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Macroeconomic effects on Private Equity funds' exit determinations

Master Thesis

by
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MSc in Finance

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Abstract

This thesis studies the external and internal exit determinants of European, Canadian and American private equity funds, using a data set of 32.881 investments completed between 1990 and 2021. The most common exits are through trade sales and sales to GP. We show that the likelihood of the different exit channels alters with changing market- and fund characteristics. The exit channels depend on the general economic environment, which significantly affects the window of opportunity for PE firms. Funds with more experience can exploit other exit opportunities while minimizing their risk of writing off investments. These results indicate that the average private equity fund is flexible and adapts depending on current and future market conditions.

Key words: Private Equity funds, exit channels, write-off, cyclicality, leveraged buyout, VIX, interest rate, great financial crisis, expertise.

Contents

List of Figures

List of Tables

1 Introduction and motivation

The Private Equity (PE) market is a rapidly growing corporate finance segment that, in many areas, differs from traditional public equity and fixed-income investments. Its importance in the financial markets is increasing, with PE funds setting new highs in fundraising and assets under management (AUM). The PE sector offers a variety of companies, such as start-ups, growth firms, middle-market firms, and firms in financial distress, faster and easier access to capital (Fenn et al., 1997). From an investor's perspective, PE funds offer access to a basket of private investments with high potential upside. The PE market is also largely exempt from many financial reporting policies governed by the Securities and Exchange Commission (SEC).

A PE fund consists of two partners; the limited partners, also referred to as LP, provide most of the capital and have limited liability related to the fund's operations. The other is general partners (GPs), the fund managers of the PE Firms (Cendrowski, 2019). The typical lifecycle of a PE fund is a finite ten years, with the possibility of prolongation by up to three years upon approval of the LPs (Kaplan and Strömberg, 2009). Figure 1 shows a standard description of a PE funds life phase.

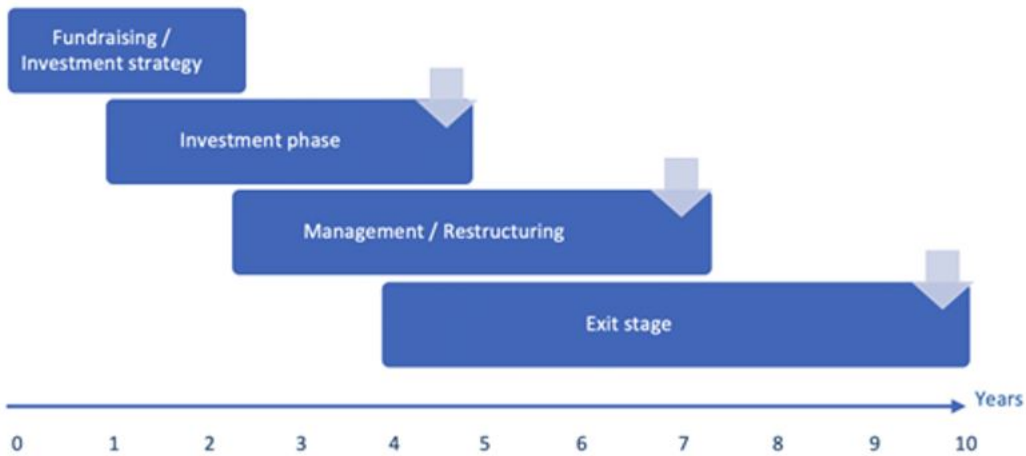

Figure 1: PE funds lifecycle(Cendrowski, 2019)

PE funds are closed-end, meaning investors cannot withdraw or commit capital at any point except at the fundraising stage. Therefore, potential investors must have a long-term investment horizon and sufficient capital levels. Ali-Yrkkö et al. (2002) find evidence that a fund's investment strategy and historical track record are critical components in an investor's willingness to invest in funds, signifying the importance of the PE fund's ability to optimize their exit channels and the returns they provide. After completing the first investment stage, the following years consist of researching and investing in prospective companies that have been reviewed and fit the fund's criteria for investment.

The management phase starts when the PE funds have invested in their preferred companies, and fund managers use their management skills to add value to the company. This phase is also where any company reorganization, add-ons, mergers, or restructuring will happen. Lastly, the exit stage is where GPs will attempt to realize any gains on their investments through an exit channel. Due to the time value of money principle, which states that money is worth more now than in the future, funds wish to accelerate this process as quickly as possible (Cendrowski, 2019)

This thesis builds on and contributes to the existing literature on PE exit strategies by analyzing a comprehensive dataset of European, Canadian, and American fund exits between 1990-2021. The data is gathered from a high-quality database, Preqin, and consists of deal- and exit dates, geographic locations, industries, investment types, and exit channels. Our focus is on the role of market specific conditions in the funds choice of exit channel. Whereas previous studies have commonly focused on inital public offering (IPO), financial sales, and write-offs (WO), we extend the analysis to eight unique exits that originate from various investment types. Moreover, by including both European and American locations, we test for similarities and differences between the two main PE markets.

We also include external market factors as variables in our multinomial logistic model (MNLM). Namely, the central bank interest rate, VIX index, and economic market cycle. This allows us to study the macroeconomic environment's influence on exit channels and how funds are able to adapt to any change in the variables. In addition, we look at the effect of the great financial crisis (GFC) in 2008 and the increase in monetary policy intervention by governments on the PE market and the fund's exit strategies. Given the changing central bank policies, the findings of our study have important implications for the future of the PE market.

The motivation for our study is to provide a thorough analysis of a crucial subject in the PE market that previously has received limited focus, combined with a growing fascination and curiosity about the PE market as part of the financial sector. The PE market offers investors a unique investment opportunity to implement change in innovative companies and innovations with capital it can provide to growing businesses. While also collecting risk premiums like illiquidity compensation, often resulting in satisfactory risk-adjusted returns, which have spurred the growth even higher. The PE sector represents 9 percent of all pension assets in the US, showing the imperative need for extensive research on the industry.

We find conflicting and supporting evidence of the results obtained by Schmidt et al. (2010). Our data capture the difference in IPO attractiveness in the American market relative to the European. We do not find compelling evidence to suggest experienced funds have better abilities in manoeuvring higher interest rate markets.

We see a strong effect of experience in an increasing interest rate environment, suggesting that more experienced funds manage to successfully exit their investments in tighter credit markets through desirable channels. Moreover, IPO is over three times as likely to be used in a boom cycle relative to a bust cycle and is largely driven by an expansionary market cycle. This coincides with Jenkinson and Sousa (2015). They argue in favor of a window of opportunity strategy instead of predetermined exit decisions, meaning that funds optimize their exits depending on the market conditions.

Furthermore, our analysis presents significant evidence of higher write-off probabilities in times of economic hardship and increased market uncertainty. Finally, we study the effect of the GFC by analyzing the results of exit prior- to, and after the recession. The results capture distinct differences, such as lower IPO likelihood during higher interest rate levels and bust cycles having a more significant effect on exit ability before the crisis. We also find diminishing effects between the European and American markets, suggesting the former has caught up to the latter.

We build on the methodological approach of Schmidt et al. (2010) and Jenkinson and Sousa (2015), who study exit strategies and determinants for LBOs by PE firms. We add value to their approaches by focusing on different variables in our model estimation and the size of our deal data, specifically, the whole investment sector of PE firms and not solely LBOs. In addition, we account for potential fixed effects of business industry, geographic location, and the initial investment type. We exclude performance metrics in our study, contrary to previous studies, allowing us to obtain a more extensive data set due to data availability. For this reason, this thesis contributes and goes beyond existing research on the topic of exit determinants.

Furthermore, we aim to provide PE firms with crucial information on optimizing their exit process during changing economic environments specific to their fund characteristic. The paper continues with a review of relevant literature, an explanation of the theory and methodology, and a description of data and preliminary analysis. Lastly, the results of our study are analyzed and discussed, and then we conclude the main results.

2 Literature review

The rapid growth in PE markets creates a need for additional research into PE market structure, fund operations and strategies, and their exit determinations. This section will summarize some key articles on the topics and how they relate to our paper.

2.1 Private Equity emergence and strategies

Kaplan and Strömberg (2009) point out that PE funds exploit market frictions in which debt markets are relatively low compared to the equity markets. The mispricing creates the potential for a profitable trade where funds can borrow cheap debt to acquire a public company and expand its growth. Kaplan and Stein (1993) also present evidence that low-cost debt may have fuelled the leveraged buyout wave in the 1980s, increasing the average Enterprise Value to EBIDTA ratio for public to private buyouts. This indicates that the PE market has periods of overheating, and the cycle affects exit decisions.

They find evidence that PE activity creates value on average, but the activity level depends on return cycles, stock market valuations, and earnings relative to debt interest rates. These findings are highly relevant to our research as they imply that PE markets can get overheated due to the interest rate level, which might affect the fund's ability to exit their investments. Our thesis builds on the theory of overheating markets, exploring the preferable exit choices in expanding and contracting markets.

Another paper by Kaplan et al. (2016) studies PE firms' daily operations, fundamental decision rules, and metrics. Building on a survey of 79 PE firm managers with $750 billion AUM, they find that managers expect to exit through an IPO on average in 18.8% of cases and that approximately 30% of the time, the sale of the company would be to another PE fund through a financial deal. The remaining 51% of investments is a strategic sale, meaning to another company in a similar industry.

The authors also look at a manager's ability to time their exits and the important factors in their exit decisions. The main factors are the capital market conditions and operational goal, which leads to a potential agency conflict between the LPs and GPs. The managers are often content with exiting when they have managed the company to the best of their ability, and the market presents good exit opportunities. On the other hand, the LPs are either unwilling or unable to adjust their performance requirements for this risk. These results also demonstrate that capital market conditions are something managers value highly in their exit decisions. Additionally, the paper can be used as a reasoning tool when analyzing market conditions' effect on exit channels.

2.2 Divestment phase

Jenkinson and Sousa (2015) studies exits of European PE leveraged buyouts from 2000 to 2014 to identify key determinants in the fund's exit process. Similar to the findings of Kaplan and Stein (1993), the authors find evidence to suggest that capital markets and the availability of equity relative to debt significantly affect the available exit channel for fund managers. In other words, the likelihood of secondary buyouts increases considerably when debt is financed cheaply, as was experienced prior to the financial crisis. Furthermore, IPOs were hard to come by after the financial crisis when equity was experiencing great turmoil. These results lead to a window of opportunity, as managers carefully consider the options available to maximize their returns.

Moreover, Jenkinson and Sousa (2015) analyze prior work by Giot and Schwienbacher (2007). They use a hazard rate to look at the conditional instantaneous probability of exit, given that the investment has not been exited. They find that funds that want to have short investment periods prefer to use IPOs as an early exit route. Still, the likelihood of a secondary buyout increases substantially as time passes. In contrast, trade sale exit probability falls rapidly around the 120 months mark, meaning that the longer the holding period is, the more likely the sale will be to a PE fund rather than another company.

The authors also conduct a trinomial logistic model regression, hypothesizing that exit decision depends on the investor, portfolio company, and market environment. They show that trade sale exits happen more frequently by experienced firms, earlier in the fund's life cycle, and for smaller companies. Similarly, an IPO is more likely in short holding periods, in companies with high growth prospects, when the stock market has been booming, or when lending requirements are higher. On the contrary, secondary sales are more attractive in companies with high margins and low capital requirements. The paper presents several findings that create room for additional studies, especially regarding the fund's life cycle stage, firm experience, and market environment. We will not be conducting studies based on company characteristics due to a lack of data in this area, but this could make for a fascinating study.

Schmidt et al. (2010) conducted an empirical analysis of the exit strategies of 672 buyout investments in Europe and the US. They perform an MNLM that estimates the predicted exit channel probabilities for varying holding periods and find that write-offs occur early in a fund's life cycle. A probable explanation is that funds recognize poor investments quickly, and rather than being held as living dead assets, the losses get cut immediately. They also find that IPO and trade sale transactions increase in probability as time passes. After cross-testing on many subsamples, the authors find no evidence of an increase in the likelihood of an IPO exit in the American market compared to the European one. These results deviate from expectations that IPOs are more likely in the US due to the size of American stock exchanges and subsequent importance. Given the inconsistent results from previous studies, we build on these articles to try and tackle the question of IPO probability between the different geographic locations. Due to the modernization of European markets in recent years, we also compare the effects pre- and post-GFC.

2.3 Supporting papers

Axelson et al. (2013) investigated the main determinants of leverage in buyout deals for PE firms acquiring public companies. They find a negative relation between leverage and fund returns in hot markets where debt is readily available. This relation suggests PE funds are willing to overpay for a firm when the condition is in effect and signifies the role debt plays in the PE market. Their paper creates channels for further discussion about capital structures and PE firms' operations and strategies.

Ljungqvist and Richardson (2003) conducts a study on the cash flow, return and risk characteristics of PE, particularly concerning the illiquidity risk facing investors. They showcase the importance of holding periods and how this affects the return generation. The authors present findings suggesting funds need six years to invest 90.5% of committed capital and over eight years to generate excess returns. These results highly depend on market conditions playing a major role in exit choice determination.

2.4 Methodological differences and similarities

Given the similar methodology and area of research, we identify the work of Schmidt et al. (2010) as the primary reference in our analysis. We wish to add to their work, creating new branches that could be further tested. By extending and separating the exit channels and looking at the exits for a longer period, we can more confidently find the macroeconomic effects on the PE market. Additionally, we can separate our sample and find differences in in its effects in different time periods and market cycles. The benefit of our dataset is the focus on readily available macroeconomic data compared to other studies, which often include firm-specific performance data that is difficult to obtain and limit the observations. This is restrictive as many deals are simply left out, and will give a skewed picture towards deals with certain factors like IPOs where reporting performance is mandatory.

