table 19: Results of OLS regression – Reported IRR and DPI

The regression results are as expected as we find negative relations between zombie funds and the number of times both IRR and DPI are reported. The model yields regression coefficients of negative 0,40 and 0,55. We therefore reject the null hypothesis that the coefficients are equal to zero at a 1 % significance level (p-values of 0,00 %) and conclude that zombie funds report IRR and DPI less frequently than non-zombie funds.

9. Conclusion

We have looked at PE zombie and non-zombie funds in the global PE market based on data from Preqin. The research question of this thesis is: "Do zombie fund performance and other characteristics differ from those of other private equity funds globally?" Out of 4 204 funds in our dataset, we identified 1 274 zombie funds. We will now summarize our findings before we offer suggestions for further research.

We distinguished all funds into seven different size categories to examine the relationship between zombie funds and fund size. Our findings suggest a significant positive relation between zombie funds and fund size below $300 mn (classified as small funds). We therefore conclude that zombie funds tend to be small.

We also looked at whether zombie funds tend to display a relation to certain fund types. None of our included fund types turned out to exhibit significant relationships to zombie funds. Thus, we do not find evidence regarding which fund types are more or less likely to become zombie funds.

Further, we investigated the existence of a relation between zombie funds and funds that did not reach target value. We did find a positive regression coefficient of 0,15, which was, however, deemed not significant. No conclusions can be made regarding whether not reaching target value makes a fund more likely to become a zombie.

To answer whether zombie funds underperform other PE funds, we looked at the performance measures IRR and TVPI. Both of these measures displayed a significant negative relation to zombie funds, indicating that zombie funds do in fact underperform other PE funds. We furthermore tested for the isolated effect of the same relationship towards the end of a fund's lifetime and found similar results.

The DPI multiple received considerable focus as it is based on cash distributions and therefore is less exposed to manipulation. We once again found a negative relation between distributions and zombie funds, and conclude that zombie funds are a negative predictor of the capital amount distributed back to investors. This relation also holds for funds near the end of their expected lifespan. We moreover investigated this relationship in more detail by looking at each vintage from 2003 to 2008 separately. Zombie funds for all the vintage years included in our sample displayed a negative relation to DPI, except for 2003 where the regression coefficient was negative, but not significant. Additionally, we examined the development of DPI for zombie and non-zombie funds. Based on our findings, we conclude that zombies deliver a slower growth in DPI than non-zombies. We observe the same inferior change in DPI for zombie funds when looking at funds near the end of their expected lifespan in isolation. Similar results are found when each vintage year is investigated separately, except for 2005 and 2006 where the results are found to be insignificant.

Lastly, after finding evidence of zombie underperformance, we looked at whether zombie funds tend to report performance data less frequently than non-zombie funds. For this purpose, we included the number of times IRR and DPI was reported to Preqin. The results were as expected, and we conclude that zombie funds report IRR and DPI less frequently than non-zombie funds.

Our general conclusion is that zombie funds underperform other funds in the global PE market. The fact that we identified 30,30 % of the funds in our dataset as zombie funds, leads us believe that this topic should be of high interest. We propose the following points for further study.

9.1 Suggestions for Further Research

- It would be interesting to look at the endogeneity of the relationships found in this thesis. For example, one could investigate whether poor performance leads to a fund becoming a zombie. Such analyses may provide insight on the direction of the relationships found above.
- Due to limited data, our dataset only contains active funds. It would be interesting to look at realized performance and distributions for liquidated funds.
- We mentioned briefly that there might be reputational effects of being involved in the management of zombie funds. What reputational effects that can be found and their possible ramifications could be a topic for further investigation.

- It would be intriguing to look at potential changes in the GP team before and after a fund turns into a zombie fund. One could investigate if and how the investment team changes after a fund can be defined as a zombie fund.

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Appendix

Appendix 1: Overview of average fund size by fund type

Value/committed capital ($ mn)				
	Obs		Mean	
	Non-zombies	zombies	Non-zombies	Zombies
All	2765	1136	534,38	233,75
Balanced	68	29	327,41	1021,88
Buyout	872	267	1028,90	403,12
Co-investment	59	13	267,01	283,93
Distressed Debt	79	8	1356,14	689,90
Early Stage	257	131	136,84	99,32
Early Stage: Seed	65	46	100,08	48,39
Early Stage: Start-up	63	34	93,48	48,52
All Early Stage	385	211	123,54	80,03
Expansion/Late Stage	88	65	168,09	135,36
Growth	279	110	280,60	181,69
Infrastructure	-		-	
Mezzanine	173	48	457,82	284,96
Natural Resources	73	20	989,09	433,28
Real Estate	1	-	137,23	-
Special Situations	58	19	386,82	356,32
Timber	23	6	275,76	280,33
Turnaround	41	7	379,75	213,61
Venture (General)	548	329	170,77	123,57
Venture Debt	18	4	282,86	111,31
All venture	566	333	174,33	123,42

Appendix 2: Overview of GP location

GP Location	*Zombies*		*Non-Zombies*	
Argentina	1	0,1 %	4	0,1 %
Australia	33	2,6 %	45	1,5 %
Austria	7	0,5 %	8	0,3 %
Bahamas	3	0,2 %	0	0,0 %
Bahrain	3	0,2 %	5	0,2 %
Bangladesh	1	0,1 %	0	0,0 %
Barbados	0	0,0 %	1	0,0 %
Belgium	4	0,3 %	12	0,4 %
Bermuda	3	0,2 %	0	0,0 %
Botswana	0	0,0 %	1	0,0 %
Brazil	8	0,6 %	21	0,7 %
British Virgin Islands	1	0,1 %	0	0,0 %
Bulgaria	1	0,1 %	2	0,1 %
Cambodia	0	0,0 %	1	0,0 %

GP Location	*Zombies*		*Non-Zombies*	
Canada	37	2,9 %	83	2,8 %
Cayman Islands	1	0,1 %	1	0,0 %
Chile	1	0,1 %	5	0,2 %
China	30	2,4 %	90	3,1 %
Colombia	0	0,0 %	3	0,1 %
Costa Rica	0	0,0 %	2	0,1 %
Croatia	0	0,0 %	2	0,1 %
Czech Republic	0	0,0 %	2	0,1 %
Denmark	8	0,6 %	22	0,8 %
Egypt	7	0,5 %	9	0,3 %
El Salvador	0	0,0 %	1	0,0 %
Estonia	1	0,1 %	2	0,1 %
Fiji	1	0,1 %	0	0,0 %
Finland	20	1,6 %	25	0,9 %
France	35	2,7 %	128	4,4 %
Germany	33	2,6 %	47	1,6 %
Ghana	2	0,2 %	0	0,0 %
Greece	5	0,4 %	4	0,1 %
Guernsey	0	0,0 %	1	0,0 %
Hong Kong	17	1,3 %	57	1,9 %
Hungary	4	0,3 %	3	0,1 %
Iceland	1	0,1 %	3	0,1 %
India	19	1,5 %	56	1,9 %
Iraq	0	0,0 %	1	0,0 %
Ireland	4	0,3 %	6	0,2 %
Israel	19	1,5 %	34	1,2 %
Italy	27	2,1 %	38	1,3 %
Jamaica	0	0,0 %	1	0,0 %
Japan	29	2,3 %	104	3,5 %
Jersey	2	0,2 %	3	0,1 %
Jordan	2	0,2 %	1	0,0 %
Kazakhstan	6	0,5 %	3	0,1 %
Kenya	1	0,1 %	1	0,0 %
Kuwait	11	0,9 %	3	0,1 %
Latvia	3	0,2 %	1	0,0 %
Lebanon	0	0,0 %	1	0,0 %
Luxembourg	8	0,6 %	10	0,3 %
Macau	1	0,1 %	0	0,0 %
Malaysia	5	0,4 %	11	0,4 %
Mauritius	4	0,3 %	8	0,3 %
Mexico	3	0,2 %	5	0,2 %
Morocco	5	0,4 %	7	0,2 %
Nepal	1	0,1 %	0	0,0 %
Netherlands	20	1,6 %	37	1,3 %
New Zealand	2	0,2 %	11	0,4 %

