Stockholm School of Economics
Department of Economics
BE551 Degree project in economics
Fall 2024

Recessionary Filtering: The Impact of the Great Recession on Venture Capital Ecosystems and Innovation in Europe

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Abstract

This study examines the effects of the Great Recession (2007–2009) on venture capital (VC)-backed firms across the current EU member states. Through quantitative analysis, we assess how adverse macroeconomic conditions influenced initial funding sizes and long-term firm performance. Results suggest that firms financed during the recession secured larger initial investments, reflecting heightened VC selectivity. While evidence on long-term outcomes remains mixed, the findings are indicative of a recessionary filtering effect that yield higher-quality startups. We explore this topic further through literature and theory, evaluating the dynamic relationship of business cycles, innovation and economic growth. This research underscores VC's pivotal function in resource allocation and innovation, particularly during economic downturns.

Keywords: *Venture Capital, European Union, Startups, Innovation, the Great Recession*

JEL: *G24, E32, O31, O40, E44*

Supervisor:	*Professor Sampreet Singh Goraya*
Date submitted:	*December 2, 2024*
Date examined:	*December 19, 2024*
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Acknowledgements

We would like to express our sincerest gratitude to our supervisor, Assistant Professor Sampreet Singh Goraya at the Department of Economics at Stockholm School of Economics, for his invaluable guidance and assistance. Furthermore, we feel fortunate to have been supported by our peers with whom we have had extensive discussions that have provided clarity when we have felt lost. We would also like to thank Maja Bohlenius, who generously provided us and others with much needed cinnamon buns and coffee bread. Finally, we extend our heartfelt appreciation to our loved ones - family and friends - who have offered us unwavering support and unlimited patience throughout this project. This paper was made possible by all mentioned, for which we are ever grateful.

Contents

1 Introduction

1.1 Research Questions and Scope of Our Study

Innovative firms born during adverse macroeconomic conditions produce more qualitative patents, grow faster, are more likely to go public, and perform better on the stock exchange, relative to their peers born at other times. These are the findings of Bias' and Ljungqvist's (2023) paper titled *Great Recession Babies: How Are Startups Shaped by Macro Conditions at Birth?*. They studied how the Great Recession 2007–2009 affected innovative startups that were born during this period in the United States (U.S.). Inspired by these findings, we decided to examine the impact the Great Recession had on venture capital (VC) - backed firms in Europe. To ensure relevance, we have based the country sample selection on the current composition of the European Union (EU), that is the member states as of December 1st, 2024, without the United Kingdom (UK). These will henceforth be referred to as the EU 27 countries[1]. Through a combination of quantitative and literary research, we aim to answer the following research questions:

1. How did the Great Recession affect venture capital-backed firms in Europe?
2. What theory could explain the dynamics through which venture capital is affected by macroeconomic conditions?
3. What broader implications do these findings suggest for venture capital's role in the economy?

Our hope is to contribute to the relatively scarce research of VC in a European context by connecting existing research in other regions to economic theory and applying them to our findings on the EU 27 countries. On a broader scale, our study aims to provide valuable insight into the dynamic influence macroeconomic conditions have on VC, innovation, and startups. It is important to note the limitations of our study. Using a single database of VC-deals (PitchBook, 2024), we do not aim to establish causal relationships or recommend policy measures, as such conclusions would require more robust analysis and comparisons with additional economic and financial metrics (e.g., employment data, macroeconomic indicators, and VC-firm data). Instead, our study focuses on identifying relationships and discussing their implications within the context of past research and economic theory.

We will begin by providing background information about venture capital, after which a summary of existing literature related to our research questions will be presented. The paper will then outline the methodology used for the quantitative analysis, as well as the data we have used and its characteristics. Finally, we present the results of our quantitative models and interpret it in the theoretical and literary context provided by

[1]The EU 27 countries are: Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, and Sweden.

our literature review.

1.2 Background

1.2.1 Introduction to Venture Capital

VC is a subset of private equity (PE). While PE investments span various stages of a company's life cycle, ranging from newly founded startups to firms in bankruptcy, VC primarily focuses on nurturing high-growth, early-stage companies (Metrick, A., 2007; Caselli, S. & Negri, G., 2020). The definitions of VC and PE have evolved over time and vary across countries. VC-funds' investments may also extend into other categories of private equity, such as late-stage funding or buyouts. Some funds even invest in publicly traded companies or are themselves publicly listed (Cumming, D, Johan, S. 2012). The Venture Capitalist is a financial intermediary focused on providing financial and managerial support (Caselli, S. & Negri, G., 2020).

1.2.2 Growth and Evolution of Venture Capital

The origins of the modern VC industry can be traced back to 1946, when General Doriot acknowledged the necessity for risk capital and established the American Research and Development Corporation (ARD), which became the first VC firm (Metrick, A., 2007).

In recent years, VC has become more prevalent. Between 2008 and 2018, global VC-investments grew dramatically, rising from EUR 30 billion to EUR 380 billion. This growth was concentrated primarily in the U.S. and China, which collectively accounted for 80% of global VC-funding in 2018. In comparison, European firms received less than 10% during the same period, reflecting the uneven distribution of investments across regions.

Although global VC-activity is dominated by the U.S. and China, Europe has shown significant growth and increasing regional collaboration. By 2018, 40% of EU VC-investments occurred across member states, highlighting strong cross-border activity. However, VC-activity within Europe remains geographically concentrated, with 80% of investments in 2018 occurring in just five countries: the UK, Germany, France, Spain, and Sweden (Bellucci, A et al., 2021).