Jenkinson and Sousa (2015) work on exit determinants also provides an excellent foundation for our thesis and presents a range of attractive hypotheses. Both papers focus solely on buyout investments, whereas we will differentiate ourselves from existing literature by analyzing the whole investment landscape of PE firms. We will not conduct any performance analysis in our study, and the sole focus is on identifying the primary conditions affecting a PE fund's exit decision.

2.5 Knowledge gap

We have reviewed a wide range of studies on investments made by PE firms. Each paper has limitations ranging from the sample size, geographic location, or time horizon. The lack of similarities in the studies makes for insufficient comparisons in how funds operate and the determination of characteristics of the divestment phase. Moreover, we find incomplete studies on how PE fund operations have changed as the market has snowballed, with key revision dates being the dot-com bubble in the early 2000s and the financial crisis in 2007-2009.

One significant change in the industry is at the rate firms can borrow, as the interest rate environment has remained low compared to historical levels, even in a booming economy. As previously mentioned, cheap debt may induce PE spending, create hot markets, and affect available exits. With this in mind, we aim to examine how the structural changes in the economy have affected

PE fund's exit channels, as easy access to capital can also increase financing costs and the investments undertaken. We also look at how the firms adapt over time as they gain experience in a cyclical but ever-growing PE sector.

All PE funds rely heavily on their ability to make suitable investments and management decisions to generate superior returns. Like any investment manager, they are vulnerable to shocks and other economic events that may hurt future revenue. Our thesis studies how specific market conditions and manager characteristics affect a fund's ability and choice to exit its investment.

3 Testable hypotheses

We will use this section of our thesis to formulate the hypotheses based on prior researchers' findings and our expectations from economic theory. We test these in the methodology part of our paper to answer the research question:

"How do market and firm specific conditions affect Private Equity fund's exit route?"

3.1 Effect of geographic location

Investors commonly view IPOs as a milestone and sign of success for private managers and entrepreneurs. Succeeding in raising public capital can signify the market participant's belief in the company's business model and that it can further expand. In addition, being a publicly listed company can attract favorable attention from customers, clients, and competitors who may view them as a stable and profitable. Moreover, companies may attract necessary capital faster and at lower costs through an IPO relative to a private sale that would need to take on high debt levels (Cendrowski, 2019). Overall, the US and Canadian markets accounted for 59% of all IPO exits in our sample, which motivates us to study whether there exists a difference in using IPO as an exit channel across the two continents, and we formulate the following hypothesis:

"The likelihood of an IPO is greater in North-America compared to the European PE market"

3.2 Effect of industry

Schwienbacher (2005) studies the VC market in Europe and US and found significant differences in the two markets. Especially regarding conflicts in the human resources department, which limits European firms from replacing employees to the same extent as American firms. Moreover, European firms monitor investments to a lesser degree, thus adding less value to their portfolio companies. The American markets are more developed and liquid, making it easier for funds to divest their portfolios. Schmidt et al. (2010) argue in favor of the American market being more receptive to IPOs from PE investments but find no significant results of such an effect. We still find value in studying the author's arguments further, as recent data on the IPO market suggest that technology companies are desirable for public listings.

A recently published report from EY (2021) describes how 2021 was a record year for the global IPO market with 2,388 public listings, up 64% from the previous year. Technology is the largest sector responsible for IPOs in the US and Europe. Combining these facts with the work of Schwienbacher (2005) and Schmidt et al. (2010), we formulate the following hypothesis:

"Companies in the technology industry have a higher probability of exiting through an IPO"

3.3 Effect of experience

Any economically minded investor will choose to invest in funds with the highest risk to reward ratio. These are funds that will have the greatest and longest track records and can successfully raise capital in their new funds. The tradeoff for are they can charge higher fees and are often limited in size, making investment competition fierce. Barber and Goold (2007) argue that PE firms have strong expertise in creating well-working teams and incentives for managers to succeed. In addition, the largest and most successful funds have critical knowledge of how to operate in varying economic markets. Permira, a well renowned and successful European fund, made more than thirty substantial acquisitions and twenty disposals of independent business from 2001 to 2006 (Barber and Goold, 2007).

Kaplan and Schoar (2005) studied performance drivers of VC and LBO firms. They found consistent results in performance persistence, meaning funds that succeed are likely to continue to perform well in subsequent ones. Funds that perform well also receive additional capital in future ventures. The authors argue that consistently performing funds gain proprietary access to investments due to the "proprietary deal flow". In addition, business management is equally vital as identifying promising investment opportunities, which is a skill that might be harder to develop. These findings further highlight the competitive advantage experienced funds can gain over smaller and less experienced funds, both in terms of consistency and in periods of market turmoil and economic crisis. Leading us to develop the following hypothesis:

"Less experienced funds have higher probabilities of write-offs generally, and especially in market troughs"

"Interest rate changes have less of an impact on experienced firms exit probability"

3.4 Effect of market cycles

Kaplan and Stein (1993) paper on LBO growth and subsequent causes argues that easily financed debt was the root cause of the buyout booms in the 1980s. A period fueled by low-interest rates relative to historical trends and raging stock markets before Black Monday hit in 1987, which saw the Dow Jones Industrial Average drop by 22.6% (Weinberg, 2013). Before the financial crisis in 2008, US housing construction saw a considerable expansion while mortgage issuers significantly reduced lending standards for previously unqualified consumers looking to purchase a home. These choices eventually resulted in a housing bubble which caused catastrophic implications for the global economy in the years to come (Weinberg, 2013). Thus, we are interested to see whether there is a difference in write-off probability between the two economic cycles.

We do not have data on the buyout boom in the 80s but extend the hypothesis to match our market boom parameter gathered by the The National Bureau of Economic Research (NBER).

"Write-offs increase in probability in bust periods or when the VIX increases"

"IPOs increase in probability in boom markets"

3.5 Effect of interest rate

When the Federal Reserve (FED) increased the central bank rate by 50 basis points in May of 2022, it was the first time since 2000 that the FED had raised the interest rates by more than 25 bps. In 1997, they increased the interest rate by 75bps to 5.5%. This was more recently done in June 2022 in an attempt to fight high inflation. Between 1990-2000, the interest rate increased by more than 50bps on five separate occasions (Foster, 2022). Similar results can be observed in the Bank of England official bank rate, as it experienced greater fluctuations prior to the GFC (BoE, 2022).

Interest rates in the US have been between 0 to 150 basis points during the same period, with more frequent hikes in 2016 and 2017 (Foster, 2022). The rate has been steady in England at around 25-50bps, decreasing in 2016 and then hiking the interest rate to 50bps in 2017. Companies and funds need to be more selective with investments in high-interest rate environments due to more expensive capital, making it more difficult for private companies to raise capital. PE funds and private companies may need alternative exit channels to realize returns. Therefore, we find it reasonable to study the relationship between interest rate and specific exit channels, primarily IPO and write-offs, and their frequency in different rate environments. This leads us to formulate the following hypothesis.

"Higher interest rates coincide with greater debt costs and less capital access; therefore, IPO and write-off exits should increase in this environment"

3.6 Effect of the GFC

Data gathered from the Organization for Economic Co-operation and Development (2022) show a clear trend that government deficits in percentage of GDP have increased since 1990. Whereas government spending seems to increase somewhat, the percentage is at higher levels post the GFC than before. The summary statistics on government deficits and spending is found in table 8 9. The average interest rate prior to the GFC is roughly 4% and only 0.60% in the years after.

All statistics further indicate a significant shift in the way governments use monetary policy to regulate the economy and handle economic crises, primarily in recent recessions. They are employing a low-interest rate to fuel economic activity while lending vast amounts to business and employee support programs. With this in mind, we find it interesting to study the effect monetary policy has had on PE fund's exit channels.

"PE deals after the GFC are less susceptible to interest rate movements on their exit channel"

4 Methodology

4.1 Multinomial Logistic Regression Model

Our model and methodology have similarities with studies performed by Schmidt et al. (2010) and Jenkinson and Sousa (2015). However, our probability model solely focuses on PE's macroeconomic conditions, giving us a more extensive dataset than previous research.

Wooldridge (2006) shows that when the dependent variable is discrete, a linear regression model is not suitable as the model's assumptions are violated. MNLMs are often used when the dependent variables are non-binary, meaning it has multiple choices. The MNLM is also considered attractive compared to other models as it does not assume normality, linearity, or homoscedasticity (Starkweather and Moske, 2011). Therefore, we use an MNLM approach to analyze macroeconomic effects on the choice of sale exits in the PE industry. As Long and Freese (2006) describe, the MLNM is thought of as simultaneously estimating binary logits for all comparisons among the dependent categories. Our model has eight unique exits, and we can examine the effects of the independent variables on the exit routes by estimating the logits. The dependent variables take the value of:

IPO – IPO

TS – Trade Sale

Merg – Merger

PP – Private Placement

GP – Sale to GP

ResCap – Restructuring & Recapitalization

WO – Write-Off

Man $-$ Sale to Management

A multinomial logistic model needs a comparison group to compute the predicted probabilities. The choice for the base group is somewhat ambiguous, though trade sale has significantly more observations than other exits at 43% of our sample, and which is why we use it as the reference category for our model. We choose the subsequent models to investigate relations between exit types and the independent variables. The regression model is then formally written as:

$$ln\Omega_{IPO|TS}(x) = ln\frac{Pr(y = IPO|x)}{Pr(y = TS|x)} = \mathbf{x}\beta_{IPO|TS}$$
$$ln\Omega_{Merg|TS}(x) = ln\frac{Pr(y = Merg|x)}{Pr(y = TS|x)} = \mathbf{x}\beta_{Merg|TS}$$
$$ln\Omega_{PP|TS}(x) = ln\frac{Pr(y = PP|x)}{Pr(y = TS|x)} = \mathbf{x}\beta_{PP|TS}$$
$$ln\Omega_{GP|TS}(x) = ln\frac{Pr(y = GP|x)}{Pr(y = TS|x)} = \mathbf{x}\beta_{GP|TS}$$
$$ln\Omega_{ResCap|TS}(x) = ln\frac{Pr(y = ResCap|x)}{Pr(y = TS|x)} = \mathbf{x}\beta_{ResCap|TS}$$
$$ln\Omega_{WO|TS}(x) = ln\frac{Pr(y = WO|x)}{Pr(y = TS|x)} = \mathbf{x}\beta_{WO|TS}$$
$$ln\Omega_{Man|TS}(x) = ln\frac{Pr(y = Man|x)}{Pr(y = TS|x)} = \mathbf{x}\beta_{Man|TS}$$

We estimate the following regression for each exit route by including the independent variables in the equations above.

$$ln\Omega_{i^*|S}(x_i^*) = \alpha + \beta_{2,i^*|S}VIX + \beta_{3,i^*|S}HP + \beta_{4,i^*|S}BoomBust + \beta_{5,i^*|S}Industry + \beta_{6,i^*|S}Country + \epsilon$$

Where i* is the different exit types

4.2 Marginal effects

A conventional method of interpreting logistic models is using marginal effects. The logit model does not follow a linear relationship and obtains the form

$$P_i = F(\beta_i + \beta_2 x_i) + u_i,$$

with F being the logistic function. The solution to understanding the relationship is by differentiating F with respect to x_{2i}, which then can be written as

$$P_i = \beta_2 F(x_{2i})(1 - F(x_2)).$$

This results in an interpretation such that one unit increase will lead to an increase in probability corresponding to

$$P_i = \beta_2 F(x_{2i})(1 - F(x_{2i}))$$

(Brooks, 2019). We estimate the marginal effects of the probability of an exit by increasing the continuous independent variable by a standard deviation (SD). We will also analyze the marginal effect by changing the categorical variable by one. Making it possible to study the different effects each dummy has on the exit channel.

4.3 Predicted probabilities

Having an MNLM with eight outcomes, interpretation can be tedious. Comparing and interpreting each independent variable against an exit type is unclear and cumbersome. Long and Freese (2006) propose computing predicted probabilities to avoid being overwhelmed by the model's output. Thus, we plot predictions across the continuous variables in our data while holding all other variables at their mean. These plots help understand and interpret the relationship between the continuous variables and the exit channel.

5 Data

5.1 Data description

We use Preqin as our primary data source throughout this thesis. With over 17 years of experience collecting private data, it is a best-in-class data provider for private asset classes, making it an ideal data source for our paper. The collection process conducted by Preqin acts in line with legal and ethical regulations, as all data are obtained under the Freedom of Information Act (Preqin, 2022). The data gathered from Preqin consist of fund names, fund id, deal id, and investor id, as well as other data we utilize in our tests.

This paper analyzes a deal dataset downloaded latest April 2022. It consists of completed exit transactions from January 1, 1990 to December 31, 2021, resulting in 36.218 observations. The selection has been done due to few reported deals in the years before 1990 and would have produced nonsignificant samples. We have focused on European, Canadian, and US geographic locations as they have the most readily available data. After removing unspecified exits from our dataset, we have 32.881 observations in our total sample.

The dominant exit type in our dataset is Trade Sale (TS), which makes up 41% of our sample, followed by Sale to GP (GP) exits which account for 28% of exits. IPOs account for 6% of exit observations, significantly deviating from previous research. Kaplan and Strömberg (2009) find that 17% of divestments happened through an IPO, whereas Kaplan et al. (2016) observed similar results of 18.8%. We believe one of the main reasons for this difference is the broad range of exit types we include in our analysis compared to other studies. The other is that they have removed exits that lacked performance-based metrics and additional deal-related information, making IPO data more readily available as public companies are required to publish their financial performance through a 10-K. Other exit channels we study are Merger, Private

Placement, and Restructuring, which we combine with Recapitalization due to similar characteristics and small sample sizes. The last exit channel variable is Write-Off, a vital aspect of any business-related studies as investments are primarily written off for negative reasons.