GP Location	*Zombies*		*Non-Zombies*	
Nigeria	1	0,1 %	1	0,0 %
Norway	13	1,0 %	32	1,1 %
Pakistan	0	0,0 %	1	0,0 %
Panama	2	0,2 %	0	0,0 %
Peru	2	0,2 %	3	0,1 %
Philippines	0	0,0 %	2	0,1 %
Poland	5	0,4 %	10	0,3 %
Portugal	2	0,2 %	13	0,4 %
Puerto Rico	1	0,1 %	0	0,0 %
Romania	0	0,0 %	1	0,0 %
Russia	20	1,6 %	14	0,5 %
Rwanda	0	0,0 %	1	0,0 %
Samoa	1	0,1 %	0	0,0 %
Saudi Arabia	2	0,2 %	6	0,2 %
Senegal	1	0,1 %	0	0,0 %
Sierra Leone	0	0,0 %	1	0,0 %
Singapore	10	0,8 %	24	0,8 %
Slovakia	4	0,3 %	0	0,0 %
Slovenia	0	0,0 %	1	0,0 %
South Africa	23	1,8 %	22	0,8 %
South Korea	7	0,5 %	87	3,0 %
Spain	32	2,5 %	30	1,0 %
Sri Lanka	0	0,0 %	2	0,1 %
Sweden	10	0,8 %	28	1,0 %
Switzerland	11	0,9 %	32	1,1 %
Taiwan	8	0,6 %	16	0,5 %
Tajikistan	1	0,1 %	0	0,0 %
Thailand	1	0,1 %	1	0,0 %
Togo	0	0,0 %	1	0,0 %
Trinidad and Tobago	0	0,0 %	1	0,0 %
Tunisia	1	0,1 %	4	0,1 %
Turkey	0	0,0 %	3	0,1 %
UK	78	6,1 %	231	7,9 %
US	581	45,6 %	1400	47,8 %
Uganda	0	0,0 %	1	0,0 %
Ukraine	3	0,2 %	2	0,1 %
United Arab Emirates	11	0,9 %	19	0,6 %
Uruguay	1	0,1 %	0	0,0 %
Vietnam	2	0,2 %	8	0,3 %

Appendix 3: Overview of industry focus

Industry Focus	*Zombie*		*Non-Zombies*	
Agriculture & Environment	22	1,8 %	61	2,1 %
Communication & Telecom	60	4,8 %	111	3,8 %
Consumer & Retail	58	4,6 %	162	5,6 %
Diversified	624	49,9 %	1550	53,7 %
Energy	46	3,7 %	136	4,7 %
Finance	17	1,4 %	62	2,1 %
Health & Biotechnology	144	11,5 %	238	8,2 %
IT & Technology	229	18,3 %	449	15,6 %
Industrial	47	3,8 %	100	3,5 %
Other	4	0,3 %	17	0,6 %
Sum	**1251**		**2886**	

Appendix 4: Fund size categories by fund type

$ mn	*zombies*	*% of total*	*non-zombies*	*% of total*
Buyout				
0-30	17	6,37 %	47	5,39 %
30-50	16	5,99 %	40	4,59 %
50-100	37	13,86 %	91	10,44 %
100-300	99	37,08 %	256	29,36 %
300-500	42	15,73 %	137	15,71 %
500-1000	30	11,24 %	125	14,33 %
>1000	26	9,74 %	176	20,18 %
	267	**100,00 %**	**872**	**100,00 %**
Venture				
0-30	111	33,33 %	145	25,62 %
30-50	36	10,81 %	69	12,19 %
50-100	60	18,02 %	113	19,96 %
100-300	92	27,63 %	137	24,20 %
300-500	25	7,51 %	62	10,95 %
500-1000	8	2,40 %	31	5,48 %
>1000	1	0,30 %	9	1,59 %
	333	100,00 %	566	100,00 %
Early Stage				
0-30	82	38,86 %	136	34,61 %
30-50	28	13,27 %	45	11,45 %
50-100	44	20,85 %	67	17,05 %
100-300	53	25,12 %	95	24,17 %
300-500	3	1,42 %	30	7,63 %
500-1000	1	0,47 %	11	2,80 %
>1000	0	0,00 %	9	2,29 %
	211	**100,00 %**	**393**	**100,00 %**
Growth				
0-30	15	13,64 %	36	12,90 %
30-50	10	9,09 %	26	9,32 %
50-100	27	24,55 %	54	19,35 %
100-300	42	38,18 %	92	32,97 %
300-500	11	10,00 %	29	10,39 %
500-1000	3	2,73 %	28	10,04 %
>1000	2	1,82 %	14	5,02 %
	110	**100,00 %**	**279**	**100,00 %**
Other				
0-30	22	10,23 %	85	12,82 %
30-50	19	8,84 %	54	8,14 %
50-100	46	21,40 %	85	12,82 %
100-300	78	36,28 %	185	27,90 %
300-500	19	8,84 %	94	14,18 %
500-1000	20	9,30 %	80	12,07 %
>1000	11	5,12 %	80	12,07 %
	215	**100,00 %**	**663**	**100,00 %**

Appendix 5: Kruskal-Wallis test for fund size

Kruskal–Wallis equality–of–populations rank test

size	Obs	Rank Sum
0	303	734122.50
1	696	1.54e+06
2	343	731784.50
3	624	1.36e+06
4	1129	2.42e+06
5	452	872606.00
6	337	624197.50
7	320	553040.00

chi–squared = **85.017** with **7** d.f.
probability = **0.0001**

chi–squared with ties = **134.176** with **7** d.f.
probability = **0.0001**

Appendix 6: Chi-squared test for fund size

Zombie	size 0	1	2	3	4	5	6	7	Total
0	165	449	234	410	765	352	275	280	2,930
1	138	247	109	214	364	100	62	40	1,274
Total	303	696	343	624	1,129	452	337	320	4,204

Pearson chi2(**7**) = **134.2086** Pr = **0.000**

Appendix 7: Results of logit regression - fund size

Dependent variable: zombie

```
Iteration 0:   log likelihood = -2331.4915
Iteration 1:   log likelihood = -2269.0946
Iteration 2:   log likelihood = -2267.9899
Iteration 3:   log likelihood = -2267.9866
Iteration 4:   log likelihood = -2267.9866

Logistic regression                               Number of obs   =       3846
                                                  LR chi2(15)     =     127.01
                                                  Prob > chi2     =     0.0000
Log likelihood = -2267.9866                       Pseudo R2       =     0.0272
```

zombie	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
v2003	-.2653865	.1435634	-1.85	0.065	-.5467655	.0159926
v2004	-.0479961	.1287008	-0.37	0.709	-.300245	.2042529
v2005	-.2164556	.1183994	-1.83	0.068	-.4485143	.015603
v2006	-.171161	.1135149	-1.51	0.132	-.393646	.051324
v2007	-.2724314	.1111767	-2.45	0.014	-.4903338	-.0545291
value1	.9937774	.2033135	4.89	0.000	.5952903	1.392264
value2	.8897126	.217954	4.08	0.000	.4625306	1.316895
value3	1.017128	.2011706	5.06	0.000	.6228408	1.411415
value4	.9761597	.1912334	5.10	0.000	.6013492	1.35097
value5	.4732554	.21225	2.23	0.026	.057253	.8892578
value6	.2936799	.2272266	1.29	0.196	-.1516762	.7390359
buyout	.0745442	.1077914	0.69	0.489	-.1367231	.2858116
allearlystage	.3624765	.120516	3.01	0.003	.1262696	.5986834
growth	.1077721	.1392713	0.77	0.439	-.1651947	.3807388
allventure	.4706603	.1076117	4.37	0.000	.2597452	.6815755
_cons	-1.740622	.2013143	-8.65	0.000	-2.135191	-1.346053

Appendix 8: Kruskal-Wallis test for fund types

Kruskal-Wallis equality-of-populations rank test

testtype	Obs	Rank Sum
1	101	217381.50
2	1185	2.35e+06
3	77	142271.50
4	94	156675.00
5	657	1.47e+06
6	164	387482.00
7	417	863353.50
8	1	3567.50
9	233	450765.50
10	96	184830.00
11	1	1465.50
12	86	168073.00
13	42	76265.00
14	50	87989.00
15	1000	2.27e+06

chi-squared = **78.964** with **14** d.f.
probability = **0.0001**

chi-squared with ties = **124.623** with **14** d.f.
probability = **0.0001**

Appendix 9: Chi-squared test for fund types

Zombie	testtype 1	2	3	4	5	Total
0	68	892	63	85	415	2,930
1	33	293	14	9	242	1,274
Total	101	1,185	77	94	657	4,204

Zombie	testtype 6	7	8	9	10	Total
0	94	297	0	181	75	2,930
1	70	120	1	52	21	1,274
Total	164	417	1	233	96	4,204

Zombie	testtype 11	12	13	14	15	Total
0	1	66	35	43	615	2,930
1	0	20	7	7	385	1,274
Total	1	86	42	50	1,000	4,204