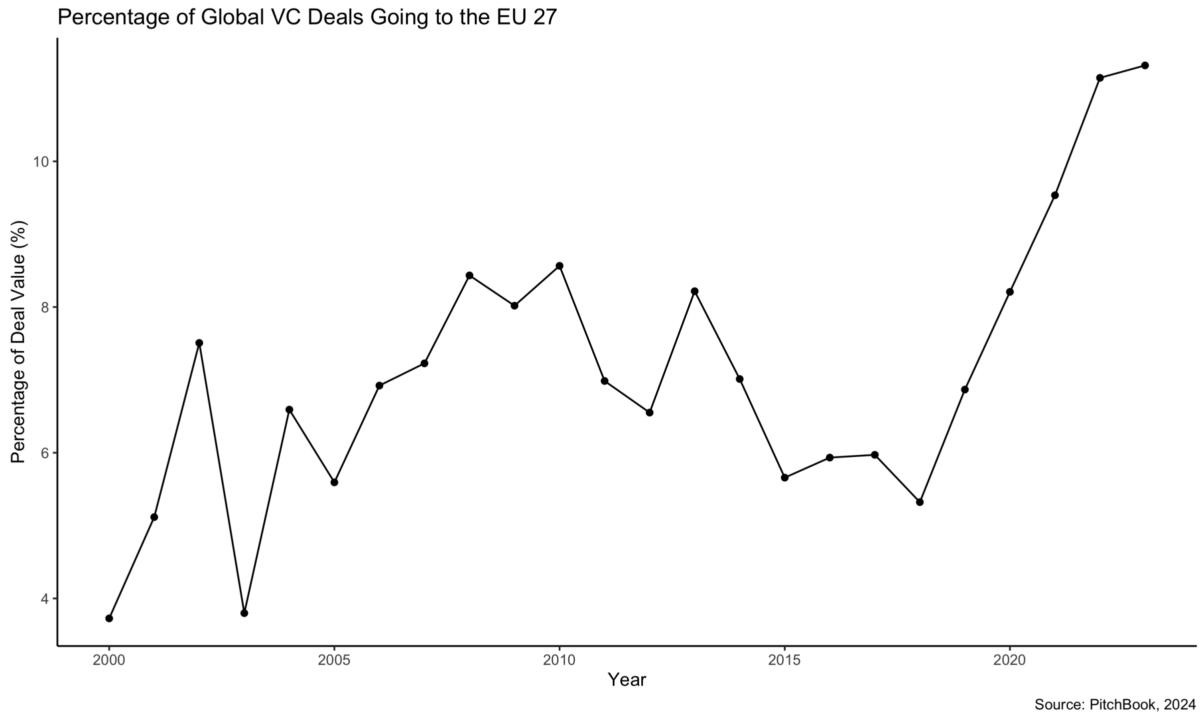

Figure 1: the EU 27's Global Share of VC Deals

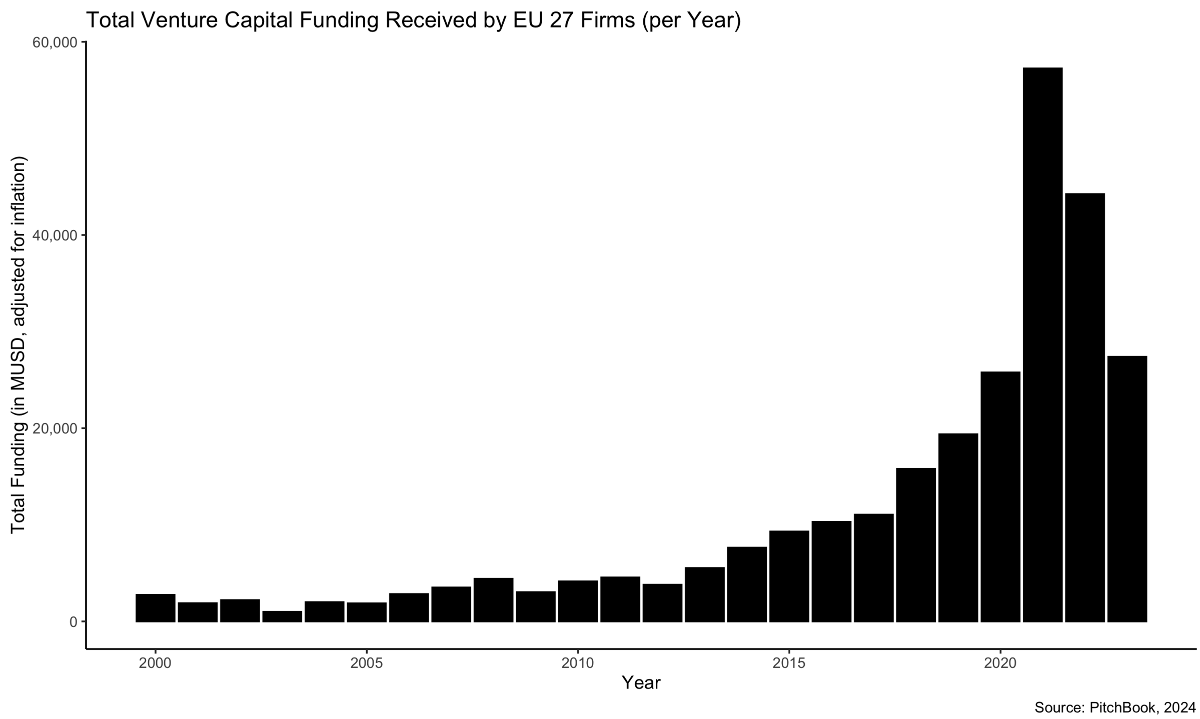

Figure 2: VC-Funding Received by EU 27 Firms

1.2.3 Structure and Mechanics of Venture Capital

VC-firms are composed of multiple individual partners, known as VC-investors, who operate within small partnerships. These firms raise money from wealthy individuals and institutional investors by creating funds that then allocate capital to startups and young companies (Da Rin, M. et al., 2013). A VC-fund is typically structured as a limited partnership. In this arrangement, the VC-firm serves as the general partner (GP), managing the fund and making investment decisions, while the investors act as limited partners (LPs) (Metrick, 2007). VC-investments operate within a predetermined and finite timeframe, typically ranging from 3 to 5 years (Caselli, S. Negri, G. 2020).

1.2.4 Challenges and Risks in Venture Capital

Since venture capitalists focus on financing young, high-potential firms, their investment strategy is inherently risky. These ventures typically lack established revenue streams or assets and are further complicated by significant uncertainty regarding a startup's potential for success. Startups often have no track record, making it challenging for investors to accurately assess their quality. As a result, venture capitalists rely on observable attributes that are presumed to correlate with unobservable factors indicating the firm's potential (Hoenig, D., & Henkel, J., 2014).

VC investments are characterized by uncertainty and information asymmetry, which heighten the risks involved. To mitigate these risks, venture capitalists engage in detailed due diligence during the selection process, with proper investigation and selection of the startup business (Mishra, S, et al., 2017). Another risk-mitigating strategy inherent to VC-investment is the staging of funding rounds, where later stages represent lower associated risks (Caselli, S., & Negri, G., 2020).

1.2.5 How Venture Capitalists Evaluate Investments

A strong history of entrepreneurial success is often a critical factor in attracting VC investments. Venture capitalists prioritize the management or founding team above all else, with 95% of firms citing it as important and 47% identifying it as the most critical factor. Other significant factors include the business model (83%), product (74%), market (68%), and industry (31%), though these are less commonly rated as the most important. Company valuation ranks fifth overall but gains importance in later-stage deals. Factors such as fit with the fund and the ability to add value are considered less significant. Early-stage investors and IT-focused investors tend to emphasize the team even more (Gompers, A. et al. 2020).

2 Literature Review

2.1 The Great Recession in Europe

The first signs of the Great Recession were seen on the EU's gross domestic product (GDP) at the end of 2007, while most state the definitive start as 2008 per Shishkin's definition of two consecutive quarters of GDP contraction (Szczepanski, M., 2019; Abberger, K. & Nierhaus, W., 2008). As the subprime mortgage market started to unravel in the U.S. by mid-2007, the European Central Bank (ECB) began taking proactive measures to ensure liquidity within the European banking system. Many institutions in the EU held assets and debt exposed to the U.S. mortgage market, which prompted swift attempts by and coordination between European central banks to limit the spread of the crisis; however, the exposure was more widespread than anticipated. As the U.S. investment bank Lehman Brothers defaulted in mid-2008, financial issues intensified within the EU. As turmoil erupted in European markets, investors shifted to lower-risk assets, such as government bonds, moving away from equity and private debt investments. To counteract the heightening tension in financial markets and stimulate the economy, European central banks implemented a more relaxed monetary policy (van Riet, E., 2010). As a result of the policies, interest rates were lowered substantially and, except for the European Sovereign Debt Crisis, further rate cuts followed in the 2010s. The ECB's deposit rate became negative by 2012, and the marginal refinancing rate, the rate at which banks borrow, reached 0% by 2016 (Figure 3).

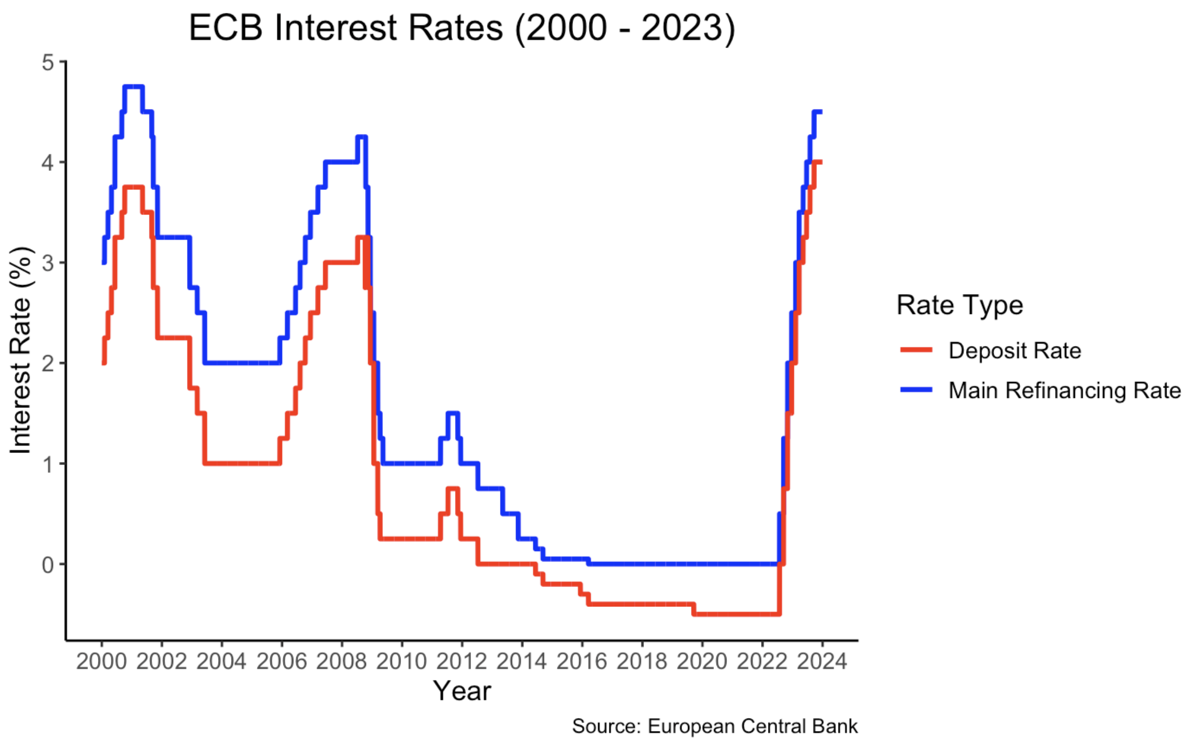

Figure 3: Changes in European Central Bank Interest Rates

While the impact of the financial crisis was felt throughout Europe, its effect was heterogeneous, with some countries experiencing a smaller economic downturn and some regions demonstrating greater resilience (Giannakis, E. & Bruggeman, A., 2019; Fratesi, U. & Perucca, G., 2017). As private investments decreased in EU 27 countries, nations like Greece, which had exhibited unstable economic patterns before the crisis, suffered a sharper decrease as uncertainty and financial constraints took hold. At the same time, the fiscal deficits and subsequent austerity measures incurred by supporting the financial system meant that EU 27 governments decreased their public investment activity (Rodriguez Palenzuela, D. & Dees, S., 2016).

Public investment is an important pillar in fostering European innovation and supporting innovative technology, through investments into education and infrastructure as well as research and development (R&D) (Cerniglia, F. & Saraceno, F., 2020). Particularly innovative European small and medium enterprises (SMEs) rely heavily on public investments in R&D to sustain their innovation (OECD, 2012). Its importance increases further during conditions of dwindling private investments into R&D, where public funding can supplant its role by providing less cyclical funding. Czarnitzki and Delanote (2015) examined the role of German policies directed towards innovative SMEs and found that firms decrease their R&D expenditures when public support decreases. Furthermore, the decreasing credit supplies during the crisis were found to have an unexpected, negative impact on R&D investments made by innovative firms. This effect was seen across all industries that relied on external financing, as well as among smaller firms that were mostly thought to have relied on equity capital rather than debt financing due to their risk profile (Peia, O. & Romelli, D., 2022).