We solely focus on PE-related investments in this thesis, excluding Venture Capital (VC) which can be viewed as a separate market. Gompers and Lerner (2001) describe VC as a financial intermediary that provides capital to small firms that struggle to raise funds due to the considerable uncertainty and risk involved in these companies, while our focus is on more mature companies. The traditional PE investment types involve secondary buyouts, growth capital, add-ons, recapitalization, public to private transactions, mergers, Private Investment in Public Equity (PIPE), and restructuring.

A drawback of our data is the lack of exit- and deal values, which could have made it possible to study performance drivers for the unique exit channels. However, it would have reduced our sample size significantly. Most of the performance metrics PE funds disclose are also self-reported, often when they recently have performed well. Therefore, including them in our sample could lead to a reporting bias and skew the sample size towards the exit channels which are most profitable for the funds. This fact is well known in the field of alternative investments, especially in the hedge fund and PE sector, with few disclosure requirements. These facts make the inclusion of performance-based metrics unattractive for our thesis. Thus, we focus solely on how market- and other firm characteristics affect the exit channels for PE funds instead.

5.2 Variables

5.2.1 Dependent Variables

Exit Type

The dependent variable we investigate in our analysis is the exit channel PE firms use when they sell a company, also identified as the exit type. As previously stated, we use an MNLM to conduct our regression with eight unique exits. Each model will result in singular likelihood estimations for company exits through the stated channel, given the effect of the independent variables.

5.2.2 Independent Variables

We divide the independent variables into two subgroups. The first focuses on macroeconomic factors affecting all funds in our sample, and the other on a microeconomic level related to each fund.

Interest Rate

The interest rate variable is an interesting variable to look at, especially considering how the impact it has on everyones economy. As interest rates increase, credit costs follow suit, encouraging consumers to save money instead of borrowing excessively. Raising interest rates leads to a decrease in money supply in circulation, and central banks often use a hike to deal with inflation and slow down economic activity. Thus, the interest rate is a powerful tool for central banks to stimulate the economy in recessions and reduce excessive growth during boom periods (O'Connell, 2022).

LBOs are the most common way for a fund to acquire a company in the PE industry, and a higher interest rate will greatly affect the cost of this debt. This may also reduce trade sales and secondary buyouts, which means funds may need to look at other exit options to realize their investment return. Like any other business, PE funds will be affected by the interest rate level, and their exit choices change, given the overall state of the economy.

A common area of study on PE activity is the IPO exit probability and growth in the capital markets. These factors make the interest rate a critical component in our analysis. We have gathered data on the interest rate directly from the US Federal Reserve, European Central Bank, Bank of England, Deutsche

Bundesbank, and Bank of France, as these are the largest countries in our sample. We use an average of the European interest rates for the remaining countries, namely the other category. We do this due to the relatively small size of the remaining countries and the fact that most countries within the EU are underlined the ECB rate.

VIX

Market uncertainty is another important macroeconomic variable of the state of the economic markets. Also called "The fear gauge", the VIX measures the expected return volatility of the S&P500 Index over the next 30 days, and is implied by the index option prices (Whaley, 2009). The correlation between S&P500 and VIX has fluctuated around negative 0.6-0.8 from its inception, meaning they tend to move in opposite directions (Moran and Liu, 2020). Szado (2009) finds that the negative correlation gets stronger during large down moves and recessions, as seen during the GFC.

The volatility aspect of the VIX index and its measures of short-term market fluctuations makes it an appealing part of our study, as it can potentially explain how future market uncertainty affects the fund's exit route decisions. We use the CBOE VIX for the complete American and Canadian sample, and as a proxy for the EU deals between 1990-1992 due to insufficient data in the first two years of the European market. The V1X, the German market equivalent to the VIX, covers the remaining period for the European sample.

Holding Period

The holding period is the number of days the PE funds hold their investment before selling through an exit channel. We calculate it by taking the difference between deal- and exit date, denoted in days, and divide it by 30 to make the data monthly. The holding period is used as a variable to study any relationship between a fund investment's rapid transition and the exit channel they end up exiting through. Schmidt et al. (2010) point out that there seems to be a connection between investment duration and the chosen exit strategy. Because of this relationship, it suits our model well, and makes for an interesting addition concerning the exit channels. One example could be the duration of write-offs compared to another exit type, as earlier literature has indicated that PE firms cut losses rapidly (Fürth and Rauch, 2015).

Market cycle

To best define what economic environment we find ourselves in, separating between expansions and contractions is most common. NBER conducts non-partisan economic research on business cycles in the US (NBER, 2022). Their job is to maintain a chronology of economic cycles, identifying the peak and through months of economic activity. In other words, they monitor when several indicators about the real economic activity reach their highest and lowest levels. Founded in 1920 and with data on US business cycles available back to 1854, the NBER has built up a remarkable reputation in macroeconomic research, and we believe their data is the best fit for our research area.

The NBER committee has identified five expansionary environments and four contractions we include in our dataset. The most recent contraction occurred due to the global pandemic at the beginning of 2020, lasting approximately three months, followed by a rapid economic expansion. There is some uncertainty if we capture any effect due to it being so recent, however, from Bernstein et al. (2017), we see that PE funds are quick to adapt during recessions making us believe we still capture some effects from the Covid-19 cycle. To include economic conditions, we create a dummy variable that will take the value of 1 when the economy is expanding and 0 when contracting.

Country

The country variable is a dummy that considers the country of origin of the investment firm. The PE market is more prominent in countries like the US and UK. Therefore, we focus on the dominant locations with the most exits in our sample. The dummy variable takes the value of 1 if the fund is UK based, 2 if its German, 3 for France, 4 if American and 5 for Canadian, and lastly, 0 for any other country. We include the dummy variable to study whether geographic location increases the likelihood of exits and control for factors that differentiate the separate countries. The relationship between North American funds and the IPO exit channel compared to other geographic locations are exciting.

Investment type

The investment type dummy variable is included to identify each investment type. Similarly to industry, the variable can help explain the relationship between investment types and how they are exited. We include it as a control variable for the different exit characteristics certain investment types have.

Fund experience

Fund experience is a dummy variable that takes the value of 1 if the fund is classified as experienced and 0 if it has the lowest experience. We estimate experience using a rolling five-year quantification of all deals, counting and identifying the 90'th percentile funds with the most deals every fifth year. By updating the estimation frequently, we avoid the potential look-ahead bias of firms that have existed for longer. As we have no data to measure experience between 1990-1995, we do not classify any funds as experienced in this period.

We categorize the funds that have gained experience in the previous five years as experienced in the next period, leaving us with 9,739 deals with an experienced investor, equivalent to 30% of the sample. We wish to test the effect of experience in our study as it could identify a clear preference in exit channels for funds with different experience levels. Moreover, external market conditions' effect on experienced funds and their exit choices may differ from inexperienced ones. For example, have the ability to divest their holdings consistently, independent of the types of investments they make. Experience is a fitting variable to test interactions with several market conditions to study the potential or lack of effects this has on their exit channel. Our a priori expectations would be that an experienced manager would be less prone to write-offs and less affected by market turmoil.

Sample limitations

During data collection, it is essential to consider whether our sample may contain biases that drive the results of our analysis, especially in such a privatized nature as the PE industry. PE funds do not face mandatory disclosure rules in any country with a significant PE industry (Cumming and Walz, 2010). Collecting self-reported data is an obvious problem, and such bias is continuously reported in previous literature as GPs are incentivized to hand-select information from only successful investments (Kaplan and Schoar, 2005).

Although more relevant for studies that use fund performance and reported IRR, selection and availability bias are still likely to be found in our data sample. There is a reasonable likelihood that our sample contains under-reporting of write-offs and secondary transactions sold for a loss. However, we still believe our dataset mitigates these biases and is suitable for research. This is due to our large dataset compared to previous research, the PE industry becoming more transparent, and the fact that Preqin gathers information through public institutions, in addition to collecting data from GP contributions.

5.3 Preliminary analysis

We report the distribution of fund locations in Figure 2, which further underlines the importance of accounting for this geographic effect in our analysis. Moreover, the US and Canadian samples account for approximately 57% of total exits, with the remaining 43% distributed across the four European country groups. We are confident the two sub-samples will not infer any sample selection bias due to any difference in data quality depending on location. Moreover, the two samples will be tested individually for robustness.

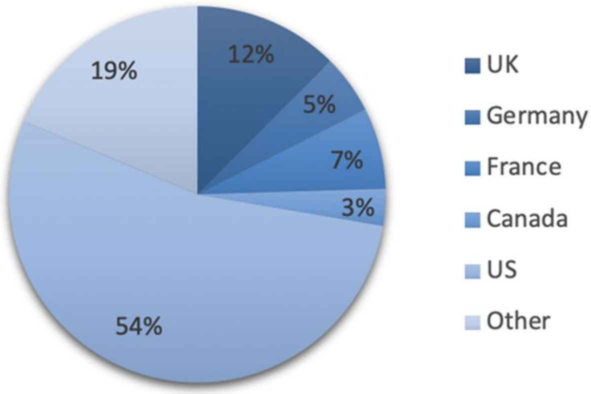

Figure 2: Geographic location of exits. The figure shows the quantity of completed exits within the five geographic locations on which this research is based. There are US, Other, UK, France, Germany, and Canada ranging from highest to lowest.

Figure 3 displays the exit type distribution for the total sample. The two most common exit types are Trade Sale (TS) and Sale to GP, whereas the remaining have a relatively even distribution. Hence, we want to understand better the economic factors driving these exits. Table 10 in the appendix outlines the total sample of exit types across all country samples.

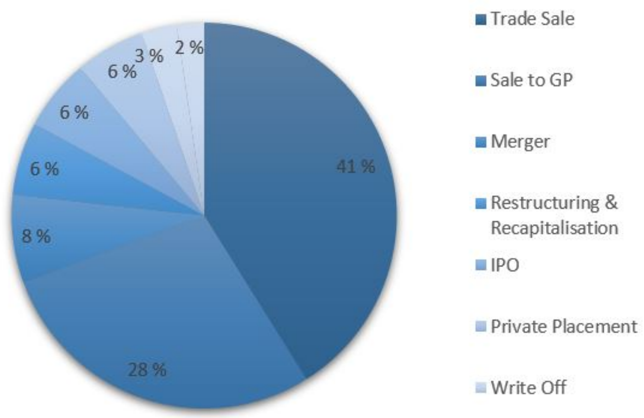

Figure 3: Exit Type Frequency. The figure shows the quantity of completed exits within the eight exit channels of our study. Ranging from highest to lowest, we have, Trade sale, Sale to GP, Merger, Restructuring & Recapitalisation, IPO, Private Placement, Write off, and Sale to Management.

Descriptive statistics for the continuous independent variables are seen in Table 1. The median is lower than the mean for all variables indicating a positively skewed distribution. The most noticeable trait is the low average interest rate levels, which have become more common. The highest interest rate observed in our dataset was at the beginning of the sample in 1990, steadily declining throughout the period. The 75th percentile signifies the historically low interest rate relative to the max value. On the other hand, the VIX index is relatively evenly distributed around its mean, with some extreme outliers observed in recessionary periods.

Statistic	Interest Rate	VIX	Holding Period
Mean	1.34%	19.39	60.13
Max	10.82%	86.01	486.57
Min	0.04%	9.14	0.5
Standard deviation	1.67	7.44	38.84
Median	0.30%	17.71	53.37
25th Percentile	0.16%	14.38	32.82
75th Percentile	1.92%	22.41	79.67

Table 1: Descriptive Statistics. The table shows descriptive statistics of the continuous independent variables for the whole sample period 1990 to 2021. Interest rate is the official effective interest rate issued by the central banks of the respective countries in our sample. The VIX are extracted from the Chicago Board Options Exchange (CBOE) for the American & Canadian sample and the V1X for the European sample. The holding period is estimated in monthly intervals as the difference between the deal- and exit date for an exit.

Furthermore, the average holding period amounts to 60 months, above Valkama et al. (2013) results of 3.58 years or 42 months. It is also half of a PE fund's total life cycle at ten years. Jenkinson and Sousa (2015) refer to investments extended over long periods despite not providing economic value as "living-dead investments", which is likely what we see at the maximum holding periods. After studying the data on unusually long holding periods, we find a clear trend that most of these investments are buyouts. We see a small sample of very short holding periods at the other end of the spectrum. These are spread across various investment types, but mergers are the most frequent exit channel.

Figure 4 displays the percentage of companies PE funds have invested in characterized by their industry. There seems to be relatively even distribution, except for some outliers. Real estate and consumer discretionary are the smallest and largest in the sample. The distribution underlines the importance of accounting for deal fixed effects in our regression models to control for differences in the segments.

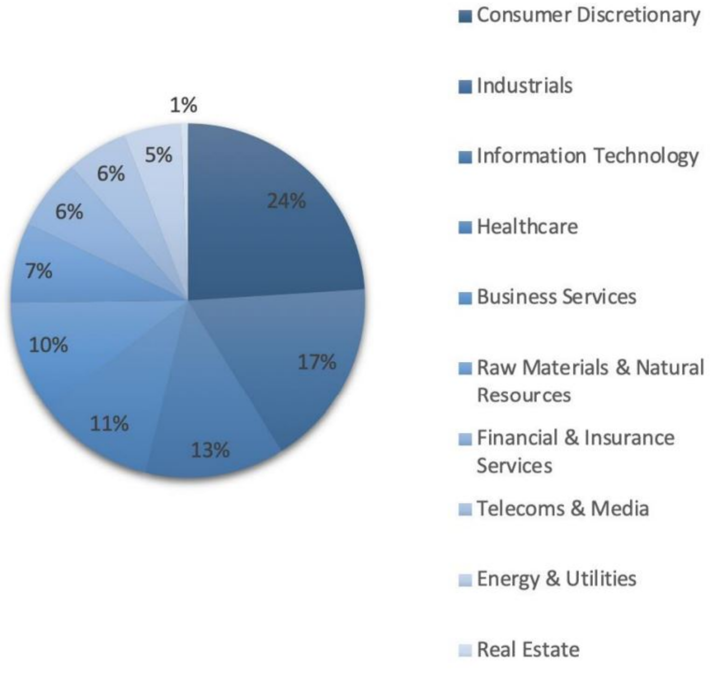

Figure 4: Fraction of exits across industry. The figure shows the quantity of completed exits within the 10-industry segments from Preqin. From highest to lowest quantity, there is: Consumer Discretionary, Industrials, Information Technology, Healthcare, Business Services, Raw Materials & Natural Resources, Financial & Insurance Services, Telecoms & Media, Energy & Utilities, and Real Estate.

