Firm Characteristics and Crisis Resilience:
An Event Study on the United States Equity Market (1990–2024)

Mauritz Röver

Dissertation written under the supervision of professor Mário Meira.

Dissertation submitted in partial fulfilment of requirements for the MSc in Finance (post–experience), at the Universidade Católica Portuguesa,

January 2026

Abstract

Major U.S. equity market crises have repeatedly challenged firms over recent decades. Even when prices fall broadly, losses vary substantially across firms. Such variation raises the question of what explains differential firm responses to crises and whether these differences vary across different stages of a crisis. This dissertation examines which firm characteristics are associated with crisis resilience across different phases of major U.S. equity market crises. Crisis resilience is measured as firm performance relative to the market using cumulative abnormal returns around the onset of crisis phases. The analysis assesses how firm characteristics relate to resilience within distinct crisis phases and whether these relationships generalize across crisis episodes.

The main findings indicate pronounced phase dependence and limited stability in firm characteristic effects when crises are examined separately. More consistent patterns emerge when crises are compared within the same phase. Lower return volatility is consistently associated with higher resilience. In contrast, higher systematic market risk is linked to greater resilience during extreme market conditions. Beyond risk exposure, higher profitability is generally related to stronger resilience, while larger firms tend to be more resilient in particularly adverse market environments.

In conclusion, the evidence indicates that crisis resilience arises from a combination of stable and phase-specific determinants rather than a single firm profile that is consistently resilient across crisis phases.

Keywords: Firm Characteristics, Crisis Resilience, Crisis Performance

Title: Firm Characteristics and Crisis Resilience: An Event Study on the United States Equity Market (1990–2024)

Author: Mauritz Röver

Resumo

As principais crises do mercado acionista dos Estados Unidos têm repetidamente desafiado as empresas nas últimas décadas. Mesmo quando os preços caem de forma generalizada, as perdas variam substancialmente entre as empresas. Esta dissertação examina quais características das empresas estão associadas à resiliência em crises ao longo das diferentes fases das crises do mercado acionista dos Estados Unidos. A resiliência em crises é medida como o desempenho das empresas em relação ao mercado, com base em retornos anormais acumulados em torno do início das fases da crise, e a análise avalia se essas relações se mantêm entre diferentes episódios de crise.

Os principais resultados indicam uma forte dependência da fase e uma estabilidade limitada dos efeitos das características das empresas quando as crises são analisadas separadamente. Padrões mais consistentes emergem quando as crises são comparadas dentro da mesma fase. Uma menor volatilidade dos retornos está consistentemente associada a uma maior resiliência. Em contraste, um maior risco sistemático de mercado está associado a uma maior resiliência durante condições extremas de mercado. Para além da exposição ao risco, uma maior rentabilidade está geralmente relacionada com uma resiliência mais forte, enquanto empresas de maior dimensão tendem a ser mais resilientes em ambientes de mercado particularmente adversos.

Em conclusão, a evidência indica que a resiliência em crises resulta de uma combinação de determinantes estáveis e específicos da fase, e não de um único perfil empresarial que seja consistentemente resiliente ao longo das fases da crise.

Palavras-chave: Características da empresa, Resiliência à crise, Desempenho em situações de crise

Título: Características da empresa e resiliência à crise: um estudo de eventos no mercado acionista dos Estados Unidos (1990–2024)

Autor: Mauritz Röver

Table of Contents

1. Introduction

Over recent decades, U.S. equity markets have experienced several major crises. While these episodes involve broad market declines, firms are affected to very different extents. Even when market prices decline sharply, some firms experience comparatively mild drawdowns, whereas others are affected much more strongly. This heterogeneity suggests that crises do not impact all firms in the same way and raises the question of which firm characteristics shape stock market outcomes during periods of stress.

Understanding why firms differ in crisis performance is relevant for investors, risk management, and corporate decision making. Previous literature has examined firm performance during crisis periods but often focuses on specific market shocks or individual crisis episodes. As a result, it remains unclear whether the relevance of firm characteristics is stable throughout a crisis or whether it changes across crisis phases.

This dissertation addresses the following research question: which firm characteristics are associated with crisis resilience across different phases of major U.S. equity market crises? Crisis resilience is defined as firm performance relative to the market at the onset of different crisis phases. The empirical analysis measures this relative performance using cumulative abnormal returns (CARs), which isolate firm-specific return components from overall market movements.

The objective of this dissertation is to examine how firm characteristics relate to crisis resilience within distinct crisis phases and to assess whether these relationships generalize across different crisis episodes. By applying a phase-based crisis design, the study contributes to the literature through a systematic comparison of firm performance within and across crises. This design allows persistent cross-phase regularities to be distinguished from effects that are specific to individual crisis episodes.

The empirical findings provide evidence of phase dependence and limited stability of firm characteristic effects at the level of individual crises. In contrast, comparing crises within the same phase reveals more stable cross-crisis regularities. A lower degree of return volatility is related to greater resilience, while higher systematic market risk is associated with higher resilience during episodes of extreme market stress. Additionally, higher profitability is generally linked to stronger resilience, and larger firms tend to perform more resiliently under particularly adverse market conditions. Other firm characteristics such as liquidity, valuation, and leverage exhibit phase specific relationships with resilience rather than consistent patterns across phases.

Regarding the structure of the dissertation, the following chapter reviews the relevant literature on financial crises and firm characteristics. The data and empirical methodology are then described. Subsequently, the empirical results are presented and discussed, and the limitations of the study are outlined. The dissertation concludes by summarizing the main findings and contributions and outlining implications and directions for future research.

2. Literature Review

This literature review provides a structured overview of crisis definitions in equity markets, the methodological challenges in their analysis, and the evidence on firm characteristics associated with resilience during crises. While the primary focus is the United States (U.S.), relevant insights from other markets and methodological approaches are incorporated to broaden the perspective. The review first examines how crises have been defined in prior research and considers the implications of these choices. Next, I outline the methodological decisions that shape study designs. The following chapter evaluates evidence on firm-level determinants of crisis outcomes, with particular attention to the characteristics most consistently examined across studies. Finally, the research gap motivating this dissertation is identified.

2.1 Crisis Definitions

The choice of definition is fundamental because it determines which episodes are identified as crises and shapes the conclusions about their causes and consequences. Literature commonly relies on three main approaches: threshold-based, draw-down based, and event-driven definitions. Beyond these, studies have also proposed alternative frameworks, including statistical and behavioral perspectives, as well as macroeconomic and narrative approaches.

Threshold-based definitions classify crises as sharp declines exceeding fixed percentage losses over a given time window. While this method captures reactions to extreme market stress, it reduces crises to isolated crash episodes and therefore offers only a partial view of crisis dynamics. Nevertheless, such rules are widely applied to examine firm behavior during extraordinary downturns, effectively treating crashes as proxies for broader crises. For instance, Wang et al. (2009) define a crash as any trading day with a loss of at least 5%, whereas Mishkin and White (2002) apply a 20% rule to identify major U.S. crashes in the twentieth century. This approach is straightforward and replicable, but it only reflects isolated crash days rather than capturing the full dynamics of a crisis.

Drawdown-based definitions classify crises as index declines from a recent peak to the subsequent trough. Building on this concept, Patel and Sarkar (1998) introduced the Cumulative Maximum (CMAX) as a measure of the current index level relative to its historical maximum. The CMAX is computed as:

$$CMAX_t = \frac{Index_t}{max_{s \leq t}(Index_s)}$$

where $Index_t$ denotes the index level at time t. This framework enables crises to be analyzed in four distinct phases: beginning, crash, trough, and recovery. The beginning marks the last local peak before the index decline starts. A crisis is triggered once the drawdown reaches the crash phase, which is defined by a fixed threshold decline of 20% in developed markets and 35% in emerging markets. The trough corresponds to the minimum index level during the crisis, and recovery is recorded once the index returns to its pre-crisis peak. Fauzi and Wahyudi (2016) adapt the CMAX method by applying a statistical threshold (the mean minus two standard deviations) and calculating CMAX relative to the maximum index level within a 260-day rolling window. In addition, they redefine the recovery phase as the point when the index exceeds its level in the preceding 260-day window rather than returning to the historical peak. Overall, the drawdown-based CMAX approach provides a structured and detailed representation of crisis dynamics across distinct phases, but results remain highly sensitive to the specific choices of thresholds, rolling windows, and recovery definitions.

Another perspective defines crises through event-driven approaches, linking them to specific announcements or external shocks rather than to index movements. Miyajima and Yafeh (2007) apply this approach to the Japanese banking crisis, using announcements such as government interventions, credit rating downgrades, and bank mergers as event markers. Ramelli and Wagner (2020) adopt a similar strategy for the COVID-19 pandemic, treating the outbreak as an external shock and using major announcements and policy measures as event triggers. They divide the first quarter of 2020 into three phases: Incubation, Outbreak, and Fever, reflecting both the progression of the pandemic and the associated policy responses. This approach is valuable because it isolates the impact of identifiable mechanisms, such as banking sector stress or international trade exposure. However, its reliance on specific events limits the generalizability of results and may overlook broader market dynamics beyond the chosen announcements.

Beyond the three common definitions, researchers have developed alternative perspectives that modify drawdown-based methods or introduce new statistical approaches. Johansen and Sornette (2010) identify crashes as statistical outliers in drawdown distributions, arguing that they constitute a distinct class of extreme events. They differentiate between endogenous episodes driven by speculative bubbles and exogenous shocks caused by external events. Furthermore, Zouaoui, Nouyrigat, and Beer (2011) extend the CMAX framework by incorporating investor sentiment, testing alternative thresholds, and adjusting the crisis-identification window. They provide evidence that elevated investor sentiment, measured by consumer confidence, significantly increases the probability of stock market crises, even after accounting for macroeconomic and financial indicators. These approaches broaden the perspective on crisis definitions, though they remain less established in the literature.

Taken together, these approaches underscore the absence of a uniform standard in crisis research. Threshold rules offer simplicity, drawdown methods capture the phase structure of crises, and event-driven designs emphasize specific mechanisms, while alternative frameworks broaden the perspective. Each approach entails specific advantages and limitations, and the chosen definition decisively shapes crisis identification and the interpretation of results. Building on these considerations, this dissertation adopts the CMAX drawdown framework with a fixed threshold, as its phase-based perspective aligns with the objective of examining firm characteristics across distinct crisis stages.

2.2 Methodological Approaches

Methodological diversity in crisis studies determines how results are obtained and interpreted. In addition to differences in event definitions, variation also arises from choices regarding return measures, treatment of statistical challenges, sample selection, and the application of adjustments or robustness tests. While these decisions are often driven by data availability or research design considerations, they introduce substantial heterogeneity in reported outcomes. Differences across crisis studies often stem from the choice of firm-level return measures.

Event-day raw returns are a common choice to capture firm performance, as in Wang et al. (2009) and Fauzi and Wahyudi (2016). By contrast, Ramelli and Wagner (2020) analyze daily returns over the entire first quarter of 2020 rather than focusing on single crash days. Apart from single-day measures, performance has also been evaluated over longer horizons. For instance, Davis and Madura (2012) calculate cumulative raw returns over a fixed crisis window, whereas Wang et al. (2011) examine holding period returns. Miyajima and Yafeh (2007) analyze short-term reactions using CARs within event windows of -5 to +5 days around banking announcements. Overall, these studies illustrate the range of time horizons and return measures applied in crisis research.

Statistical challenges are central in crisis studies because they directly affect the validity of empirical results. Volatility typically rises sharply during crises, inflating standard errors and distorting the estimation of risk variables. To mitigate this, researchers often calculate risk metrics using return histories from periods prior to the crisis. For example, Wang et al. (2009) and Fauzi and Wahyudi (2016) estimate the standard deviation of daily returns over the interval from -252 to -30 trading days, thereby avoiding distortions from crisis-related turbulence. Another statistical challenge is cross-sectional dependence, as firms often react simultaneously to market-wide shocks. Davis and Madura (2012) address this by grouping firms into portfolios of winners and losers instead of relying on firm-level regressions. A further complication arises from overlapping events, which occur when crises follow in close succession or when event windows capture multiple shocks. Miyajima and Yafeh (2007) highlight this problem in the context of banking sector announcements, where repeated interventions complicate the isolation of single events. Patel and Sarkar (1998) treat repeated drawdown breaches as a single event, whereas Zouaoui et al. (2011) exclude crises occurring within twelve months of each other to avoid double counting.

Regarding sample selection, a common practice in crisis studies is to exclude financials and utilities, as their regulatory and accounting characteristics limit comparability with industrial firms (Wang et al., 2009; Wang et al., 2011; Davis & Madura, 2012). Alongside sample selection, most studies also include control variables, such as additional firm characteristics or industry dummies, to account for systematic differences across firms or sectors.

In addition, studies often apply statistical adjustments and robustness tests to enhance the reliability of their findings. A common adjustment concerns the treatment of outliers. For instance, Wang et al. (2009) and Wang et al. (2011) apply winsorization to firm characteristics to reduce the influence of extreme values. Many studies also use logarithmic transformations, most commonly defining firm size as the natural log of market capitalization (Wang et al., 2009; Wang et al., 2011; Fauzi & Wahyudi, 2016; Miyajima & Yafeh, 2007; Ramelli & Wagner, 2020). Robustness tests also vary considerably across studies. For example, Miyajima and Yafeh (2007) test alternative event windows and compare raw with abnormal returns, and they also employ different definitions of firm characteristics such as profitability. Similarly, Ramelli and Wagner (2020) examine alternative leverage definitions, while Wang et al. (2009) redefine firm size to test robustness. These examples illustrate the diversity of approaches, which enhance the reliability of individual findings but also reflect different methodological priorities across studies.

2.3 Evidence on Firm Characteristics

Prior research has investigated a broad set of firm characteristics in the context of equity market crises. The most consistently examined variables can be grouped into four categories: risk exposure, size and valuation, capital structure and liquidity, and profitability. These categories reflect the dimensions along which firm-level resilience has most frequently been analyzed in the literature.

Risk exposure has been a central focus in studies of equity market crises and is typically measured by market beta and return volatility. Wang et al. (2009) document that stocks with higher betas experience larger losses on crash days, a finding confirmed by Wang et al. (2011) in a longer-horizon analysis. Davis and Madura (2012) likewise find that high-beta and high-volatility stocks underperform during the financial crisis. Similarly, Ramelli and Wagner (2020) report evidence for the COVID-19 shock, where market beta and pre-crisis volatility are associated with lower returns. Overall, literature consistently links higher beta and volatility to greater vulnerability in crises, although the strength of these effects varies across episodes and methodological choices.

Firm size and valuation are frequently examined as determinants of crisis performance. Evidence from multiple studies indicates that smaller firms are generally more exposed to losses, while larger firms tend to be more resilient (Wang et al., 2011; Davis and Madura, 2012; Fauzi and Wahyudi, 2016; Ramelli and Wagner, 2020; Miyajima and Yafeh, 2007). Valuation is typically measured through book-to-market ratios. Davis and Madura (2012) report that value stocks underperform, whereas glamour stocks tend to be more resilient. Value stocks are defined by high book-to-market ratios, whereas glamour stocks refer to firms with high valuations or growth prospects. Similar findings are reported by Wang et al. (2011) and Fauzi and Wahyudi (2016), confirming that value firms tend to be more vulnerable during downturns. All in all, smaller and value-oriented firms tend to be more exposed to losses, while larger and growth-oriented firms are relatively more resilient.

Capital structure and liquidity are central variables in studies of crisis performance. Leverage is consistently associated with weaker outcomes during crises. Wang et al. (2011) show that firms with higher debt ratios lost more during the 2007–2009 downturn. Davis and Madura (2012) provide similar evidence for the global financial crisis. Fauzi and Wahyudi (2016) and Miyajima and Yafeh (2007) likewise document that highly leveraged firms are more vulnerable, a pattern confirmed by Ramelli and Wagner (2020) for the COVID-19 episode. In contrast, the role of liquidity is less uniform, ranging from corporate liquidity such as cash holdings to market liquidity measures such as Amihud’s illiquidity. Wang et al. (2011) employ both cash holdings and Amihud’s illiquidity measure and show that their effects differ across crisis phases. Ramelli and Wagner (2020) find that cash holdings protected firms during the COVID-19 market collapse, while Davis and Madura (2012) report that liquidity measures such as the current ratio and dividend yield are linked to stronger performance. Taken together, high leverage consistently worsens crisis outcomes, whereas the role of liquidity depends strongly on the specific measure and context.