2.2 Venture Capital and Innovative Growth

While VC has its limitations, it has long been touted as an important vehicle for technological and economic growth. Despite only 0.5% of U.S. firms receiving VC funding, they represent more than half of the ventures going public. VC firms have supported some of the most innovative companies within a broad variety of fields, from biotechnology to software. In 2019, VC-backed firms represented 89% of R&D spending by U.S. public firms. Furthermore, seven out of the top eight firms in terms of market capitalization globally in 2020 had received VC before going public (Lerner, J. & Nanda, R., 2020). The expertise provided by venture capitalists, as opposed to banks, is also observed to have a positive effect on innovation, as VC-funded firms are better at producing patents. Through employment and innovation, VC has become a crucial part of economic growth. Removing VC from the U.S. would lead to an estimated 28% decrease in aggregate growth (Akcigit, U. et al., 2019).

The impact of VC goes beyond the U.S., as a cross-country study (Khan, N. et al.,

2021) finds that VC-backed firms outperform non-backed firms in innovation in a wide sample of countries. Moreover, VC has a global role of providing financing to firms that cannot access it from institutional investors, both in developed and undeveloped economies. A study made in Austria in 2007 (Peneder, M., 2010) lifts VC as an alternative when other sources of financing are not preferable, and while the study could not assert its impact on innovation, it did detect increased firm growth. Another study, focusing on Italian new technology-based firms in the period 1994-2003, also found a positive impact on employment growth as well as sales growth as they received VC. This effect was proven to be causal, as a main concern could be the VC firms' screening capabilities allowing them to identify high-growth companies early on (Bertoni, F. et al., 2011). Some argue that VC is conducive to innovation as it allows young companies with new ideas to enter the market. This effect held true for most industries, fostering entrepreneurial activity in the economy (Popov, A. & Roosenboom, P., 2013).

2.3 Innovation, Growth and Recessions

Schumpeter's theory of Creative Destruction implies a relationship between economic downturns and innovation. This dynamic relies on the reallocation of resources from incumbent firms to new firms, as the exit of non-efficient firms allows new firms to enter the market (Schumpeter, J., 1939). A microeconomic study based on the dynamics of firm churn-rate, exit of old and entry of new firms, in Croatia during the years 2008-2012, examined the impact of creative destruction on total factor productivity (TFP) growth. While the specific case found that TFP growth decreased, and firm entries were outpaced by exits, knowledge-intensive services experienced a more promising churn-rate. However, the authors partially attributed these findings to reduced creative destruction due to stagnant economic growth in the country as higher GDP per capita was associated with a higher degree of firm entries during the period examined (Iootty, M. et al., 2014).

Another study conducted in the Netherlands during the 1990s did find that firm churn-rate within the service sector, though not in the manufacturing sector, contributed to regional productivity growth but also suggested that the creative destruction puts pressure on existing firms to become more efficient (Bosma, N. et al., 2009). Conversely, the entry of new firms in the manufacturing sector was estimated to make up more than half of the TFP growth in China during the years 1998-2006 (Brandt, L. et al., 2009). While the latter studies do not relate to recessions in particular, they offer interesting insights into how the creative destruction process can differ between countries and sectors, and the impact it has on economic growth.

Cleansing events induced by recessions play an important role for economic growth and innovation, as the very existence of inefficient firms can have a detrimental effect on both. This does not only apply to the siphoning of resources in terms of capital, but also human capital as they "bind" high-skill labor that could have been more productive in efficient firms. New entrants can act as a catalyst for the reallocation, as their innovation could replace or surpass that of the incumbents (Acemoglu, et al., 2018). When incumbent firms face financial distress, they lose their ability to retain high-skilled workers who in some cases leave and pursue entrepreneurship. A study focusing on the subsequent spread of economic activity shows that these workers go on to start innovative, high-quality firms, compensating for some of the job losses at their previous firms. This effect is observed to be amplified within high-tech and service sectors (Babina, T., 2019).

The effect that an economic downturn has on new entrants is also a selective one. While the isolated collapse of a company might be conducive to new venture creation, the effect of a larger crisis also affects the cohort of new entrants. They are fewer but observed to be of higher quality than those not entering during a crisis. Ates' and Saffie's (2021) examination of new entrants during the Chilean financial crisis in 1998 gave results that showed a 29% decrease in the size of the cohort, but the cohort showed 64% higher productivity over their lifetime compared to firms who entered at other times. This indicates that adverse market conditions can have a filtering effect, in terms of the quality of new entrants.

2.4 Venture Capital and Macroeconomic Conditions

Keynesian economics posits that investments decrease as an economy slows down, hampered by faltering consumption (Jahan, S. et al., 2013). Neoclassical extensions thus suggest that the best countermeasure to stimulate the economy is through decreasing interest rates, as it decreases the rewards of saving and thus incentivizes spending. A simplification of this relationship is at the heart of the IS-LM (Investment-Saving–Liquidity Preferences–Money Supply) model, where interest rates are negatively correlated with investment, and the opposite for savings. As shown earlier, this theory guided the European Economic Recovery Plan as the ECB cut its interest rates, but the effects were slightly diminished as investor sentiments related to financial uncertainty also decreased private investments (van Riet, E., 2010; Figure 3). In general, investments, public and private, decreased in Europe (Rodriguez Palenzuela, D. & Dees, S., 2016; Fratesi, U. & Perucca, G., 2017).

The effect of adverse conditions on VC is more ambiguous. VC follows supply-and-demand dynamics that are, among other things, sensitive to changes in interest rates. Lower interest rates increase the attractiveness of VC funds for investors, as safer assets provide lower returns, thus increasing the supply of VC through fundraising. Higher interest rates, on the other hand, increase the demand for VC as borrowing becomes more expensive for entrepreneurs seeking external financing, and subsequently increases investment (Bellavitis, C. & Matanova, N., 2017). This hints at a counterbalancing dynamic between VC fundraising and firm fundraising.

A study of innovative startups in the U.S. found that funding from VC firms did not completely "dry up" during the Great Recession but tightened as it decreased by 27.2% between 2007 and 2009. It also found that firms receiving their first patent during the recession did not experience significant scarring in the long run. Instead, they were more resilient than non-recession-started firms, grew faster in terms of sales and employees, were more likely to go public, and if they went public, they performed better on the stock exchange (Bias, D. & Ljungqvist, A., 2023).

3 Methodology

3.1 Data

Our study is based on Pitchbook's Deal Database (2024), a comprehensive dataset mapping global VC deals going back as far as 1974 and as recent as 2024. It contains company information, such as name, industry, location of headquarters, total capital raised, and first financing date, which we have merged with an accompanying dataset that connects company information to financial information, such as deal dates, individual deal sizes, and stage of fundraising rounds. The combined data set provides information about 385,208 unique companies with 898,474 unique deals.

3.1.1 Data Manipulation

For the aim of our study, we have created a smaller dataset only comprised of companies headquartered in an EU 27 country, which we did by assigning each country a dummy variable if the location of the headquarters was labeled as one of the countries. We further filtered the data to ensure that the deals are at least partially related to VC, e.g., a VC firm could be participating in a fundraising round alongside angel investors or a PE firm, and limited the time-period so that the dataset only contains firms that received their first financing round from January 1, 2000, up until December 31, 2023. Finally, we removed all observations that contained missing values on our variables of interest, which will be outlined further below.

Since all monetary sums were already converted to the U.S. Dollar (USD) value of the transaction at the time it took place, we adjusted for inflation by using the Federal Reserve Economic Data's (FRED) CPI index (for All Urban Consumers), benchmarked at the January 1, 2010, USD value. We subsequently summed all deal sizes for each company with the new inflation-adjusted deal size to calculate a new value for *Total Raised*, as it had previously summed all deal sizes regardless of the time differences between them. While the actual currencies used in the deals most likely depreciated or appreciated differently than the USD, we have used the simplifying assumption that the capital was "consumed" and converted to equity at the time of the transaction, thus ceasing to exist. The inflation adjustment was done mainly to facilitate interpretation.

After cleaning the data, we were left with complete cases of 18,299 unique companies.

3.1.2 Summary Statistics

Table 1 provides a summary of the key statistics for the dataset used in this study, with Total Raised and First Financing Size presented in millions of USD adjusted for inflation. Figure 4 presents the percentage of total EU 27 funding going to each region[2] between 2000 and 2023, note that lower total stock in VC funding in the early 2000s mean higher variation.

Table 1: Summary Statistics

Variable	**Value**
Number of Observations	18,299
Firms started during Great Recession	601
Public Firms	221
Company Failures	2,516
Total Raised (Mean)	9.641
Total Raised (SD)	71.183
Total Raised (Min)	0.0002
Total Raised (Max)	5,364.674
Total Raised (Median)	1.349
First Financing Size (Mean)	2.047
First Financing Size (SD)	10.080
First Financing Size (Min)	0.0001
First Financing Size (Max)	735.335
First Financing Size (Median)	0.476

PitchBook, 2024

[2]**Eastern Europe**: Bulgaria, Croatia, Czech Republic, Hungary, Poland, Romania, Slovakia, and Slovenia. **Northern Europe**: Denmark, Estonia, Finland, Latvia, Lithuania, and Sweden. **Southern Europe**: Cyprus, Greece, Italy, Spain, Malta, and Portugal. **Western Europe**: Austria, Belgium, France, Germany, Ireland, Luxembourg, and Netherlands.