5.4 Preliminary Testing

5.4.1 Model fit

Upon creating a multinomial model, a key aspect is to test the validity of each independent variable, in other words, if the number of predictor variables is suitable. The most common method of addressing this is conducting the likelihood ratio test (LRT) and Wald test. The models want to find the number of parameters that maximizes the likelihood function value (Bruin, 2021a). The LRT test estimates two models and compares their fit against each other. Often, a model will have less explanatory power when removing variables. However, the observed differences are still required to be statistically significant. You do this by comparing the log-likelihood of both models, and if we find a statistically significant difference, then we can say that the full model fits the data optimally (Johnston and Dinardo, 1997). The formula for the test statistic is written as

$$LR = -2ln\left(\frac{L(m_1)}{L(m_2)}\right) = 2\left(loglik(m_2) - loglik(m_1)\right)$$

Where $L(m_i)$ denotes the likelihood of the respective model, and $loglik(m_i)$ is the natural log of the model's final probability. Moreover, m_1 is the more restrictive model, and m_2 is the less restrictive model.

Table 11 in the appendix presents the chi-squared test statistic, degrees of freedom, and the corresponding p-value. All variables are statistically significant at all levels, and we conclude that the complete model is the best suitable alternative given the variables we have. We elect not to present the results of the Wald test due to the large test statistics obtained in the LRT test and the large degree of significance observed.

5.4.2 Model independence

An MNLM also has some assumptions that we need to test. The assumption of independence of irrelevant alternatives (IIA) is one. If the model is independent, adding or deleting outcomes does not affect the probabilities among the remaining outcomes. Simply put, the odds do not depend on other available outcomes (Long and Freese, 2006). The assumption is restrictive of the MNLM, and (McFadden (1974),p113) notes: "Application of the model should be limited to situations where the alternatives can plausibly be assumed to be distinct and weighed independently in the eyes of each decision-maker." Table 2 presents the results of the Hausman-McFadden under the corresponding null hypothesis: *Odds (outcome-J vs Outcome-K) are independent of other alternatives*

Exit channel	chi2	df	$P > chi2$	evidence
IPO	31.013	157	1.000	for H0
Trade Sale	-15.003	158	.	for H0
Merger	26.839	156	1.000	for H0
Private Placement	-23.796	157	.	for H0
Sale to GP	402.169	158	0.000	against H0
Restructuring	13.476	157	1.000	for H0
Write-off	20.380	158	1.000	for H0
Sale to Management	-3.036	157	.	for H0

Table 2: Hausman Test. The table shows the test statistic of the Hausman test for the assumption of independence of irrelevant alternatives. DF represents the degrees of freedom of the test. P represents the corresponding p-value signaling the significance level of the test.

All other variables except Sale to GP provide evidence for the null hypothesis. Hausman and McFadden (1984) note the possibility and conclude that negative chi-squared values should infer proof for H0. However, this outcome is uncertain. Vijverberg (2011) proposes that judging the outcome of the standard Hausman-McFadden test by the upper tail of the chi-squared distribution may lead to incorrect statistical inference, and a violation of IIA may still lead to large negative test values. Therefore, we also use the Small-Hsiao test of independence of irrelevant alternatives. Small and Hsiao (1985) later improved the likelihood ratio test, and we can test for the same conditions in our model.

In contrast to the likelihood ratio model, the Small-Hsiao test provides consistent results for H0, which can be seen in Table 3. The test is based on a random division mechanism every time it is run, and after repeated testing, we get significant results on all variables. Thus, we conclude that the IIA is not violated.

	lnL(full)	lnL(omit)	chi2	df	$P > chi2$	evidence
IPO	-2.13e+04	-2.13e+04	160.051	162	0.529	for H0
Trade Sale	-1.39e+04	-1.38e+04	175.767	162	0.217	for H0
Merger	-2.10e+04	-2.10e+04	184.074	162	0.113	for H0
Private Placement	-2.15e+04	-2.14e+04	173224	162	0.259	for H0
Sale to GP	-1.53e+04	-1.52e+04	179.179	162	0.169	for H0
Restructuring	-2.27e+04	-2.26e+04	169.029	162	0.337	for H0
Write-off	-2.13e+04	-2.12e+04	169.697	162	0.324	for H0
Sale to Management	-2.32e+04	-2.31e+04	152.851	162	0.685	for H0

Table 3: Small-Hsiao Test. The table shows the test statistic of the Small-Hsiao test of assumption of independence of irrelevant alternatives. DF represents the degrees of freedom of the test. P represents the corresponding p-value signaling the significance level of the test.

5.4.3 Multicollinearity

A typical data problem when dealing with a greater number of variables in multiple regression models is multicollinearity. It refers to a linear relation among two or more independent variables and can cause inaccurate estimates of the model coefficients. High correlations between variables can be seen as a special case of multicollinearity and are often implicitly used to test for it Alin (2010). Table 4 presents the correlations between the independent factor variables in our models. The results show limited relations between the continuous variables. Hence, we conclude that our data do not suffer from multicollinearity.

	Interest Rate	VIX	Holding Period
Interest Rate	1		
VIX	0.0028	1	
Holding Period	-0.1331	-0.0331	1

Table 4: Multicollinearity. The table presents a correlation analysis of the continuous independent variables of this research. Respectively, interest rate, VIX and holding period. Each number represents the correlation coefficient between the selected variables.

5.4.4 Pearson's chi-squared test

When dealing with variables of categorical type, it is crucial to verify their independence. Meaning that the outcome of one variable does not affect the outcome of another. To test for this effect, we perform the Pearson's chi-squared test, which takes the mathematical form:

$$\chi^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i}$$

The test compares the outcome of the data relative to a model estimated distribution that assumes independence. If the estimation outcome does not fit the data, the likelihood of dependence increases, thus violating the null hypothesis. Table 5 displays the test statistic and p-values of the respective categorical variables. Every variable relationship is statistically significant at the 5% level, while most is significant at 1%. We then conclude that the variables do not depend on each other, and we can include them in our models.

	Cycle	Investment Type	Experience	Industry	Country
Cycle	1				
Investment Type	16.46 0.021**	1			
Experience	62.63 0.000***	628.29 0.000***	1		
Industry	38.93 0.000***	1,400 0.000***	71.07 0.000***	1	
Country	11.20 0.047**	2.100 0.000***	225.23 0.000***	1,300 0.000***	1

Table 5: Pearson Chi-Squared Test. The table shows the outputs of the Pearson Chi-squared test of independence. The number below the chi-squared statistic represents the corresponding p-value. Significance level for the P-value of the estimated statistics is denoted by *** for 1%, ** for 5 and * for 10%.

6 Results and analysis

This section presents the main results of the MNLM and subsequent marginal effect and predicted probability estimations. The findings are introduced following the order of the initial hypothesizes and ends with a general discussion of additional conclusions.

6.1 Primary multionmial logistic regression

It can be challenging to interpret an MNLM. That is why we exponentiate the logit coefficients to analyze the numbers in relative risk ratios (RRR). The methodology section in our thesis states that the common interpretation of exponentiated coefficients is as odds ratios. In other words, for a unit change in the predicted variable, the RRRs relative to the base outcome is expected to change by a factor of the respective parameter estimate, given the remaining variables are held constant (Bruin, 2021b). An RRR above one indicates a higher chance to fall into the comparison group, while lower than one means that the base category is more likely. All coefficients are relative to our base category Trade Sale and is interpreted as such.

	Logit	Coefficient	Std.Error	t-value	e^{coef}	%
Interest Rate	IPO/TS	0.225	0.013	17.68***	1.252	25.2
	Merger/TS	-0.136	0.015	-9.02***	0.873	-12.7
	PP/TS	-0.106	0.019	-5.67***	0.900	-10.0
	GP/TS	-0.045	0.009	-5.11***	0.956	-4.4
	Res/TS	-0.161	0.024	-6.63***	0.851	-14.9
	WO/TS	-0.132	0.017	-7.85***	0.876	-12.4
	Man/TS	0.047	0.024	1.99*	1.048	4.8
VIX	IPO/TS	-0.016	0.004	-3.89***	0.984	-1.6
	Merger/TS	-0.010	0.04	-2.69***	0.99	-1.0
	PP/TS	-0.015	0.004	-3.55***	0.985	-1.5
	GP/TS	-0.01	0.002	-4.67***	0.99	-1.0
	Res/TS	0.037	0.001	9.64***	1.037	3.7
	WO/TS	0.02	0.003	6.07***	1.02	2.0
	Man/TS	-0.08	0.006	-1.43	0.992	-0.08
Holding Period	IPO/TS	-0.01	0.001	-13.11***	0.990	-1
	Merger/TS	-0.032	0.001	-33.66***	0.969	-3.1
	PP/TS	0.006	0.001	11.23***	1.006	0.6
	GP/TS	0	0	0.67	1	0
	Res/TS	-0.001	0.001	-1.67*	0.999	-0.01
	WO/TS	-0.007	0.001	-10.01***	0.993	-0.7
	Man/TS	0.004	0.001	4.80***	1.004	0.4
Cycle = 1	IPO/TS	1.139	0.155	7.37***	3.124	212.4
	Merger/TS	0.042	0.111	0.38	1.043	4.3
	PP/TS	0.177	0.146	0.80	1.124	12.4
	GP/TS	0.024	0.067	0.35	1.024	2.4
	Res/TS	-0.65	0.127	-5.12***	0.522	-47.8
	WO/TS	-0.402	0.102	-3.94***	0.669	-33.1
	Man/TS	-0.296	0.161	1.84*	0.744	-25.6
Experience = 1	IPO/TS	0.22	0.051	4.32***	1.212	21.2
	Merger/TS	0.202	0.0484	4.20***	1.246	24.6
	PP/TS	0.413	0.054	7.71***	1.511	51.1
	GP/TS	0.048	0.031	1.57	1.049	4.9
	Res/TS	0.285	0.072	3.97***	1.330	33.0
	WO/TS	0.173	0.054	3.19***	1.188	18.8
	Man/TS	-0.077	0.086	-0.90	0.926	-7.4
Country fixed effects			Included			
Industry fixed effects			Included			
Industry			Included			
Pseudo r-squared = 0.067	Number of obs = 32881			Chi-square = 7106.678		
**** p<.01, ** p<.05, * p<.1*						

Table 6: Primary Multinomial Logistic Regression. The table shows the results obtained by the MNLM with the dependent variables, IPO, Merger, Private Placement, Sale to GP, Restructuring & Recapitalisation, Write-off, and Sale to Management. Lastly, Trade Sale is estimated as the base outcome variable, meaning all results are relative to their likelihood. The independent variables are listed in the first column. The second column denotes the dependent variables relative to the base outcome. The third column presents the model coefficients, denoting the effect's direction. The following two columns show the standard errors and t-value of the coefficients. The exponentiated coefficient presents the effect on the dependent variable for a unit change in the independent variable. The significance level for the p-value of the estimated coefficients is denoted by *** for 1%, ** for 5%, and * for 10%.

6.2 Industry

We hypothesized that technology firms have a higher probability of going public through an IPO than other sectors. To get a more straightforward interpretation, we have fine-tuned our MNLM such that Information Technology is the base category for this sub-section. The new IPO industry coefficients can be seen in table 12 in the appendix. The coefficients dismiss our hypothesis, as several industries seem to have a higher probability of an IPO. Financial Insurance Services and Real Estate firms have more than double the probability of an IPO over Information Technology, significant at 1%. Consumer Discretionary and the Energy sector also have a significantly higher likelihood of 31% and 28.7%, at the 1% level.

The technology sector has grown exponentially across our sample, and has an increased impact in daily operations for people and firms. The report from EY (2021) shows that technology is the largest sector responsible for IPOs in the US and Europe. To do a robustness check on our results, we use a new sample ranging from 2010-2021 to test for similarities between the two samples. We find that the effects are almost identical, and PE-backed technology firms are not more prone to IPOs than other industries. Furthermore, we find no significant results when looking at the marginal change for industries. This means IT companies are either not significantly larger than peer industries or are less likely to be exited through an IPO relative to the other sectors. Hence, we reject the hypothesis.

6.3 Geographic locations

The IPO and WO results for country effects in the MLNM can be found in Table 13. We find insignificant results when comparing IPO probability between the US and the base category Other.

To investigate further, we compute the marginal change between each geographic location specifically which can be found in table 14. We note that the probability of an IPO is 0.7% lower in the US compared to the smaller European markets. Further, when comparing the US with the more analogous European markets, we see a higher probability of IPO for the American market. It has a 1.2%, and 2.9% higher probability over the German and French markets, with 5% significance. On the other hand, Canadian funds' IPO likelihood is significantly higher than all European markets, ranging from 2.9% against Other category, to 6.5% higher than the French market, all significant at the 1% level. Although there seems to be a tilt towards a greater IPO probability in North-America, we cannot confidently accept our initial hypothesis.