Pearson chi2(14) = 124.6513   Pr = 0.000

Appendix 10: Results of logit regression – fund types

Dependent variable: zombie

```
Iteration 0:   log likelihood = -2578.8263
Iteration 1:   log likelihood = -2497.9276
Iteration 2:   log likelihood =  -2496.084
Iteration 3:   log likelihood = -2496.0754
Iteration 4:   log likelihood = -2496.0754

Logistic regression                         Number of obs   =       4204
                                            LR chi2(24)     =     165.50
                                            Prob > chi2     =     0.0000
Log likelihood = -2496.0754                 Pseudo R2       =     0.0321
```

zombie	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
v2003	-.206951	.1345325	-1.54	0.124	-.4706298	.0567278
v2004	.0181638	.1222632	0.15	0.882	-.2214677	.2577953
v2005	-.2204978	.1138089	-1.94	0.053	-.4435593	.0025636
v2006	-.1941943	.1089152	-1.78	0.075	-.4076643	.0192756
v2007	-.2649411	.1061522	-2.50	0.013	-.4729956	-.0568866
value1	.0238874	.1259128	0.19	0.850	-.2228972	.270672
value2	-.0626302	.1504853	-0.42	0.677	-.3575761	.2323156
value3	.0846311	.1263593	0.67	0.503	-.1630285	.3322907
value4	.0944461	.1120189	0.84	0.399	-.1251069	.313999
value5	-.3642125	.1463048	-2.49	0.013	-.6509646	-.0774604
value6	-.5180939	.1689495	-3.07	0.002	-.8492288	-.186959
balanced	-.723872	1.431597	-0.51	0.613	-3.529751	2.082007
buyout	-1.066641	1.416893	-0.75	0.452	-3.843701	1.710419
coinvestment	-1.492963	1.446391	-1.03	0.302	-4.327837	1.34191
distressed	-2.210078	1.458192	-1.52	0.130	-5.068081	.6479254
allearlystage	-.5797431	1.418142	-0.41	0.683	-3.359251	2.199765
expansion	-.3250376	1.424546	-0.23	0.820	-3.117097	2.467022
growth	-.9252609	1.419677	-0.65	0.515	-3.707778	1.857256
mezzanine	-1.216633	1.424447	-0.85	0.393	-4.008498	1.575231
natural	-1.197337	1.437114	-0.83	0.405	-4.014028	1.619354
special	-1.187807	1.438524	-0.83	0.409	-4.007262	1.631648
timber	-1.607135	1.474812	-1.09	0.276	-4.497713	1.283443
turnaround	-1.844921	1.473605	-1.25	0.211	-4.733133	1.043291
allventure	-.4908961	1.417295	-0.35	0.729	-3.268744	2.286951
_cons	.1823447	1.418372	0.13	0.898	-2.597613	2.962303

Appendix 11: Results of logit regression – target value

Dependent variable: Zombie

```
Iteration 0:   log likelihood = -1430.7955
Iteration 1:   log likelihood = -1362.1962
Iteration 2:   log likelihood = -1359.7877
Iteration 3:   log likelihood = -1359.7354
Iteration 4:   log likelihood = -1359.7352
Iteration 5:   log likelihood = -1359.7352

Logistic regression                               Number of obs   =       2356
                                                  LR chi2(17)     =     142.12
                                                  Prob > chi2     =     0.0000
Log likelihood = -1359.7352                       Pseudo R2       =     0.0497
```

zombie	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
notreachedtarget	.15015	.1011505	1.48	0.138	-.0481014	.3484014
targetvalue	-.0001312	.0000905	-1.45	0.147	-.0003085	.0000461
v2003	-.1761973	.1968754	-0.89	0.371	-.5620661	.2096714
v2004	.0319361	.1686133	0.19	0.850	-.29854	.3624121
v2005	-.1560936	.154443	-1.01	0.312	-.4587963	.1466091
v2006	-.1220709	.1437414	-0.85	0.396	-.4037989	.1596571
v2007	-.2515282	.140779	-1.79	0.074	-.52745	.0243936
value1	1.192491	.3265895	3.65	0.000	.5523871	1.832594
value2	1.082161	.3359575	3.22	0.001	.4236968	1.740626
value3	1.041417	.3106204	3.35	0.001	.4326124	1.650222
value4	.99194	.2875316	3.45	0.001	.4283883	1.555492
value5	.3884411	.2963224	1.31	0.190	-.1923402	.9692225
value6	.2299766	.2963422	0.78	0.438	-.3508435	.8107966
buyout	.0391731	.1359985	0.29	0.773	-.2273791	.3057254
allearlystage	.2799523	.1606185	1.74	0.081	-.0348542	.5947588
growth	.041884	.1827032	0.23	0.819	-.3162077	.3999757
allventure	.2701062	.1454207	1.86	0.063	-.0149131	.5551256
_cons	-1.667816	.3123965	-5.34	0.000	-2.280102	-1.05553

Appendix 12: Results of GLS regression – IRR

Dependent variable: IRR

```
Random-effects GLS regression                   Number of obs      =      3993
Group variable: f                               Number of groups   =      1146

R-sq:  within  = 0.3363                         Obs per group: min =         1
       between = 0.9064                                        avg =       3.5
       overall = 0.8700                                        max =         8

                                                Wald chi2(24)      =  10243.39
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

irr	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
zombie	-2.413936	.3372835	-7.16	0.000	-3.075	-1.752873
irr						
L1.	.7099799	.0079118	89.74	0.000	.6944731	.7254867
value1	-.4654956	.7522728	-0.62	0.536	-1.939923	1.008932
value2	-1.165996	.7993125	-1.46	0.145	-2.73262	.4006273
value3	-.5042281	.5599512	-0.90	0.368	-1.601712	.5932561
value4	.5621418	.3822717	1.47	0.141	-.1870969	1.31138
value5	.7387633	.4171685	1.77	0.077	-.0788719	1.556399
value6	.106319	.4194293	0.25	0.800	-.7157474	.9283854
v2003	-.7241183	.5624231	-1.29	0.198	-1.826447	.3782107
v2004	-1.103644	.506582	-2.18	0.029	-2.096526	-.1107615
v2005	-1.771705	.4262905	-4.16	0.000	-2.607219	-.9361915
v2006	-1.741059	.4132206	-4.21	0.000	-2.550956	-.931161
v2007	-.9805792	.4133493	-2.37	0.018	-1.790729	-.1704295
buyout	1.726387	.3326409	5.19	0.000	1.074423	2.378352
allventure	-.5916166	.4246925	-1.39	0.164	-1.423999	.2407655
allearlystage	-.0670654	.496294	-0.14	0.893	-1.039784	.905653
growth	.8449512	.5586623	1.51	0.130	-.2500068	1.939909
y2007	4.016668	.7379162	5.44	0.000	2.570379	5.462957
y2008	-6.565074	.4796448	-13.69	0.000	-7.50516	-5.624987
y2009	-.2072944	.3336706	-0.62	0.534	-.8612767	.446688
y2010	2.032369	.268225	7.58	0.000	1.506658	2.558081
y2011	.1394903	.2251812	0.62	0.536	-.3018568	.5808373
y2012	-.0881912	.204173	-0.43	0.666	-.4883628	.3119805
y2013	.2770052	.197586	1.40	0.161	-.1102563	.6642668
_cons	3.822088	.4604012	8.30	0.000	2.919719	4.724458
sigma_u	3.1011548					
sigma_e	3.5581796					
rho	.43169252	(fraction of variance due to u_i)				

Appendix 13: Results of GLS regression – IRR and time zombie

Dependent variable: IRR

```
Random-effects GLS regression                   Number of obs      =      1720
Group variable: f                               Number of groups   =       822

R-sq:  within  = 0.0810                         Obs per group: min =         1
       between = 0.9699                                        avg =       2.1
       overall = 0.9574                                        max =         5

                                                Wald chi2(20)      =  20893.55
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

irr	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
timezombie	-.456232	.2448965	-1.86	0.062	-.9362203	.0237564
irr						
L1.	.9316369	.0071461	130.37	0.000	.9176308	.9456431
value1	-.0812369	.5389334	-0.15	0.880	-1.137527	.9750531
value2	-1.325238	.5366146	-2.47	0.014	-2.376983	-.2734927
value3	-.7082391	.4086673	-1.73	0.083	-1.509212	.0927341
value4	.0236621	.278994	0.08	0.932	-.5231561	.5704803
value5	.1179697	.2995957	0.39	0.694	-.4692271	.7051665
value6	-.109873	.2998116	-0.37	0.714	-.6974929	.4777469
v2003	-.2591098	.3702253	-0.70	0.484	-.9847381	.4665184
v2004	-.2039705	.3434142	-0.59	0.553	-.8770499	.469109
v2005	-.3090294	.298291	-1.04	0.300	-.8936689	.2756102
v2006	-.2027276	.2956176	-0.69	0.493	-.7821275	.3766723
buyout	.5167878	.2418448	2.14	0.033	.0427807	.9907949
allventure	.3337999	.309219	1.08	0.280	-.2722582	.939858
allearlystage	1.04691	.357433	2.93	0.003	.3463541	1.747466
growth	.8467803	.4259909	1.99	0.047	.0118535	1.681707
y2010	1.207445	.4220608	2.86	0.004	.3802209	2.034669
y2011	-.083001	.2824678	-0.29	0.769	-.6366278	.4706257
y2012	-.0791301	.2052624	-0.39	0.700	-.481437	.3231768
y2013	.1702136	.1641754	1.04	0.300	-.1515642	.4919914
_cons	.8164103	.3210487	2.54	0.011	.1871664	1.445654
sigma_u	1.4665629					
sigma_e	2.1220146					
rho	.32324717	(fraction of variance due to u_i)				