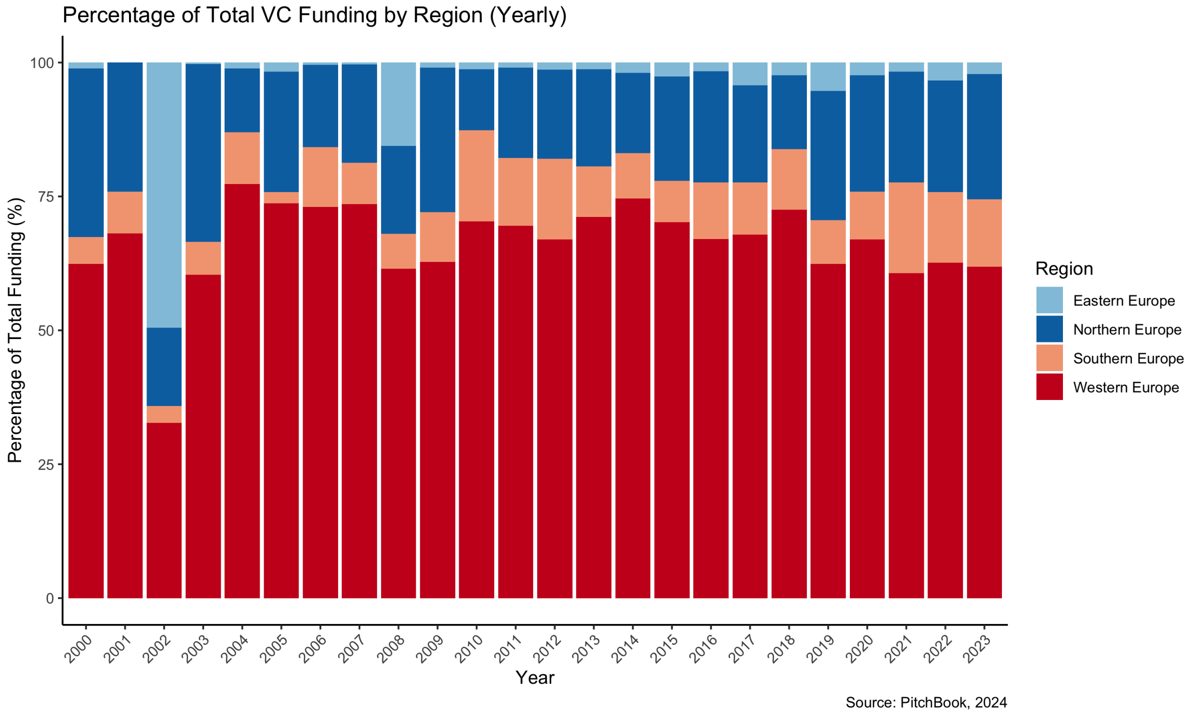

Figure 4: Regional funding distribution

3.1.3 Data Imbalances

As indicated in the summary statistics, VC within the EU 27 is heterogeneous as some countries receive more funding and more deals than others. This implies that the quality of our findings differs based on the country. While we want to study the overall impact the Great Recession had on VC-backed firms, the limited observations for some countries in specific years impose limits on the robustness checks we can use to validate our results.

3.1.4 Selection Bias

Whereas other challenges will be discussed in relation to our research questions, selection bias is inherent to the dataset. All observations are subject to selection bias due to the nature of VC being an active process undertaken by the firms. The screening of young firms is subjective due to the limited information investors use as a basis for their decision to invest. This means endogeneity and omitted variable bias are concerns that are present regardless of the controls we introduce. Examples of endogenous properties we cannot control for include prior relationships between entrepreneur and investor, the existing track record of the entrepreneur, exceptional pitch presentations, changes in investor attitudes, and the total pool of applicants in a particular year as well as their quality, to name a few. We acknowledge this limitation and will weigh our findings against it in the discussion.

3.1.5 Power-Law Distributed Outcomes

The performance of VC investments is often suggested to follow a power-law distribution, i.e., one out of many portfolio companies succeeds spectacularly, which naturally generates heteroskedasticity, high variability in residual errors, together with the presence of extreme outliers. While this complicates statistical inference from our models, it does not necessarily invalidate it but requires keeping the real-world references in mind. Since it is a feature rather than a bug, we have tried to limit the detrimental effects. We will outline how we have addressed these issues further down.

3.1.6 Inaccurate Data Entries

After conducting control checks of the most extreme observations, we have removed some dubious entries. The Hungarian company Makery World is reported to have received \$535 million USD in one deal, which is the number reported on PitchBook's website (PitchBook: Makery World, 2024). Crunchbase only reported one investment of seed money amounting to €519,000 (Crunchbase: Makery World, 2024), and we could not find any other sources online to corroborate the investment of \$535 million. Another similar observation is a Maltese e-commerce platform called CacaShop that raised \$500 million USD as their "first financing". Online sources suggested that this investment took place, including a blog post by a PitchBook senior reporter (Hodgson, L., 2023), and one website that referred to the S&P Capital IQ database (Marketscreener, 2024). However, after entering the company name in the database, there was no mention of the deal. While we removed these observations, they could be indicative of a problematic pattern within the data itself.

3.2 Variables

3.2.1 Dependent Variables

First Financing Size represents the millions of USD sum of funding the company received during their first sourcing of VC. The maturity of the company when receiving their first financing differs, with some receiving seed money and others late-stage VC. This is important as later-stage venture capital typically means larger investments.

Total Raised represents the millions of USD raised by a firm up until December 31, 2023, calculated by summing all deal sizes present in the data. We are using *Total Raised* as a proxy for company performance, which we recognize can be flawed as a company that is performing well enough might not require further financing. However, as VC investors reduce information asymmetry through staging, they are more likely to invest in companies that have reached key milestones and performed well on their key metrics, which by extension makes it an appropriate proxy for company performance and other unobservable characteristics. A key consideration is the nature of *Total Raised* as it simply sums up the total amount of capital the company has raised to a specific date. It does not adjust for the age of the company, which penalizes firms that started close to the predefined end date of our sampling period.

Company Failure represents companies whose business status is labeled as either "Out of Business" or "Bankruptcy: Liquidation" in the PitchBook data. We acknowledge that this definition of failure is absolute; defining a failed business can be more ambiguous. For example, a firm that has received financing once and generates revenue but has not grown since its first capital injection could be considered a failure. From the investor's perspective, it also differs, as VC firms typically invest with an exit in mind and a predefined investment horizon. In our case, we are mainly interested in firm outcome rather than investment outcome and will thus use our simpler definition.

Public is a dummy variable for companies that were labeled as *Publicly Held* in the dataset. Since a company that enters the public markets through an Initial Public Offering (IPO) is more likely to have a large impact on the economy of a country, we believe that this variable is of particular interest to examine the effect of economic downturns on VC-backed firms. From the investor's perspective, the companies that IPO are the most successful outcomes.

3.2.2 Independent Variables

Great Recession is a dummy for companies that received their first financing round during the Great Recession, which we have initially defined as the period 2007-12-01 to 2009-06-30. The exact period of the Great Recession is difficult to define, particularly when taking the extended European Sovereign Debt Crisis into account. Further complicating the matter is when investors believed the crisis started and ended, as this would impact their active investment decisions. We landed on the end of 2007 as the effect of GDP contraction roughly began around this time in Europe.

Pre-Recession is a dummy for companies that received their first financing from 2001-01-01 up until 2007-12-01, and **Post-Recession** is a dummy for companies that received their first financing after 2009-06-30 up until 2023-12-31. These are used to examine the effects related to the conditions before and after the recession, which should capture more dynamic patterns.

3.2.3 Control Variables

First Financing Date represents the day, month, and year that the company received their first financing.

Country × Year is an interaction term that captures country-specific time-trends. We use it to account for the heterogeneity within the EU 27, both with regards to economic factors such as GDP, interest rates, and policies, but also the effect that the recession has had on a particular country's VC-activity. For example, some countries, such as Sweden, have more companies receiving VC as their VC-ecosystem is more developed than that of Hungary. As we seek to isolate the effect a recession has on VC-backed company performance, the interaction term should address some of the issues. The decision to fix it at the country level assumes that an entrepreneur seeking VC faces no significant constraints within their country, i.e., they can freely access VC regardless of the city in which they are based.

Year is defined as the year the company received their first financing. The Year fixed effects adjust for the increase in venture capital stock and deals the EU has experienced in the last decades, which most likely influences the sums raised, the access to financing, and the average sizes of deals. It also controls for the lifetime of the company, as older companies would have had more time to raise capital, and quality of firms receiving financing a certain year due to unobserved effects such as competitive pool of applicants.

The interaction term should also address the impact of the European Sovereign Debt Crisis, which affected some countries more than others.