From the results above, it seems to be a correlation between IPO probability and the size of the PE markets. Canada, together with Other variable which is pooled with small markets, have a much higher likelihood across the whole sample. From table 13, we see that only Canada has a higher probability of using an IPO compared to Other. In fact, the UK has a 21.7% less likelihood of using an IPO. Germany and France are at 26%, and 36.2% respectively, all significant at 1% or 5% level. This contradicts Cendrowski (2019), who argues for an increase of IPO probability in mature and developed markets. It is difficult to say why we find conflicting results, however, lower barriers and smaller firms going public in these markets might explain some of it. Nevertheless, this is an intriguing result and it would be interesting to do more research on the subject.

6.4 Experience

Due to competitive advantages we expect large, experienced firms to have over less established firms, we hypothesized that there would be an inverse relationship between experience and write-off probability. In table 6, wee see the RRR coefficient of experience relative to low experience for WO stands at 1.188, significant at the 1% level. This means higher experienced funds are 18.8% more likely to have their investment written off, compared to funds with less experience. This is in contrast to our expectations, as we argued that experienced firms would have more foresight of economic conditions and better managerial skills and thus have fewer write-offs. Therefore, we dismiss our initial hypothesis.

Although the results differ from our expectation, the explanation might be straightforward. As mentioned earlier, Schmidt et al. (2010) find that PE firms generally recognize poor investments and cut losses instead of holding them as living dead assets. Our result may indicate that experienced companies are better, or at least use the exit channel more frequently, to quickly write off unsatisfactory investments, and focus time and capital on prominent companies instead. This explanation works well with the result of a higher probability of Sale to management for inexperienced firms, which may indicate that managers hold on to the bad investments, to continue developing the company and force it through another exit channel. However, the Sale to Man variable is not significant, and we cannot make any conclusion based on this speculation.

6.4.1 Market Cycle

We further estimate the marginal change in probability between market cycle and experience. More precisely, we check if there is an increase in likelihood of WOs for experienced funds relative to inexperienced ones, when in different economic cycles. We do this by taking the coefficients from the main MNLM, predicting the exit type using only the Cycle and Experience variables, holding everything else constant. From Table 7, we observe that WOs are 0.82% more likely in experienced funds in bust periods, significant at the 5% level. This coincides with our earlier discussion and we reject the hypothesis that experienced funds suffer fewer WOs than inexperienced funds, even when accounting for market cycles.

Cycle	Experience	IPO	TS	Merger	PP	Sale to GP	Res	WO	Sale to Man
Bust	Low	0.0171	0.4581	0.0450	0.0394	0.2941	0.0420	0.0788	0.0255
Bust	High	0.0193	0.4257	0.0522	0.0553	0.2867	0.0519	0.0870	0.0220
Boom	Low	0.0537	0.4592	0.0471	0.0443	0.3019	0.0220	0.0528	0.0190
Boom	High	0.0604	0.4266	0.0543	0.0622	0.2943	0.0272	0.0583	0.0164
Marginal Change Bust		0.0022**	-0.0324***	0.0081***	-0.0159***	-0.0073	0.0099***	0.0082**	0.0036*
Marginal Change Boom		0.0067**	-0.0326***	0.0074***	0.0179***	-0.0076	0.0052***	0.0055**	0.0027*

Table 7: Effect of Cycle & Experience on predicted probabilities. The table shows the marginal change in predicted probabilities for a variety of independent variables, holding all other variables constant at their mean. The respective first four rows presents the average marginal change for all exit channels by changing either the market cycle variable or the experience variable. The following two rows show the change in the predicted probability as the experience variable changes from low to high during a Bust and Boom cycle. The significance level for the p-value of the difference in predicted probability is denoted by *** for 1%, ** for 5%, and * for 10%.

The MNLM model does not directly capture the cyclical economic aspect with experience, resulting in the need for an interaction term between them. However, it does not provide statistically significant results for any exit channel, implying we should reject the initial hypothesis again.

6.4.2 Interest Rate

We also hypothesized that interest rate fluctuations would affect the experienced fund's exit probability less. To test this effect, we estimate an interactive regression like the one above by replacing Cycle as an independent variable with Interest Rate.

$$ln\Omega_{i^*|S}(x_{i^*}) = \alpha + \beta_{1,i^*|S}IR + \beta_{2,i^*|S}Experience + \beta_{3,i^*|S}IR, Experience + \epsilon$$

, where i* equals the exit types.

The results are found in table 15 in the appendix. We note that for a 25 bps increase in the interest rate, IPO is 27.3% times more likely to be exited relative to trade sale, similar to the original MNLM model. We will use the interaction coefficients to test the hypothesis, which is interpreted as follows. For IPO exit, the exponentiated coefficient of 0.932 is the change in the slope of the interest rate for a one-unit increase in experience. Since the experience variable is a dummy, it means when the experience goes from low to high.

The probability of an WO is significantly lower at -9.8% for experienced funds relative to inexperienced as the rate increases. IPO and WO are the only significant exit variables, at 5%. They both indicate a lower likelihood of exit for higher interest rates and in experienced funds relative to inexperienced ones. This result suggests that experience is positively associated with funds' ability to maneuver their portfolios in tighter capital markets, thus achieving successful exits.

This is difficult to interpret over time, so we estimate the conditional marginal change in probability, and plot the effects for each exit channel for experienced funds relative to inexperienced ones, as the interest rate increases from 0 to 10. The graph is seen in Figure 5.

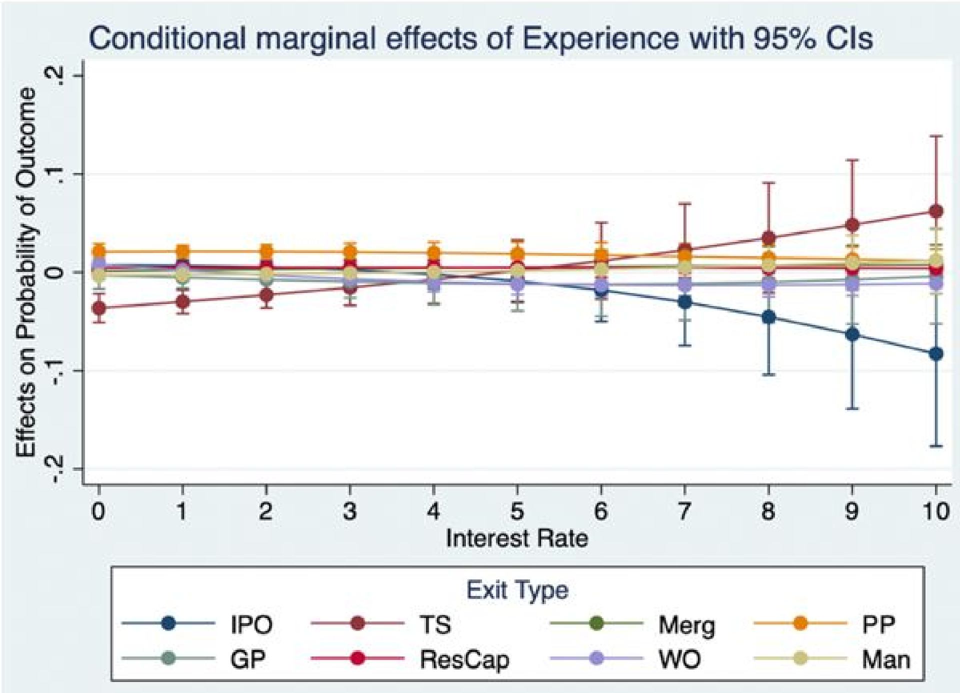

Figure 5: Conditional Marginal Effects of Experience on Interest Rates. The figure presents the estimates of the predicted probabilities for each eight of the dependent exit variables under the interaction term experience & interest rate. The estimates are based upon the marginal effect in probability for a 1% change in the interest rate, while holding all other variables constant at their mean. The plot signals the difference in probability for experienced firms relative to inexperienced firms.

The stated effects can also be seen in table 16. For IPOs, the figure provides significant effects only between 0-2% interest rate, leading us to argue that the stated effect in table 15 only accounts for low interest rate levels. Given the reality of this environment in the last decade, we still find this result useful, with significant differences in probabilities at the different levels. WOs effect seems to be constant across most interest rates, indicating that the change in WO probability only comes from experience, and not the change in rates. Hence, we can not confidently conclude that experienced funds are affected less by changes in the interest rates.

6.4.3 VIX

Next, we test the effect of experience on the VIX index and run an interactive regression. We find no significant results on any exit channel, an outcome explained by the short-term measure of VIX and the long life-cycle of PE. Overall, the results of the experience interactions, highlight interest rate as the variable of great significance for the PE sector and the subesquent difference in behavior between experienced and inexperienced funds for other variables are minimal.

6.5 Market cycle

Next, we analyze the occurrence of write-offs in recessions. First, the man regression results from table 6 provide a significantly lower likelihood of write-offs in boom periods at -33.1% compared to bust. The reasoning behind this is fairly straight forward, in economic troughs the activity levels decline and the markets tighten. There is less access to capital and buyers willing to take risk. Bad investments are therefore written off, since there is no buyers for the prospective company. Table 14 in the appendix, which shows the marginal effects, further supports this hypothesis. The likelihood of WOs marginally decrease by 2.7% in an expanding cycle relative to a contracting one. We accept our hypothesis of an increase in WOs, when market conditions are though.

Previously, we talked about IPO hot markets, and how cheap debt might help create them. We wanted to test for whether the general economic conditions might help produce them as well. The primary MNLM shows that IPOs are 3.1 times more likely in Boom periods relative to Bust, significant at the 1% level. The marginal change table 14 provides strong results in favor of the hypothesis, with a 4.2% change as the market cycle goes from contraction to expansion. In great economic markets, people are more willing to take risks and access to capital is easier to find.

The results from the economic cycle analysis is expected, and underlines the importance of focus on macroeconomic variables when setting up the fund. The returns it seek are connected with the economic outlook, and it is important to understand the future macro-risk when investing, or waiting to sell.

6.5.1 VIX

Given the importance of economic cycle in exit determination, we look at the VIX to see if it has any effect on exit types. Implying future 30-day volatility from options, it tells us the volatility expectation over the coming month.

Figure 6 plots the predicted probability for all levels of the VIX index, revealing some interesting findings. The movement of the index has an apparent effect on WO and Restructuring exits, equivalent to chapter 11 bankruptcy. High VIX levels are often seen as an indicator of market turmoil and uncertainty, so it is no surprise to see businesses fail or need to restructure their debt in uncertain times.

Furthermore, Sale to GP decreases as much as 20%, possibly due to PE funds not wanting to take on additional investments and risk in uncertain times. IPO probability suffers a fall from roughly 8% to almost 0, a natural reaction because of the inverse relationship between the VIX index and the stock market. This makes IPO a less viable alternative for companies to raise capital, as investors seek to protect their holdings. However, public offerings are a lengthy process, and many IPOs are likely to only be postponed due to unpredictability of the markets. The results clearly show that the volatility the VIX predicts, has effects on the exit choice for PE funds. Further research could look at the long-term VIX, which uses option prices several months in the future, and see if the effect is greater or smaller. This could show how forward looking PE funds are when it comes to market volatility, and the question could be further studied when include experience parameters.

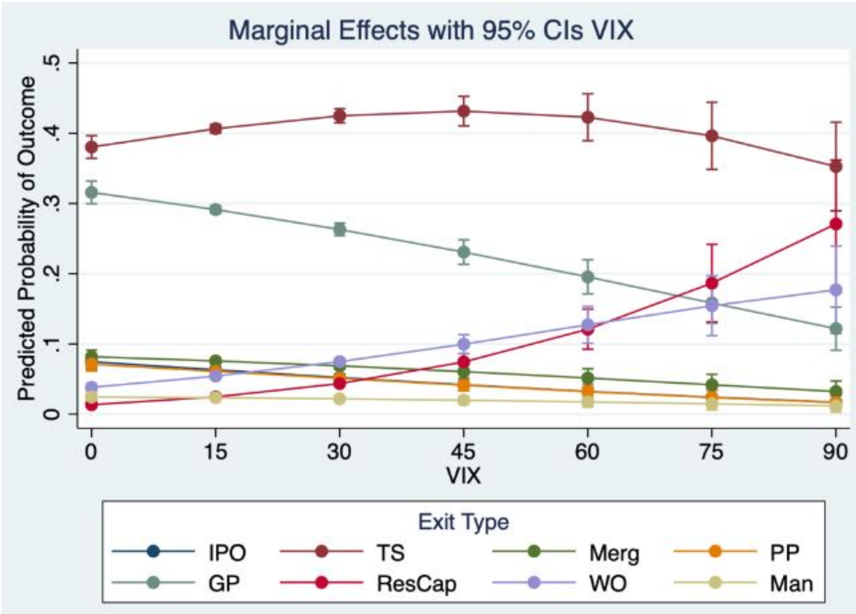

Figure 6: Predicted Outcome Probability for VIX. The figure shows the estimates of the predicted probabilities for every one of the eight dependent exit variables for a change in the continuous VIX variable, while holding all other variables constant at their mean. The estimates are based upon the marginal effect in probability for a change of 15% in the VIX index, presented in a range of 0 to 90%.

6.6 Interest Rate

We hypothesized that IPO likelihood increases as an exit choice when interest rates increase due to the tightening in credit markets and subsequently greater debt-related fees for other exits. Therefore, IPO should be a more enticing and viable alternative for firms seeking capital. We see from table 6 that for a unit change in interest rates, the probability of an IPO increases by 25.2%. In table 14, the marginal effect tells us that the likelihood of IPOs increases by 2.9%, for every standard deviation (1.67%) increase in interest rates.

Figure 7 presents the predicted probability of each exit channel as the interest rate increases to 10%. IPO increases exponentially from a relatively low likelihood to a 32% probability, and we interpret it as a clear sign supporting the hypothesis. However, we would also expect the size of the public offerings to be smaller in high interest rate environments due to a slower economy. We conclude that the evidence supports our hypothesis, and IPOs are more likely in high-interest rate environments.