Appendix 14: Results of GLS regression – TVPI

Dependent variable: TVPI

```
Random-effects GLS regression                   Number of obs      =      6272
Group variable: f                               Number of groups   =      1310

R-sq:  within  = 0.5734                         Obs per group: min =         1
       between = 0.9033                                        avg =       4.8
       overall = 0.8135                                        max =        11

                                                Wald chi2(24)      =  18637.56
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

tvpi	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
zombie	-7.949495	.9365726	-8.49	0.000	-9.785143	-6.113846
tvpi						
L1.	.8494831	.0072921	116.49	0.000	.8351909	.8637753
value1	-3.48706	2.320021	-1.50	0.133	-8.034218	1.060098
value2	-3.186353	2.418648	-1.32	0.188	-7.926815	1.55411
value3	-1.290106	1.582276	-0.82	0.415	-4.391309	1.811097
value4	1.910466	1.094172	1.75	0.081	-.2340709	4.055003
value5	2.314303	1.202265	1.92	0.054	-.0420936	4.670699
value6	.8197179	1.185472	0.69	0.489	-1.503765	3.143201
v2003	.4063313	1.584537	0.26	0.798	-2.699304	3.511967
v2004	.4863153	1.440012	0.34	0.736	-2.336056	3.308687
v2005	-1.307807	1.216471	-1.08	0.282	-3.692047	1.076433
v2006	-1.388428	1.172464	-1.18	0.236	-3.686415	.9095594
v2007	.2434012	1.167475	0.21	0.835	-2.044807	2.531609
buyout	3.888568	.9690346	4.01	0.000	1.989295	5.787841
allventure	-1.24902	1.209523	-1.03	0.302	-3.619642	1.121602
allearlystage	-.0313025	1.427511	-0.02	0.983	-2.829173	2.766568
growth	1.625219	1.593885	1.02	0.308	-1.498738	4.749177
y2007	4.130136	1.244988	3.32	0.001	1.690004	6.570268
y2008	-21.89246	1.081236	-20.25	0.000	-24.01165	-19.77328
y2009	-5.495275	1.003041	-5.48	0.000	-7.461199	-3.529352
y2010	1.366249	.9429182	1.45	0.147	-.4818369	3.214334
y2011	-1.986839	.8962819	-2.22	0.027	-3.74352	-.2301591
y2012	-1.769868	.8730803	-2.03	0.043	-3.481073	-.0586616
y2013	1.033171	.8619109	1.20	0.231	-.656143	2.722486
_cons	27.63081	1.639028	16.86	0.000	24.41838	30.84325
sigma_u	8.3698913					
sigma_e	18.881897					
rho	.16422453	(fraction of variance due to u_i)				

Appendix 15: Results of GLS regression – TVPI and time zombie

Dependent variable TVPI

```
Random-effects GLS regression                   Number of obs      =      1828
Group variable: f                               Number of groups   =       875

R-sq:  within  = 0.1880                         Obs per group: min =         1
       between = 0.9485                                        avg =       2.1
       overall = 0.8826                                        max =         5

                                                Wald chi2(20)      =  13591.04
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

tvpi	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
timezombie	-4.597558	1.80029	-2.55	0.011	-8.126062	-1.069054
tvpi						
L1.	1.030165	.0094574	108.93	0.000	1.011629	1.048701
value1	-6.055189	4.249577	-1.42	0.154	-14.38421	2.273829
value2	-4.982187	4.03661	-1.23	0.217	-12.8938	2.929422
value3	-4.323773	3.072442	-1.41	0.159	-10.34565	1.698102
value4	1.886137	2.102153	0.90	0.370	-2.234007	6.006281
value5	.1313618	2.274297	0.06	0.954	-4.326178	4.588902
value6	-.5274583	2.279168	-0.23	0.817	-4.994545	3.939629
v2003	-7.896116	3.025741	-2.61	0.009	-13.82646	-1.965773
v2004	-4.907748	2.898947	-1.69	0.090	-10.58958	.7740839
v2005	-4.147336	2.605312	-1.59	0.111	-9.253654	.9589808
v2006	-2.344742	2.603737	-0.90	0.368	-7.447973	2.758488
buyout	1.830304	1.850665	0.99	0.323	-1.796932	5.457541
allventure	2.612488	2.310326	1.13	0.258	-1.915668	7.140644
allearlystage	7.143842	2.747244	2.60	0.009	1.759343	12.52834
growth	5.651786	3.270394	1.73	0.084	-.7580695	12.06164
y2010	9.910486	4.678812	2.12	0.034	.7401836	19.08079
y2011	6.054448	3.045878	1.99	0.047	.0846358	12.02426
y2012	4.001616	2.2028	1.82	0.069	-.3157915	8.319024
y2013	4.670464	1.788761	2.61	0.009	1.164557	8.176371
_cons	1.99196	2.984987	0.67	0.505	-3.858506	7.842427
sigma_u	0					
sigma_e	25.006689					
rho	0	(fraction of variance due to u_i)				

Appendix 16: Results of GLS regression – DPI

Dependent variable: DPI

```
Random-effects GLS regression                   Number of obs      =      4045
Group variable: f                               Number of groups   =      1165

R-sq:  within  = 0.6743                         Obs per group: min =         1
       between = 0.9282                                        avg =       3.5
       overall = 0.8809                                        max =         8

                                                Wald chi2(25)      =  23103.82
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

dpi	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
zombie	-3.515107	.9585304	-3.67	0.000	-5.393792	-1.636422
dpi						
L1.	.8774597	.0106553	82.35	0.000	.8565756	.8983437
irr						
L1.	.532398	.0309427	17.21	0.000	.4717515	.5930446
value1	-1.85747	2.248741	-0.83	0.409	-6.264922	2.549982
value2	-1.164188	2.35266	-0.49	0.621	-5.775317	3.446941
value3	-4.298528	1.621062	-2.65	0.008	-7.475751	-1.121306
value4	-.7226821	1.086551	-0.67	0.506	-2.852282	1.406918
value5	-.8385195	1.178301	-0.71	0.477	-3.147947	1.470908
value6	-2.125817	1.174421	-1.81	0.070	-4.427639	.1760058
v2003	9.530651	1.802512	5.29	0.000	5.997792	13.06351
v2004	9.559303	1.61014	5.94	0.000	6.403486	12.71512
v2005	8.21996	1.35173	6.08	0.000	5.570618	10.8693
v2006	7.561014	1.270464	5.95	0.000	5.07095	10.05108
v2007	3.899512	1.25292	3.11	0.002	1.443833	6.35519
buyout	1.024268	.952296	1.08	0.282	-.842198	2.890734
allventure	-2.399336	1.220887	-1.97	0.049	-4.792231	-.0064403
allearlystage	-4.13847	1.421603	-2.91	0.004	-6.924761	-1.352179
growth	.5378281	1.613957	0.33	0.739	-2.62547	3.701126
y2007	-5.048846	3.282211	-1.54	0.124	-11.48186	1.384168
y2008	-15.20991	2.2405	-6.79	0.000	-19.60121	-10.81861
y2009	-14.19992	1.56634	-9.07	0.000	-17.26989	-11.12995
y2010	-5.709848	1.262405	-4.52	0.000	-8.184117	-3.235579
y2011	-2.940004	1.068434	-2.75	0.006	-5.034097	-.8459111
y2012	-1.785715	.9273835	-1.93	0.054	-3.603353	.0319236
y2013	.5435864	.8784571	0.62	0.536	-1.178158	2.265331
_cons	12.87552	1.459078	8.82	0.000	10.01578	15.73526
sigma_u	6.6296086					
sigma_e	17.547998					
rho	.124904	(fraction of variance due to u_i)				

Appendix 17: Results of GLS regression – DPI and time zombie

Dependent variable: DPI

```
Random-effects GLS regression                   Number of obs      =      1874
Group variable: f                               Number of groups   =       893

R-sq:  within  = 0.5593                         Obs per group: min =         1
       between = 0.9109                                        avg =       2.1
       overall = 0.8776                                        max =         5

                                                Wald chi2(20)      =  12645.47
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

dpi	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
timezombie	-4.176174	1.521222	-2.75	0.006	-7.157714	-1.194635
dpi						
L1.	1.113596	.011586	96.12	0.000	1.090888	1.136304
value1	-7.376591	3.497646	-2.11	0.035	-14.23185	-.521331
value2	.3038248	3.374609	0.09	0.928	-6.310288	6.917937
value3	-5.567353	2.575825	-2.16	0.031	-10.61588	-.5188283
value4	-.621298	1.785372	-0.35	0.728	-4.120562	2.877966
value5	-1.814249	1.930404	-0.94	0.347	-5.597772	1.969274
value6	-1.641119	1.928637	-0.85	0.395	-5.421179	2.13894
v2003	-10.87788	2.654748	-4.10	0.000	-16.08109	-5.674667
v2004	-5.777082	2.491404	-2.32	0.020	-10.66015	-.8940191
v2005	-4.083311	2.198071	-1.86	0.063	-8.391452	.22483
v2006	-1.421622	2.162772	-0.66	0.511	-5.660576	2.817333
buyout	2.774897	1.56163	1.78	0.076	-.2858412	5.835635
allventure	1.571784	1.974756	0.80	0.426	-2.298667	5.442235
allearlystage	4.917925	2.317327	2.12	0.034	.3760473	9.459802
growth	3.716063	2.772278	1.34	0.180	-1.717501	9.149628
y2010	7.061483	3.743438	1.89	0.059	-.2755213	14.39849
y2011	9.703652	2.475221	3.92	0.000	4.852307	14.555
y2012	4.569986	1.802737	2.54	0.011	1.036686	8.103285
y2013	4.621106	1.453134	3.18	0.001	1.773015	7.469197
_cons	7.742865	2.328321	3.33	0.001	3.17944	12.30629
sigma_u	4.4537083					
sigma_e	22.200918					
rho	.03868712	(fraction of variance due to u_i)				