Sector × Year is an interaction term that captures time-trends at the sector level. The Primary Industry Sector is the broad definition of the industry within which a firm operates. We have included this as a control variable to capture industry effects on Total Raised and first funding. The reasoning behind this is accounting for the required amount of capital, some being more capital intensive than others. Controlling for linear trends adjusts for differences in funding going to different industries, which should capture industry bubbles and crashes, such as the Dotcom Crash in the early 2000s.

Stage of Entry denotes the maturity of the firm when receiving funding, as some companies only seek VC-funding when having reached a mature stage, which would be denoted as Later Stage VC. As mentioned, the stage of entry impacts the size of the first financing, as well as the need for subsequent funding rounds.

3.3 Empirical Method

3.3.1 OLS Regression

Our first model utilizes ordinary least squares, with incremental introduction of the control variables:

$$\text{Dependent Variable}_i = \beta_0 + \beta_1 \cdot \text{Great Recession}_i + \gamma_d + \delta_{cy} + \omega_{sy} + \epsilon_i$$

where $\text{Dependent Variable}_i$ denotes either *First Financing Size* or *Total Raised*, Great Recession_i denotes whether a company has received their first financing round during the Great Recession, γ_d represents the fixed effect of stage of entry, i.e., maturity of the firm when receiving first financing, δ_{cy} is the interaction term of country and year capturing country-fixed time-trends, and ω_{sy} is the interaction term of sector and year capturing sector-fixed time-trends. The idea is to get an initial overview of the data, but we expect there will be violations to the assumptions of the model that are detrimental to the potential for inference from the estimated coefficients. First, as discussed regarding the data, it most likely contains endogeneity which will bias the coefficient. Secondly, errors are most likely not independent, which is partially mitigated by the introduction of the interaction terms but whose introduction introduces multicollinearity, e.g., through capturing sector-shocks that are correlated with economic shocks and does not control for within-country correlation. Finally, due to the outliers, the model most likely has heteroskedastic errors as well as an upward bias on the coefficients. Due to the large interval and skewed distribution caused by very successful firms, which most likely have experienced compounding growth effects, there is reasonable doubt concerning the linearity of the model.

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3.3.2 Log-Transformed OLS Regression

Our second model uses the natural logarithm of the dependent variable to decrease the influence of outliers:

$$\ln(\text{Dependent Variable}_i + 1) = \beta_0 + \beta_1 \cdot \text{Great Recession}_i + \gamma_d + \delta_{cy} + \omega_{sy} + \epsilon_i$$

This should reduce the bias caused by successful firms and offer a better estimate of the coefficients. However, it will probably not solve other issues, such as heteroskedasticity, but for our research question, we are more focused on the coefficients.

3.3.3 OLS Regression Models with Clustered Standard Errors

We employ this model to address within-cluster, country correlation, and to conduct another robustness check. We will use clustered standard errors for both the first and second equations. Since we are clustering at the country level, we will omit the Country-Year interaction term, as the Year-effect should be captured by the Sector-Year interaction term included in the regression. One key consideration is the violation of the assumption relating to cross-cluster correlation of errors, which most likely exists due to the integrated market of the EU countries as well as the shared currency within the Eurozone. This means this method is imperfect for calculating variability but should provide better estimations. Since our complex model has multicollinearity, we had to weigh between simplifying the model to use robust standard errors or go with our time-trends and cluster standard errors despite the cross-cluster correlation. We also recognize that the number of clusters is not ideal (Rule of Thumb: $n \geq 30$), but once again, we are not necessarily concerned with finding the true variability of errors.

3.3.4 Post- and Pre-Recession OLS Regression

This model provides a better picture of the dynamics of VC, before and after the recession:

$$\ln(\text{Dependent Variable}_i + 1) = \beta_0 + \beta_1 \cdot \text{preRecession}_i + \beta_2 \cdot \text{postRecession}_i + \gamma_d + \delta_{cy} + \omega_{sy} + \epsilon_i$$

The idea of this model is to examine the relationship with Great Recession firms and those financed before and after the recession, which could provide information on how they differ relative to each other. However, it should be noted that it is difficult to disentangle the effect of decreased interest rates or overall venture capital supply the years following the recession, which diminishes the value of the model.

3.3.5 Post- and Pre-Recession with Clustered Standard Errors

The method will be the same as with the other models, which implies the same issues of cross-cluster correlation. Nonetheless, it can improve the rigor of the model and give us a better approximation of how the outcomes differed.

3.3.6 Logit-Model on Outcome

We employ a logit-model on the binary outcome variables to examine whether firms first financed during the Great Recession are more likely to fail or go public:

$$\ln\left(\frac{\Pr(\text{Outcome}_i)}{1-\Pr(\text{Outcome}_i)}\right) = \beta_0 + \beta_1 \cdot \text{Great Recession}_i + \beta_2 \cdot C_i + \beta_3 \cdot Y_i + \beta_4 \cdot D_i + \beta_5 \cdot S_i$$

where Outcome_i is a dummy variable that represents whether a company has failed or gone public.

To simplify the model, we have simply used fixed effects rather than controlling for more dynamic relationships such as time-trends. This most likely means our model is too simplistic to capture unobserved conditions that can increase the likelihood of either outcome, for example many IPOs in a certain country and year might increase the likelihood of going public for companies in that country, it would also miss detrimental sector-shocks effect on failure, such as the Dotcom crash. Nonetheless, it will provide an overview of the outcomes of the Great Recession first financed firms (GRFFFs) while controlling for country, sector, year, and stage of entry fixed effects.

3.3.7 Sensitivity to Great Recession Period Definition

To examine the reliability of our results, we will re-run the regression while slightly altering the defined time-period for the Great Recession. Our baseline period, December 2007 to June 2009, might be inaccurate as the effects of the recession might not have become evident until a later stage of the Financial Crisis. As stated, it is difficult to determine an exact time when the Great Recession started to influence VC-firms' decisions, and when it "stopped". This is a sensitivity analysis to examine the consistency of our findings and the robustness of them, it should also address the accidental encapsulation of single outliers that saw immense success. We start by providing three redefined periods, with monthly delays for start- and end-dates, then we finish by delaying the start and end of the recession by a year from the initial period. The monthly adjustments should address accidental capture of outliers by too specified start- and end-dates, the one-year delay should ensure that the recession is fully evident to VC-investors.

4 Results

4.1 OLS Regression

Initially, the linear regression model shows that firms first financed during the recession received higher funding in their first financing round, as well as raised more capital.

Table 2: Regression Results for First Financing Size and Total Raised

	First Financing Size				Total Raised			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Great Recession	1.291***	0.580	1.174	0.801	5.142*	4.496	4.474	4.929
	(0.418)	(0.408)	(0.910)	(0.909)	(2.952)	(2.971)	(6.686)	(6.744)
(Intercept)	2.004***	0.123	2.160	2.115	9.472***	3.726**	1.115	51.404
	(0.076)	(0.252)	(5.532)	(6.026)	(0.535)	(1.837)	(40.629)	(44.694)
Stage of Entry FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Country-Year FE	No	No	Yes	Yes	No	No	Yes	Yes
Sector-Year FE	No	No	No	Yes	No	No	No	Yes
N	18,299	18,299	18,299	18,299	18,299	18,299	18,299	18,299
R^2	0.001	0.060	0.126	0.153	0.0002	0.002	0.055	0.066
Adjusted R^2	0.0005	0.059	0.099	0.121	0.0001	0.001	0.026	0.030

PitchBook, 2024

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

While the statistical significance decreased as controls were added, which confirms the high variability of standard errors, all coefficients remained positive and relatively large with regards to the standard errors. The explanatory power of the model also shows promising increases, which indicates that the controls were helpful in explaining variance in the dependent variables. However, adding the Sector-Year interaction term provided less explanatory value than the other controls, which could be due to correlation with the Country-Year interaction term. The intercept for Total Raised models 7 and 8 seemed excessively large, which confirms the large variability a firm raises depending on both country and year.

4.2 Log-Transformed Regression

The log-transformation of the dependent variables increased the explanatory power of all models, which suggests, as suspected, that the relationship between the dependent and independent variable, as well as the controls, is non-linear. As the log-transformation better handles extreme outliers, we also see an improvement in standard errors of the estimates. The results suggest that firms receiving their first financing received more capital than firms that were first financed during another time. This effect holds, while slightly diminished, even as all controls have been introduced (this is not conclusive, as it could be due to selection bias). All models show positive estimates for Total Raised, but the statistical significance recedes as the controls are introduced, which suggests they carry some of the explanatory value.

Table 3: Regression Results for Log-Transformed First Financing Size and Total Raised

	First Financing Size (Log-Transformed)				Total Raised (Log-Transformed)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Great Recession	0.320***	0.192***	0.126**	0.124**	0.307***	0.241***	0.053	0.035
	(0.029)	(0.027)	(0.058)	(0.058)	(0.046)	(0.046)	(0.099)	(0.098)
(Intercept)	0.621***	0.091***	0.772**	0.680*	1.172***	0.813***	1.233**	1.113*
	(0.005)	(0.017)	(0.354)	(0.385)	(0.008)	(0.028)	(0.600)	(0.651)
Stage of Entry FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Country-Year FE	No	No	Yes	Yes	No	No	Yes	Yes
Sector-Year FE	No	No	No	Yes	No	No	No	Yes
N	18,299	18,299	18,299	18,299	18,299	18,299	18,299	18,299
R^2	0.006	0.164	0.284	0.308	0.002	0.020	0.151	0.183
Adjusted R^2	0.006	0.163	0.262	0.281	0.002	0.018	0.124	0.152

PitchBook, 2024

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

4.3 Models with Clustered Standard Errors

Running the model while clustering standard errors by country had an ambiguous effect. While all coefficients remained positive, the explanatory value of the models decreased as seen by the R^2 of all iterations. Some of the coefficients even experienced higher variability of their estimates. This is most likely due to the simplification of the model, removing country time-trends and relying on the Sector-Year control to capture them. It also suggests that the suspicions about cross-cluster correlation could be valid.