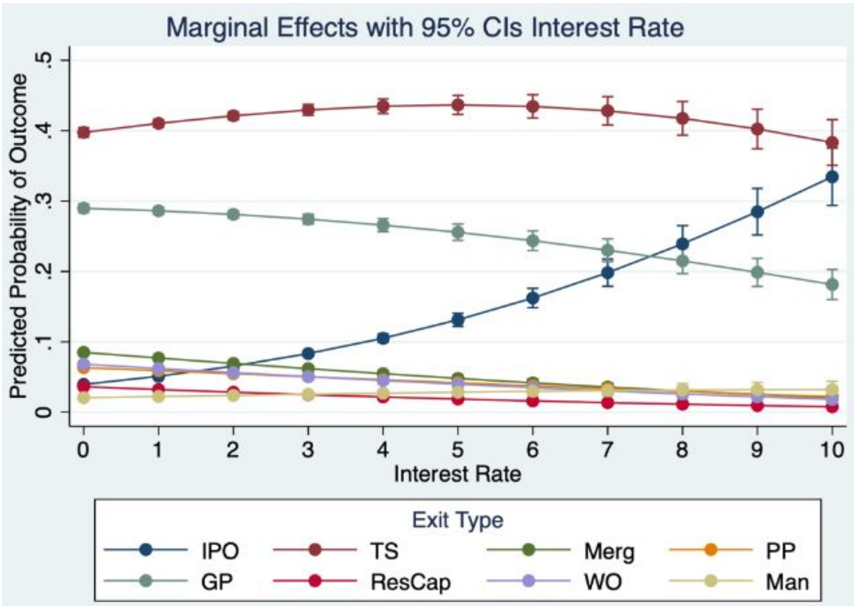

Figure 7: Change in Predicted Outcome Probability for Interest Rates. The figure shows the estimates of the predicted probabilities for every one of the eight dependent exit variables for a change in the continuous interest rate variable. The estimates are based upon the marginal effect in probability for a change of 1% in the interest rate, while holding all other variables constant at their mean. The plot is presented in a range of 0 to 10%.

6.6.1 Market Cycle

To further study the IPO − interest rate relationship, we conduct an interacted regression with market cycle and interest rate to better understand where the increasing probability is coming from. One would expect to see higher interest rate levels in times of economic booms to prevent overheating of the economy, and lower rates in contractions to stimulate economic activity. We find the opposite in our data, with an average interest rate in busts to be 2,68% and 1,26% in booms. The reason for this is likely the skewness our dataset has towards new deals, as funds have become more open to reporting them. Table

17 in the appendix display the results of the interaction regression model and the results provide some interesting findings.

IPO has a 23,3% higher probability of occurring in booms when interest rate increases by 25 bps, as opposed to in bust periods. This means in expansionary periods, an interest rate increase will give a higher probability increase of IPOs in boom periods. The effect would not be as prominent in bust periods. We also find that the likelihood of WOs occurring in boom periods increase by 39% when interest rate increases by 25bps. To easier see the effects we plot the marginal effects on probability of outcome, which can be seen in table 8.

IPO has a 36% higher probability in boom relative to bust at the highest interest rate level, higher than 32% from figure 7 when not accounting for market cycles. Hence, we expect there to be a negative effect of IPO probability for higher interest rate levels in Bust periods. In 8, we can also see the conditional effects on market cycle, going from negative when interest rates are low, towards equal probability in boom/bust when it is high. These results further underlines the importance of market cycles on the occurrence of IPO, however to further investigate the interest rate and IPO relationship we conduct further tests before and after the GFC due to the large difference in interest rate levels.

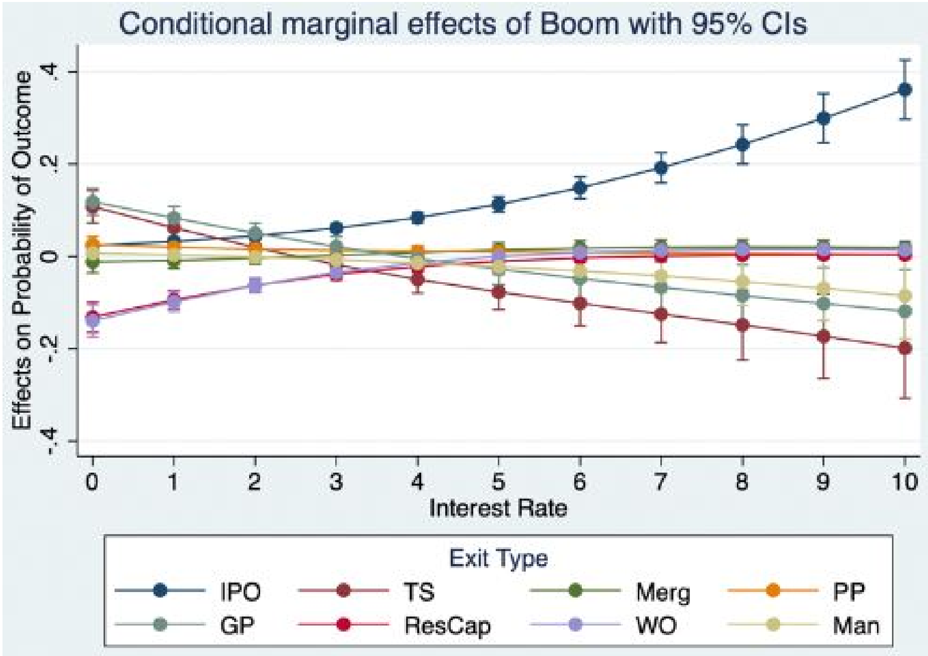

Figure 8: Conditional Marginal Effect of Cycle on Interest Rates. The figure presents the estimates of the predicted probabilities for each eight of the dependent exit variables under the interaction term market cycle & interest rate. The estimates are based upon the marginal effect in probability for a 1% change in the interest rate, while holding all other variables constant at their mean. The plot signals the difference in probability for a boom cycle relative to a bust cycle.

6.7 Great Financial Crisis

A critical aspect of the data used throughout this study is how the macroeconomic effects has changed across the sample. As a result, we want to study the potential impact the GFC has had on the PE market but also the general economic environment and monetary policy actions. In addition, we attempt to account for how the PE market has changed over time, as the sector has had a cyclical but stable growth over the last 30 years. Table 18 in the appendix presents the results of a new MNLM of the two sub-periods.

6.7.1 Interest Rate

Figure 9 plots the predicted probability of the two samples and display two distinct differences in the exit probability with an increasing interest rate. There seems to be a prominent change in exit choice among IPO, TS, and GP when the interest rate increases between the two samples. In the pre-GFC sample, IPO and TS probability seems to increase together with the interest rate, while Sale to GP decreases. The opposite is true for the exits in the post sample. One possible explanation for the negative effect can be the increasing use of monetary policy for central banks to guide markets, have changed the way PE funds plan their exit channels.

The IPO effect is especially interesting, as it seems the effect between higher interest rates and high IPO probability has been removed completely. This may be due to estimation errors because of only low interest rates in our sample, making it easy for funds to find leveraged buyers, or other economic factors not included in our analysis. There seems to be an inverse relationship between the three main significant variables, IPO, TS, and GP between the two samples. It is difficult to fully grasp the economic reasoning behind this, and more research must be done on financial changes that has come from the GFC. However, we note that in the late sample (LS) the interest rates have been very stable with few changes and have not risen over 2.5%, and we therefore must extrapolate the effects we see in the LS. Therefore, this plot might be subject to time-period bias and making any significant conclusions about the interest rate effect difficult.

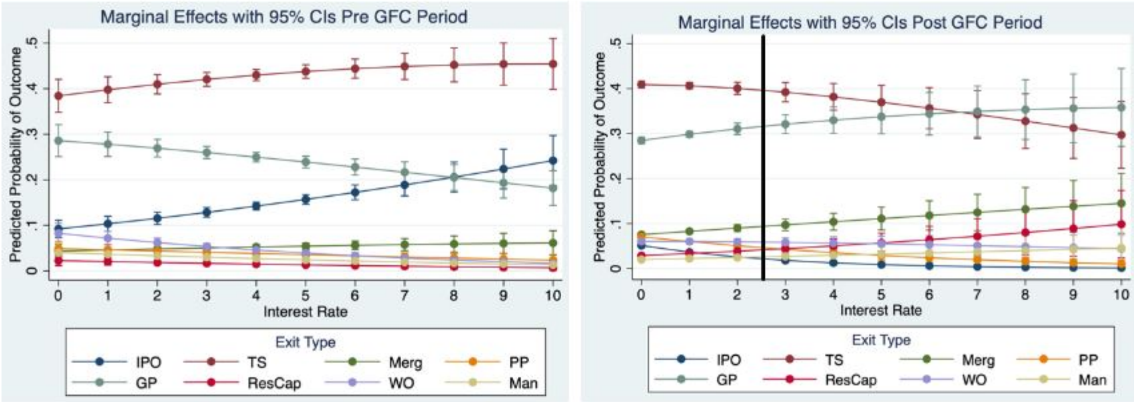

Figure 9: Predicted probability change for various interest rate levels pre- and post-GFC. The figure presents the estimates of the predicted probabilities for each eight of the dependent exit variables under the interaction term market cycle & interest rate, before and after the Great Financial Crisis. The estimates are based upon the marginal effect in probability for a 1% change in the interest rate, while holding all other variables constant at their mean. The plot signals the difference in probability for a boom cycle relative to a bust cycle and is presented in an interest rate range of 0 to 10%, in which the thick line indicates the highest observed interest rate value in the sample period. The remaining plot is based upon extrapolation of the interest rate and are solely theoretical estimations.

Table 19 present the marginal change for a standard deviation increase in the independent variable. Pre-crisis interest rates have a SD of 1.44%, whereas post-crisis is at 0.70%. After looking at the predicted probabilities, GP has a negative outcome probability of approximately -1.5% in the ES, whereas it increases by 0.9% in the LS. IPO has the opposite marginal effect, from a 2.1% probability change to -0.9% across the samples.

The complete picture of the marginal effects is more interesting for our hypothesis than single differences. Overall, we observe smaller changes in the LS, indicating that the interest rate effect has diminished in newer times. This is likely due to the low and stable interest rate environment which PE funds have experienced after the GFC, making adjustments predictable with little effect. The significant variables are also the ones with the highest SD change. Their marginal effects on outcome probability in percentage terms are lower, supporting our hypothesis. Since we observe less SD effects in the post sample on several significant marginal effect exits, we accept our hypothesis that interest rates have less influence on exit determinations. However, we note again that results can be uncertain due to extrapolations of interest rates in the LS.

6.7.2 Market Cycle and Interest Rate

We further study the effect of market cycles and interest rates on the IPO probability before and after the GFC. Figure 10 in the appendix shares a lot of similarities with figure 8. This is expected given the long bust cycles and high interest rate levels during this period. There are still some notable differences in the plots, regarding lower effects of IPO at higher interest rate levels, and a slightly convex shape in the RR exit. Furthermore, as interest rate increases, we observe an even stronger decreasing effect in Sale to GP. Again, evidence points to lower interest rate influence on exits, even when accounting for cycles.

The ES predicted probability estimates show a contrasting effect compared to the LS and full sample. We note that cycle and interest rate has almost no impact on IPO probability, coinciding with the results in figure 10 that the interest rate effect on IPO probability has diminished after the GFC. However, we can conclude that changes in the market cycle and interest rate still have significant implications on exit channels. The change of interest rate movements and economic cycles still affect exit determination, however the effect has reduced somewhat, especially on IPO and WO probability.

6.7.3 Geographic location

We test whether the difference in IPO probability in the American and European market can be verified in the pre- and post-GFC samples. Table 20 in the appendix shows the marginal change estimates for every geographic location combination. The country probabilities are similar to what we found in section 6.3. What we can see is that the general differences has gotten smaller after the GFC, and markets seems to become more similar as they mature. Technology has made it easier to provide and access opportunities and investment channels, reducing the differences between separate markets, as the world has become more connected.

Further we see the effect from smaller countries has slightly reduced. The Canadian market has particularly lower marginal effects for IPOs in the LS, when compared to ES or the full sample. Table 20 presents the LS estimates, showing a different picture. US have a 0.8% higher probability than Other; this is however not significant. Following, we find a 2%, 3% and 4,2% higher probability than UK, Germany, and France, with the results being significant at 5% and 1% respectively. These results can be explained by a maturing of the European markets, in which London and Frankfurt have grown to become important global financial hubs.

6.8 Discussion

In this section, we will discuss additional results we find that can make for an interesting area of focus for further research.

An intriguing result from the MNLM is the high likelihood of investments being written off in the US relative to the other countries. In particular, we see from table 13 that the US has a 2.63 times higher probability of using WOs as an exit channel, compared to the "Other" countries. This effect can be observed against every geographic location. One explanation might be the regulatory conditions for taking risk is lower in the US compared to other countries, but nonetheless this is an interesting result.

Further analysis of WOs shows a significantly larger likelihood of consumer discretionary companies being written off relative to the remaining industries in our data. A possible explanation could be due to the non essential aspect of many companies in the sector. However, the marginal change in probability results provides no significant findings in either direction of WO likelihood, leading us to inconsistent conclusions.

The pre/post GFC sample study makes for future comparisons of the central banks' contrasting interest rate and monetary policy environments. Looking at the output of the MNLM in table 18, there seem to be few different effects across the two samples, with some exceptions. First and foremost, the IPO likelihood decrease in the LS relative to trade sale as the interest rate increase by one unit of 25 bps. This result also contrasts the initial hypothesis on the subject. An important notation on the results is the difference in the quantity of IPOs in each sample, as the ES has a significantly larger fraction of deals exiting as an IPO. Moreover, the lower levels of interest rate in the LS may not be able to capture the effect to the same extent.