Profitability is often linked to better outcomes during crises. Wang et al. (2011) show that firms with higher return on assets performed better during the 2007–2009 downturn. Likewise, Ramelli and Wagner (2020) confirm that firms with higher return on assets experienced smaller losses during the COVID-19 episode. Additionally, Davis and Madura (2012) report that stronger operating cash flows were associated with winner portfolios. In summary, profitability generally supports resilience, although the magnitude of its effect varies across crises and samples.

In conclusion, the literature identifies several firm characteristics that shape resilience during equity market crises. Market risk exposure and leverage emerge as consistently adverse, while size, valuation, liquidity, and profitability show more context- and horizon-dependent effects. Overall, the evidence indicates that firm outcomes in crises reflect both structural weaknesses and operating strengths. However, differences in definitions and measures make comparisons across studies challenging.

2.4 Research Gap

The existing literature on firm performance during equity market crises employs a wide range of empirical approaches. However, prior research has rarely examined how the relevance of firm characteristics varies across distinct crisis phases and whether observed patterns persist across different crisis episodes. This dissertation addresses this gap by adopting a phase-based perspective on equity market crises, enabling a systematic investigation of how firm characteristics are associated with crisis resilience within and across crisis phases.

3. Data and Methodology

The data and methodology chapter outlines the data sources, sample construction, and key variables used in the analysis. It also introduces the event driven framework applied to identify crisis and summarizes the methodological approach that guides the empirical examination.

3.1 Event Definition

The identification of crisis events builds on the CMAX approach introduced by Patel and Sarkar (1998). By applying this method to the U.S. equity market, the entire cycle of a crisis can be systematically identified and structured into distinct phases. Extending the original framework, a three-step procedure is employed. It includes reconstructing the market index, detecting crisis episodes using the CMAX approach, and validating events through a minimum-separation criterion.

The market index is based on the Center for Research in Security Prices (CRSP) value-weighted total return index (VWRETD). I extracted daily returns from CRSP, from January 1990 to December 2024. As the CRSP database provides only return series, a price index is reconstructed. Index levels are obtained by compounding daily returns sequentially, starting from an initial base value of 100, as shown below:

$$Index_t = Index_{t-1} \times (1 + r_t), \qquad Index_0 = 100$$

Crisis events are identified using CMAX, which is calculated from the reconstructed index. It measures the relative decline of the reconstructed index from its most recent peak. By comparing the current index level with the highest value observed so far, CMAX provides a transparent and objective criterion for detecting market downturns. Formally, CMAX is defined as:

$$CMAX_t = \frac{Index_t}{max_{s \leq t}(Index_s)}$$

Once the CMAX value falls below the fixed threshold level of 0.80, a crisis is triggered. This corresponds to a decline of 20% from the previous peak and is consistent with Patel and Sarkar (1998), who also applied a 20% threshold in developed markets. In addition, a statistical threshold of $\overline{CMAX} - 2\sigma$, as used by Fauzi and Wahyudi (2016) and Zouaoui et al. (2011), is tested. In the present CMAX sample, this statistical rule yields a threshold value of 0.68.

However, this approach proves overly restrictive, as it identifies substantially fewer episodes of market distress. Figure 1 illustrates this contrast, showing how the statistical threshold only captures the most extreme drawdowns, while the fixed threshold provides a broader identification of crises. Considering all these aspects, the fixed threshold is applied as the baseline definition throughout the analysis.

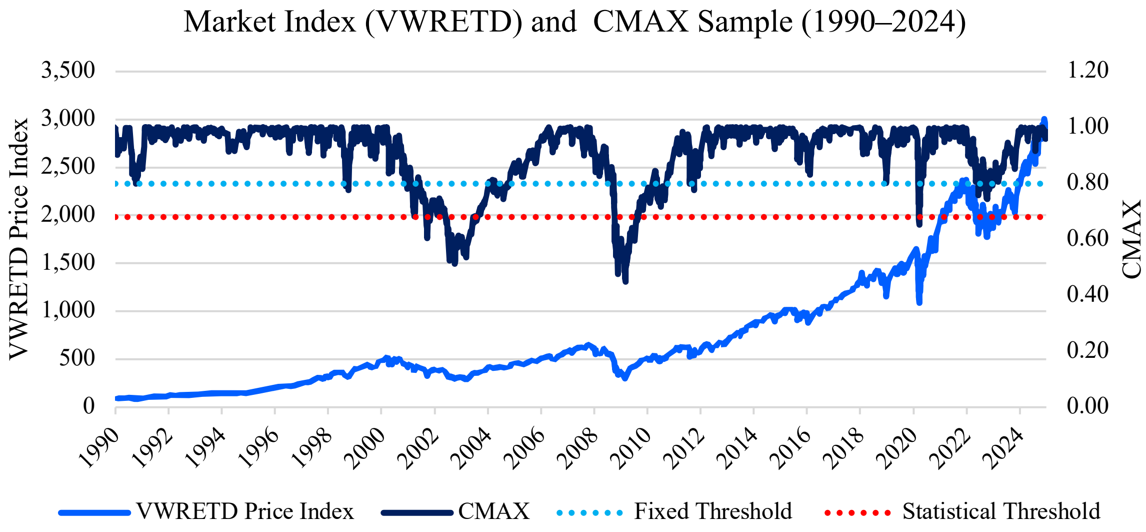

Figure 1. VWRETD Price Index and CMAX ratio, 1990 – 2024, with fixed threshold ($\tau = 0.80$) and statistical threshold ($\overline{CMAX} - 2\sigma = 0.68$)

To capture the full dynamics of a crisis, the analysis employs a four-phase framework consisting of the beginning, crash, trough, and recovery. Firstly, the beginning of a crisis is defined as the most recent local peak before the downturn:

$$Beginning_t\colon\ CMAX_t = 1$$

Secondly, the crash phase is determined by the first date at which the CMAX falls below the fixed threshold level. Crossing the threshold marks the point at which the crisis is formally identified:

$$Crash_t\colon\ CMAX_t < \tau, \qquad \tau = 0.80$$

Thirdly, the trough corresponds to the date of the lowest index value observed between the crash and the recovery phase:

$$Trough_t = min\ (Index_{Crash}, \dots, Index_{Recovery})$$

Finally, the recovery phase is reached once the index regains its pre-crisis peak level:

$$Recovery_t\colon\ CMAX_t = 1$$

To ensure the phase validity, selection criteria are applied. Regarding the minimum-separation criterion, each phase must be at least 30 trading days apart. This restriction prevents overlapping or excessively short intervals and ensures that each phase represents a distinct period of market dynamics suitable for empirical analysis. Crisis episodes in which any two phases occur within a shorter time span are excluded from the sample. Furthermore, multiple threshold breaches within the same drawdown are treated as a single event to avoid double counting, following Patel and Sarkar (1998). In total, six crises are initially identified (Appendix Table A.1). However, as shown in Appendix Table A.2, three of them violate the minimum-separation criterion and are excluded. Accordingly, the final sample consists of three crises, as reported in Table 1.

Crisis	Beginning	Crash	Trough	Recovery
Crisis 1 (2000 – 2006)	24 March 2000	20 December 2000	09 October 2002	05 April 2006
Crisis 2 (2007 – 2012)	09 October 2007	15 September 2008	09 March 2009	16 March 2012
Crisis 3 (2021 – 2024)	08 November 2021	13 June 2022	14 October 2022	23 January 2024

Table 1. Final crises identified for analysis

Various macro-financial conditions shaped each crisis and help explain the market dynamics observed during their respective phases. The first identified crisis corresponds to the Dot-com bubble, which emerged as technology and internet-related firms became heavily overvalued due to unrealistic expectations of future growth. OECD (2001) notes that equity markets began to correct after peaking in early 2000, and U.S. high-technology stocks lost more than half of their value once these valuations became apparent. Nasdaq prices ultimately declined by nearly 78% from peak to trough, reflecting a broad collapse in speculative expectations and the failure of numerous firms (Hayes, 2025). Reduced confidence in the technology sector, combined with a gradual adjustment of market valuations, resulted in an equity market recovery that extended into the mid-2000s.

The second crisis refers to the Global Financial Crisis, triggered by the collapse of the housing market and severe disruptions within the financial system. According to Federal Reserve

History (2013), the U.S. entered a deep recession in late 2007, and the S&P 500 lost more than half of its value between October 2007 and the trough in early 2009. The Financial Crisis Inquiry Commission (2011) highlights rising mortgage delinquencies, major institutional failures, and a sharp decline in confidence as central elements that intensified the downturn. Recovery progressed slowly because banks and firms reduced leverage and rebuilt capital positions, extending the adjustment into the early 2010s.

The third crisis, referred to as the monetary tightening and inflation crisis, arose from persistent inflation, post-pandemic supply disruptions, and a sharp tightening of monetary policy. This crisis differs from the first two crises because its phases reflect the combined effects of several macro-financial shocks rather than a single dominant trigger. Inflation began rising in late 2021 and intensified in 2022, with consumer prices increasing 9.1% over the 12 months ending June 2022, the largest annual increase in four decades (U.S. Bureau of Labor Statistics, 2023). The Federal Reserve responded by raising the target range for the federal funds rate from 0 to 0.25% to 4.25 to 4.50% during 2022 (Federal Reserve Bank of St. Louis, 2023). Equity markets declined as higher inflation and rising interest rates weighed on valuations. Additional uncertainty arose from the failure of several regional banks, including Silicon Valley Bank, which exposed further vulnerabilities in the financial system (Board of Governors of the Federal Reserve System, 2023). The recovery extended into 2024 because these overlapping shocks constrained investor confidence and extended the adjustment of market valuations and credit conditions.

3.2 Data and Sample Selection

The data collection relies on two primary sources of U.S.-listed firms. Stock market information is obtained from the CRSP, and complementary firm-level accounting data are retrieved from Compustat. Industry classifications are based on the Fama–French 12-industry scheme to account for sectoral heterogeneity. Originally, the index returns used for the crisis identification were collected for the period from 1990 to 2024. This horizon is required to construct the CMAX series and to detect the crises and their respective phases reported in Table 1. For the empirical analysis, however, only firm-level observations that fall within these identified crisis phases are retained. All U.S.-listed firms covered by CRSP and Compustat during the identified crisis phases are included in the sample. Firms with incomplete coverage in either database are excluded to ensure consistency of the firm-level information. Table 2 presents the sample composition, listing the number of firms with complete data coverage in each crisis phase.

Crisis	Beginning	Crash	Trough	Recovery
Crisis 1 (2000–2006)	3,967	4,008	3,941	4,012
Crisis 2 (2007–2012)	3,549	3,491	3,653	3,577
Crisis 3 (2021–2024)	3,302	3,350	3,354	3,425

Table 2. Sample size of firms by crisis and phase

Beyond the distribution across crises and phases, describing the sectoral composition of the sample provides additional context for the subsequent analysis. The full sample comprises 43,629 firm-phase observations and is classified into industries using the Fama–French 12-industry scheme, as reported in Table 3. Business Equipment, Healthcare, Finance and Other represent the largest sectors in the sample.

Industry	Frequency	Percent
Consumer Nondurables – Food, Tobacco, Textiles, Apparel, Leather, Toys	1,907	4.37
Consumer Durables – Cars, TVs, Furniture, Household Appliances	1,039	2.38
Manufacturing – Machinery, Trucks, Planes, Off Furn, Paper, Com Printing	4,019	9.21
Oil, Gas, and Coal Extraction and Products	1,583	3.63
Chemicals and Allied Products	1,042	2.39
Business Equipment – Computers, Software, and Electronic Equipment	7,772	17.81
Telephone and Television Transmission	1,136	2.60
Utilities	1,270	2.91
Wholesale, Retail, and Some Services (Laundries, Repair Shops)	3,713	8.51
Healthcare, Medical Equipment, and Drugs	6,117	14.02
Finance	8,551	19.60
Other – Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment	5,480	12.56
Total	**43,629**	**100**

Table 3. Industry composition of the full firm sample (Fama–French 12-industry classification)

3.3 Variables

This chapter provides an overview of the variables used in the empirical analysis. It defines the dependent and explanatory variables, motivates the choice of cumulative abnormal return windows, presents descriptive statistics, and describes the data transformations applied prior to the regression analysis.

3.3.1 Variable Definition

The empirical analysis employs a set of variables that capture firm-specific characteristics commonly associated with resilience during equity market crises. Variables are structured into three components: the dependent performance variable, explanatory variables, and industry-level controls. Detailed definitions, data sources, and reference periods for all variables are provided in Appendix Table A.3.

The dependent variable, CAR, captures firm-specific performance reactions to crisis events. I construct the performance measure as follows. Abnormal returns are obtained from the CRSP U.S. Daily Event Study Tool, which estimates firm-level excess returns using the market model (CAPM) based on daily stock data. The estimation window comprises 252 trading days and ends 20 trading days before the start of the event window. At least 200 non-missing return observations are required to ensure estimation reliability. As CRSP provides abnormal returns in discrete form, they are converted into continuously compounded returns using the natural logarithm to ensure temporal additivity. Logarithmic abnormal returns are used because they can be added consistently across days, allowing the cumulative effect to be captured without introducing compounding distortions. In contrast, discrete returns must be multiplied over time, which means they cannot be summed directly and would otherwise lead to inconsistent aggregation. CARs are then computed by summing the log-transformed abnormal returns across the respective event windows, providing an economically meaningful and comparable measure of firm-level performance during crisis periods.

The explanatory variables capture firm-specific characteristics that may affect how companies respond during crisis periods. They are grouped into market-based measures and accounting-based measures. Market-based measures describe how firms are positioned with respect to financial market risks. Beta (BETA) captures systematic market exposure and is estimated using the market model (CAPM) on daily log returns. The computation relies on a five-year estimation window (1260 trading days) ending five trading days before the event (T-5), with at least three years of non-missing observations required to ensure reliability. Idiosyncratic risk is measured through return volatility (VOL) at the firm level. VOL is calculated as the standard deviation of daily log returns over the 252 trading days preceding the crisis phase, with the measurement window ending 30 trading days prior to the event (T-30). This window ensures that volatility is calculated before any crisis-related movements begin to affect returns. As commonly applied in literature, firm size (SIZE) is defined as the natural logarithm of market capitalization and reflects how the scale of a firm affects its responsiveness to changing market conditions. SIZE is measured on the fifth trading day before the event (T-5), using absolute price values to account for negative price coding conventions in CRSP. Both BETA and SIZE are measured at T–5 to ensure that the variables capture firm characteristics immediately before the crisis window without being influenced by pre-event return movements or price adjustments. The book-to-market ratio (BEME) serves as a valuation indicator that shows how the market value compares to its underlying accounting equity and reflects whether it is priced low or high relative to book value. Accounting-based variables reflect the financial structure and performance of firms. Leverage (LEV) captures financial risk by relating debt levels to total assets, while Return on Assets (ROA) measures profitability relative to total assets. Liquidity (LIQ) indicates short-term solvency by comparing cash and short-term investments to total assets. BEME and all accounting-based variables (LEV, ROA, and LIQ) rely on information from quarterly financial statements, which are reported with a delay relative to market data. Using financial information that becomes publicly available only after the beginning of a crisis phase would create look-ahead bias, because it would incorporate data that market participants could not have observed at that time. To prevent this issue, each variable is constructed using the report date of quarterly earnings (rdq) to identify the most recent financial statement with a report date that precedes the beginning of the respective crisis phase. This procedure ensures that only information available to the market at that point in time enters the analysis, thereby preventing any form of look-ahead bias.

Industry fixed effects are included as control variables to capture systematic differences across sectors. Based on the Fama–French 12-industry classification, these controls ensure that estimated effects of firm characteristics are not driven by sector-specific heterogeneity.

3.3.2 Cumulative Abnormal Returns Window Selection

CAR windows determine the period over which CARs are aggregated and therefore shape how return adjustments around crisis phases are measured. Different window lengths capture distinct components of the adjustment process, ranging from immediate return reactions to broader short-term adjustments. Since pre-event windows primarily reflect anticipation and post-event windows capture follow-up dynamics, the analysis concentrates on windows centered around the phase onset, where the event-proximate adjustment occurs. Selecting an appropriate window is essential, as the empirical design must capture this reaction while avoiding distortions from unrelated movements.