4.4 Pre- and Post-Recession Regression

While the negative coefficient for Total Raised for Post-Recession funded firms can be expected due to their shorter existence, thus shorter timeframe to raise capital, the negative coefficient for first financing size post-recession is curious. Furthermore, it seems to be persistent as controls are added. This could signal a change in strategy on VC-firms' side, but the control for stage of entry suggests it does not imply an increase in earlier entries. Models 3 and 4 indicate that our earlier findings hold, with GRFFFs receiving larger sums during their first fundraising than both pre- and post-recession firms. Model 7 also suggests that GRFFFs raised more capital.

Table 4: Regression Results for Log-Transformed First Financing Size and Total Raised (Pre- and Post-Recession)

	First Financing Size (Log-Transformed)				Total Raised (Log-Transformed)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pre-Recession	0.369***	0.324***	−0.135	−0.139	0.427***	0.431***	0.091	0.051
	(0.035)	(0.032)	(0.108)	(0.107)	(0.055)	(0.055)	(0.183)	(0.181)
Post-Recession	−0.366***	−0.242***	−0.122*	−0.118*	−0.356***	−0.305***	−0.111	−0.071
	(0.029)	(0.027)	(0.069)	(0.069)	(0.045)	(0.045)	(0.117)	(0.117)
(Intercept)	0.941***	0.330***	0.907**	0.819**	1.479***	1.114***	1.142*	1.062
	(0.028)	(0.031)	(0.370)	(0.400)	(0.045)	(0.053)	(0.627)	(0.676)
Stage of Entry FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Country-Year FE	No	No	Yes	Yes	No	No	Yes	Yes
Sector-Year FE	No	No	No	Yes	No	No	No	Yes
N	18,299	18,299	18,299	18,299	18,299	18,299	18,299	18,299
R^2	0.066	0.198	0.284	0.308	0.030	0.044	0.151	0.183
Adjusted R^2	0.066	0.197	0.262	0.281	0.030	0.042	0.124	0.152

PitchBook, 2024

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

4.5 Pre- and Post-Recession Regression with Clustered Standard Errors

When clustering standard errors by country, the explanatory value of the models decreases, again indicating cross-cluster correlation. The negative trend across all Post-Recession measurements persists, with First Financing Size being the dependent variable of interest.

4.6 Logit-Model for Probability of Company Failure

Table 5: Logistic Regression Results for Probability of Company Failure (Incremental Controls)

	Probability of Company Failure				
	(1)	(2)	(3)	(4)	(5)
First Financing During Great Recession	0.787***	0.851***	−0.232	−0.193	−0.199
	(0.096)	(0.098)	(0.217)	(0.220)	(0.220)
(Intercept)	−1.870***	−1.721***	−1.244***	−1.289***	−1.225***
	(0.022)	(0.184)	(0.298)	(0.310)	(0.316)
Country FE	No	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
Stage of Entry FE	No	No	No	Yes	Yes
Sector FE	No	No	No	No	Yes
N	18,299	18,299	18,299	18,299	18,299
Log Likelihood	−7,297.407	−7,211.415	−6,692.207	−6,571.362	−6,550.015
Akaike Inf. Crit.	14,598.810	14,478.830	13,486.410	13,288.720	13,258.030

PitchBook, 2024

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

As seen by the intercept, the overall likelihood of Company Failure was low among VC-backed firms. Models 1 and 2 indicate that companies receiving first financing during the recession were more likely to fail, particularly when introducing country-fixed effects. However, once the other controls are introduced, the coefficient switches sign, suggesting a lower likelihood of going out of business. This could be due to the year-fixed effects capturing some of the effect for the recession years. However, the intercept also increased, which could be due to older firms having more time to fail as well as capturing some of the effects of the European Sovereign Debt Crisis.

4.7 Logit-Model for Probability of Going Public

Table 6: Logistic Regression Results (IPO Likelihood)

	Dependent variable:				
	Probability of IPO				
	(1)	(2)	(3)	(4)	(5)
First Financing During Great Recession	1.401***	1.403***	0.254	0.274	0.287
	(0.213)	(0.218)	(0.453)	(0.463)	(0.480)
Intercept	−4.497***	−19.633	−18.246	−20.812	−21.823
	(0.072)	(712.912)	(677.187)	(1,099.326)	(1,065.856)
Country FE	No	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
Stage of Entry FE	No	No	No	Yes	Yes
Sector FE	No	No	No	No	Yes
Observations	18,299	18,299	18,299	18,299	18,299
Log Likelihood	−1,180.104	−1,089.226	−997.503	−965.338	−918.568
Akaike Inf. Crit.	2,364.209	2,234.452	2,097.006	2,076.676	1,995.136

PitchBook, 2024 *p<0.1; **p<0.05; ***p<0.01

While the simpler models point to a strong and positive correlation between Great Recession first financing and the likelihood of going public, the introduction of additional controls shows that other factors might play a bigger role. Once again, there is the issue that the year-fixed effects cannibalize the Great Recession variable, as these are partially collinear. The model fit statistics show that the model improves as controls are introduced. Since the dataset contains relatively few firms that have gone public, it is expected that the results are unstable.

4.8 Redefining the Period of the Great Recession

Our sensitivity analyses show that the coefficient estimates vary in magnitude when changing the period defining GRFFFs. While the performance models mostly remain positive, the differences highlight the impact that certain outliers can have on the results. The Pre- and Post-Recession models proved to show the most consistency, without any major proof of sign-switching, but this could also be due to outliers that were first financed years before the recession or years after and thus are not impacted by redefining the period. As expected, our outcome logit-models are the ones most susceptible to change of period as they assess outcomes that are relatively rare in relation to the total observations.

5 Discussion

5.1 Discussion of Results

As Bias and Ljungqvist (2023), we did not find evidence of any scarring caused by the Great Recession on European firms that received their first financing during the crisis; there did not seem to be a negative effect on Total Raised, First Financing Size, or the likelihood of Going Public or Company Failure. While our initial OLS did find a significant, positive relationship between capital raised and GRFFFs, the effect did not hold when transforming the dependent variable. This was most likely due to outliers that were funded during the recession and then went on to raise large amounts of capital. The pattern of initial significance and positive effects extended to our logit models as well. Curiously, GRFFFs were initially more likely both to go public and to fail, which would suggest that they turned out to be riskier than firms funded at other times. The significance did not hold, however, as controls were introduced, which means our results were inconclusive. This could be attributed to multicollinearity with the Year control.

First Financing Sizes did grow during the recession and decreased after it. These findings were mostly consistent even after robustness checks and sensitivity analyses. The coefficient for Pre-Recession first financing size switched sign and lost significance after the introduction of controls, which might hint at multicollinearity, as standard errors increased, or overfitting. It does, however, mean we cannot assert the relationship between first financing during the Great Recession and after it, as we do not know whether the former saw an increase or the latter saw a decrease. Nonetheless, we will refer to our literature to examine what dynamics could explain our findings.

5.2 Venture Capital Demand-and-Supply

A possible explanation for an increased First Financing Size could be that debt financing became more difficult to obtain as credit supplies tightened during the recession (Peia, O. & Romelli, D., 2022), leading to firms seeking more equity capital to sustain operations. Venture capital has been singled out as an important alternative source of financing when other sources are difficult to access (Peneder, M., 2010; Khan, N. et al., 2021). Peia and Romelli found that innovative, small companies, belonging to the target group for VC-firms, potentially relied more on credit than previously thought, which would suggest an increased demand for VC. On the other hand, the cut interest rates following the recession could mean that the demand for VC decreased as entrepreneurs could seek debt financing, which became cheaper, rather than sell equity (Bellavitis, C. & Matanova, N., 2017). However, this could have been counteracted by the value, in terms of the signaling and guidance associated with VC investments, compared to debt financing (Akcigit, U. et al., 2019), as the number of deals only increased following the recession. This could also mean that entrepreneurs mainly sought VC for the value it provided beyond financing, thus reducing their ask in early stages of funding. It is difficult to ascertain how entrepreneurs assess the trade-off between equity and debt financing. Banks are more risk-sensitive, and VC-firms are more innovation-oriented, which would imply constraints on what source of external financing is accessible to which firm.

5.3 Creative Destruction and Selectivity

While creative destruction does not always occur in an impactful way (Iootty, M. et al., 2014), the study conducted on China's manufacturing sector (Brandt, L., et al., 2009) might offer the most comparable results. As VC focuses on innovative and emerging technologies (Mishra, S et al., 2017; Metrick, A., 2007), the market conditions of high growth and low incumbency could be argued to resemble those of the emerging manufacturing powerhouse at the time of the study, the years 1998-2006. This would imply that the archetypical firm primarily backed by VC would benefit from similar firm churn rates that are exacerbated during recessions (Schumpeter, J., 1939), and in turn contribute to economic growth through innovation as they enter the market (Popov, A. & Roosenboom, P., 2013).