7 Conclusion

This thesis study the effect of market conditions and firm characteristics on PE fund's final exit route. We focus on a selection of market variables, precisely interest rate, VIX index, and economic cycle, to capture the influence of external conditions on fund's ability to exit their investments. We also study firm-specific conditions, such as experience and holding periods. Lastly, we account for the fixed effects of geographic location, industrial differences and investment types, and the potential difference in approach between them.

We identify clear effects of both market conditions and firm characteristics on the choice of exit channel for PE funds. Most notably, we identify a significant, positive relationship between IPO probability during a booming economic environment and in an increasing interest rate environment. However, the interest rate effect seems to be decreasing in the aftermath of the GFC. We believe the effect is reduced due to central banks monetary policy choices to keep rates low, even in great economic periods. Moreover, we find differences in IPO likelihood in North-America compared to the large European markets of UK, Germany, and France. The results contrasts Schmidt et al. (2010), which finds no difference in IPO probability. Additionally, we find that smaller PE markets seem to have a higher probability of exiting through an IPO, a result we hope future studies will be performed on.

There is significant evidence of Write-offs occurring during contracting economic environments and subsequently higher market volatility, measured by the VIX index. These WOs cause the most significant decrease in the sale to GP probability, indicating that PE funds minimize their investments in these times. We found conflicting evidence of more experienced funds being able to withstand these economic environments, and have more stable exit determinations. The interest rate seems not to affect WO probability in interaction with fund experience, showing that the differences in WO probability between experienced and inexperienced firms does not come from interest rate changes.

We recognize a potential limitation of our research, caused by how PE funds have historically reported deal information. The lack of required reporting on the PE sector could result in GPs hand-picking successful investments to boost fund image and track record, leading to reporting bias. We expect this problem to mainly apply to WOs, but we are confident that our dataset alleviates these biases due to its size.

We consider there to be two critical areas to study further on the topic of exit determinants. First is the size of an investment regarding company value and the capital structure implemented. This means the market value of the company and the debt-to-equity ratio used to finance the acquisition. We believe this would yield crucial information in the exit process for PE funds in terms of how the size and capital structure are affected by the market and firm characteristics. Second, by having access to exhaustive deal-related purchase and selling price information, one could measure the returns generated by funds depending on the exit route they have used. This is the holy grail of PE research and would make for more accurate analysis. With the inclusion of this data, one could further build on, and improve the results found in this paper.

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APPENDIX

A Appendix

	Canada	US	Europe	Total
Pre GFC	-1.41%	-4.01%	-2.72%	-2.71%
Post GFC	-2.47%	-8.55%	-3.37%	-4.80%
Difference	-1.06%	-4.54%	-0.66%	-2.08%
Total	-1.79%	-5.96%	-3.01%	-3.59%

Table 8: Government deficit in percentage of GDP. The table shows the average government budget deficit in percentage of gross domestic product. The data is gathered from the OECD database, and we obtain data on Canada, US, and a selection of large European countries, as well as the total sample average. The first row presents the results in the period 1990-2007 and accounts for the period before the great financial crisis. The second row show the period after the great financial crisis from 2009-2021. The second too last row show the difference in deficit in the post GFC period compared to before. Finally, we find the total budget deficit over the whole sample period.

	US	Europe	Total
Pre GFC	36.93%	46.12%	41.52%
Post GFC	40.30%	48.02%	44.16%
Difference	3.37%	1.91%	2.64%
Total	38.32%	-46.96%	42.63%

Table 9: Government Spending in Percentage of GDP. The table shows the average government budget spending in percentage of gross domestic product. The data is gathered from the OECD database, and we obtain data on US and a selection of large European countries, as well as the total sample average. The first row presents the results in the period 1990-2007 and accounts for the period before the great financial crisis. The second row show the period after the great financial crisis from 2009-2021. The second too last row show the difference in spending in the post GFC period compared to before. Finally, we find the total budget spending over the whole sample period.

Exit Type / Country	UK	Germany	France	Canada	US	Other	Total
IPO	256	75	66	94	1,074	416	1,981
	6.2%	4.5%	2.9%	9.0%	6.1%	6.8%	6.0%
Merger	226	86	80	89	1,574	368	2,423
	5.5%	5.2%	3.5%	8.5%	8.9%	6.0%	7.4%
Trade Sale	1,835	705	719	488	7,078	2,691	13,516
	44.7%	42.3%	31.4%	46.9%	40.1%	43.9%	41.1%
Private Placement	152	81	96	109	1,093	385	1,916
	3.7%	4.9%	4.2%	10.5%	6.2%	6.3%	5.8%
Sale to GP	1,155	509	1,098	176	4,673	1,684	9,295
	28.1%	30.6%	47.9%	16.9%	26.5%	27.5%	28.3%
Restructuring	231	99	82	46	1,338	215	2,011
	5.6%	5.9%	3.6%	4.4%	7.6%	3.5%	6.1%
Write Off	127	51	20	28	638	124	988
	3.1%	3.1%	0.9%	2.7%	3.6%	2.0%	3.0%
Sale to Man	122	59	131	11	179	249	751
	3.0%	3.5%	5.7%	1.1%	1.0%	4.1%	2.3%
Total	4,104	1,665	2,292	1,041	17,647	6,132	32,881
	100%	100%	100%	100%	100%	100%	100%

Table 10: Summary Statistics. The table shows the dependent variables quantity for the five geographic locations analyzed in this study. Corresponding to UK, Germany, France, Canada, US and Other. The first number present the number of exits conducted through the channel in any given country. The percentage term represents the fraction of exit in the same country.

Variables	chi2	df	$P > chi2$
Interest Rate	656.776	6	0
VIX	235.423	6	0
Holding Period	1970.145	6	0
Industry			
Consumer discretionary	179.596	6	0
Industrials	412.407	6	0
Information tech	72.455	6	0
Natural resources	171.286	6	0
Energy and utilities	268.701	6	0
Business services	251.835	6	0
Real estate	30.544	6	0
Telecoms and media	149.599	6	0
Healthcare	248.572	6	0
Cycle	108.276	6	0
Investment Types			
Merger	61.648	6	0
Growth Capital	71.584	6	0
PIPE	646.839	6	0
Public to Private	191.735	6	0
Recapitalization	35.328	6	0
Add-Ons	72.292	6	0
Restructuring	77.801	6	0
Countries			
UK	68.807	6	0
Germany	43.408	6	0
France	350.080	6	0
US	342.427	6	0
Canada	69.503	6	0
Experience	40.126	6	0

Table 11: Likelihood-ratio Test. The table shows the Chi-squared test statistic of the likelihood ratio test. DF represents the degrees of freedom of the test. P represents the corresponding p-value signaling the significance level of the test.

Industry	Logit	Coefficient	t-value	eˆcoef
Industrial / Tech	IPO/TS	-0.103	-1.08	0.903
Consumer Disc / Tech	IPO/TS	0.268	3.13***	1.307
Natural Res / Tech	IPO/TS	-0.13	-0.11	0.987
Energy / Tech	IPO/TS	0.251	2.17**	1.285
Bus Services / Tech	IPO/TS	-0.244	-2.21**	0.784
Fin Services / Tech	IPO/TS	0.705	6.77**	2.024
Real Estate / Tech	IPO/TS	0.744	2.95***	2.105
Telecoms / Tech	IPO/TS	-0.147	-1.21	0.863
Healthcare/ Tech	IPO/TS	-0.111	.1,05	0.895

Table 12: Industry Estimates of the Primary Multinomial Logistic Regression. The table show the IPO estimates of the refined MNLM in which Information Technology is selected as the base outcome variable. Trade Sale is the dependent base outcome variable, meaning all IPO estimates are relative to their likelihood. The second column denotes the industry variable relative to the base outcome. The following two columns presents the model coefficients, denoting the effect's direction and t-value of the coefficients. The exponentiated coefficient presents the effect on the dependent variable for a unit change in the independent variable. The significance level for the p-value of the estimated coefficients is denoted by * for 1%, ** for 5%, and * for 10%.

Country	Logit	Coefficient	t-value	e^{coef}
UK	IPO/TS	-0.245	-2.81***	0.783
	WO/TS	0.319	3.08***	1.375
Germany	IPO/TS	-0.302	-2.25**	0.740
	WO/TS	0.463	3.41***	1.590
France	IPO/TS	-4.59	-3.27***	0.632
	WO/TS	0.001	0.001	1.001
US	IPO/TS	-0.43	-0.66	0.958
	WO/TS	0.966	12,22***	2.627
Canada	IPO/TS	0.282	2.18**	1.326
	WO/TS	0.155	0.88	1.168

Table 13: Geographic Estimates of the Primary Multinomial Logistic Regression. The table shows the geographic estimates of IPO and Write-off from the primary MNLM from table 6. The Other location is estimated as the base outcome, meaning all interpretations are relative to their likelihood. The second column denotes the country variables relative to the base outcome. The following two columns presents the model coefficients, denoting the effectâ€™s direction and t-value of the coefficients. The exponentiated coefficient presents the effect on the dependent variable for a unit change in the independent variable. The significance level for the p-value of the estimated coefficients is denoted by * for 1%, ** for 5%, and * for 10%.

Variable / Exit Type	IPO	Trade Sale	Merger	Private Placement	Sale to GP	Rescap	Write-Off	Sale to Man
Interest rate	0.029	0.014	-0.012	-0.007	-0.011	-0.006	-0.010	-0.003
	0.000***	0.000***	0.000***	0.000***	0.00***	0.000***	0.000***	0.005***
VIX	-0.005	0.009	-0.004	-0.005	-0.014	0.010	0.010	-0.001
	0.000***	0.004***	0.024**	0.001***	0.000***	0.000***	0.000***	0.361
Holding Period	-0.016	0.032	-0.049	0.020	0.018	0.0	0.011	0.005
	0.000***	0.000***	0.000***	0.000***	0.000***	0.614	0.000***	0.000***
Cycle	0.042	-0.001	0.003	0.007	0.008	-0.025	-0.027	-0.008
Boom vs Bust	0.000***	0.984	0.704	0.309	0.522	0.000***	0.000***	0.084*
Experience	0.006	-0.033	0.010	0.019	-0.009	0.006	0.005	-0.003
High vs Low	0.032**	0.000***	0.003***	0.000***	0.096*	0.006***	0.100	0.053*
Country								
UK vs Other	-0.013	0.013	-0.008	-0.026	0.015	0.015	0.014	-0.011
	0.006***	0,178	0.094*	0.000***	0.093*	0.000***	0.001***	0.003***
Germany vs Other	-0.019	-0.017	-0.014	-0.010	0.027	0.019	0.017	-0.003
	0.003***	0.201	0.020**	0.139	0.029**	0.000***	0.003***	0.581
France vs Other	-0.036	-0.122	-0.022	-0.023	0.198	-0.001	-0.009	0.016
	0.000***	0.000***	0.000***	0.000***	0.000***	0.878	0.015**	0.003***
US vs Other	-0.007	-0.031	0.023	-0.004	-0.013	0.016	0.046	-0.029
	0.045**	0.000***	0.000***	0.255	0.054*	0.000***	0.000***	0.000***
Canada vs Other	0.029	0.042	0.019	0.013	-0.090	0.008	0.009	-0.029
	0.004***	0.014**	0.031**	0.120	0.000***	0.120	0.179	0.000***
Germany vs UK	-0.006	0.031	-0.006	0.016	0.012	0.004	0.003	0.007
	0.324	0.032**	0.334	0.014**	0.368	0.412	0.589	0.173
France vs UK	-0.024	-0.136	-0.014	0.003	0.183	-0.015	-0.023	0.026
	0.000***	0.000***	0.011**	0.550	0.000***	0.000***	0.000***	0.000***
US vs UK	0.005	-0.045	0.030	0.022	-0.028	0.001	0.033	-0.018
	0.185	0.000***	0.000***	0.000***	0.000***	0.683	0.000***	0.000***
Canada vs UK	0.041	0.028	0.027	0.038	-0.106	-0.006	-0.005	-0.018
	0.000***	0.110	0.003***	0.000***	0.000***	0.266	0.530	0.000***
France vs Germany	-0.017	-0.105	-0.008	-0.013	0.171	-0.020	-0.026	0.019
	0.009***	0.000***	0.218	0.069*	0.000***	0.000***	0.000***	0.004***
US vs Germany	0.012	-0.014	0.036	0.006	-0.040	-0.03	0.029	-0.026
	0.047**	0.275	0.000***	0.361	0.001***	0.502	0.000***	0.000***
Canada vs Germany	0.048	0.059	0.033	0.022	-0.118	-0.011	-0.008	-0.026
	0.000***	0.003***	0.001***	0.180	0.000***	0.114	0.343	0.000***
US vs France	0.029	0.091	0.045	0.019	-0.211	0.016	0.056	-0.045
	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Canada vs France	0.065	0.164	0.041	0.035	-0.288	0.009	0.019	-0.045
	0.000***	0.000***	0.000***	0.000***	0.000***	0.128	0.009***	0.000***
Canada vs US	0.036	0.073	-0.003	0.017	-0.077	-0.008	-0.037	0.000
	0.000***	0.000***	0.682	0.028**	0.000***	0.138	0.000***	0.981

Table 14: Marginal Effects. The table shows the marginal change in probability of the dependent variables for a standard deviation change in the continuous variable and a change of 1 in the categorical variables. The p-values are displayed below the estimated outcome variable. The significance level for the p-value is denoted by *** for 1%, ** for 5%, and * for 10%.