Appendix 18: Results of GLS regression – DPI for vintage 2003

Dependent variable: DPI

```
Random-effects GLS regression                   Number of obs      =       788
Group variable: f                               Number of groups   =       135

R-sq:  within  = 0.2070                         Obs per group: min =         1
       between = 0.4052                                        avg =       5.8
       overall = 0.3269                                        max =        12

                                                Wald chi2(18)      =    254.57
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

dpi	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
zombie	-10.68285	10.71826	-1.00	0.319	-31.69024	10.32455
value1	-6.965291	18.82448	-0.37	0.711	-43.86059	29.93001
value2	-13.96834	16.76454	-0.83	0.405	-46.82624	18.88956
value3	7.956582	17.70972	0.45	0.653	-26.75383	42.66699
value4	.4739175	14.16558	0.03	0.973	-27.29012	28.23795
value5	-7.662461	17.66499	-0.43	0.664	-42.2852	26.96027
value6	-2.345178	15.29575	-0.15	0.878	-32.32429	27.63393
buyout	12.23116	11.29947	1.08	0.279	-9.915398	34.37772
allventure	-49.52555	13.30485	-3.72	0.000	-75.60259	-23.44852
allearlystage	-60.27355	15.17299	-3.97	0.000	-90.01207	-30.53504
growth	-56.22478	35.50065	-1.58	0.113	-125.8048	13.35521
y2007	8.092757	6.158648	1.31	0.189	-3.977972	20.16348
y2008	12.4415	6.423836	1.94	0.053	-.1489832	25.03199
y2009	14.66332	5.846014	2.51	0.012	3.205345	26.1213
y2010	24.36869	5.629414	4.33	0.000	13.33524	35.40214
y2011	38.26528	5.475491	6.99	0.000	27.53352	48.99705
y2012	48.2687	5.526632	8.73	0.000	37.4367	59.1007
y2013	63.40148	5.542346	11.44	0.000	52.53869	74.26428
_cons	72.64314	13.40593	5.42	0.000	46.36799	98.91829
sigma_u	40.883487					
sigma_e	41.881117					
rho	.48794792	(fraction of variance due to u_i)				

Appendix 19: Results of GLS regression – DPI for vintage 2004

Dependent variable: DPI

```
Random-effects GLS regression                   Number of obs      =      1033
Group variable: f                               Number of groups   =       175

R-sq:  within  = 0.1986                         Obs per group: min =         1
       between = 0.3083                                        avg =       5.9
       overall = 0.2961                                        max =        11

                                                Wald chi2(18)      =    290.30
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

dpi	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
zombie	-36.38322	8.996382	-4.04	0.000	-54.0158	-18.75064
value1	11.22479	18.86143	0.60	0.552	-25.74293	48.19251
value2	21.57213	18.99925	1.14	0.256	-15.66571	58.80997
value3	18.76529	15.63075	1.20	0.230	-11.87042	49.40099
value4	-1.732958	12.66618	-0.14	0.891	-26.55822	23.0923
value5	5.298781	13.3389	0.40	0.691	-20.84499	31.44255
value6	1.890961	15.64444	0.12	0.904	-28.77158	32.55351
buyout	14.20187	10.30612	1.38	0.168	-5.997756	34.4015
allventure	-37.93897	12.30008	-3.08	0.002	-62.04669	-13.83124
allearlystage	-43.47615	13.2129	-3.29	0.001	-69.37295	-17.57935
growth	-17.35343	21.21251	-0.82	0.413	-58.92919	24.22232
y2007	-6.545987	5.268444	-1.24	0.214	-16.87195	3.779973
y2008	-.4544884	5.464809	-0.08	0.934	-11.16532	10.25634
y2009	2.574113	5.175537	0.50	0.619	-7.569753	12.71798
y2010	14.15728	5.07505	2.79	0.005	4.210364	24.1042
y2011	33.36293	4.879816	6.84	0.000	23.79866	42.92719
y2012	42.80803	4.925685	8.69	0.000	33.15387	52.4622
y2013	55.68436	5.0293	11.07	0.000	45.82711	65.54161
_cons	60.59764	12.63227	4.80	0.000	35.83884	85.35644
sigma_u	43.267					
sigma_e	42.92484					
rho	.50396969	(fraction of variance due to u_i)				

Appendix 20: Results of GLS regression – DPI for vintage 2005

Dependent variable: DPI

```
Random-effects GLS regression                   Number of obs      =      1728
Group variable: f                               Number of groups   =       297

R-sq:  within  = 0.2267                         Obs per group: min =         1
       between = 0.2459                                        avg =       5.8
       overall = 0.2418                                        max =        10

                                                Wald chi2(18)      =    513.37
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

dpi	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
zombie	-18.12449	6.17047	-2.94	0.003	-30.21839	-6.030589
value1	41.98959	13.5671	3.09	0.002	15.39857	68.58062
value2	-4.929926	14.89252	-0.33	0.741	-34.11874	24.25889
value3	2.99651	10.77868	0.28	0.781	-18.12932	24.12234
value4	12.406	8.210804	1.51	0.131	-3.686879	28.49888
value5	10.09294	9.150918	1.10	0.270	-7.842534	28.02841
value6	-7.95052	9.083013	-0.88	0.381	-25.7529	9.851859
buyout	15.59773	6.426519	2.43	0.015	3.001988	28.19348
allventure	-18.74222	8.165464	-2.30	0.022	-34.74624	-2.738206
allearlystage	-38.93968	10.20387	-3.82	0.000	-58.93889	-18.94046
growth	9.011028	10.51786	0.86	0.392	-11.60359	29.62565
y2007	-27.18277	3.503549	-7.76	0.000	-34.0496	-20.31594
y2008	-23.62733	3.432257	-6.88	0.000	-30.35443	-16.90023
y2009	-21.19952	3.340463	-6.35	0.000	-27.74671	-14.65234
y2010	-7.794663	3.186076	-2.45	0.014	-14.03926	-1.550069
y2011	6.213596	3.108719	2.00	0.046	.1206198	12.30657
y2012	19.52521	3.096904	6.30	0.000	13.45539	25.59503
y2013	36.1393	3.023804	11.95	0.000	30.21275	42.06584
_cons	49.72163	8.293573	6.00	0.000	33.46652	65.97673
sigma_u	39.070141					
sigma_e	35.839848					
rho	.54304229	(fraction of variance due to u_i)				

Appendix 21: Results of GLS regression – DPI for vintage 2006

Dependent variable: DPI

```
Random-effects GLS regression                   Number of obs      =      1839
Group variable: f                               Number of groups   =       345

R-sq:  within  = 0.3528                         Obs per group: min =         1
       between = 0.2945                                        avg =       5.3
       overall = 0.3020                                        max =         9

                                                Wald chi2(18)      =    936.81
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

dpi	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
zombie	-13.85376	3.806418	-3.64	0.000	-21.3142	-6.393318
value1	12.57973	7.446258	1.69	0.091	-2.014673	27.17412
value2	19.95702	9.69136	2.06	0.039	.9622982	38.95173
value3	10.37317	6.882595	1.51	0.132	-3.116468	23.86281
value4	2.804205	5.007657	0.56	0.575	-7.010622	12.61903
value5	.4595545	5.407405	0.08	0.932	-10.13876	11.05787
value6	-3.028684	5.174335	-0.59	0.558	-13.1702	7.112826
buyout	-4.45368	4.266354	-1.04	0.297	-12.81558	3.90822
allventure	-16.00412	5.346258	-2.99	0.003	-26.4826	-5.52565
allearlystage	-18.91917	6.264723	-3.02	0.003	-31.19781	-6.640543
growth	-9.243669	6.229324	-1.48	0.138	-21.45292	2.965582
y2007	-42.69748	2.550301	-16.74	0.000	-47.69598	-37.69898
y2008	-41.08033	2.54072	-16.17	0.000	-46.06005	-36.10061
y2009	-39.88609	2.454212	-16.25	0.000	-44.69625	-35.07592
y2010	-33.72213	2.331269	-14.47	0.000	-38.29134	-29.15293
y2011	-20.84851	2.285889	-9.12	0.000	-25.32877	-16.36825
y2012	-5.149902	2.227076	-2.31	0.021	-9.51489	-.7849138
y2013	10.20223	2.227695	4.58	0.000	5.83603	14.56843
_cons	59.77396	4.791372	12.48	0.000	50.38304	69.16488
sigma_u	25.788445					
sigma_e	26.69717					
rho	.4826914	(fraction of variance due to u_i)				