Three CAR windows are used to capture distinct segments of the adjustment around the phase onset. An immediate reaction is observed in the (-1,+1) window, which focuses on the return response in the days directly surrounding the event and is therefore particularly sensitive to short-lived fluctuations. A broader perspective emerges in the (-3,+3) window, which extends the horizon to include early corrections while still maintaining a close alignment with the phase transition. The (-5,+5) window widens the horizon even further, allowing slower information processing and delayed market reactions to be reflected. To evaluate how consistently these windows capture the adjustment around each phase, I calculated cumulative average abnormal returns (CAARs) across crises and phases. CAARs summarize the cross-sectional average of firm-level CARs for a given window and provide an indication of how each horizon reflects the underlying phase dynamics. Examining these averages offers an empirical basis for comparing the three CAR windows.

Crisis	**Phase**	**Immediate Adjustment**	**Short-Term Adjustment**	**Extended Adjustment**
		(-1,+1)	**(-3,+3)**	**(-5,+5)**
Crisis 1 (2000–2006)	Beginning	-0.83%	-3.16%	-4.59%
	Crash	-2.87%	-5.20%	-4.53%
	Trough	-3.32%	-5.53%	-5.73%
	Recovery	-0.39%	-0.76%	-0.31%
Crisis 2 (2007–2012)	Beginning	-0.30%	-0.29%	-0.24%
	Crash	-0.74%	-1.78%	-1.67%
	Trough	-0.71%	-0.32%	-3.09%
	Recovery	0.23%	-0.41%	0.16%
Crisis 3 (2021–2024)	Beginning	0.24%	-0.43%	-0.60%
	Crash	-0.68%	0.27%	0.45%
	Trough	-0.70%	-1.56%	-2.67%
	Recovery	0.44%	-0.62%	-2.34%

Table 4. CAARs by crisis, phase, and CAR window

Table 4 reports the CAARs for each crisis and phase across the three windows. The values provide a descriptive overview of how the magnitude and direction of the adjustment vary with the width of the window. In general, wider windows tend to produce CAARs of greater absolute magnitude, although the pattern is not uniform across crises. Immediate reactions in the (-1,+1) window are relatively small, whereas the (-3,+3) window shows more pronounced and consistent differences across phases. The extended (-5,+5) window yields the largest adjustments, capturing a wider portion of the short-term reaction around each phase. Based on these patterns, the (-3,+3) window is selected as the baseline specification. It offers the most balanced representation of the event-proximate adjustment, capturing early corrections while remaining closely tied to the phase onset. Compared with the narrower (-1,+1) window, it provides a clearer differentiation across phases and is less sensitive to short-lived fluctuations. At the same time, it avoids the broader drift and delayed reactions that can enter the (-5,+5) window. Overall, the (-3,+3) horizon delivers a stable and interpretable measure of short-term adjustment that is well suited for the baseline regression analysis. To assess the sensitivity of the results to the choice of event window, the (-1,+1) and (-5,+5) windows are used as robustness specifications.

3.3.3 Descriptive Statistics

The descriptive statistics provide an overview of the variables used in the empirical analysis. This chapter summarizes the distribution of the explanatory variables and then reports the distribution of CARs for the chosen baseline event window (-3,+3).

Variable	N	Mean	SD	Min	P25	Median	P75	Max
BETA	43,629	0.867	0.472	-0.947	0.518	0.860	1.185	3.894
VOL	43,629	0.036	0.021	0.002	0.021	0.031	0.045	0.259
SIZE	43,629	19.921	2.282	12.278	18.248	19.865	21.473	28.696
BEME	43,629	0.642	3.660	-674.845	0.273	0.524	0.888	43.069
LEV	43,629	0.241	0.252	0.000	0.043	0.190	0.364	5.321
ROA	43,629	-0.010	0.251	-8.888	-0.009	0.005	0.018	41.146
LIQ	43,629	0.192	0.233	-0.006	0.029	0.089	0.265	1.000

Table 5. Descriptive statistics of explanatory variables (raw data)

Table 5 summarises the descriptive statistics of the explanatory variables across the full sample of firm-level observations from the three crises. The table reports the number of observations together with the mean, standard deviation, minimum and maximum values, and selected percentiles. The variables exhibit substantial cross-sectional variation, which is also reflected in the distribution plots in Appendix Figures A.1–A.7 BETA is concentrated within the interquartile range from 0.518 to 1.185, with a median of 0.860. This indicates that most firms cluster around moderate levels of systematic risk, while observations outside this range occur infrequently. VOL exhibits a compact distribution, consistent with its mean of 0.036 and standard deviation of 0.021. As displayed in Figure A.2, the highest frequencies appear between approximately 0.021 and 0.045, reflecting limited dispersion in short-term return volatility. SIZE shows an approximately symmetric distribution, with most values between 18.248 and 21.473. The standard deviation of 2.282 reflects meaningful differences in firm scale, while the logarithmic transformation contributes to a more stable distribution. BEME spans a wide numerical range. Although the median of 0.524 lies near the center of the distribution, the combination of a high standard deviation and extreme minimum and maximum values indicate the presence of a small number of outlying observations. However, most firms remain within the interquartile range. LEV contains a notable share of zero values, which account for roughly

11% of the sample. The remaining observations fall mainly between 0.043 and 0.364, with higher leverage ratios occurring only in a limited number of cases. ROA is centered close to zero, with a median of 0.005 and an interquartile interval from -0.009 to 0.018. The negative mean of -0.010 reflects the influence of a small number of firms with substantially negative earnings relative to assets. LIQ ranges from -0.006 to 1.000 and has an interquartile interval from 0.029 to 0.265. The mean of 0.192 exceeds the median of 0.089, indicating that some firms hold comparatively high levels of cash and short-term investments. Values above 0.500 occur only in a small fraction of the sample, as shown in Figure A.7.

To provide additional detail, Appendix Tables A.4.a–A.4.c report the same statistics separately for each crisis and phase. The distributions remain broadly consistent across periods. For variables such as BETA, VOL, and SIZE, both the interquartile ranges and central tendencies are similar across phases. Variables with wider natural variation, including BEME and LEV, display comparable distributional shapes despite differences in extremes. ROA and LIQ also show stable patterns across periods, with limited variation in their central ranges. Overall, the phase-level statistics indicate that the core properties of the explanatory variables remain broadly comparable across crises.

The distribution of the dependent variable is summarized using firm-level CARs for the baseline event window (-3,+3). Table 6 reports these CARs separately for each crisis and phase, providing an overview of how short-term performance varies across the periods.

Crisis	Phase	N	Mean	SD	Min	P25	Median	P75	Max
Crisis 1 (2000–2006)	Beginning	3,967	-0.032	0.123	-1.121	-0.082	-0.016	0.031	0.920
	Crash	4,008	-0.052	0.179	-2.311	-0.118	-0.014	0.047	0.988
	Trough	3,941	-0.055	0.135	-3.111	-0.099	-0.039	0.002	1.250
	Recovery	4,012	-0.008	0.073	-1.726	-0.032	-0.006	0.020	0.663
Crisis 2 (2007–2012)	Beginning	3,549	-0.003	0.076	-0.814	-0.032	-0.004	0.025	1.897
	Crash	3,491	-0.018	0.193	-7.517	-0.069	-0.008	0.055	0.642
	Trough	3,653	-0.003	0.157	-1.446	-0.070	-0.006	0.066	1.198
	Recovery	3,577	-0.004	0.068	-0.811	-0.035	-0.010	0.018	0.746
Crisis 3 (2021–2024)	Beginning	3,302	-0.004	0.095	-1.304	-0.037	0.003	0.038	0.430
	Crash	3,350	0.003	0.111	-1.208	-0.052	-0.004	0.048	1.329
	Trough	3,354	-0.016	0.093	-1.253	-0.051	-0.004	0.029	0.573
	Recovery	3,425	-0.006	0.097	-1.551	-0.037	-0.003	0.028	1.469

Table 6. Descriptive statistics of dependent variable, CAR (-3,+3), by crisis and phase

Across the three crises, CARs exhibit several consistent patterns. Mean and median values are predominantly negative, which indicates that short-term abnormal returns tend to fall below zero across most phases. Crash and trough phases combine the most negative central values with markedly higher variation in CARs, whereas beginning and recovery phases show values closer to zero. The distributions also show substantial dispersion, with standard deviations ranging from roughly 0.076 to 0.193 throughout the phases. Additionally, the interquartile range spans negative values at the lower quartile and positive values at the upper quartile in all phases, which points to a broad distribution of CARs around slightly negative centers. Minimum and maximum CARs reveal the presence of extreme observations in every crisis and phase. Overall, the baseline CAR distributions are characterized by mildly negative centers, high variability and heavy tails.

3.3.4 Data Transformations

Data transformation is required to reduce the influence of extreme observations that commonly arise in firm-level datasets. To mitigate this impact while preserving the underlying economic variation, all explanatory variables are winsorized at the 1st and 99th percentiles of the pooled sample. This transformation replaces only the most extreme values with their respective cutoff values and does not remove any observations. The dependent variable CAR remains unaltered, as extreme return reactions are economically meaningful and represent the variation the analysis aims to explain. CAR captures the actual market response around each crisis phase. Accordingly, large return movements are interpreted as economically meaningful market adjustments rather than statistical noise.

Variable	Min	Max	P1	P99	P5	P95
BETA	-0.947	3.894	-0.001	2.057	0.130	1.656
VOL	0.002	0.259	0.010	0.107	0.014	0.076
SIZE	12.278	28.696	15.190	25.407	16.331	23.843
BEME	-674.845	43.069	-0.705	3.823	0.029	1.906
LEV	0.000	5.321	0.000	0.990	0.000	0.669
ROA	-8.888	41.146	-0.396	0.119	-0.150	0.050
LIQ	-0.006	1.000	0.000	0.938	0.005	0.750

Note: The table reports the raw minimum and maximum values together with the percentile cutoffs used for the 1%/99% winsorization and the 5%/95% winsorization.

Table 7. Winsorization cutoff values

Table 7 reports the cutoff values used in the 1%/99% winsorization and illustrates how the transformation constrains the extreme tails of each variable. The corresponding summary statistics after the transformation are documented in Appendix Table A.5. As an additional robustness check, an alternative 5%/95% winsorization is applied, and the resulting summary statistics are reported in Appendix Table A6. Overall, the transformation limits the influence of outliers while retaining the distributional characteristics that are relevant for the empirical analysis.

3.4 Empirical Strategy and Regression Design

This chapter outlines the empirical strategy used to examine firm-level crisis resilience, defined as firm performance relative to the market across different crisis phases. Resilience is measured using CARs in short windows around phase onset dates, with each crisis phase represented by a single-phase onset date rather than its full duration. Higher CARs indicate stronger crisis resilience by capturing relative performance around phase onset dates. The empirical analysis follows an event driven approach and regresses CARs to firm level characteristics to explain variation in crisis resilience. All regressions use CARs computed over the baseline (-3,+3) event window. To capture both within-crisis dynamics and cross-crisis regularities, two complementary regression designs are applied. The first is an event-level regression design and the second is a pooled crisis-phase regression design.

The event-level regression design estimates separate models for each crisis and phase to capture heterogeneity in CARs within a given crisis environment. By focusing on within-crisis variation, the specification identifies how firm level characteristics relate to CARs under the specific market conditions that define each crisis phase. To ensure comparability across phases within a crisis, only firms observed in all phases of that crisis are included. This restriction implies that firms exiting the market or missing observations in intermediate phases do not enter the estimation. Sample sizes of firm phase observations are reported in Appendix Table A.7. The event-level regression model is specified as:

$$CAR_{i,c,p} = \beta_{c,p} + \beta_1 BETA_{i,c,p} + \beta_2 VOL_{i,c,p} + \beta_3 SIZE_{i,c,p} + \beta_4 LEV_{i,c,p} + \beta_5 ROA_{i,c,p} + \beta_6 BEME_{i,c,p} + \beta_7 LIQ_{i,c,p} + \gamma_{j(i)} + \varepsilon_{i,c,p}$$

In this context, $CAR_{i,c,p}$ denotes the CAR of firm i in crisis c and phase p. Industry fixed effects $\gamma_{j(i)}$ based on the Fama–French 12 industry classification are included to absorb systematic sector-level differences in crisis sensitivity, ensuring that the estimated coefficients reflect within-industry variation. Standard errors $\varepsilon_{i,c,p}$ are heteroskedasticity-robust, as firms contribute only a single observation to each regression. This approach provides insight into the mechanisms that shape firm resilience within distinct phases of individual crises.

The pooled crisis-phase regression design groups observations across crises within the same phase to identify systematic patterns in how firm characteristics relate to CARs across different crisis episodes. By combining firms observed during equivalent stages of the Dot-com bubble, the Global Financial Crisis, and the monetary tightening and inflation crisis, this approach focuses on cross-crisis regularities rather than crisis specific dynamics. In contrast to the event level design, all firms observed in a given phase are included, regardless of whether they appear in every phase of a crisis. Sample sizes for each pooled phase are reported in Appendix Table A.7. The pooled specification estimated for each phase is:

$$CAR_{i,c,p} = \beta_0 + \beta_1 BETA_{i,c,p} + \beta_2 VOL_{i,c,p} + \beta_3 SIZE_{i,c,p} + \beta_4 LEV_{i,c,p} + \beta_5 ROA_{i,c,p} + \beta_6 BEME_{i,c,p} + \beta_7 LIQ_{i,c,p} + \gamma_{j(i)} + \delta_c + \varepsilon_{i,c,p}$$

In this specification, observations from all crises that contain phase p are combined, while $CAR_{i,c,p}$ denotes the CAR of firm i in crisis c and phase p. Industry fixed effects $\gamma_{j(i)}$ are included to absorb persistent sector-level heterogeneity. Crisis fixed effects δ_c control for all crisis-specific components that affect CARs uniformly within a given crisis and would otherwise confound the estimated relationship between firm characteristics and CARs. By absorbing persistent differences across the crises, these fixed effects ensure that the coefficients on firm-level regressors are identified from within-phase variation across crises rather than from structural differences between crisis episodes. Firm fixed effects are not included, as they would absorb the cross-sectional variation in structural firm characteristics that this specification aims to explain. Standard errors $\varepsilon_{i,c,p}$ are clustered at the firm level to account for residual correlation arising from firms contributing multiple observations across different crises within the same phase. This pooled specification provides a complementary perspective to the event-level regressions by identifying whether firm characteristics exhibit consistent associations with abnormal returns across distinct crisis episodes.

3.5 Robustness Checks

The robustness checks assess whether the main empirical findings remain stable under standard modifications of the empirical setup. Specifically, they examine CAR-window sensitivity, the treatment of extreme observations, and sector-level heterogeneity. Some checks are implemented for both regression designs, while others are restricted to the event-level specification.

The first robustness check evaluates CAR-window sensitivity by re-estimating all models using alternative event windows, CAR (-1,+1) and CAR (-5,+5), in addition to the baseline CAR (-3,+3). These specifications capture a narrower and a broader adjustment horizon and assess whether the estimated relationships are sensitive to the length of the return accumulation interval.

The second robustness check examines sensitivity to the treatment of extreme firm-level observations. While the baseline specification applies winsorization at the 1st and 99th percentiles, all models are additionally estimated using a stricter 5th and 95th percentile threshold. This adjustment is applied to the baseline event window, as window sensitivity is addressed separately. The check is particularly relevant for the event-level regressions, which rely exclusively on cross-sectional variation for identification.

Additional robustness tests are conducted for the event-level regressions using the baseline CAR(-3,+3) window. First, all models are re-estimated without industry fixed effects to assess whether the results depend on controlling for sector-level heterogeneity. Second, following common practice, a sector exclusion robustness check is performed by removing firms in the financial and utility sectors. These sectors differ in regulatory environment and accounting structures, which may influence their crisis responses, and their exclusion provides an additional assessment of whether the main findings are driven by sector specific dynamics. The restricted sample excludes firms classified as financials (SIC 6000–6999) and utilities (SIC 4900–4949). The sector exclusion is not implemented in specifications that include industry fixed effects, as these already absorb systematic sector-level variation. It is likewise not applied to the pooled crisis-phase regressions, where industry fixed effects and crisis fixed effects are central to the identification strategy.

4. Results

This chapter presents the empirical results of the dissertation. The analysis proceeds in three steps. First, the event-level regressions are reported for each crisis. Second, the pooled crisis phase regressions are presented. Third, a set of robustness checks evaluates the stability of the findings under alternative event windows, different treatments of extreme observations, and modified model specifications.