The creative destruction theory also ties into our issue of selection bias, as indicated by the study on Chilean new entrants (Ate, S. & Saffie, F., 2021), but offers a more optimistic interpretation. Due to the pressure that a recession exerts on financial markets, VC-investors are more inclined to ensure that they allocate their resources to good firms. This would mean that cleansing events, such as recessions, lead to the entry of new, high-potential and high-quality firms because of exiting inefficient firms and the more selective process undertaken by VC-investors. The financial distress of incumbent firms could also increase the pool of high-quality firms seeking VC, as they leak talent that goes on to start entrepreneurial ventures (Babina, T., 2019). Furthermore, the cleansing of incumbents during a recession provides favorable conditions as it frees up human capital (Acemoglu, D. et al., 2018) and allows it to be allocated towards these new high-quality ventures. One big caveat to our sequential reasoning is that the papers did not specifically examine the effects of the Great Recession, but Bias and Ljungqvist (2023) also identified the access to and retention of talent as primary contributors to the resilience and better performance of Great Recession-started firms. This suggests these mechanisms could explain why our results showed firms receiving their first financing during the Great Recession had larger

First Financing Sizes; they were of higher quality as VC-firms became more selective. While we could not conclude that they performed better in terms of total raised or likelihood of going public, our results point to a weak but positive correlation. It would follow that if the GRFFFs were of higher quality and had better access to talent from the onset, they would also perform better than other firms in the long run.

5.4 Economic Implications

As our discussion outlines, VC has an important role as a catalyst, which becomes even more important during economic downturns. In their article, Lerner and Nanda (2020) cite the 1972 Nobel Laureate in Economics Kenneth Arrow (Federal Reserve Bank of Minneapolis, 1995), who stated that "venture capital has done much more, I think, to improve efficiency than anything else", referring to the efficiency of staging and increasing investments in innovative firms incrementally as they progress. This point of view, however, refers to the risks and rewards carried by the VC-firms themselves. We believe they also provide economic efficiency through the information gathering they undertake on behalf of the market. This means that VC is responsible for sourcing high-quality firms with high potential based on very limited information, then can incrementally fuel those who turned out to be good firms and finally introduce them to public markets through an IPO. VC-investments essentially become an efficient filtering process that takes great firms with great ideas to the public market, where they can be allocated more resources. This process is both supported by and supports creative destruction during economic downturns, as VC-backed firms can facilitate an optimized redistribution of talent leaving failing incumbent firms. Essentially, their financial support of new entrants during the crisis enables an efficient reallocation of resources that can improve productivity and, by extension, aid economic recovery through economic growth.

It is the screening process and willingness to take risks that represents the most important contribution of VC to the economy. Had this risky endeavor not been undertaken in a systematic way, one could argue that firms such as Google, Microsoft, and Alibaba would not have existed. Identifying and refining ideas to then promote resource allocation towards cutting-edge technology and high-quality firms is VC at its very best. It drives innovation and fuels economic growth. While we could not provide sufficient evidence that recession-started firms outperformed their peers in terms of growth, our results did not indicate that they were adversely affected by the Great Recession.

5.5 Topics for Further Research

VC has become an important engine for growth and innovation, and its prevalence in Europe has grown in the last decade. We hope to see that its increased presence leads to an increase in studies focusing on its dynamics in a European context. Considering the supply-and-demand forces observed by Bellavitis and Matanova (2017), we were interested in whether this extended to the equity cost of capital. This means that supply-side increases with demand-side decreases could lead to a lower price-per-percentage as venture capitalists would compete for firms to invest in. If this holds, it suggests a systemic overvaluation of VC-backed firms during periods with low interest rates.

Another topic that would benefit from additional attention would be the role of VC in creative destruction, particularly during recessions. Our study did not set out to determine how VC contributed to creative destruction but merely offered it as a potential explanation for our findings. It might be that we failed to find research on the topic, but our anecdotal experience was that its role was implied but never specified.

5.6 Limitations

As stated earlier, it is difficult to assess whether the true effect of being a GRFFF is captured by our initial period, December 2007 to June 2009. The sensitivity analyses showed significant variation in the estimates when redefining the period. Further complicating the analysis of results is the impact that capturing outlier firms could have on the estimates, which leads to difficulties in estimating the true treatment effect.

One major threat to the value of our findings is potential inaccuracy in the data itself. The identification and removal of extreme outliers that are most likely misreported in the data mitigated the most harmful effects of this issue, but there could be smaller inaccuracies that are difficult to identify and would be too painstaking to manually validate without another comprehensive database that could provide cross-validation. We acknowledge that these measurement errors could remain but believe that they do not assert excessive harm on our conclusions, particularly as our observed patterns are similar to the findings of Bias and Ljungqvist (2023), and Ates and Saffie (2021), namely that the Great Recession did not scar firms born during this period and that it promoted high-quality firms.

6 Conclusion

Our findings examining the impact of the Great Recession on VC-backed firms within the EU 27 were varying, perhaps partially attributed to heterogeneity both in VC-ecosystems and the experience of the recession among its member countries. We did find patterns in the results that hinted at similar characteristics as Bias and Ljungqvist (2023) found in U.S. startups that received their first patent during the Great Recession, but had to rely on theoretical explanations as some of our results were not consistent. Regardless, we successfully addressed our research questions and believe our paper can contribute to understanding the relationship between European VC, macroeconomic conditions, and economic growth.

The effect of being first financed during the Great Recession seemed to have a significant and positive effect on the size of the first financing round, but this effect could be due to VC-firms' increased selectiveness as well as capturing effects of a decrease in first-financing sizes following the recession due to potential changes in entrepreneurs' demand. The quantitative assessment of the long-term effects of being first financed during the Great Recession was inconclusive, while exhibiting a weak but positive correlation with the performance metrics Total Raised, Going Public, and Company Failure. This could be due to the design of the study being flawed, with issues such as multicollinearity potentially affecting the time-dynamic dependent variables as opposed to the static variable of the first financing size received. However, the results did not suggest that the Great Recession had an adverse effect on the capacity to raise capital, nor likelihood of going public. These findings could mean that VC-firms can play a pivotal role in supporting economic recovery as they can identify high-quality firms, particularly during volatile market conditions, and allocate the necessary resources towards them. Although our findings have flaws, one can assert that while investments may be cyclical, great ideas that need them are not.

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Appendix

Table 7: Regression Results for First Financing Size and Total Raised (Clustered SE by Country, Non-Log Transformed)

	First Financing Size			Total Raised		
	(1)	(2)	(3)	(4)	(5)	(6)
Great Recession	1.291*	0.580	0.593	5.142	4.496	5.692
	(0.666)	(0.480)	(0.674)	(3.221)	(3.261)	(4.149)
(Intercept)	2.004***	0.123***	5.421***	9.472***	3.726***	51.754
	(0.198)	(0.011)	(1.651)	(1.394)	(0.794)	(42.182)
Stage of Entry FE	No	Yes	Yes	No	Yes	Yes
Sector-Year FE	No	No	Yes	No	No	Yes
N	18,299	18,299	18,299	18,299	18,299	18,299
R^2	0.001	0.060	0.122	0.0002	0.002	0.035
Adjusted R^2	0.0005	0.059	0.113	0.0001	0.001	0.025

PitchBook, 2024

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 8: Regression Results for Log-Transformed First Financing Size and Total Raised (Clustered SE by Country)

	First Financing Size (Log-Transformed)			Total Raised (Log-Transformed)		
	(1)	(2)	(3)	(4)	(5)	(6)
Great Recession	0.320***	0.192***	0.117	0.307***	0.241***	0.058
	(0.057)	(0.050)	(0.088)	(0.057)	(0.052)	(0.145)
(Intercept)	0.621***	0.091***	1.033***	1.172***	0.813***	1.828***
	(0.042)	(0.007)	(0.170)	(0.073)	(0.095)	(0.309)
Stage of Entry FE	No	Yes	Yes	No	Yes	Yes
Sector-Year FE	No	No	Yes	No	No	Yes
N	18,299	18,299	18,299	18,299	18,299	18,299
R^2	0.006	0.164	0.240	0.002	0.020	0.108
Adjusted R^2	0.006	0.163	0.232	0.002	0.018	0.099

PitchBook, 2024

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 9: Regression Results for Log-Transformed First Financing Size and Total Raised (Pre- and Post-Recession, Clustered SE by Country)

	First Financing Size (Log-Transformed)			Total Raised (Log-Transformed)		
	(1)	(2)	(3)	(4)	(5)	(6)
Pre-Recession	0.369***	0.324***	−0.132	0.427***	0.431***	0.014
	(0.032)	(0.027)	(0.146)	(0.039)	(0.043)	(0.202)
Post-Recession	−0.366***	−0.242***	−0.110	−0.356***	−0.305***	−0.088
	(0.056)	(0.051)	(0.073)	(0.058)	(0.055)	(0.143)
(Intercept)	0.941***	0.330***	1.165***	1.479***	1.114***	1.815***
	(0.037)	(0.051)	(0.241)	(0.052)	(0.071)	(0.436)
Stage of Entry FE	No	Yes	Yes	No	Yes	Yes
Sector-Year FE	No	No	Yes	No	No	Yes
N	18,299	18,299	18,299	18,299	18,299	18,299
R^2	0.066	0.198	0.240	0.030	0.044	0.108
Adjusted R^2	0.066	0.197	0.232	0.030	0.042	0.099