Appendix 22: Results of GLS regression – DPI for vintage 2007

Dependent variable: DPI

```
Random-effects GLS regression                   Number of obs      =      1810
Group variable: f                               Number of groups   =       348

R-sq:  within  = 0.2710                         Obs per group: min =         1
       between = 0.1988                                        avg =       5.2
       overall = 0.2225                                        max =         8

                                                Wald chi2(17)      =    617.35
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

dpi	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
zombie	-19.88999	3.762382	-5.29	0.000	-27.26413	-12.51586
value1	17.66375	7.373742	2.40	0.017	3.211478	32.11601
value2	8.62784	8.229854	1.05	0.294	-7.502377	24.75806
value3	7.088762	5.47151	1.30	0.195	-3.6352	17.81272
value4	10.82267	3.864245	2.80	0.005	3.248893	18.39645
value5	6.114299	4.61446	1.33	0.185	-2.929876	15.15847
value6	-.1479508	4.799505	-0.03	0.975	-9.554807	9.258905
buyout	2.409895	3.584288	0.67	0.501	-4.61518	9.43497
allventure	-12.81104	4.419914	-2.90	0.004	-21.47391	-4.148172
allearlystage	-15.21659	5.107971	-2.98	0.003	-25.22803	-5.205149
growth	-5.579637	5.553539	-1.00	0.315	-16.46437	5.3051
y2008	-35.78574	2.559749	-13.98	0.000	-40.80276	-30.76873
y2009	-33.8263	2.432616	-13.91	0.000	-38.59413	-29.05846
y2010	-26.81942	2.316773	-11.58	0.000	-31.36021	-22.27863
y2011	-15.46624	2.301356	-6.72	0.000	-19.97681	-10.95566
y2012	-2.296678	2.289249	-1.00	0.316	-6.783524	2.190169
y2013	10.87918	2.243792	4.85	0.000	6.481431	15.27693
_cons	39.42974	3.728893	10.57	0.000	32.12124	46.73824
sigma_u	21.172402					
sigma_e	28.137128					
rho	.36151772	(fraction of variance due to u_i)				

Appendix 23: Results of GLS regression – DPI for vintage 2008

Dependent variable: DPI

```
Random-effects GLS regression                   Number of obs      =      1407
Group variable: f                               Number of groups   =       327

R-sq:  within  = 0.2291                         Obs per group: min =         1
       between = 0.1086                                        avg =       4.3
       overall = 0.1705                                        max =         7

                                                Wald chi2(16)      =    363.00
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

dpi	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
zombie	-12.75356	4.282884	-2.98	0.003	-21.14786	-4.359262
value1	17.56176	8.954337	1.96	0.050	.0115798	35.11194
value2	7.643466	9.375042	0.82	0.415	-10.73128	26.01821
value3	4.97813	6.574684	0.76	0.449	-7.908014	17.86427
value4	1.021007	5.419596	0.19	0.851	-9.601207	11.64322
value5	-.6332231	5.981587	-0.11	0.916	-12.35692	11.09047
value6	-3.334434	6.208149	-0.54	0.591	-15.50218	8.833315
buyout	-7.241003	4.676241	-1.55	0.122	-16.40627	1.924261
allventure	-12.94481	5.653472	-2.29	0.022	-24.02541	-1.864212
allearlystage	-19.73234	6.928577	-2.85	0.004	-33.3121	-6.152577
growth	-13.95179	6.211972	-2.25	0.025	-26.12703	-1.776551
y2009	-30.92146	2.356172	-13.12	0.000	-35.53947	-26.30345
y2010	-27.7847	2.266877	-12.26	0.000	-32.2277	-23.34171
y2011	-17.29461	2.165519	-7.99	0.000	-21.53895	-13.05027
y2012	-9.460731	2.101084	-4.50	0.000	-13.57878	-5.342683
y2013	3.417247	2.096515	1.63	0.103	-.6918462	7.526341
_cons	47.95785	4.791347	10.01	0.000	38.56699	57.34872
sigma_u	28.838721					
sigma_e	24.577085					
rho	.57927769	(fraction of variance due to u_i)				

Appendix 24: Average change in DPI for zombie funds and non-zombie funds

Zombies

Variable	Obs	Mean	Std. Dev.	Min	Max
changedpi	807	.1993739	.4496872	-.8888889	1.944444

Non-zombies

Variable	Obs	Mean	Std. Dev.	Min	Max
changedpi	3350	.2977972	.4666686	-1	1.995816

Appendix 25: Results of GLS regression – Change in DPI

Dependent variable: change in DPI

```
Random-effects GLS regression                   Number of obs      =      2708
Group variable: f                               Number of groups   =       903

R-sq:  within  = 0.0691                         Obs per group: min =         1
       between = 0.1223                                        avg =       3.0
       overall = 0.0984                                        max =         9

                                                Wald chi2(21)      =    282.23
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

changedpi	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
zombie	-.0962018	.0220011	-4.37	0.000	-.1393232	-.0530804
changedpi						
L1.	.0551543	.0161238	3.42	0.001	.0235523	.0867563
dpi						
L1.	-.0016712	.0001711	-9.77	0.000	-.0020065	-.0013358
value1	-.1322688	.0618764	-2.14	0.033	-.2535443	-.0109934
value2	-.134858	.0586876	-2.30	0.022	-.2498835	-.0198325
value3	-.0781688	.0379033	-2.06	0.039	-.1524578	-.0038798
value4	-.0850109	.0245477	-3.46	0.001	-.1331236	-.0368982
value5	-.0408938	.0265136	-1.54	0.123	-.0928596	.011072
value6	-.0495067	.025317	-1.96	0.051	-.0991271	.0001136
v2003	-.0398391	.0305755	-1.30	0.193	-.099766	.0200879
v2004	-.0333272	.028155	-1.18	0.237	-.0885099	.0218556
v2005	-.0461615	.0237551	-1.94	0.052	-.0927206	.0003975
v2006	.0148292	.0241583	0.61	0.539	-.0325202	.0621786
buyout	.011685	.021248	0.55	0.582	-.0299604	.0533304
allventure	-.0197815	.0277488	-0.71	0.476	-.0741682	.0346051
allearlystage	-.0967435	.0332922	-2.91	0.004	-.1619951	-.0314919
growth	-.0342163	.0391881	-0.87	0.383	-.1110235	.0425909
y2010	.1126037	.0288656	3.90	0.000	.0560281	.1691793
y2011	.0966444	.0260196	3.71	0.000	.0456469	.1476419
y2012	.115685	.0223058	5.19	0.000	.0719665	.1594035
y2013	.0914182	.0204136	4.48	0.000	.0514082	.1314281
_cons	.3886253	.0287787	13.50	0.000	.3322201	.4450305
sigma_u	.072228					
sigma_e	.37294048					
rho	.03615267	(fraction of variance due to u_i)				

Appendix 26: Results of GLS regression – Change in DPI and time zombie

Dependent variable change in DPI

Random-effects GLS regression		Number of obs =	1405
Group variable: f		Number of groups =	678
R-sq:	within = 0.2121	Obs per group: min =	1
	between = 0.0509	avg =	2.1
	overall = 0.0769	max =	5
		Wald chi2(21) =	170.27
corr(u_i, X)	= 0 (assumed)	Prob > chi2 =	0.0000

changedpi	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
timezombie	-.0904488	.0298349	-3.03	0.002	-.1489241	-.0319735
changedpi						
L1.	-.0483475	.0216372	-2.23	0.025	-.0907557	-.0059394
dpi						
L1.	-.0017497	.000212	-8.25	0.000	-.0021651	-.0013342
value1	-.1247198	.0765124	-1.63	0.103	-.2746813	.0252418
value2	-.1040495	.0712773	-1.46	0.144	-.2437505	.0356515
value3	-.0801573	.0508801	-1.58	0.115	-.1798804	.0195658
value4	-.0584502	.0341721	-1.71	0.087	-.1254263	.0085259
value5	-.0203329	.0364978	-0.56	0.577	-.0918672	.0512014
value6	-.0343338	.0363165	-0.95	0.344	-.1055128	.0368453
v2003	-.1086588	.0479608	-2.27	0.023	-.2026603	-.0146573
v2004	-.095097	.0444842	-2.14	0.033	-.1822844	-.0079097
v2005	-.0750028	.0383163	-1.96	0.050	-.1501013	.0000958
v2006	-.0095969	.0374304	-0.26	0.798	-.082959	.0637653
buyout	.0561745	.0296769	1.89	0.058	-.001991	.1143401
allventure	.0169043	.0377603	0.45	0.654	-.0571045	.0909131
allearlystage	-.0291482	.0455245	-0.64	0.522	-.1183745	.060078
growth	.0376716	.0539459	0.70	0.485	-.0680605	.1434036
y2010	.0565749	.0528651	1.07	0.285	-.0470387	.1601885
y2011	.1212949	.033748	3.59	0.000	.05515	.1874398
y2012	.0962994	.0244976	3.93	0.000	.0482849	.1443139
y2013	.0782058	.0190966	4.10	0.000	.0407771	.1156345
_cons	.4285911	.0428605	10.00	0.000	.3445861	.512596
sigma_u	.20193133					
sigma_e	.25444069					
rho	.38644506	(fraction of variance due to u_i)				

Appendix 27: Results of GLS regression – Change in DPI for vintage 2003

Dependent variable: Change in DPI

```
Random-effects GLS regression                   Number of obs      =       477
Group variable: f                               Number of groups   =       101