4.1 Event-Level Regression Results

The event-level regressions examine how firm characteristics relate to CARs within each crisis and phase. By estimating separate regressions for each crisis, the analysis captures crisis-specific patterns in firm responses across comparable stages of market stress. The first crisis corresponds to the Dot-com period from 2000 to 2006. Table 8 reports event-level regression results for the four crisis phases, each containing 2,050 firm observations.

Explanatory Variable	Crisis 1 (2000 – 2006), CAR (-3,+3)			
	Beginning	Crash	Trough	Recovery
Intercept	0.041	-0.315***	-0.120***	0.037
	(0.039)	(0.047)	(0.042)	(0.027)
BETA	0.008	-0.022	0.011	-0.001
	(0.010)	(0.014)	(0.009)	(0.004)
VOL	-1.736***	-2.110***	-0.594**	-0.646**
	(0.218)	(0.309)	(0.260)	(0.285)
SIZE	0.000	0.018***	0.005***	-0.002
	(0.002)	(0.002)	(0.002)	(0.001)
BEME	-0.014	0.036**	-0.051***	-0.005
	(0.013)	(0.016)	(0.015)	(0.009)
LEV	0.030	0.233***	0.043	0.013
	(0.060)	(0.082)	(0.063)	(0.066)
ROA	0.010*	0.030***	-0.003	0.012***
	(0.005)	(0.006)	(0.007)	(0.005)
LIQ	-0.027	0.047**	0.002	-0.012
	(0.018)	(0.022)	(0.019)	(0.013)
Mean CAR	-0.026	-0.027	-0.053	-0.007
N	2,050	2,050	2,050	2,050
Adj. R^2	0.176	0.300	0.057	0.037
F-statistic	16.374	36.400	8.190	3.922
IND FE	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses.

*Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.*

Table 8. Event-level regression results for crisis 1 (2000 – 2006)

Mean CARs are negative in all phases, with values ranging from -0.007 in the recovery phase to -0.053 at the trough. The explanatory power of the regressions differs across phases. Adjusted R^2 values range from 0.037 to 0.300, with the highest value observed during the crash phase. F-statistics indicate that the regressors are jointly significant in all four phases. In the beginning phase, VOL exhibits a strong negative and statistically significant association with CARs. ROA is positively related to CARs, although the estimated effect is smaller in magnitude. During the crash phase, several firm characteristics become statistically relevant. VOL remains strongly and significantly negatively associated with CARs and stands out as the most consistently relevant characteristic in this phase. In addition, SIZE, BEME, LEV, ROA, and LIQ all display positive and statistically significant associations with CARs. In the trough phase, the number of statistically significant coefficients declines. VOL continues to exhibit a negative association with CARs, although the estimated effect is smaller than during the crash phase. SIZE remains positively related to CARs, while BEME shows a statistically significant negative association. The recovery phase is characterized by statistical significance only for VOL and ROA. Both effects are weaker relative to earlier phases, suggesting more limited systematic cross-sectional variation in CARs during the recovery period. Taken together, the results for Crisis 1 indicate that VOL is the most consistently significant firm characteristic across all phases. The relevance of other firm characteristics is strongly phase dependent. SIZE and BEME are primarily associated with CARs during the crash and trough phases, while ROA is significant outside the trough. BETA remains statistically insignificant throughout the crisis, and LEV and LIQ are relevant only during the crash phase. Overall, the findings highlight pronounced phase dependence in the cross-sectional determinants of CARs during the Dot-com period.

Crisis 2 relates to the Global Financial Crisis and covers the years 2007 to 2012. The regression estimates are reported in Table 9. Each phase includes 2,379 firm observations. Mean CARs remain slightly negative across all stages, ranging from -0.002 to -0.005. Adjusted R^2 values lie between 0.020 and 0.123, with the highest value in the crash phase. The F-statistics confirm that the regressors are jointly significant in every phase.

Explanatory Variable	Crisis 2 (2007 – 2012), CAR (-3,+3)			
	Beginning	Crash	Trough	Recovery
Intercept	-0.096	0.016	-0.077*	-0.026
	(0.062)	(0.054)	(0.046)	(0.022)
BETA	-0.021***	0.086***	0.021**	0.005
	(0.008)	(0.006)	(0.010)	(0.004)
VOL	0.884	-1.169***	-0.042	0.075
	(0.757)	(0.313)	(0.295)	(0.229)
SIZE	0.003	-0.002	0.001	-0.000
	(0.003)	(0.002)	(0.002)	(0.001)
BEME	-0.007	-0.040***	0.008	0.017**
	(0.009)	(0.014)	(0.020)	(0.008)
LEV	-0.076	-0.057	-0.005	0.001
	(0.115)	(0.069)	(0.056)	(0.048)
ROA	0.009	-0.007	0.017***	0.017***
	(0.009)	(0.007)	(0.006)	(0.003)
LIQ	0.007	-0.050***	0.042**	0.021**
	(0.011)	(0.015)	(0.017)	(0.010)
Mean CAR	-0.002	-0.004	-0.005	-0.004
N	2,379	2,379	2,379	2,379
Adj. R^2	0.039	0.123	0.020	0.057
F-statistic	6.134	17.930	4.972	15.957
IND FE	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses.

*Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.10.*

Table 9. Event-level regression results for crisis 2 (2007 – 2012)

At the beginning of the crisis, BETA is the only firm characteristic that exhibits a statistically significant association with CARs, with a negative coefficient. During the crash phase, the number of statistically significant coefficients increases considerably. BETA turns positive and highly significant, representing a reversal relative to the beginning phase. VOL exhibits a strong negative association with CARs. In addition, BEME and LIQ are negatively and statistically significantly related to CARs. The pattern of statistically significant associations shifts again in the trough phase. BETA remains positively associated with CARs, while ROA and LIQ display positive and statistically significant coefficients. Compared to the crash phase, the explanatory power of the regressions declines substantially. In the recovery phase, ROA and LIQ continue to be positively and statistically significantly associated with CARs. BEME also becomes positive and statistically significant, while no other firm characteristics display systematic associations with CARs. Overall, the results for Crisis 2 indicate pronounced phase dependence in the cross-sectional determinants of CARs during the Global Financial Crisis. BETA, BEME, and LIQ exhibit sign changes across phases, highlighting the sensitivity of their associations with CARs to the stage of the crisis. VOL is statistically relevant during the crash phase, while ROA becomes significant only from the trough phase onward. By contrast, SIZE and LEV do not display statistically significant associations in any phase.

The third crisis corresponds to the post-pandemic tightening cycle from 2021 to 2024. Table 10 reports the event-level regression estimates for this period, with 2,723 firm observations in each phase. Mean CARs are slightly negative throughout the crisis and range from -0.001 in the crash phase to -0.011 at the trough. The explanatory power of the regressions varies substantially, with adjusted R^2 values between 0.036 and 0.211. The highest model fit is observed during the crash phase. In all phases, the F-statistics indicate joint significance of the explanatory variables.

Explanatory Variable	Crisis 3 (2021 – 2024), CAR (-3,+3)			
	Beginning	Crash	Trough	Recovery
Intercept	0.167***	-0.023	0.071***	0.125***
	(0.028)	(0.030)	(0.022)	(0.030)
BETA	0.024***	0.034***	-0.007	0.017**
	(0.005)	(0.008)	(0.006)	(0.007)
VOL	-1.467***	0.849**	-1.281***	-1.094***
	(0.180)	(0.338)	(0.198)	(0.288)
SIZE	-0.006***	-0.001	-0.002*	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
BEME	-0.005	-0.060***	-0.006	-0.001
	(0.009)	(0.010)	(0.011)	(0.010)
LEV	0.144***	-0.089*	-0.019	-0.067
	(0.047)	(0.052)	(0.055)	(0.052)
ROA	-0.003	0.004	0.006	0.006*
	(0.004)	(0.006)	(0.004)	(0.003)
LIQ	0.006	0.029**	-0.032***	-0.020*
	(0.010)	(0.014)	(0.012)	(0.011)
Mean CAR	-0.002	-0.001	-0.011	-0.003
N	2,723	2,723	2,723	2,723
Adj. R^2	0.125	0.211	0.097	0.036
F-statistic	13.987	41.790	14.186	5.477
IND FE	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses.

*Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.*

Table 10. Event-level regression results for crisis 3 (2021 – 2024)

At the beginning of the tightening cycle, several firm characteristics are statistically significant. BETA exhibits a positive association with CARs, while VOL and SIZE display negative and statistically significant coefficients. LEV is also positively and significantly related to CARs. During the crash phase, the pattern of significant associations changes. BETA remains positive and highly significant, while VOL turns positive and statistically significant. BEME exhibits a negative association with CARs, whereas LIQ is positively and statistically significantly related to CARs. LEV enters with a negative coefficient that is weakly significant. In the trough phase, the composition of statistically significant coefficients changes. VOL reverts to a negative and statistically significant association with CARs, and LIQ also enters with a negative and significant coefficient. SIZE is weakly significant and negative. The recovery phase is characterized by a positive and statistically significant association between BETA and CARs. VOL remains negatively and significantly related to CARs, and SIZE enters with a negative and highly significant coefficient. ROA becomes positive and weakly significant, while LIQ continues to display a negative and statistically significant association with CARs. Taken together, the results for Crisis 3 indicate pronounced phase dependence in the cross-sectional determinants of CARs during the post-pandemic tightening cycle. VOL is statistically significant in all phases, although the sign of its association varies across stages of the crisis. SIZE is predominantly negatively associated with CARs outside the crash phase, while BETA displays positive associations in most phases except the trough. LEV and LIQ exhibit shifts in sign and statistical significance across phases, whereas ROA and BEME are relevant only in specific stages of the tightening cycle.

4.2 Pooled Crisis-Phase Regression Results

The pooled-regression design summarizes systematic cross-crisis patterns within each crisis phase while controlling for industry and crisis fixed effects. Table 11 reports the corresponding pooled crisis-phase regression results. Across all phases, mean CARs are negative, ranging from -0.006 in the recovery phase to -0.026 at the trough. The F-statistics show that the regressors are jointly significant throughout all four phases, confirming the relevance of firm characteristics for explaining cross-sectional variation in CARs within each phase.

Explanatory Variable	Pooled Crisis-Phase Regression, CAR(-3,+3)			
	Beginning	Crash	Trough	Recovery
Intercept	0.098***	-0.042*	-0.059***	0.050***
	(0.016)	(0.024)	(0.018)	(0.014)
BETA	0.001	0.035***	0.016***	0.001
	(0.003)	(0.006)	(0.004)	(0.002)
VOL	-1.546***	-2.195***	-0.737***	-0.687***
	(0.105)	(0.158)	(0.118)	(0.135)
SIZE	-0.004***	0.003***	0.001	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
BEME	-0.001	-0.012	-0.023***	0.001
	(0.005)	(0.013)	(0.008)	(0.005)
LEV	0.049*	0.088	0.011	-0.016
	(0.029)	(0.059)	(0.027)	(0.026)
ROA	0.004	0.022***	0.010***	0.010***
	(0.003)	(0.004)	(0.003)	(0.002)
LIQ	0.007	0.061***	-0.004	-0.006
	(0.006)	(0.011)	(0.008)	(0.006)
Mean CAR	-0.014	-0.024	-0.026	-0.006
N	10,818	10,849	10,948	11,014
Adj. R^2	0.103	0.103	0.052	0.024
F-statistic	31.590	33.078	26.354	11.670
IND FE	Yes	Yes	Yes	Yes
Crisis FE	Yes	Yes	Yes	Yes

Note: Standard errors clustered at the firm level in parentheses.
*Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.*

Table 11. Pooled crisis-phase regression

In the beginning phase, the pooled regression is estimated based on 10,818 firm-phase observations, with a mean CAR of -0.014. VOL exhibits a negative and statistically significant association with CARs, while SIZE also enters with a negative and significant coefficient. LEV is positive and weakly significant in this phase. The crash phase is based on a pooled sample of

10,849 observations with a mean CAR of -0.024. VOL remains negative and statistically significant. In addition, BETA and SIZE are positive and statistically significant, and ROA and LIQ also enter positively and significantly. The pooled trough phase includes 10,948 observations with a mean CAR of -0.026. VOL continues to be negatively and statistically significantly associated with CARs. BETA and ROA remain positive and significant, while BEME enters with a negative and statistically significant coefficient. In the recovery phase, mean CARs amount to -0.006 based on a pooled sample of 11,014 observations. VOL and SIZE are negative and statistically significant, and ROA remains positively and significantly associated with CARs. Overall, the pooled results show pronounced phase dependence in the cross-sectional determinants of CARs. VOL is consistently negative and statistically significant across all four phases. ROA is positively associated with CARs from the crash phase onward, while BETA is statistically significant only during the crash and trough phases. LIQ is significant exclusively in the crash phase, and BEME is relevant only at the trough, where it enters with a negative coefficient. LEV is weakly significant only in the beginning phase. SIZE varies across phases, entering negatively in the beginning and recovery phases and positively during the crash, while it is not statistically significant at the trough. These systematic patterns form the empirical basis for the interpretation in the subsequent discussion chapter.

4.3 Robustness Checks Results

The robustness analysis examines whether the empirical findings are sensitive to specific modelling choices. The first set of robustness checks evaluates sensitivity to the width of the CAR event window. All regressions are re-estimated using alternative windows CAR (-1,+1) and CAR (-5,+5). For the event-level regressions, the main patterns observed in the baseline specification remain intact across the alternative windows. Given the large number of crisis-phase regressions, some variation in coefficient estimates and significance is expected. Changes in sign or statistical significance are generally limited and do not affect the interpretation of the core results. The corresponding estimates are reported in Tables A.8.a–A.8.c. The pooled crisis-phase regressions exhibit a high degree of stability across alternative event windows. Coefficient signs are largely consistent across specifications, with only minor variation in statistical significance for a small number of coefficients. Overall, no systematic reversals in the estimated relationships are observed, indicating that the pooled findings are not driven by the specific choice of the return accumulation window. The corresponding results are reported in Table A.9.

The second robustness check examines sensitivity to the treatment of extreme observations. All regressions are re-estimated using 5th and 95th percentile winsorization instead of the baseline 1st and 99th percentile threshold. For the event-level regressions, the overall pattern of results remains robust, with only limited deviations across specifications. The pooled crisis-phase regressions display even greater stability, with coefficient signs and significance levels closely aligned with the baseline specification. The corresponding estimates are reported in Tables A.10.a–A.10.c and Table A.11.

An additional robustness check assesses whether the event-level results depend on controlling for sector-level heterogeneity by re-estimating all event-level regressions without industry fixed effects. Across crises and phases, the direction and significance of the key coefficients are preserved. These results are reported in Tables A.12.a–A.12.c.

The final robustness check evaluates whether the event-level findings are sensitive to industry exclusion. All event-level regressions are therefore re-estimated after excluding financial and utility firms. Across the three crises and all phases, the core patterns of the baseline specification remain largely unchanged, with only limited deviations observed. The corresponding estimates are reported in Tables A.13.a–A.13.c.

In conclusion, the robustness checks demonstrate that the empirical results are robust under a wide range of reasonable modifications to the empirical setup. Varying the CAR event window, tightening the winsorization threshold, removing industry fixed effects, and excluding financial and utility firms leaves the core findings largely unaffected. Any deviations that arise remain limited and do not affect the overall conclusions.

5. Discussion

This chapter discusses the empirical results and places them into a broader economic and empirical context. It first examines crisis-specific patterns in firm resilience, then examines systematic cross-phase regularities, and finally relates the findings to the existing empirical literature. The discussion highlights how crisis resilience reflects both phase-dependent dynamics and more stable firm-level determinants.

5.1 Crisis-Specific Evidence on Resilience

The following discussion presents event-level evidence on firm resilience across individual crises. Focusing on crisis-specific dynamics provides insight into how resilience varies across phases and crises.

The Dot-com crisis was driven by the correction of inflated growth expectations and an extended reassessment of equity valuations. In this environment, crisis resilience is most consistently associated with lower uncertainty. Firms with higher return volatility exhibit weaker abnormal performance in every phase, which implies that they were less resilient throughout the episode. The phase results further show that resilience varies across phases. During the crash and trough phases, larger firms display comparatively stronger abnormal performance, pointing to a temporary resilience advantage when market stress intensifies. Outside the trough, resilience appears to be more closely linked to operating strength. Higher profitability is associated with stronger abnormal performance at the beginning of the crisis and during the recovery. At the same time, valuation signals do not produce a stable resilience ranking, as their association changes across phases. This instability indicates that resilience cannot be attributed to a single persistent firm profile throughout the crisis.