Exit Type	Variable	Coefficient	Standard Error	z	RRR
IPO	Interest Rate	0.242	0.014	17.38***	1.274
	Experience	0.276	0.073	3.76***	1.318
	IR&Exp	-0.0697	0.028	-2.44**	0.933
Merger	Interest Rate	-0.079	0.016	-4.82***	0.923
	Experience	0.107	0.06	1.78*	1.13
	IR&Exp	-0.0045	0.034	-0.14	0.995
PP	Interest Rate	-0.175	0.021	-8.14***	0.840
	Experience	0.383	0.063	6.07***	1.467
	IR&Exp	0.027	0.037	0.72	1.027
Sale to GP	Interest Rate	-0.034	0.009	-3.64***	0.966
	Experience	0.081	0.037	2.17**	1.085
	IR&Exp	-0.0266	0.019	-1.36	0.974
Recap	Interest Rate	-0.128	0.026	-4.78***	0.879
	Experience	0.219	0.085	2.55**	1.245
	IR&Exp	0.019	0.05	0.04	1.002
Write Off	Interest Rate	-0.085	0.018	-4.74***	0.018
	Experience	0.209	0.065	3.22***	1.233
	IR&Exp	-0.102	0.039	-2.58***	0.902
Sale to Man	Interest Rate	0.056	0.024	2.37**	1.058
	Experience	-0.055	0.110	-0.5	0.946
	IR&Exp	0.021	0.049	0.43	1.02
Number of observations = 32,881					
Pseudo R2 = 0.0071					

Table 15: Multinomial logit estimates of IR − Experience interaction. The table presents the estimates obtained by the multinomial logit model the dependent variables IPO, Merger, Private Placement, Sale to GP, Restructuring & Recapitalisation, Write-off, and Sale to Management. Lastly, Trade Sale is estimated as the base outcome variable, meaning all results are relative to its likelihood. The independent variables are Interest rate, Experience, and Interest-Rate,Experience interaction term. The significance level for the p-value of the estimated coefficients is denoted by *** for 1%, ** for 5%, and * for 10%.

Exit Type	Interest Rates										
	0	1	2	3	4	5	6	7	8	9	10
IPO	0.00753***	0.00692**	0.00538*	0.00254	-0.002024	-0.0087	-0.018	-0.01301	-0.0452	-0.0629	-0.0827*
TS	-0.03629***	-0.02986***	-0.02295***	-0.01546*	-0.00732	0.0017	0.0117	0.02277	0.03505	0.04835	0.06236
Merger	0.001166	0.0022	0.00309	0.0038	0.00455	0.00518	0.0057	0.00684	0.0073	0.00733	0.0077
PP	0.021***	0.0214***	0.0213***	0.0208***	0.01993***	0.0188***	0.01755***	0.01618**	0.01474**	0.01328**	0.01183*
Sale to GP	-0.003	-0.00526	-0.0074	-0.00938	-0.0109	-0.012	-0.0122	-0.0116	-0.0099	-0.00836	-0.00393
Restructuring	0.00456	0.0048**	0.00499**	0.00504	0.00501	0.00491	0.00478	0.0046	0.00443	0.00421	0.00398
Write-Off	0.008**	0.00204	-0.00283	-0.0066	-0.00955*	-0.01143**	-0.0127**	-0.01317**	-0.013**	-0.01239**	-0.0113**
Sale to Man	-0.0029	-0.00233	-0.0016089	-0.00712	0.00037	0.00169	0.00324	0.005006	0.00716	0.00953	0.01214

Table 16: Effect of Experience Interest rate on predicted probabilities. The table shows the marginal change in predicted probabilities for a combination of the independent variables, holding all other variables constant at their mean. Each row presents the marginal change in the predicted probability as the experience variable changes from low to high for all interest rate level ranging from 0-10%. The significance level for the p-value of the difference in predicted probability is denoted by * for 1%, ** for 5%, and * for 10%.

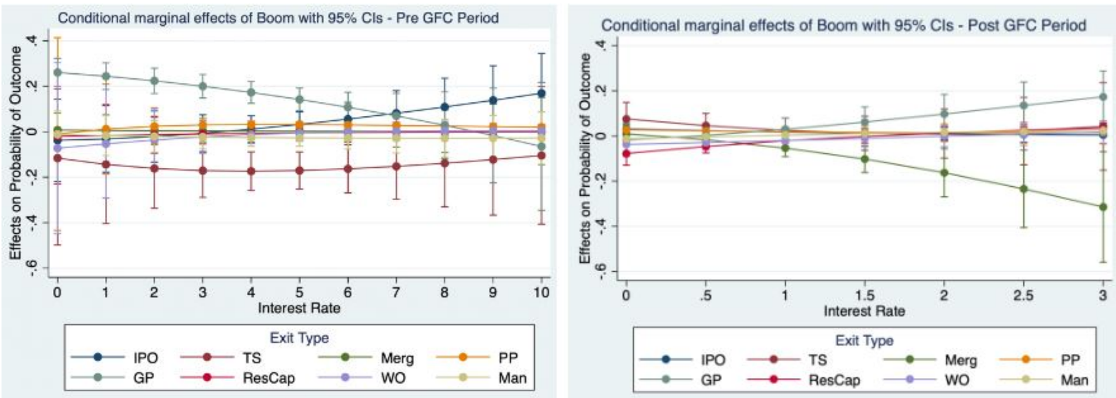

Figure 10: Conditional marginal effect of Cycle for various interest rate levels pre and post GFC . The figure presents the estimates of the predicted probabilities for each eight of the dependent exit variables under the interaction term market cycle & interest rate, prior to the Great Financial Crisis. The estimates are based upon the marginal effect in probability for a 1% change in the interest rate, while holding all other variables constant at their mean. The plot signals the difference in probability for a boom cycle relative to a bust cycle and is presented in a interest rate range of 0 to 10% in pre sample, and 0 to 3% in post sample.

	Variable	Coefficient	Standard errors	t-value	e^{coef}
IPO	Interest Rate	0.041	0.077	0.54	1.042
	Cycle	0.570	0.285	2.00**	1.768
	Cycle & IR	0.210	0.077	2.71***	1.233
Merger	Interest Rate	-0.246	0.053	-4.68***	0.782
	Cycle	-0.451	0.157	-2.88***	0.637
	Cycle & IR	0.177	0.055	3.24***	1.194
PP	Interest Rate	-0.234	0.072	-3.26***	0.7911
	Cycle	0.153	0.212	0.73	1.166
	Cycle & IR	0.076	0.074	1.02	1.078
Sale to GP	Interest Rate	-0.011	0.031	-0.35	0.989
	Cycle	0.206	0.111	1.84	1.228
	Cycle & IR	-0.028	0.032	-0.88	0.972
Rescap	Interest Rate	-0.464	0.055	-8.41***	0.628
	Cycle	-1.946	0.139	-13.95***	0.143
	Cycle & IR	0.327	0.061	5.38***	1.387
Write-Off	Interest Rate	-0.430	0.048	-8.93***	0.650
	Cycle	-1.478	0.126	-11.74***	0.228
	Cycle & IR	0.329	0.051	6.42***	1.390
Sale to Man	Interest Rate	0.153	0.071	2.14**	1.165
	Cycle	0.121	0.292	0.41	1.128
	Cycle & IR	-0.110	0.075	-1.46	0.896
Number of observations = 32,881					
Pseudo R2 = 0.0107					

Table 17: Multinomial logit estimates of IR – Cycle interactions. The table presents the estimates obtained by the multinomial logit model with the dependent variables IPO, Merger, Private Placement, Sale to GP, Restructuring & Recapitalisation, Write-off, and Sale to Management. Lastly, Trade Sale is estimated as the base outcome variable, meaning all results are relative to its likelihood. The independent variables are Interest rate, Market cycle, and Interest-Rate,Market Cycle interaction term. The significance level for the p-value of the estimated coefficients is denoted by *** for 1%, ** for 5%, and * for 10%.

Variables	Logit	Pre GFC (1990-2006) Coefficient	t-value	RRR	Post GFC (2010-2022) Coefficient	t-value	RRR
Interest Rate	IPO/TS	0.084	2.95***	1.087	-0.337	-6.19***	0.714
	Merg/TS	0.021	0.51	1.022	0.104	2.99***	1.109
	PP/TS	-0.096	-2.07**	0.908	-0.167	-3.92***	0.846
	GP/TS	-0.067	-2.82***	0.935	0.057	-2.58***	1.058
	Res/TS	-0.145	-2.17**	0.865	0.158	3.13***	1.171
	WO/TS	-0.181	-4.56***	0.834	0.003	0.07	1.003
	Man/TS	-0.130	-1.90*	0.878	0.115	1.76*	1.122
VIX	IPO/TS	-0.021	-3.11***	0.980	-0.016	-2.80***	0.984
	Merg/TS	-0.009	-0.97	0.991	-0.005	-1.34	0.994
	PP/TS	-0.023	-1.94*	0.977	-0.014	-2.95***	0.986
	GP/TS	-0.019	-3.66***	0.981	-0.006	-2.41**	0.994
	Res/TS	0.066	5.67***	1.068	0.038	7.66***	1.039
	WO/TS	0.012	1.34	1.012	0.017	4.18***	1.017
	Man/TS	-0.022	-1.67*	0.978	0.000	0.07	1
Holding Period	IPO/TS	-0.014	-9.49***	0.986	-0.007	-7.77***	0.993
	Merg/TS	-0.02	-8.16***	0.980	-0.034	-32.46***	0.967
	PP/TS	0.007	3.90***	1.007	0.006	10.25***	1.006
	GP/TS	0	-0.11	1	0	-0.26	1
	Res/TS	-0.001	-0.28	0.999	-0.002	-1.62	0.998
	WO/TS	-0.010	-4.76***	0.989	-0.07	-8.42***	0.993
	Man/TS	0.003	1.63	1.003	0.004	4.31***	1.004
Cycle = 1	IPO/TS	0.386	1.49	1.471	0.437	1.10	1.547
	Merg/TS	0.354	0.92	1.425	0.563	2.96***	0.570
	PP/TS	2.322	2.27**	10.197	0.218	0.77	1.244
	GP/TS	1.066	3.72***	2.903	-0.127	0.92	0.880
	Res/TS	0.948	1.49	2.582	-0.239	-0.90	0.787
	WO/TS	0.402	1.01	1.495	-0.198	-0.89	0.820
	Man/TS	-0.709	-1.75*	0.492	-0.191	-0.50	0.826
Experience = 1	IPO/TS	0.075	0.77	1.078	0.302	4.39***	1.353
	Merg/TS	0.176	1.16	1.193	0.183	3.31***	1.201
	PP/TS	0.482	3.06***	1.619	0.414	7.14***	1.513
	GP/TS	-0.232	-2.76***	0.792	0.084	2.5**	1.088
	Res/TS	0.044	0.15	1.045	0.281	3.57***	1.325
	WO/TS	-0.278	-1.55	0.757	0.245	4.14***	1.277
	Man/TS	-0.255	-1.26	0.775	-0.051	-0.52	0.950
Country fixed effects			Included				
Industry fixed effects			Included				
Industry			Included				
Pseudo r-squared pre = 0.0641	Number of observations pre = 6,097						
Pseudo r-squared post = 0.0652	Number of observations post = 25,416						
**** p<.01, ** p<.05, * p<.1*							

Table 18: Multinomial logit estimates pre & post the GFC. The table presents the estimates of the multinomial logistic model for the respective periods 1990-2007 and 2009-2021. The significance level for the p-value of the estimated coefficients is denoted by *** for 1%, ** for 5%, and * for 10%.

	PRE-GFC							
	IPO	TS	Me	PP	GP	Rec	WO	Man
Interest Rate								
+SD Change	0.021	0.010	0.003	-0.004	-0.015	-0.002	-0.009	-0.004
p-value	0.000***	0.104	0.362	0.068*	0.005***	0.053*	0.000***	0.087*
VIX								
+SD Change	-0.012	0.021	-0.001	-0.004	-0.017	0.009	0.006	-0.002
p-value	0.008***	0.001***	0.798	0.111	0.002***	0.000***	0.027**	0.246
	POST-GFC							
	IPO	TS	Me	PP	GP	Rec	WO	Man
Interest Rate								
+SD Change	-0.009	0.003	0.005	-0.007	0.009	0.003	-0.000	0.002
p-value	0.000***	0.358	0.003***	0.000***	0.001***	0.003***	0.801***	0.111
VIX								
+SD Change	-0.004	0.003	-0.002	-0.005	-0.009	0.009	0.008	-0.000
p-value	0.004***	0.318	0.239	0.001	0.002***	0.000***	0.000***	0.769

Table 19: Marginal effects of exit probability between IR and VIX pre- & post-GFC. The table shows the marginal change in probability of the dependent variables for a standard deviation change in the Interest rate and VIX. The sample consists of exits completed before and after the GFC. The p-values are displayed below the estimated outcome variable. The significance level for the p-value is denoted by *** for 1%, ** for 5%, and * for 10%.

Country	Marginal Effects	
	Pre GFC	Post GFC
UK vs Other	-0.014	-0.012**
Germany vs Other	-0.08	-0.022***
France vs Other	-0.059***	-0.033***
US vs Other	-0.002	-0.014***
Canada vs Other	0.102***	0.008
Germany vs UK	0.007	-0.010
France vs UK	-0.045**	-0.022***
US vs UK	0.012	-0.002
Canada vs UK	0.116***	0.020**
France vs Germany	-0.051**	-0.012*
US vs Germany	0.006	0.008
Canada vs Germany	0.109***	0.030***
US vs France	0.057***	0.020***
Canada vs France	0.161***	0.042***
Canada vs US	0.104***	0.022***

Table 20: Marginal effects of IPO exits between geographic locations. The table shows the marginal change in probability of IPO between two locations before and after the GFC. The p-values are displayed below the estimated outcome variable. The significance level for the p-value is denoted by *** for 1%, ** for 5%, and * for 10%.