R-sq:  within  = 0.0638                         Obs per group: min =         1
       between = 0.2251                                        avg =       4.7
       overall = 0.1146                                        max =        10

                                                Wald chi2(18)      =     52.83
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

changedpi	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
zombie	-.1423974	.0610277	-2.33	0.020	-.2620094	-.0227854
value1	-.077571	.1184219	-0.66	0.512	-.3096737	.1545318
value2	-.1311676	.0938579	-1.40	0.162	-.3151258	.0527905
value3	.0544119	.0928373	0.59	0.558	-.1275458	.2363696
value4	.0805374	.0729464	1.10	0.270	-.0624349	.2235097
value5	-.0113541	.0898386	-0.13	0.899	-.1874345	.1647262
value6	-.0534567	.0728037	-0.73	0.463	-.1961494	.0892359
buyout	-.0169075	.0620219	-0.27	0.785	-.1384682	.1046532
allventure	.0723395	.0748627	0.97	0.334	-.0743888	.2190677
allearlystage	-.0410439	.08757	-0.47	0.639	-.2126778	.1305901
growth	.4526448	.2253491	2.01	0.045	.0109686	.894321
y2007	.2835898	.0725012	3.91	0.000	.14149	.4256895
y2008	-.038749	.0703977	-0.55	0.582	-.176726	.0992279
y2009	-.0721481	.0690786	-1.04	0.296	-.2075396	.0632434
y2010	-.0283295	.0655272	-0.43	0.666	-.1567605	.1001015
y2011	-.0169286	.0607433	-0.28	0.780	-.1359832	.102126
y2012	-.040451	.0595441	-0.68	0.497	-.1571553	.0762532
y2013	-.0913077	.0599569	-1.52	0.128	-.2088211	.0262058
_cons	.2362827	.0750689	3.15	0.002	.0891504	.383415
sigma_u	.11532657					
sigma_e	.38668695					
rho	.08168312	(fraction of variance due to u_i)				

Appendix 28: Results of GLS regression – Change in DPI for vintage 2004

Dependent variable: Change in DPI

```
Random-effects GLS regression                   Number of obs      =       571
Group variable: f                               Number of groups   =       120

R-sq:  within  = 0.0751                         Obs per group: min =         1
       between = 0.1964                                        avg =       4.8
       overall = 0.0925                                        max =         9

                                                Wald chi2(18)      =     56.26
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

changedpi	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
zombie	-.1119928	.0419421	-2.67	0.008	-.1941978	-.0297877
value1	-.0528819	.1189071	-0.44	0.657	-.2859355	.1801718
value2	.1273488	.1038347	1.23	0.220	-.0761635	.3308612
value3	-.0343513	.0787378	-0.44	0.663	-.1886746	.119972
value4	.0560595	.0506167	1.11	0.268	-.0431475	.1552665
value5	-.0213384	.0497938	-0.43	0.668	-.1189324	.0762557
value6	.0076905	.0576433	0.13	0.894	-.1052882	.1206693
buyout	.0035122	.04276	0.08	0.935	-.0802958	.0873201
allventure	.0248436	.0544023	0.46	0.648	-.081783	.1314702
allearlystage	-.0743704	.0656012	-1.13	0.257	-.2029463	.0542055
growth	-.1197118	.0922211	-1.30	0.194	-.300462	.0610383
y2007	.2709505	.0767622	3.53	0.000	.1204993	.4214017
y2008	.0999314	.065558	1.52	0.127	-.0285599	.2284227
y2009	-.0211103	.0611069	-0.35	0.730	-.1408778	.0986571
y2010	.2502019	.0591177	4.23	0.000	.1343332	.3660706
y2011	.2352176	.0564291	4.17	0.000	.1246186	.3458166
y2012	.0701576	.0542009	1.29	0.196	-.0360742	.1763894
y2013	.0816495	.0554336	1.47	0.141	-.0269984	.1902974
_cons	.1359476	.0574888	2.36	0.018	.0232716	.2486236
sigma_u	0					
sigma_e	.3836463					
rho	0	(fraction of variance due to u_i)				

Appendix 29: Results of GLS regression – Change in DPI for vintage 2005

Dependent variable: Change in DPI

```
Random-effects GLS regression                   Number of obs      =       974
Group variable: f                               Number of groups   =       232

R-sq:  within  = 0.0799                         Obs per group: min =         1
       between = 0.0801                                        avg =       4.2
       overall = 0.0870                                        max =         9

                                                Wald chi2(18)      =     90.64
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

changedpi	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
zombie	-.0116991	.0329553	-0.35	0.723	-.0762902	.052892
value1	-.128343	.1264615	-1.01	0.310	-.3762029	.1195169
value2	-.1413091	.1171131	-1.21	0.228	-.3708465	.0882283
value3	-.1659749	.060294	-2.75	0.006	-.284149	-.0478008
value4	-.1434453	.0400741	-3.58	0.000	-.2219891	-.0649015
value5	-.1075538	.0425602	-2.53	0.012	-.1909703	-.0241373
value6	-.0832059	.0410943	-2.02	0.043	-.1637492	-.0026627
buyout	-.0737839	.0333798	-2.21	0.027	-.1392072	-.0083606
allventure	-.0968436	.0445725	-2.17	0.030	-.1842041	-.0094832
allearlystage	-.1328275	.0572488	-2.32	0.020	-.2450331	-.020622
growth	-.0196478	.062252	-0.32	0.752	-.1416594	.1023638
y2007	.2638585	.0748521	3.53	0.000	.1171511	.4105659
y2008	.0720298	.0539747	1.33	0.182	-.0337587	.1778183
y2009	-.0446537	.049338	-0.91	0.365	-.1413544	.052047
y2010	.2699853	.0487762	5.54	0.000	.1743856	.3655849
y2011	.178445	.0450331	3.96	0.000	.0901818	.2667082
y2012	.1806954	.0430171	4.20	0.000	.0963835	.2650073
y2013	.122507	.0420422	2.91	0.004	.0401059	.2049082
_cons	.3051195	.0469756	6.50	0.000	.213049	.3971899
sigma_u	.02833931					
sigma_e	.39364101					
rho	.00515623	(fraction of variance due to u_i)				

Appendix 30: Results of GLS regression – Change in DPI for vintage 2006

Dependent variable: Change in DPI

```
Random-effects GLS regression                   Number of obs      =       876
Group variable: f                               Number of groups   =       248

R-sq:  within  = 0.0627                         Obs per group: min =         1
       between = 0.1331                                        avg =       3.5
       overall = 0.1064                                        max =         8

                                                Wald chi2(18)      =    100.18
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

changedpi	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
zombie	-.0589865	.0444603	-1.33	0.185	-.1461271	.028154
value1	-.3341563	.1038698	-3.22	0.001	-.5377374	-.1305752
value2	-.1532936	.1576638	-0.97	0.331	-.462309	.1557217
value3	-.1475233	.0909419	-1.62	0.105	-.3257662	.0307196
value4	-.1835811	.0515204	-3.56	0.000	-.2845592	-.082603
value5	-.0779424	.0534283	-1.46	0.145	-.1826601	.0267752
value6	-.1001682	.0468825	-2.14	0.033	-.1920563	-.0082802
buyout	.0127546	.0434164	0.29	0.769	-.0723401	.0978492
allventure	-.0461844	.0587165	-0.79	0.432	-.1612667	.0688979
allearlystage	-.1427261	.0646259	-2.21	0.027	-.2693905	-.0160616
growth	.0225761	.0693676	0.33	0.745	-.1133819	.158534
y2007	-.3887751	.1541866	-2.52	0.012	-.6909753	-.0865748
y2008	-.2498599	.0795585	-3.14	0.002	-.4057916	-.0939281
y2009	-.1231686	.0687679	-1.79	0.073	-.2579512	.0116139
y2010	.0877928	.0606687	1.45	0.148	-.0311157	.2067013
y2011	.1791314	.0550644	3.25	0.001	.0712072	.2870557
y2012	.164952	.0506141	3.26	0.001	.0657503	.2641537
y2013	.1100745	.0477639	2.30	0.021	.016459	.20369
_cons	.3757181	.054193	6.93	0.000	.2695019	.4819344
sigma_u	.04773657					
sigma_e	.47063058					
rho	.01018349	(fraction of variance due to u_i)				

Appendix 31: Results of GLS regression – Change in DPI for vintage 2007

Dependent variable: Change in DPI

```
Random-effects GLS regression                   Number of obs      =       739
Group variable: f                               Number of groups   =       258

R-sq:  within  = 0.0336                         Obs per group: min =         1
       between = 0.1120                                        avg =       2.9
       overall = 0.0662                                        max =         7