The Global Financial Crisis was triggered by the collapse of the housing market and severe disruptions in the financial system. Major institutional failures and a sharp loss of confidence shaped the downturn, followed by a slow recovery marked by deleveraging and capital rebuilding. From a resilience perspective, the event-level evidence suggests that the market did not rely on a single, stable firm profile across phases. At the onset of the crisis, firms with stronger exposure to market-wide movements exhibit weaker abnormal performance, indicating lower resilience in the early stage of the crisis, even after adjusting for expected market risk.

As stress intensifies, resilience becomes more closely associated with lower uncertainty and the ability to withstand liquidity pressure. During the crash phase, higher uncertainty is linked to weaker abnormal performance, and firms with limited liquidity appear less resilient. In contrast, liquidity becomes positively associated with resilience in the trough and recovery phases, indicating that the attributes supporting resilience shift as market conditions evolve across crisis phases. Operating strength only becomes relevant from the trough onward. This pattern is consistent with resilience increasingly reflecting firm-level differentiation once markets move beyond systemic panic and begin to reassess fundamentals. Two findings stand out in the context of the crisis. Leverage does not exhibit a significant association with abnormal performance in any phase, despite the central role of balance-sheet stress in the crisis. In addition, sign reversals across phases indicate that perceptions of resilience changed over the course of the crisis, rather than reflecting a fixed ranking of firms that consistently outperformed.

The third crisis was characterized by a policy-driven repricing episode triggered by persistent inflation and rapid monetary tightening. Regarding crisis resilience, the event-level evidence points to pronounced phase dependence and a particularly unstable definition of what constituted resilience. At the beginning of the tightening cycle, resilience favored firms with more stable return profiles. As the episode progressed, resilience became more closely linked to market exposure, although this relationship weakened at the trough. The crash phase is particularly informative for interpreting resilience in this episode. In the broader sample reported in Table 6, mean CARs around the crash are positive. In contrast, crash-phase mean CARs in the event-level regression sample are close to zero and only slightly negative. This difference suggests that the event-level regression sample reflects not only price declines but also temporary price reversals within the fixed event window. In this setting, return volatility turns positive and liquidity is positively associated with abnormal performance. Taken together, these patterns suggest that crash-phase results are more strongly influenced by short-term market dynamics than by persistent firm-level resilience. In the trough and recovery phases, volatility again becomes negatively associated with abnormal performance, while liquidity turns negative, indicating that the criteria underlying resilience rotated as the episode moved from acute repricing toward its low point and into recovery. Firm size also plays a distinct role. Outside the crash phase, smaller firms achieve relatively stronger abnormal performance, suggesting that resilience in this episode was not concentrated among large firms, in contrast to the peak stress phases of the Dot-com crisis. Finally, profitability is linked to resilience only in the recovery phase, implying that firm fundamentals become more relevant once the tightening shock is partially absorbed and markets begin to differentiate again.

The event-level evidence shows that crisis resilience is context dependent and varies across phases, with cross-sectional relationships shifting as crises progress. This motivates the pooled crisis-phase regressions, which examine whether common phase-level patterns emerge across crisis. By moving beyond single-crisis estimates, the pooled analysis distinguishes recurring phase-specific regularities from crisis-specific effects. Overall, the event-level results highlight the limits of crisis-by-crisis generalization and support a phase-based view of resilience rather than the notion of a single firm profile that consistently outperforms during market stress.

5.2 Cross-Phase Patterns in Crisis Resilience

The pooled crisis-phase regressions provide evidence on which firm characteristics are systematically associated with stronger crisis resilience, measured by abnormal stock performance around phase events. By pooling observations across crises within the same phase and controlling for industry and crisis fixed effects, the results isolate recurring phase regularities rather than crisis specific patterns.

In the beginning phase, resilience is primarily associated with lower firm-specific uncertainty. Firms with lower return volatility exhibit stronger abnormal performance, indicating that predictability is valued as markets transition from normal conditions into stress. Firm size is also relevant at crisis onset, with smaller firms displaying greater resilience. Leverage exhibits a positive association at a marginal significance level, suggesting that higher leverage may be linked to stronger resilience, although the evidence remains weak.

During the crash phase, resilience is shaped by a broader set of firm characteristics. Lower return volatility remains a central advantage and represents the most economically important effect in this phase. At the same time, higher market beta is associated with stronger relative performance, indicating that resilience during the sharp downturn is not confined to low-beta firms. Beyond risk, higher profitability and stronger liquidity are associated with greater resilience, consistent with markets differentiating more strongly as short-term funding conditions tighten. Larger firms also show higher resilience in this phase.

At the trough, resilience still reflects risk exposure and fundamentals, although the specific drivers change again. Lower return volatility remains beneficial, and higher market beta continues to be positively associated with resilience. Profitability remains positively associated with resilience, indicating that operating strength becomes more relevant as the downturn reaches its low point and investors begin to reassess firms more selectively. Valuation becomes relevant only in this phase, with firms exhibiting higher book-to-market ratios showing weaker resilience. This pattern is consistent with weaker relative performance among firms with higher book-to-market ratios, which are often associated with greater financial distress or lower growth expectations.

In the recovery phase, resilience shifts further toward fundamentals and away from market-wide risk exposure. Lower return volatility continues to support stronger relative performance, and profitability remains positively related to resilience. Firm size turns negative in recovery, implying that smaller firms experience a stronger rebound in abnormal performance terms.

Across crisis phases, the pooled evidence highlights recurring patterns in how several firm characteristics shape resilience. First, low return volatility is the only characteristic that is consistently associated with higher resilience across phases, indicating that firm-specific uncertainty represents the most stable component of crisis resilience. Second, higher profitability is generally associated with greater resilience across phases but becomes statistically significant only from the crash onward. Third, the positive association between market beta and resilience indicates that systematic market exposure is not uniformly associated with weaker abnormal performance during crises. This relationship is empirically most pronounced during the crash and trough phases, where estimated effects are larger and statistically significant. Finally, firm size displays a phase-dependent role. Larger firms are more resilient during the crash and trough phases, although the effect at the trough is not statistically significant. Other firm characteristics do not exhibit consistent patterns across phases.

Taken together, the pooled evidence directly answers the research question by showing which firm characteristics are systematically associated with crisis resilience across crisis phases. Crisis resilience reflects a combination of stable and phase-specific determinants.

5.3 Comparison with Existing Empirical Evidence

This chapter relates the pooled crisis-phase results to the empirical evidence reviewed in Chapter 2.3. Any comparison should be interpreted with caution, as prior studies employ diverse crisis definitions, return horizons, and empirical designs, which can affect both the estimated signs and their statistical significance. Against this background, the pooled crisis-phase regressions provide the most appropriate basis for comparison, as they abstract from crisis-specific idiosyncrasies and identify recurring patterns that are robust across different crises, while preserving the phase structure.

The pooled regression results align closely with the existing literature with respect to firm-specific risk. Prior empirical studies consistently link higher volatility to weaker crisis outcomes. This is strongly supported by the empirical findings of this dissertation. Lower return volatility is associated with higher resilience in every phase, and the estimated effects are sizeable in magnitude, for example -2.195 in the crash phase. Systematic risk exposure contrasts with much of the existing literature. While prior studies typically associate higher market beta with weaker crisis performance, the pooled results do not indicate a systematic negative relationship between beta and resilience. This suggests that the role of systematic exposure depends on the empirical design used to assess crisis performance.

Firm size shows overall alignment with the existing literature. Prior empirical evidence suggests that larger firms tend to be more resilient during crises. The pooled results are broadly consistent with this finding but indicate that the size advantage is phase dependent. Larger firms exhibit higher resilience during the crash phase, while the size effect remains positive but not statistically significant at the trough. In contrast, smaller firms are relatively more resilient in the beginning and recovery phases. This pattern is consistent with the existing evidence, which typically focuses on periods of peak market stress and therefore captures primarily the most severe stages of downturns.

Valuation shows partial alignment with the existing literature, but its role is clearly confined to specific stages of a crisis. Previous studies often document that firms with higher book-to-market ratios underperform relative to growth-oriented firms during crisis periods. The pooled results are consistent with this pattern in terms of direction, but indicate that valuation differences matter mainly at the trough. At this point, firms with higher book-to-market ratios display significantly weaker resilience (−0.023, $p < 0.01$), suggesting that valuation becomes informative for resilience primarily when market stress reaches its peak.

Capital structure and liquidity display different degrees of alignment with the existing empirical evidence reviewed in Chapter 2.3. Prior empirical studies characterise leverage as being consistently associated with weaker crisis outcomes, whereas liquidity effects are widely documented as less uniform and strongly context dependent. In the pooled regressions, leverage does not exhibit a robust relationship with resilience. It is only weakly significant in the beginning phase (0.049, $p < 0.10$) and statistically insignificant in all subsequent phases, including the recovery phase where the estimated coefficient turns negative. This divergence may reflect the methodological heterogeneity emphasised in the review, including differences in return measures, horizons, and control variables across studies. By contrast, liquidity is more consistent with prior evidence highlighting strong context dependence. In the pooled results, higher liquidity is statistically significant only in the crash phase (0.061, $p < 0.01$) and does not contribute to explaining resilience in the remaining phases.

Finally, the pooled profitability results fully align with the existing empirical evidence. Prior studies generally associate higher profitability with better crisis outcomes. The pooled regressions confirm this pattern, showing that profitability becomes statistically relevant from the crash phase onwards, while it is not significant at the initial onset of the crisis.

Overall, the comparison confirms key insights from prior evidence while highlighting that the relevance of firm characteristics for crisis resilience depends on the crisis phase. The phase-based design helps identify in which stages of a crisis different firm characteristics become relevant for resilience.

6. Limitations

This chapter outlines the main limitations of the empirical design. Crises are identified using a threshold-based CMAX framework with an explicit phase structure. While this approach allows a differentiated examination of firm behaviour across crisis stages, it limits direct comparability with prior research, which often treats crises as single episodes. In addition, the recovery phase extends until the previous market peak is fully reached, resulting in long periods that may encompass heterogeneous market conditions. This complicates the interpretation of firm-level behaviour within this phase and may dilute underlying patterns. Moreover, due to the relatively short time spans between several crisis episodes and the application of a minimum separation criterion, the final sample is restricted to three distinct crises, which limits the generalisability of the results.

The findings are further shaped by modelling choices in the event study design. Abnormal returns are estimated using the market model, which controls only for market-wide movements and does not account for additional risk factors. Finally, the results reflect the characteristics of U.S. listed firms, so conclusions should not be generalised beyond this specific market environment.

7. Conclusion

The empirical evidence indicates that firm-level resilience is strongly phase dependent and only partly stable when crises are analyzed separately. Event-level regressions show that cross-sectional relationships frequently shift across episodes, which limits generalization across individual crises. In contrast, more systematic patterns emerge when crises are compared within the same phase using pooled regressions with industry and crisis fixed effects. Across phases, lower return volatility is always linked with higher resilience, representing the most robust relationship identified in the analysis. Beyond volatility, systematic market risk is associated with greater resilience in the crash and trough phases. Furthermore, higher profitability is generally related to greater resilience. Firm size displays pronounced phase variation, with a positive association during the crash phase but negative associations in the beginning and recovery phases. Accordingly, larger firms tend to exhibit stronger resilience under particularly heightened market stress, whereas smaller firms display relatively stronger resilience at the onset of crises and the recovery phase. Beyond these more systematic patterns, some firm characteristics exhibit relevance only at specific crisis stages, underscoring the importance of a phase-based perspective. Overall, the main findings imply that resilience reflects a combination of stable and phase-specific determinants rather than a single firm type that outperforms uniformly throughout a crisis.

The dissertation contributes to the literature by adopting a phase-based crisis design that preserves the internal dynamics of crises and enables a systematic comparison of firm characteristics across comparable stages of market stress. Moreover, the combined use of event-level and pooled crisis-phase regressions helps separate crisis-specific effects from recurring phase patterns, thereby clarifying which firm characteristics exhibit more reliable and recurring associations with resilience. Robustness checks across alternative event windows, outlier treatments, and sector-based sensitivity analyses further support the stability of the main findings.

The findings have important implications for investors. In particular, they indicate that relative firm performance during market crises cannot be captured by a single, time-invariant measure of crisis resilience, but varies systematically across crisis phases. As a result, resilience-oriented investment strategies and portfolio allocations should explicitly account for the changing relevance of firm characteristics in order to enhance relative performance across different crisis phases.

The interpretation of the results is subject to several limitations, which also motivate future research. Future research could assess whether the documented patterns persist under alternative recovery definitions that shorten the recovery phase. In addition, computing abnormal returns with multi-factor models, such as Fama–French specifications, would help evaluate the robustness of the results. Extending the analysis to other market environments would further clarify the generality of phase-specific determinants of resilience.

8. Appendices

Number	Beginning	Crash	Trough	Recovery
1	16 July 1990	11 October 1990	11 October 1990	11 February 1991
2	17 July 1998	31 August 1998	08 October 1998	23 December 1998
3	24 March 2000	20 December 2000	09 October 2002	05 April 2006
4	09 October 2007	15 September 2008	09 March 2009	16 March 2012
5	19 February 2020	12 March 2020	23 March 2020	12 August 2020
6	08 November 2021	13 June 2022	14 October 2022	23 January 2024

Table A.1. All identified crisis before applying separation criterion

Number	Beginning – Crash	Crash – Trough	Trough – Recovery	Beginning – Recovery
1	62	0	84	146
2	31	27	53	111
3	188	449	878	1515
4	235	120	763	1118
5	16	7	99	122
6	149	86	318	553

Table A.2. Trading days between identified crisis phases (values in red indicate violations of the minimum separation criterion)

Type	Category	Variable	Abbr.	Formula	Source	Reference Period	Notes
Dependent	Performance Measure	Cumulative Abnormal Return	CAR	$CAR_i(T_1,T_2) = \sum_{t=T_1}^{T_2} ln(1 + Abnormal\ Return_{i,t}^{discrete})$	CRSP	Baseline window: (-3,+3) Robustness windows: (-1,+1), (-5,+5)	Abnormal returns (AR) are estimated with the market model (CAPM). Discrete AR are converted to continuously compounded returns via ln. The estimation window comprises 252 trading days with a 20-day gap, requiring at least 200 non-missing observations.
Explanatory	Market-based	Beta	BETA	$R_{i,t} = \alpha_i + \beta_i R_{m,t}$	WRDS Beta Suite / CRSP	Five-year estimation window (252 trading days per year), ending on the fifth trading day before the event (T-5)	Estimated using the market model (CAPM) on daily log returns. A minimum of three years of non-missing daily observations (756 trading days) is required to ensure estimation reliability.
		Return Volatility	VOL	$VOL_i = \ Standard\ Deviation(ln(1 + r_{i,t}))$	CRSP	252 trading days, ending T-30	Computed from daily log returns (pre-event window).
		Firm Size	SIZE	$SIZE_i\ = ln(Price \times Number\ of\ \ Shares\ Outstanding)$	CRSP	Fifth trading day prior to the event (T-5)	Calculated as the natural logarithm of market capitalization. Absolute prices are used to correct for negative price coding for short-sale/bid–ask conventions.
		Book-to-Market	BEME	$BEME_i = \frac{Common\ \ Ordinarty\ Equity\ Total}{Price\ Close \times Common\ Shares\ Outstanding}$	Compustat	Most recent quarterly report before the event date	Based on the Report Date of Quarterly Earnings (last published report with rdq < event date)
	Accounting-based	Leverage	LEV	$LEV_i = \frac{Debt\ in\ Current\ Liabilities + Long\ Term\ Debt}{Total\ Assets}$	Compustat	Most recent quarterly report before the event date	Based on the Report Date of Quarterly Earnings (last published report with rdq < event date)
		Return on Assets	ROA	$ROA_i = \frac{Net\ Income}{Total\ Assets}$	Compustat	Most recent quarterly report before the event date	Based on the Report Date of Quarterly Earnings (last published report with rdq < event date)
		Liquidity	LIQ	$LIQ_i = \frac{Cash\ and\ Short\ Term\ Investments}{Total\ Assets}$	Compustat	Most recent quarterly report before the event date	Based on the Report Date of Quarterly Earnings (last published report with rdq < event date)
Controls	Controls	Industry Fixed Effects	IND FE	-	Fama-French	Static (time-invariant)	Mapped from firm SIC codes using Fama-French industry file