PitchBook, 2024

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 10: Logistic Regression Results for Probability of Company Failure (Robust Standard Errors)

	Probability of Company Failure				
	(1)	(2)	(3)	(4)	(5)
First Financing During Great Recession	0.787***	0.851***	−0.232	−0.193	−0.199
	(0.096)	(0.097)	(0.218)	(0.221)	(0.222)
(Intercept)	−1.870***	−1.721***	−1.244***	−1.289***	−1.225***
	(0.022)	(0.184)	(0.292)	(0.304)	(0.312)
Country FE	No	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
Stage of Entry FE	No	No	No	Yes	Yes
Sector FE	No	No	No	No	Yes
N	18,299	18,299	18,299	18,299	18,299
Log Likelihood	−7,297.407	−7,211.415	−6,692.207	−6,571.362	−6,550.015
Akaike Inf. Crit.	14,598.810	14,478.830	13,486.410	13,288.720	13,258.030

PitchBook, 2024

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 11: Logistic Regression Results With Robust Standard Errors (IPO Likelihood)

	Dependent variable:				
	Probability of IPO				
	(1)	(2)	(3)	(4)	(5)
First Financing During Great Recession	1.401***	1.403***	0.254	0.274	0.287
	(0.213)	(0.215)	(0.423)	(0.443)	(0.462)
Intercept	−4.497***	−19.633	−18.246***	−20.812	−21.823***
	(0.072)		(1.246)		(2.348)
Country FE	No	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
Stage of Entry FE	No	No	No	Yes	Yes
Sector FE	No	No	No	No	Yes
Observations	18,299	18,299	18,299	18,299	18,299
Log Likelihood	−1,180.104	−1,089.226	−997.503	−965.338	−918.568
Akaike Inf. Crit.	2,364.209	2,234.452	2,097.006	2,076.676	1,995.136

PitchBook, 2024 *p<0.1; **p<0.05; ***p<0.01

Table 12: Linear Regression Results (Great Recession: 2008-01-01 to 2009-07-30)

	First Financing Size	Total Raised
	(1)	(2)
Great Recession	1.162	6.684
	(1.138)	(8.339)
(Intercept)	33.361***	−1.680
	(9.573)	(70.147)
N	18,360	18,360
R^2	0.173	0.068
Adjusted R^2	0.139	0.030

PitchBook, 2024 ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 13: Log Regression Results (Great Recession: 2008-01-01 to 2009-07-30)

	Log First Financing Size	Log Total Raised
	(1)	(2)
Great Recession	0.114	0.007
	(0.072)	(0.121)
(Intercept)	2.745***	0.540
	(0.605)	(1.022)
N	18,360	18,360
R^2	0.315	0.192
Adjusted R^2	0.287	0.159

PitchBook, 2024 ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 14: Pre/Post Regression Results (Great Recession: 2008-01-01 to 2009-07-30)

	Log First Financing Size	Log Total Raised
	(1)	(2)
Pre-Recession	2.238***	−0.285
	(0.628)	(1.061)
Post-Recession	−0.114	−0.007
	(0.072)	(0.121)
(Intercept)	0.508***	0.825***
	(0.171)	(0.288)
N	18,360	18,360
R^2	0.315	0.192
Adjusted R^2	0.287	0.159
PitchBook, 2024	***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.	

Table 15: Logit Regression Results (Great Recession: 2008-01-01 to 2009-07-30)

	Probability of IPO
Great Recession	0.285
	(0.561)
(Intercept)	−47.670
	(13,052.250)
N	23,351
Log Likelihood	−1,356.605
Akaike Inf. Crit.	2,899.210
PitchBook, 2024	***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

Table 16: Linear Regression Results (Great Recession: 2008-02-01 to 2009-08-31)

	First Financing Size	Total Raised
	(1)	(2)
Great Recession	0.963	−10.187
	(0.886)	(6.490)
(Intercept)	33.361***	−1.649
	(9.573)	(70.143)
N	18,360	18,360
R^2	0.173	0.068
Adjusted R^2	0.139	0.030

PitchBook, 2024 ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 17: Log Regression Results (Great Recession: 2008-02-01 to 2009-08-31)

	Log First Financing Size	Log Total Raised
	(1)	(2)
Great Recession	0.060	−0.053
	(0.056)	(0.095)
(Intercept)	2.746***	0.540
	(0.605)	(1.022)
N	18,360	18,360
R^2	0.315	0.192
Adjusted R^2	0.287	0.159

PitchBook, 2024 ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 18: Pre/Post Regression Results (Great Recession: 2008-02-01 to 2009-08-31)

	Log First Financing Size	Log Total Raised
	(1)	(2)
Pre-Recession	0.028	0.155
	(0.086)	(0.145)
Post-Recession	-0.124^{*}	-0.022
	(0.074)	(0.124)
(Intercept)	2.717^{***}	0.385
	(0.611)	(1.032)
N	18,360	18,360
R^2	0.315	0.192
Adjusted R^2	0.287	0.159

PitchBook, 2024 — ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

Table 19: Logit Regression Results (Great Recession: 2008-02-01 to 2009-08-31)

	Probability of IPO
Great Recession	-0.367
	(0.366)
(Intercept)	-47.690
	(13,053.150)
N	23,351
Log Likelihood	$-1,356.254$
Akaike Inf. Crit.	2,898.508

PitchBook, 2024 — ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

Table 20: Linear Regression Results (Great Recession: 2008-03-01 to 2009-09-31)

	First Financing Size	Total Raised
	(1)	(2)
Great Recession	1.173	-8.269
	(0.888)	(6.504)
(Intercept)	33.364***	-1.675
	(9.572)	(70.145)
N	18,360	18,360
R^2	0.173	0.068
Adjusted R^2	0.139	0.030

PitchBook, 2024 ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 21: Log Regression Results (Great Recession: 2008-03-01 to 2009-09-31)

	Log First Financing Size	Log Total Raised
	(1)	(2)
Great Recession	0.069	0.024
	(0.056)	(0.095)
(Intercept)	2.746***	0.540
	(0.605)	(1.022)
N	18,360	18,360
R^2	0.315	0.192
Adjusted R^2	0.287	0.159

PitchBook, 2024 ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 22: Pre/Post Regression Results (Great Recession: 2008-03-01 to 2009-09-31)

	Log First Financing Size	Log Total Raised
	(1)	(2)
Pre-Recession	0.031	0.026
	(0.075)	(0.127)
Post-Recession	-0.194^{**}	-0.087
	(0.084)	(0.142)
(Intercept)	2.715^{***}	0.514
	(0.610)	(1.030)
N	18,360	18,360
R^2	0.315	0.192
Adjusted R^2	0.287	0.159

PitchBook, 2024

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 23: Logit Regression Results (Great Recession: 2008-03-01 to 2009-09-31)

	Probability of IPO
Great Recession	-0.323
	(0.374)
(Intercept)	-47.678
	(13,053.010)
N	23,351
Log Likelihood	$-1,356.378$
Akaike Inf. Crit.	2,898.756

PitchBook, 2024

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 24: Linear Regression Results (Great Recession: 2008-12-01 to 2010-06-30)

	First Financing Size	Total Raised
	(1)	(2)
Great Recession	−0.294	2.282
	(0.876)	(6.419)
(Intercept)	33.363***	−1.665
	(9.573)	(70.148)
N	18,360	18,360
R^2	0.173	0.068
Adjusted R^2	0.139	0.030

PitchBook, 2024 ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 25: Log Regression Results (Great Recession: 2008-12-01 to 2010-06-30)

	Log First Financing Size	Log Total Raised
	(1)	(2)
Great Recession	0.013	0.112
	(0.055)	(0.094)
(Intercept)	2.746***	0.540
	(0.605)	(1.022)
N	18,360	18,360
R^2	0.315	0.192
Adjusted R^2	0.287	0.159

PitchBook, 2024 ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 26: Pre/Post Regression Results (Great Recession: 2008-12-01 to 2010-06-30)

	Log First Financing Size	Log Total Raised
	(1)	(2)
Pre-Recession	0.106	0.107
	(0.113)	(0.191)
Post-Recession	−0.051	−0.182*
	(0.064)	(0.107)
(Intercept)	2.640***	0.433
	(0.615)	(1.039)
N	18,360	18,360
R^2	0.315	0.192
Adjusted R^2	0.287	0.159

PitchBook, 2024

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 27: Logit Regression Results (Great Recession: 2008-12-01 to 2010-06-30)

	Probability of IPO
Great Recession	−0.381
	(0.435)
(Intercept)	−47.694
	(13,054.450)
N	23,351
Log Likelihood	−1,356.349
Akaike Inf. Crit.	2,898.697

PitchBook, 2024

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Use of Artificial Intelligence: We want to disclose the usage of ChatGPT to assist with writing code in R and LaTeX-script. This has enabled us to make the process of coding more efficient when we had issues with the code. However, we acknowledge that this implies a risk that we lose control of the code, but we have been careful to understand the processes. We also stress that ChatGPT has not been used to determine the design of the study nor write any of the content we present in this thesis.