                                                Wald chi2(17)      =     49.95
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

changedpi	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
zombie	-.101686	.0614327	-1.66	0.098	-.2220919	.0187199
value1	-.2121717	.1432154	-1.48	0.138	-.4928688	.0685253
value2	-.3256561	.1294071	-2.52	0.012	-.5792894	-.0720228
value3	-.1616083	.0868742	-1.86	0.063	-.3318787	.008662
value4	-.1513065	.0544043	-2.78	0.005	-.2579369	-.0446761
value5	-.0867101	.0669954	-1.29	0.196	-.2180188	.0445985
value6	-.1883813	.0671351	-2.81	0.005	-.3199637	-.0567989
buyout	-.0122694	.0503829	-0.24	0.808	-.111018	.0864792
allventure	.0125467	.0661256	0.19	0.850	-.1170571	.1421504
allearlystage	-.0117677	.0825308	-0.14	0.887	-.1735252	.1499898
growth	-.0804243	.0837039	-0.96	0.337	-.2444809	.0836324
y2008	-.5117415	.1287339	-3.98	0.000	-.7640554	-.2594277
y2009	-.1327373	.0880587	-1.51	0.132	-.3053292	.0398547
y2010	.0512469	.0789566	0.65	0.516	-.1035052	.2059991
y2011	.088675	.0626921	1.41	0.157	-.0341993	.2115493
y2012	.0869711	.0565128	1.54	0.124	-.023792	.1977341
y2013	.023626	.0539247	0.44	0.661	-.0820645	.1293166
_cons	.4216508	.0568228	7.42	0.000	.3102801	.5330215
sigma_u	.06365485					
sigma_e	.50506054					
rho	.01563622	(fraction of variance due to u_i)				

Appendix 32: Results of GLS regression – Change in DPI for vintage 2008

Dependent variable: Change in DPI

```
Random-effects GLS regression                   Number of obs      =       527
Group variable: f                               Number of groups   =       213

R-sq:  within  = 0.0547                         Obs per group: min =         1
       between = 0.0853                                        avg =       2.5
       overall = 0.0753                                        max =         5

                                                Wald chi2(16)      =     41.55
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0005
```

changedpi	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
zombie	-.1178586	.0616912	-1.91	0.056	-.238771	.0030539
value1	-.1523874	.1590294	-0.96	0.338	-.4640792	.1593045
value2	-.3281717	.2249942	-1.46	0.145	-.7691522	.1128088
value3	-.1872911	.0939309	-1.99	0.046	-.3713923	-.0031899
value4	-.1775786	.0679423	-2.61	0.009	-.310743	-.0444141
value5	-.0523659	.0764015	-0.69	0.493	-.20211	.0973782
value6	-.0317378	.0735218	-0.43	0.666	-.1758378	.1123622
buyout	-.0691721	.0587522	-1.18	0.239	-.1843242	.0459801
allventure	-.0425193	.076787	-0.55	0.580	-.193019	.1079804
allearlystage	-.1627209	.0926026	-1.76	0.079	-.3442188	.0187769
growth	-.0960412	.0901992	-1.06	0.287	-.2728284	.080746
y2009	.0330394	.2046832	0.16	0.872	-.3681323	.4342112
y2010	-.1954736	.1007841	-1.94	0.052	-.3930069	.0020597
y2011	.0144557	.0772843	0.19	0.852	-.1370188	.1659302
y2012	.040882	.0635801	0.64	0.520	-.0837328	.1654968
y2013	.1716552	.0609688	2.82	0.005	.0521585	.2911518
_cons	.4456697	.0650961	6.85	0.000	.3180837	.5732558
sigma_u	0					
sigma_e	.53504554					
rho	0	(fraction of variance due to u_i)				

Appendix 33: Results of OLS regression – Reported IRR

Dependent variable: Reported IRR

Source	SS	df	MS
Model	3259.52609	16	203.720381
Residual	18042.4613	4187	4.309162
Total	21301.9874	4203	5.06828156

Number of obs	=	4204
F(16, 4187)	=	47.28
Prob > F	=	0.0000
R-squared	=	0.1530
Adj R-squared	=	0.1498
Root MSE	=	2.0759

reportedirr	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
zombie	-.4035109	.0706454	-5.71	0.000	-.5420134	-.2650084
value1	-1.774471	.1188331	-14.93	0.000	-2.007446	-1.541495
value2	-1.551974	.1412736	-10.99	0.000	-1.828945	-1.275003
value3	-1.344491	.1188745	-11.31	0.000	-1.577548	-1.111433
value4	-.6821141	.1040285	-6.56	0.000	-.8860651	-.4781631
value5	-.058015	.1285355	-0.45	0.652	-.3100128	.1939828
value6	.4372327	.1410237	3.10	0.002	.1607514	.7137141
v2003	.5217085	.1268018	4.11	0.000	.2731097	.7703072
v2004	.5548074	.1176217	4.72	0.000	.3242064	.7854084
v2005	.6394494	.1067374	5.99	0.000	.4301876	.8487113
v2006	.397607	.1023724	3.88	0.000	.1969027	.5983112
v2007	.0907889	.0993473	0.91	0.361	-.1039845	.2855622
buyout	.4569468	.0910233	5.02	0.000	.2784928	.6354009
allventure	-.0650137	.0961171	-0.68	0.499	-.2534541	.1234267
allearlystage	.070362	.1084696	0.65	0.517	-.142296	.28302
growth	-.2537256	.1225944	-2.07	0.039	-.4940757	-.0133756
_cons	1.839132	.1208566	15.22	0.000	1.602189	2.076075

Appendix 34: Results of OLS regression – Reported DPI

Dependent variable: Reported DPI

Source	SS	df	MS
Model	6934.33078	16	433.395674
Residual	35861.9632	4187	8.56507361
Total	42796.294	4203	10.1823207

Number of obs	=	4204
F(16, 4187)	=	50.60
Prob > F	=	0.0000
R-squared	=	0.1620
Adj R-squared	=	0.1588
Root MSE	=	2.9266

reporteddpi	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
zombie	-.5512739	.0995986	-5.53	0.000	-.7465399	-.3560079
value1	-2.721728	.1675354	-16.25	0.000	-3.050186	-2.393269
value2	-2.445499	.1991728	-12.28	0.000	-2.835983	-2.055015
value3	-2.03838	.1675938	-12.16	0.000	-2.366953	-1.709807
value4	-1.021215	.1466632	-6.96	0.000	-1.308752	-.7336767
value5	-.2212776	.1812142	-1.22	0.222	-.5765536	.1339984
value6	.7267701	.1988206	3.66	0.000	.3369762	1.116564
v2003	.4835706	.1787699	2.70	0.007	.1330867	.8340546
v2004	.5735856	.1658276	3.46	0.001	.2484756	.8986957
v2005	.685505	.1504824	4.56	0.000	.3904797	.9805303
v2006	.4265297	.1443285	2.96	0.003	.1435693	.7094901
v2007	.1457378	.1400635	1.04	0.298	-.128861	.4203367
buyout	.762896	.1283281	5.94	0.000	.5113048	1.014487
allventure	.1385082	.1355095	1.02	0.307	-.1271623	.4041786
allearlystage	.258897	.1529246	1.69	0.091	-.0409163	.5587103
growth	-.1866795	.1728382	-1.08	0.280	-.5255341	.152175
_cons	2.790466	.1703883	16.38	0.000	2.456415	3.124518

Appendix 35: Private Equity Glossary

- Buyout - A transaction in which a company is acquired from the current shareholders.
- Carried Interest - Compensation received by a PE fund's management team once the investor's have received repayment of their original investment in the fund plus a specified hurdle rate. Carried interest is typically up to 20 % of fund profits, while the hurdle rate is usually around 8 %.
- Committed Capital - The contributed capital that was initially raised (committed by investors), which has been drawn down in the PE fund.
- Dependent Variable - A variable in a functional relation whose value is dependent upon the values of other (independent) variables in the relation.
- DPI - A measure of the cumulative distributions returned to investors as a proportion of the cumulative paid-in capital.
- Early Stage Fund - PE funds focused on investing in companies at the early part of their lives.
- Fund Size - The total amount of capital committed to a fund.
- General Partner - A partner in a PE management company that who is responsible for managing the investments within the PE fund.
- Independent Variable - A variable in a functional relation whose value is not dependent upon the values of other variables in the relation.
- Growth Capital - Investments in relatively mature companies that are looking for capital to aid growth, restructuring or entering new markets.
- IRR - The internal rate of return. This rate represents the net return earned by investors from the fund's activity from fund inception to a stated date.
- Limited Partner - An investor that the investment team (GP) of a PE fund raises capital from. These are often institutional investors such as pension funds, universities, insurance companies, foundations, endowments and high net worth individuals.
- Management Fees - Compensation received by a PE fund's management team. This fee is charged annually and is equal to a given percentage of the investor's initial capital commitment to the fund.
- Paid-in Capital - The amount of committed capital that investors have actually transferred to a fund.

- Regression Coefficient - The constant that represents the rate of change of one variable (dependent) as a function of changes in another variable (independent).
- RVPI - A measure of the current value of remaining investments within a fund in proportion to cumulative paid-in capital.
- TVPI - A measure of the current value of remaining investments within a fund plus the total value of all distributions to date, in proportion to cumulative paid-in capital.
- Venture Capital - Professional equity co-invested with the entrepreneur of the target company to fund early stage or expansion venture.
- Vintage year - The year when the first incursion of investment capital is delivered to a portfolio company. This is when capital is first distributed by the PE fund to a company, which is drawn down from the investors. The vintage year is the year in which the fund was raised. The vintage year can differ from the fundraising launch date.