Table A.3. Variable definitions, formulas, and data source

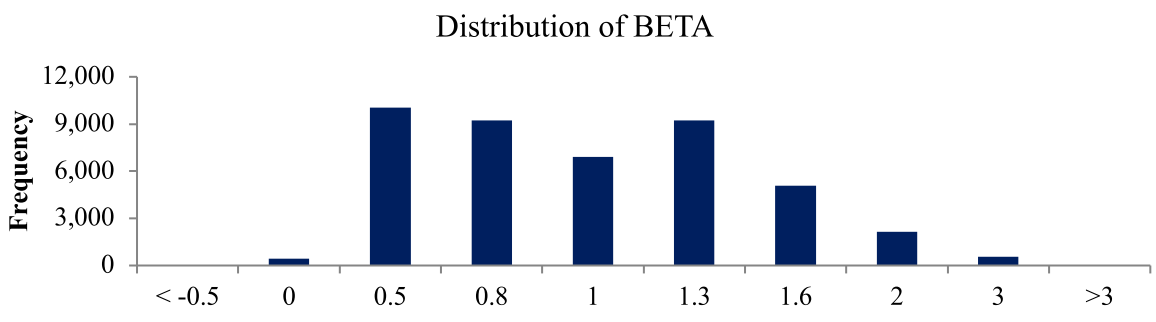

Figure A.1. Distribution of BETA (raw data)

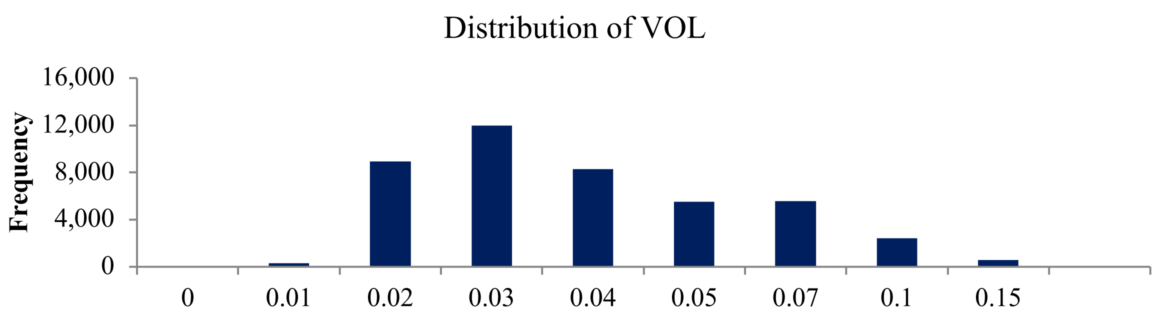

Figure A.2. Distribution of VOL (raw data)

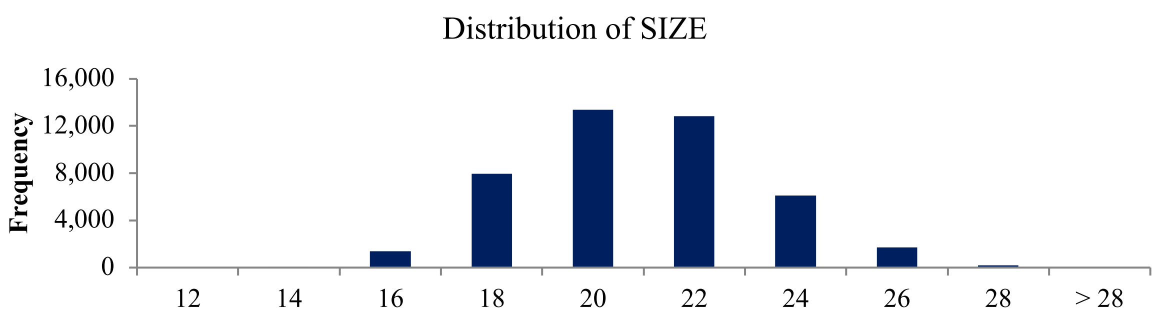

Figure A.3. Distribution of SIZE (raw data)

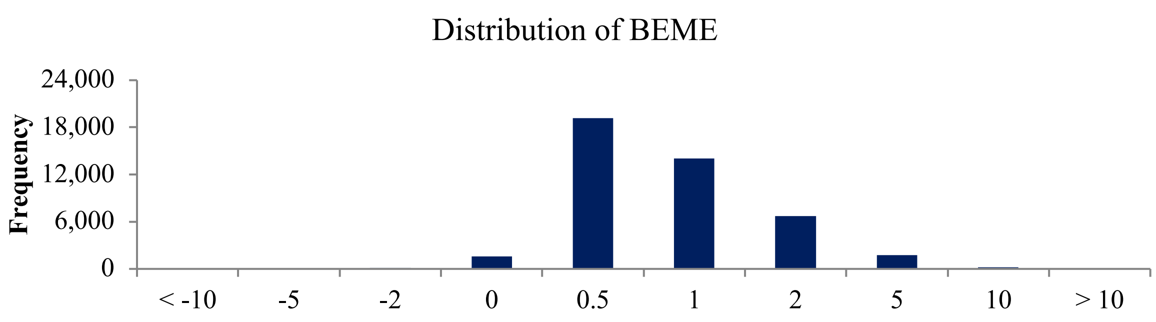

Figure A.4. Distribution of BEME (raw data)

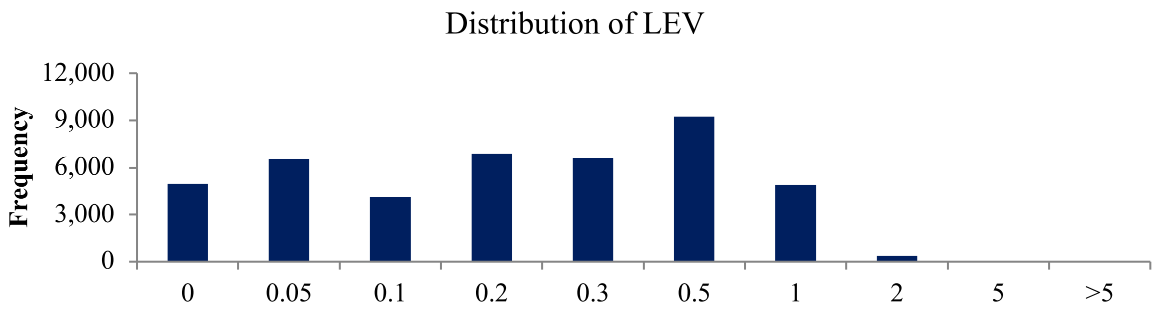

Figure A.5. Distribution of LEV (raw data)

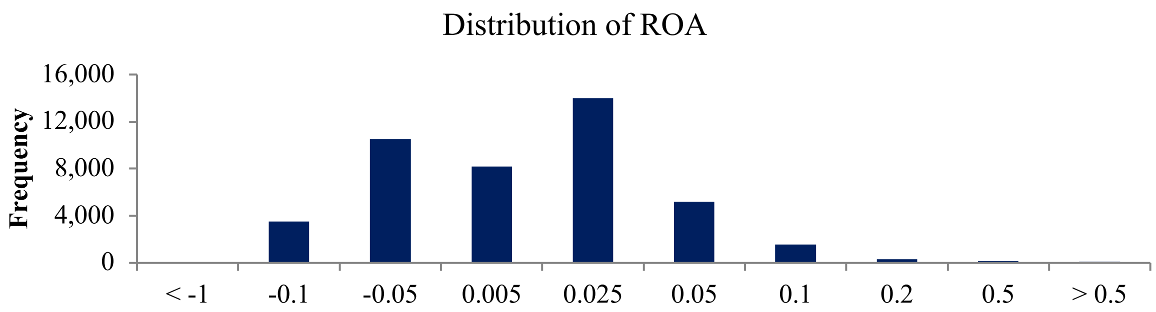

Figure A.6. Distribution of ROA (raw data)

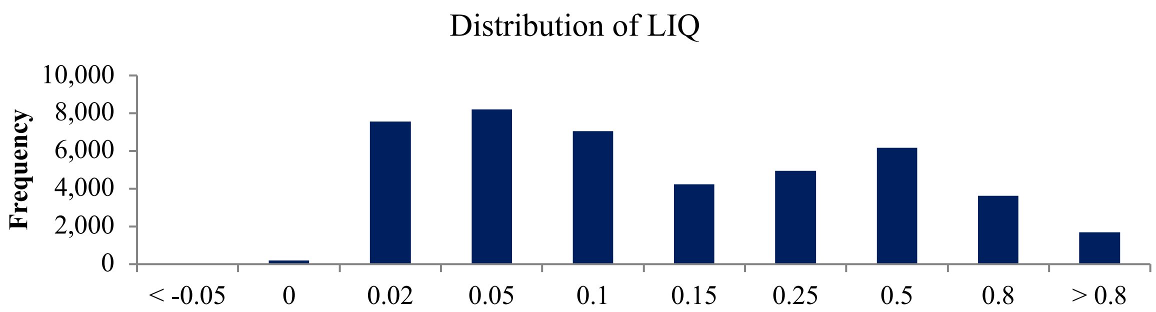

Figure A.7. Distribution of LIQ (raw data)

Variable	Phase	N	Mean	SD	Min	P25	Median	P75	Max
Beta	Beginning	3,967	0.596	0.391	-0.516	0.301	0.546	0.818	2.743
	Crash	4,008	0.611	0.446	-0.430	0.280	0.530	0.830	2.940
	Trough	3,941	0.672	0.516	-0.521	0.300	0.576	0.889	3.260
	Recovery	4,012	0.774	0.510	-0.500	0.400	0.720	1.050	2.860
VOL	Beginning	3,967	0.041	0.022	0.005	0.024	0.036	0.052	0.171
	Crash	4,008	0.047	0.024	0.006	0.028	0.041	0.061	0.222
	Trough	3,941	0.040	0.022	0.006	0.024	0.034	0.052	0.169
	Recovery	4,012	0.024	0.013	0.006	0.016	0.021	0.029	0.121
SIZE	Beginning	3,967	19.369	2.053	13.553	17.881	19.164	20.657	26.963
	Crash	4,008	19.004	2.238	12.378	17.340	18.777	20.493	26.987
	Trough	3,941	18.955	2.145	12.646	17.422	18.854	20.410	26.232
	Recovery	4,012	20.091	1.955	13.653	18.698	20.046	21.357	26.648
BEME	Beginning	3,967	0.672	0.711	-7.607	0.254	0.544	0.914	9.475
	Crash	4,008	0.600	10.710	-674.845	0.279	0.579	1.009	16.880
	Trough	3,941	0.688	1.351	-49.222	0.347	0.569	0.906	18.393
	Recovery	4,012	0.478	0.636	-24.190	0.276	0.446	0.661	8.157
LEV	Beginning	3,967	0.247	0.240	0.000	0.053	0.211	0.373	3.258
	Crash	4,008	0.236	0.227	0.000	0.042	0.201	0.365	2.575
	Trough	3,941	0.225	0.249	0.000	0.030	0.179	0.343	5.022
	Recovery	4,012	0.202	0.216	0.000	0.019	0.156	0.302	3.096
ROA	Beginning	3,967	-0.004	0.087	-2.630	-0.002	0.006	0.019	1.061
	Crash	4,008	-0.006	0.087	-0.977	-0.005	0.005	0.019	1.613
	Trough	3,941	-0.015	0.118	-3.172	-0.007	0.004	0.015	1.326
	Recovery	4,012	0.003	0.120	-1.540	0.001	0.009	0.022	4.418
LIQ	Beginning	3,967	0.147	0.202	0.000	0.017	0.051	0.189	1.000
	Crash	4,008	0.150	0.211	-0.006	0.016	0.048	0.198	1.000
	Trough	3,941	0.168	0.210	0.000	0.025	0.073	0.234	1.000
	Recovery	4,012	0.188	0.217	0.000	0.030	0.095	0.274	1.000

Table A.4.a. Descriptive statistics of explanatory variables, crisis 1 (2000–2006), raw data

Variable	Phase	N	Mean	SD	Min	P25	Median	P75	Max
Beta	Beginning	3,549	0.873	0.479	-0.391	0.537	0.875	1.185	2.667
	Crash	3,491	0.965	0.483	-0.365	0.611	1.005	1.329	2.467
	Trough	3,653	0.966	0.476	-0.648	0.636	0.991	1.291	3.894
	Recovery	3,577	1.017	0.491	-0.177	0.676	1.030	1.364	3.630
VOL	Beginning	3,549	0.024	0.012	0.005	0.016	0.021	0.028	0.119
	Crash	3,491	0.034	0.015	0.008	0.025	0.032	0.040	0.159
	Trough	3,653	0.052	0.022	0.017	0.037	0.048	0.062	0.226
	Recovery	3,577	0.031	0.013	0.008	0.022	0.029	0.037	0.146
SIZE	Beginning	3,549	20.185	2.008	12.632	18.712	20.093	21.544	26.961
	Crash	3,491	19.953	2.084	13.617	18.430	19.921	21.394	26.712
	Trough	3,653	19.193	2.164	13.004	17.588	19.176	20.680	26.501
	Recovery	3,577	20.174	2.090	14.236	18.698	20.195	21.646	26.954
BEME	Beginning	3,549	0.450	0.508	-17.444	0.249	0.422	0.633	3.110
	Crash	3,491	0.627	2.414	-115.468	0.310	0.565	0.929	21.065
	Trough	3,653	0.913	4.425	-190.271	0.433	0.769	1.281	26.630
	Recovery	3,577	0.804	1.338	-56.001	0.343	0.636	1.060	14.242
LEV	Beginning	3,549	0.205	0.237	0.000	0.018	0.149	0.305	3.608
	Crash	3,491	0.219	0.246	0.000	0.029	0.169	0.326	3.937
	Trough	3,653	0.234	0.249	0.000	0.037	0.184	0.351	3.676
	Recovery	3,577	0.207	0.224	0.000	0.020	0.149	0.320	3.020
ROA	Beginning	3,549	0.002	0.125	-1.441	0.000	0.008	0.021	4.837
	Crash	3,491	-0.003	0.200	-2.605	-0.004	0.006	0.019	9.485
	Trough	3,653	-0.023	0.260	-2.367	-0.024	0.002	0.014	12.488
	Recovery	3,577	0.013	0.694	-1.312	-0.001	0.006	0.019	41.146
LIQ	Beginning	3,549	0.187	0.227	0.000	0.027	0.086	0.268	1.000
	Crash	3,491	0.171	0.212	0.000	0.027	0.078	0.229	1.000
	Trough	3,653	0.170	0.207	0.000	0.028	0.083	0.234	1.000
	Recovery	3,577	0.181	0.207	0.000	0.038	0.101	0.248	1.000

Table A.4.b. Descriptive statistics of explanatory variables, crisis 2 (2007–2012), raw data

Variable	Phase	N	Mean	SD	Min	P25	Median	P75	Max
Beta	Beginning	3,302	1.013	0.358	-0.947	0.793	1.031	1.240	2.605
	Crash	3,350	1.001	0.347	-0.709	0.780	1.007	1.227	2.273
	Trough	3,354	0.999	0.345	-0.559	0.779	1.007	1.223	2.225
	Recovery	3,425	1.046	0.383	-0.407	0.797	1.034	1.282	2.774
VOL	Beginning	3,302	0.034	0.020	0.007	0.021	0.028	0.043	0.166
	Crash	3,350	0.032	0.017	0.007	0.019	0.028	0.041	0.148
	Trough	3,354	0.035	0.019	0.002	0.020	0.030	0.045	0.152
	Recovery	3,425	0.035	0.022	0.007	0.020	0.028	0.045	0.259
SIZE	Beginning	3,302	20.958	2.195	13.490	19.295	20.923	22.454	28.536
	Crash	3,350	20.636	2.370	13.462	18.800	20.716	22.280	28.492
	Trough	3,354	20.491	2.397	13.322	18.706	20.567	22.140	28.435
	Recovery	3,425	20.497	2.562	12.278	18.786	20.591	22.266	28.696
BEME	Beginning	3,302	0.480	0.586	-7.117	0.166	0.371	0.708	9.162
	Crash	3,350	0.556	0.715	-8.804	0.200	0.438	0.796	9.714
	Trough	3,354	0.677	0.983	-10.631	0.246	0.533	0.932	17.198
	Recovery	3,425	0.756	1.532	-31.380	0.248	0.552	1.023	43.069
LEV	Beginning	3,302	0.273	0.257	0.000	0.057	0.233	0.417	3.004
	Crash	3,350	0.284	0.287	0.000	0.059	0.241	0.421	4.279
	Trough	3,354	0.284	0.280	0.000	0.065	0.239	0.418	5.321
	Recovery	3,425	0.287	0.286	0.000	0.070	0.235	0.420	4.014
ROA	Beginning	3,302	-0.011	0.114	-2.865	-0.014	0.005	0.019	1.605
	Crash	3,350	-0.022	0.177	-4.700	-0.026	0.003	0.016	2.513
	Trough	3,354	-0.024	0.222	-8.888	-0.027	0.003	0.018	3.875
	Recovery	3,425	-0.033	0.167	-2.581	-0.032	0.002	0.015	1.688
LIQ	Beginning	3,302	0.257	0.271	0.000	0.058	0.146	0.366	1.000
	Crash	3,350	0.240	0.267	0.000	0.045	0.123	0.343	1.000
	Trough	3,354	0.233	0.267	0.000	0.040	0.115	0.334	1.000
	Recovery	3,425	0.232	0.268	0.000	0.038	0.109	0.343	1.000

Table A.4.c. Descriptive statistics of explanatory variables, crisis 3 (2021–2024), raw data

Variable	N	Mean	SD	Min	Max
BETA	43,629	0.866	0.463	-0.001	2.057
VOL	43,629	0.036	0.020	0.010	0.107
SIZE	43,629	19.920	2.251	15.190	25.407
BEME	43,629	0.674	0.665	-0.705	3.823
LEV	43,629	0.236	0.222	0.000	0.990
ROA	43,629	-0.011	0.071	-0.396	0.119
LIQ	43,629	0.191	0.232	0.000	0.938

Table A.5. Summary statistics after 1%/99% winsorization

Variable	N	Mean	SD	Min	Max
BETA	43,629	0.859	0.436	0.130	1.656
VOL	43,629	0.035	0.018	0.014	0.076
SIZE	43,629	19.909	2.113	16.331	23.843
BEME	43,629	0.644	0.495	0.029	1.906
LEV	43,629	0.228	0.201	0.000	0.669
ROA	43,629	-0.007	0.048	-0.150	0.050
LIQ	43,629	0.186	0.217	0.005	0.750

Table A.6. Summary statistics after 5%/95% winsorization

Crisis	Beginning	Crash	Trough	Recovery	Firms in all Phases
Crisis 1 (2000–2006)	3,967	4,008	3,941	4,012	**2,050**
Crisis 2 (2007–2012)	3,549	3,491	3,653	3,577	**2,379**
Crisis 3 (2021–2024)	3,302	3,350	3,354	3,425	**2,723**
Total Firms per Phase	**10,818**	**10,849**	**10,948**	**11,014**	-

Table A.7. Firm-phase sample structure across crises and phase

Explanatory Variable	CAR-Window Robustness: Event-Level Regression, Crisis 1 (2000 – 2006)											
	Beginning			Crash			Trough			Recovery		
	(-1,+1)	(-3,+3)	(-5,+5)	(-1,+1)	(-3,+3)	(-5,+5)	(-1,+1)	(-3,+3)	(-5,+5)	(-1,+1)	(-3,+3)	(-5,+5)
Intercept	0.048	0.041	0.063	-0.095***	-0.315***	-0.168***	-0.082***	-0.120***	0.005	-0.025	0.037	0.071**
	(0.029)	(0.039)	(0.051)	(0.033)	(0.047)	(0.054)	(0.027)	(0.042)	(0.057)	(0.020)	(0.027)	(0.029)
BETA	0.000	0.008	0.018	0.006	-0.022	-0.000	0.003	0.011	-0.003	-0.000	-0.001	0.005
	(0.007)	(0.010)	(0.013)	(0.010)	(0.014)	(0.017)	(0.007)	(0.009)	(0.012)	(0.003)	(0.004)	(0.005)
VOL	-0.645***	-1.736***	-2.780***	-1.360***	-2.110***	-2.782***	-0.334*	-0.594**	-0.898**	0.065	-0.646**	-0.716**
	(0.158)	(0.218)	(0.281)	(0.201)	(0.309)	(0.328)	(0.179)	(0.260)	(0.373)	(0.186)	(0.285)	(0.313)
SIZE	-0.002	0.000	0.001	0.006***	0.018***	0.013***	0.004***	0.005***	0.001	0.001	-0.002	-0.003***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
BEME	0.001	-0.014	-0.000	-0.004	0.036**	0.034*	-0.047***	-0.051***	-0.073***	-0.004	-0.005	-0.005
	(0.009)	(0.013)	(0.017)	(0.011)	(0.016)	(0.020)	(0.011)	(0.015)	(0.018)	(0.005)	(0.009)	(0.010)
LEV	-0.032	0.030	0.152**	0.013	0.233***	0.300***	-0.029	0.043	-0.024	0.049	0.013	-0.032
	(0.039)	(0.060)	(0.070)	(0.054)	(0.082)	(0.091)	(0.043)	(0.063)	(0.085)	(0.042)	(0.066)	(0.077)
ROA	0.005	0.010*	0.019**	0.021***	0.030***	0.020***	-0.006	-0.003	-0.007	0.009**	0.012***	0.013**
	(0.004)	(0.005)	(0.007)	(0.004)	(0.006)	(0.007)	(0.004)	(0.007)	(0.008)	(0.004)	(0.005)	(0.006)
LIQ	0.011	-0.027	-0.068***	0.009	0.047**	0.005	-0.011	0.002	0.023	-0.003	-0.012	-0.023
	(0.013)	(0.018)	(0.026)	(0.016)	(0.022)	(0.025)	(0.013)	(0.019)	(0.022)	(0.008)	(0.013)	(0.014)
Mean CAR	-0.010	-0.026	-0.034	-0.016	-0.027	-0.015	-0.030	-0.053	-0.054	-0.005	-0.007	-0.003
N	2,050	2,050	2,050	2,050	2,050	2,050	2,050	2,050	2,050	2,050	2,050	2,050
Adj. R^2	0.050	0.176	0.264	0.157	0.300	0.276	0.065	0.057	0.036	0.028	0.037	0.035
F-statistic	6.405	16.374	26.799	14.847	36.400	34.139	9.105	8.190	4.037	3.662	3.922	4.143
IND FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses.

*Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.*

Table A.8.a. CAR-window robustness: event-level regression, crisis 1 (2000–2006)

CAR-Window Robustness: Event-Level Regression, Crisis 2 (2007 – 2012)												
Explanatory Variable	Beginning			Crash			Trough			Recovery		
	(-1,+1)	(-3,+3)	(-5,+5)	(-1,+1)	(-3,+3)	(-5,+5)	(-1,+1)	(-3,+3)	(-5,+5)	(-1,+1)	(-3,+3)	(-5,+5)
Intercept	-0.099*	-0.096	-0.081	0.033	0.016	0.104**	-0.067*	-0.077*	-0.205***	-0.015	-0.026	0.086***
	(0.057)	(0.062)	(0.069)	(0.039)	(0.054)	(0.050)	(0.037)	(0.046)	(0.053)	(0.015)	(0.022)	(0.026)
BETA	-0.019***	-0.021***	-0.016*	0.043***	0.086***	0.090***	0.022***	0.021**	0.009	0.008***	0.005	0.015***
	(0.007)	(0.008)	(0.009)	(0.004)	(0.006)	(0.007)	(0.008)	(0.010)	(0.012)	(0.003)	(0.004)	(0.005)
VOL	1.095	0.884	0.894	-0.687***	-1.169***	-1.680***	0.059	-0.042	-0.172	-0.123	0.075	-0.327
	(0.691)	(0.757)	(0.832)	(0.210)	(0.313)	(0.342)	(0.246)	(0.295)	(0.367)	(0.156)	(0.229)	(0.272)
SIZE	0.004	0.003	0.002	-0.002	-0.002	-0.005**	0.001	0.001	0.008***	-0.000	-0.000	-0.005***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
BEME	-0.001	-0.007	0.001	-0.025**	-0.040***	-0.034*	-0.021	0.008	-0.003	0.005	0.017**	0.013
	(0.007)	(0.009)	(0.011)	(0.010)	(0.014)	(0.018)	(0.015)	(0.020)	(0.022)	(0.006)	(0.008)	(0.010)
LEV	-0.081	-0.076	-0.103	0.039	-0.057	0.030	-0.020	-0.005	-0.022	-0.013	0.001	0.015
	(0.106)	(0.115)	(0.125)	(0.044)	(0.069)	(0.063)	(0.039)	(0.056)	(0.064)	(0.033)	(0.048)	(0.056)
ROA	0.003	0.009	0.018*	-0.004	-0.007	0.011*	0.009**	0.017***	0.020***	0.009***	0.017***	0.013***
	(0.007)	(0.009)	(0.011)	(0.004)	(0.007)	(0.007)	(0.005)	(0.006)	(0.007)	(0.003)	(0.003)	(0.004)
LIQ	0.007	0.007	0.037***	-0.024**	-0.050***	-0.048***	0.012	0.042**	0.020	0.011*	0.021**	0.009
	(0.007)	(0.011)	(0.013)	(0.010)	(0.015)	(0.016)	(0.013)	(0.017)	(0.021)	(0.006)	(0.010)	(0.012)
Mean CAR	-0.002	-0.002	-0.001	0.001	-0.004	-0.002	-0.008	-0.005	-0.031	0.002	-0.004	0.002
N	2,379	2,379	2,379	2,379	2,379	2,379	2,379	2,379	2,379	2,379	2,379	2,379
Adj. R^2	0.058	0.039	0.051	0.089	0.123	0.139	0.034	0.020	0.019	0.039	0.057	0.057
F-statistic	6.321	6.134	6.522	12.940	17.930	20.025	6.569	4.972	3.813	9.096	15.957	13.736
IND FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses.

*Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.*

Table A.8.b. CAR-window robustness: event-level regression, crisis 2 (2007–2012)

Explanatory Variable	CAR-Window Robustness: Event-Level Regression, Crisis 3 (2021 – 2024)											
	Beginning			Crash			Trough			Recovery		
	(-1,+1)	(-3,+3)	(-5,+5)	(-1,+1)	(-3,+3)	(-5,+5)	(-1,+1)	(-3,+3)	(-5,+5)	(-1,+1)	(-3,+3)	(-5,+5)
Intercept	0.084***	0.167***	0.175***	-0.083***	-0.023	-0.090**	0.038***	0.071***	0.080***	0.052***	0.125***	0.122***
	(0.017)	(0.028)	(0.033)	(0.021)	(0.030)	(0.036)	(0.014)	(0.022)	(0.028)	(0.016)	(0.030)	(0.041)
BETA	0.013***	0.024***	0.019***	0.022***	0.034***	0.036***	-0.004	-0.007	0.012	0.012***	0.017**	0.017*
	(0.003)	(0.005)	(0.007)	(0.005)	(0.008)	(0.008)	(0.004)	(0.006)	(0.008)	(0.004)	(0.007)	(0.009)
VOL	-0.511***	-1.467***	-1.797***	0.272	0.849**	0.654*	-0.875***	-1.281***	-1.950***	-0.079	-1.094***	-1.754***
	(0.119)	(0.180)	(0.222)	(0.202)	(0.338)	(0.359)	(0.144)	(0.198)	(0.246)	(0.154)	(0.288)	(0.422)
SIZE	-0.004***	-0.006***	-0.006***	0.003***	-0.001	0.002	-0.001	-0.002*	-0.002	-0.003***	-0.006***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
BEME	0.012**	-0.005	-0.009	-0.029***	-0.060***	-0.042***	-0.009	-0.006	-0.012	-0.007	-0.001	-0.004
	(0.006)	(0.009)	(0.011)	(0.006)	(0.010)	(0.011)	(0.009)	(0.011)	(0.012)	(0.005)	(0.010)	(0.013)
LEV	0.082***	0.144***	0.117**	0.066**	-0.089*	-0.095	-0.058	-0.019	0.138**	-0.030	-0.067	-0.163*
	(0.031)	(0.047)	(0.056)	(0.032)	(0.052)	(0.063)	(0.040)	(0.055)	(0.062)	(0.029)	(0.052)	(0.085)
ROA	0.001	-0.003	-0.000	0.004	0.004	0.013*	0.004	0.006	0.010**	0.002	0.006*	0.001
	(0.003)	(0.004)	(0.005)	(0.003)	(0.006)	(0.007)	(0.004)	(0.004)	(0.005)	(0.002)	(0.003)	(0.004)
LIQ	0.006	0.006	0.026**	0.004	0.029**	0.089***	-0.029***	-0.032***	-0.023*	-0.009	-0.020*	-0.025*
	(0.007)	(0.010)	(0.013)	(0.009)	(0.014)	(0.016)	(0.009)	(0.012)	(0.014)	(0.006)	(0.011)	(0.015)
Mean CAR	0.004	-0.002	-0.003	-0.006	-0.001	-0.000	-0.004	-0.011	-0.021	0.004	-0.003	-0.016
N	2,723	2,723	2,723	2,723	2,723	2,723	2,723	2,723	2,723.	2,723	2,723	2,723
Adj. R^2	0.080	0.125	0.098	0.107	0.211	0.214	0.091	0.097	0.140	0.031	0.036	0.039
F-statistic	10.596	13.987	11.931	28.098	41.790	36.538	22.040	14.186	12.508	7.894	5.477	4.764
IND FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses.

*Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.*

Table A.8.c. CAR-window robustness: event-level regression, crisis 3 (2021–2024)

Explanatory Variable	CAR-Window Robustness: Pooled Crisis-Phase Regression											
	Beginning			Crash			Trough			Recovery		
	(-1,+1)	(-3,+3)	(-5,+5)	(-1,+1)	(-3,+3)	(-5,+5)	(-1,+1)	(-3,+3)	(-5,+5)	(-1,+1)	(-3,+3)	(-5,+5)
Intercept	0.037***	0.098***	0.134***	-0.023	-0.042*	0.010	-0.053***	-0.059***	-0.051**	0.011	0.050***	0.083***
	(0.011)	(0.016)	(0.020)	(0.015)	(0.024)	(0.030)	(0.014)	(0.018)	(0.022)	(0.009)	(0.014)	(0.017)
BETA	-0.004*	0.001	-0.003	0.020***	0.035***	0.037***	0.016***	0.016***	0.013**	0.006***	0.001	0.004
	(0.002)	(0.003)	(0.004)	(0.003)	(0.006)	(0.006)	(0.003)	(0.004)	(0.006)	(0.001)	(0.002)	(0.003)
VOL	-0.387***	-1.546***	-2.317***	-1.134***	-2.195***	-2.735***	-0.415***	-0.737***	-0.965***	-0.132	-0.687***	-1.057***
	(0.080)	(0.105)	(0.134)	(0.102)	(0.158)	(0.187)	(0.092)	(0.118)	(0.157)	(0.085)	(0.135)	(0.170)
SIZE	-0.002***	-0.004***	-0.004***	0.002***	0.003***	0.002	0.001**	0.001	0.001	-0.001***	-0.002***	-0.003***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
BEME	0.002	-0.001	0.005	-0.016**	-0.012	-0.010	-0.026***	-0.023***	-0.037***	-0.000	0.001	0.001
	(0.004)	(0.005)	(0.006)	(0.008)	(0.013)	(0.015)	(0.006)	(0.008)	(0.009)	(0.003)	(0.005)	(0.006)
LEV	0.010	0.049*	0.086**	0.076**	0.088	0.155**	-0.014	0.011	0.061*	-0.013	-0.016	0.002
	(0.022)	(0.029)	(0.036)	(0.032)	(0.059)	(0.064)	(0.018)	(0.027)	(0.033)	(0.016)	(0.026)	(0.035)
ROA	0.002	0.004	0.010***	0.011***	0.022***	0.030***	0.004*	0.010***	0.012***	0.006***	0.010***	0.009***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.004)	(0.005)	(0.002)	(0.003)	(0.003)	(0.001)	(0.002)	(0.003)
LIQ	0.006	0.007	0.025***	0.010	0.061***	0.072***	-0.016***	-0.004	-0.008	0.001	-0.006	-0.005
	(0.004)	(0.006)	(0.008)	(0.006)	(0.011)	(0.012)	(0.006)	(0.008)	(0.009)	(0.004)	(0.006)	(0.008)
Mean CAR	-0.003	-0.014	-0.019	-0.015	-0.024	-0.021	-0.016	-0.026	-0.039	0.001	-0.006	-0.008
N	10,818	10,818	10.818	10,849	10,849	10,849	10,948	10,948	10,948	11,014	11,014	11,014
Adj. R^2	0.024	0.103	0.133	0.081	0.103	0.106	0.045	0.052	0.036	0.021	0.024	0.037
F-statistic	10.142	31.590	38.860	21.680	33.078	30.600	23.426	26.354	13.037	14.173	11.670	13.898
IND FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crisis FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors clustered at the firm level in parentheses.

*Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.*

Table A.9. CAR-window robustness: pooled crises-phase regressions

	Winsorization Robustness: Event-Level Regression, Crisis 1 (2000 – 2006)							
Explanatory	CAR (-3,+3), Wins. 1%/99%				CAR (-3,+3), Wins. 5%/99%			
Variable	Beginning	Crash	Trough	Recovery	Beginning	Crash	Trough	Recovery
Intercept	0.041	-0.315***	-0.120***	0.037	0.011	-0.437***	-0.119***	0.031
	(0.039)	(0.047)	(0.042)	(0.027)	(0.043)	(0.052)	(0.045)	(0.029)
BETA	0.008	-0.022	0.011	-0.001	0.007	-0.033**	0.013	-0.002
	(0.010)	(0.014)	(0.009)	(0.004)	(0.011)	(0.015)	(0.010)	(0.005)
VOL	-1.736***	-2.110***	-0.594**	-0.646**	-1.683***	-1.964***	-0.735***	-0.639**
	(0.218)	(0.309)	(0.260)	(0.285)	(0.238)	(0.333)	(0.275)	(0.312)
SIZE	0.000	0.018***	0.005***	-0.002	0.002	0.023***	0.005***	-0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
BEME	-0.014	0.036**	-0.051***	-0.005	-0.013	0.045**	-0.052***	-0.009
	(0.013)	(0.016)	(0.015)	(0.009)	(0.014)	(0.018)	(0.015)	(0.010)
LEV	0.030	0.233***	0.043	0.013	0.135	0.439***	0.135	0.035
	(0.060)	(0.082)	(0.063)	(0.066)	(0.090)	(0.109)	(0.103)	(0.081)
ROA	0.010*	0.030***	-0.003	0.012***	0.016**	0.050***	-0.002	0.016***
	(0.005)	(0.006)	(0.007)	(0.005)	(0.006)	(0.008)	(0.008)	(0.006)
LIQ	-0.027	0.047**	0.002	-0.012	-0.026	0.063***	0.007	-0.010
	(0.018)	(0.022)	(0.019)	(0.013)	(0.020)	(0.023)	(0.021)	(0.013)
Mean CAR	-0.026	-0.027	-0.053	-0.007	-0.026	-0.027	-0.053	-0.007
N	2,050	2,050	2,050	2,050	2,050	2,050	2,050	2,050
Adj. R^2	0.176	0.300	0.057	0.037	0.169	0.307	0.061	0.037
F-statistic	16.374	36.400	8.190	3.922	15.855	38.321	8.630	3.899
IND FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses.

*Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.*

Table A.10.a. Winsorization robustness: event-level regression, crisis 1 (2000–2006)

	Winsorization Robustness: Event-Level Regression, Crisis 2 (2007 – 2012)							
Explanatory	CAR (-3,+3), Wins. 1%/99%				CAR (-3,+3), Wins. 5%/99%			
Variable	Beginning	Crash	Trough	Recovery	Beginning	Crash	Trough	Recovery
Intercept	-0.096	0.016	-0.077*	-0.026	-0.091*	0.013	-0.045	-0.030
	(0.062)	(0.054)	(0.046)	(0.022)	(0.054)	(0.056)	(0.049)	(0.025)
BETA	-0.021***	0.086***	0.021**	0.005	-0.022***	0.090***	0.024**	0.004
	(0.008)	(0.006)	(0.010)	(0.004)	(0.007)	(0.007)	(0.011)	(0.004)
VOL	0.884	-1.169***	-0.042	0.075	0.720	-1.190***	-0.084	0.123
	(0.757)	(0.313)	(0.295)	(0.229)	(0.625)	(0.339)	(0.312)	(0.244)
SIZE	0.003	-0.002	0.001	-0.000	0.003	-0.002	-0.000	-0.000
	(0.003)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
BEME	-0.007	-0.040***	0.008	0.017**	-0.007	-0.040***	0.013	0.021**
	(0.009)	(0.014)	(0.020)	(0.008)	(0.008)	(0.015)	(0.021)	(0.008)
LEV	-0.076	-0.057	-0.005	0.001	-0.050	-0.093	-0.037	-0.012
	(0.115)	(0.069)	(0.056)	(0.048)	(0.074)	(0.087)	(0.083)	(0.066)
ROA	0.009	-0.007	0.017***	0.017***	0.010	-0.009	0.014*	0.021***
	(0.009)	(0.007)	(0.006)	(0.003)	(0.010)	(0.007)	(0.008)	(0.005)
LIQ	0.007	-0.050***	0.042**	0.021**	0.013	-0.055***	0.040**	0.022**
	(0.011)	(0.015)	(0.017)	(0.010)	(0.010)	(0.016)	(0.019)	(0.010)
Mean CAR	-0.002	-0.004	-0.005	-0.004	-0.002	-0.004	-0.005	-0.004
N	2,379	2,379	2,379	2,379	2,379	2,379	2,379	2,379
Adj. R^2	0.039	0.123	0.020	0.057	0.033	0.122	0.017	0.053
F-statistic	6.134	17.930	4.972	15.957	6.153	17.592	4.827	16.629
IND FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses.

*Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.10.*

Table A.10.b. Winsorization robustness: event-level regression, crisis 2 (2007–2012)

	Winsorization Robustness: Event-Level Regression, Crisis 3 (2021 – 2024)							
Explanatory	CAR (-3,+3), Wins. 1%/99%				CAR (-3,+3), Wins. 5%/99%			
Variable	Beginning	Crash	Trough	Recovery	Beginning	Crash	Trough	Recovery
Intercept	0.167***	-0.023	0.071***	0.125***	0.167***	-0.034	0.092***	0.139***
	(0.028)	(0.030)	(0.022)	(0.030)	(0.032)	(0.033)	(0.026)	(0.029)
BETA	0.024***	0.034***	-0.007	0.017**	0.029***	0.032***	-0.004	0.019***
	(0.005)	(0.008)	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)	(0.006)
VOL	-1.467***	0.849**	-1.281***	-1.094***	-1.524***	1.132***	-1.507***	-1.169***
	(0.180)	(0.338)	(0.198)	(0.288)	(0.216)	(0.311)	(0.204)	(0.256)
SIZE	-0.006***	-0.001	-0.002*	-0.006***	-0.007***	-0.000	-0.002**	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
BEME	-0.005	-0.060***	-0.006	-0.001	-0.004	-0.066***	-0.003	0.002
	(0.009)	(0.010)	(0.011)	(0.010)	(0.010)	(0.011)	(0.010)	(0.012)
LEV	0.144***	-0.089*	-0.019	-0.067	0.209***	-0.090	-0.002	-0.078
	(0.047)	(0.052)	(0.055)	(0.052)	(0.070)	(0.077)	(0.057)	(0.069)
ROA	-0.003	0.004	0.006	0.006*	0.002	0.001	0.007	0.008*
	(0.004)	(0.006)	(0.004)	(0.003)	(0.005)	(0.006)	(0.005)	(0.004)
LIQ	0.006	0.029**	-0.032***	-0.020*	0.012	0.030**	-0.033***	-0.022*
	(0.010)	(0.014)	(0.012)	(0.011)	(0.011)	(0.015)	(0.013)	(0.012)
Mean CAR	-0.002	-0.001	-0.011	-0.003	-0.002	-0.001	-0.011	-0.003
N	2,723	2,723	2,723	2,723	2,723	2,723	2,723	2,723
Adj. R^2	0.125	0.211	0.097	0.036	0.117	0.213	0.103	0.034
F-statistic	13.987	41.790	14.186	5.477	13.915	41.653	15.272	6.261
IND FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses.

*Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.*

Table A.10.c. Winsorization robustness: event-level regression, crisis 3 (2021–2024)

Explanatory Variable	Winsorization Robustness: Pooled Crisis-Phase Regression							
	CAR (-3,+3), Wins.1%,99%				CAR (-3,+3), Wins. 5%/95%			
	Beginning	Crash	Trough	Recovery	Beginning	Crash	Trough	Recovery
Intercept	0.098***	-0.042*	-0.059***	0.050***	0.093***	-0.108***	-0.047**	0.037***
	(0.016)	(0.024)	(0.018)	(0.014)	(0.018)	(0.026)	(0.020)	(0.014)
BETA	0.001	0.035***	0.016***	0.001	0.002	0.032***	0.018***	0.001
	(0.003)	(0.006)	(0.004)	(0.002)	(0.003)	(0.006)	(0.005)	(0.002)
VOL	-1.546***	-2.195***	-0.737***	-0.687***	-1.612***	-2.074***	-0.881***	-0.603***
	(0.105)	(0.158)	(0.118)	(0.135)	(0.113)	(0.169)	(0.119)	(0.128)
SIZE	-0.004***	0.003***	0.001	-0.002***	-0.003***	0.005***	0.000	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
BEME	-0.001	-0.012	-0.023***	0.001	0.001	-0.003	-0.021**	0.003
	(0.005)	(0.013)	(0.008)	(0.005)	(0.005)	(0.012)	(0.008)	(0.005)
LEV	0.049*	0.088	0.011	-0.016	0.086**	0.165**	0.066	0.010
	(0.029)	(0.059)	(0.027)	(0.026)	(0.036)	(0.078)	(0.041)	(0.034)
ROA	0.004	0.022***	0.010***	0.010***	0.006**	0.034***	0.012***	0.016***
	(0.003)	(0.004)	(0.003)	(0.002)	(0.003)	(0.005)	(0.003)	(0.002)
LIQ	0.007	0.061***	-0.004	-0.006	0.010	0.073***	0.001	-0.004
	(0.006)	(0.011)	(0.008)	(0.006)	(0.007)	(0.012)	(0.009)	(0.006)
Mean CAR	-0.014	-0.024	-0.026	-0.006	-0.014	-0.024	-0.026	-0.006
N	10,818	10,849	10,948	11,014	10,818	10,849	10,948	11,014
Adj. R^2	0.103	0.103	0.052	0.024	0.096	0.094	0.051	0.022
F-statistic	31.590	33.078	26.354	11.670	31.534	32.188	26.811	12.764

Note: Standard errors clustered at the firm level in parentheses.

*Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.*

Table A.11. Winsorization robustness: pooled crisis-phase regressions

Explanatory Variable	Excluding Industry Fixed Effects: Event-Level Regression, Crisis 1 (2000 – 2006)							
	CAR (-3,+3)				CAR (-3,+3)			
	Beginning	Crash	Trough	Recovery	Beginning	Crash	Trough	Recovery
Intercept	0.035	-0.312***	-0.111***	0.029	0.041	-0.315***	-0.120***	0.037
	(0.037)	(0.044)	(0.041)	(0.026)	(0.039)	(0.047)	(0.042)	(0.027)
BETA	0.008	-0.045***	0.011	0.000	0.008	-0.022	0.011	-0.001
	(0.009)	(0.013)	(0.009)	(0.004)	(0.010)	(0.014)	(0.009)	(0.004)
VOL	-1.915***	-2.281***	-0.708***	-0.483*	-1.736***	-2.110***	-0.594**	-0.646**
	(0.205)	(0.288)	(0.244)	(0.266)	(0.218)	(0.309)	(0.260)	(0.285)
SIZE	0.000	0.019***	0.005**	-0.001	0.000	0.018***	0.005***	-0.002
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
BEME	-0.011	0.039**	-0.060***	-0.005	-0.014	0.036**	-0.051***	-0.005
	(0.012)	(0.015)	(0.014)	(0.008)	(0.013)	(0.016)	(0.015)	(0.009)
LEV	0.067	0.211***	0.043	0.040	0.030	0.233***	0.043	0.013
	(0.059)	(0.080)	(0.062)	(0.064)	(0.060)	(0.082)	(0.063)	(0.066)
ROA	0.016***	0.028***	-0.004	0.011**	0.010*	0.030***	-0.003	0.012***
	(0.005)	(0.006)	(0.007)	(0.005)	(0.005)	(0.006)	(0.007)	(0.005)
LIQ	-0.058***	0.053**	-0.003	-0.024*	-0.027	0.047**	0.002	-0.012
	(0.018)	(0.021)	(0.018)	(0.012)	(0.018)	(0.022)	(0.019)	(0.013)
Mean CAR	-0.026	-0.027	-0.053	-0.007	-0.026	-0.027	-0.053	-0.007
N	2,050	2,050	2,050	2,050	2,050	2,050	2,050	2,050
Adj. R^2	0.150	0.268	0.048	0.023	0.176	0.300	0.057	0.037
F-statistic	32.744	69.434	11.913	3.758	16.374	36.400	8.190	3.922
IND FE	No	No	No	No	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses.

*Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.*

Table A.12.a. Excluding industry fixed effects: event-level regression, crisis 1 (2000–2006)

Explanatory Variable	Excluding Industry Fixed Effects: Event-Level Regression, Crisis 2 (2007 – 2012)							
	CAR (-3,+3)				CAR (-3,+3)			
	Beginning	Crash	Trough	Recovery	Beginning	Crash	Trough	Recovery
Intercept	-0.085	-0.021	-0.038	-0.022	-0.096	0.016	-0.077*	-0.026
	(0.060)	(0.053)	(0.044)	(0.022)	(0.062)	(0.054)	(0.046)	(0.022)
BETA	-0.020**	0.075***	0.024**	0.004	-0.021***	0.086***	0.021**	0.005
	(0.008)	(0.006)	(0.010)	(0.004)	(0.008)	(0.006)	(0.010)	(0.004)
VOL	0.946	-1.104***	-0.086	0.086	0.884	-1.169***	-0.042	0.075
	(0.732)	(0.308)	(0.289)	(0.215)	(0.757)	(0.313)	(0.295)	(0.229)
SIZE	0.004	-0.000	-0.000	-0.001	0.003	-0.002	0.001	-0.000
	(0.002)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)
BEME	-0.006	-0.035**	-0.008	0.016**	-0.007	-0.040***	0.008	0.017**
	(0.009)	(0.014)	(0.019)	(0.008)	(0.009)	(0.014)	(0.020)	(0.008)
LEV	-0.066	-0.073	0.005	0.006	-0.076	-0.057	-0.005	0.001
	(0.115)	(0.065)	(0.055)	(0.047)	(0.115)	(0.069)	(0.056)	(0.048)
ROA	0.010	-0.001	0.018***	0.019***	0.009	-0.007	0.017***	0.017***
	(0.009)	(0.007)	(0.006)	(0.003)	(0.009)	(0.007)	(0.006)	(0.003)
LIQ	0.009	-0.069***	0.044***	0.029***	0.007	-0.050***	0.042**	0.021**
	(0.010)	(0.014)	(0.016)	(0.009)	(0.011)	(0.015)	(0.017)	(0.010)
Mean CAR	-0.002	-0.004	-0.005	-0.004	-0.002	-0.004	-0.005	-0.004
N	2,379	2,379	2,379	2,379	2,379	2,379	2,379	2,379
Adj. R^2	0.025	0.087	0.013	0.043	0.039	0.123	0.020	0.057
F-statistic	2.368	31.788	4.028	11.438	6.134	17.930	4.972	15.957
IND FE	No	No	No	No	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses.

*Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.10.*

Table A.12.b. Excluding industry fixed effects: event-level regression, crisis 2 (2007–2012)

Explanatory Variable	Excluding Industry Fixed Effects: Event-Level Regression, Crisis 3 (2021 – 2024)							
	CAR (-3,+3)				CAR (-3,+3)			
	Beginning	Crash	Trough	Recovery	Beginning	Crash	Trough	Recovery
Intercept	0.167***	-0.006	0.071***	0.132***	0.167***	-0.023	0.071***	0.125***
	(0.027)	(0.031)	(0.020)	(0.028)	(0.028)	(0.030)	(0.022)	(0.030)
BETA	0.023***	0.035***	-0.008	0.019***	0.024***	0.034***	-0.007	0.017**
	(0.005)	(0.008)	(0.006)	(0.006)	(0.005)	(0.008)	(0.006)	(0.007)
VOL	-1.433***	0.630*	-1.245***	-1.086***	-1.467***	0.849**	-1.281***	-1.094***
	(0.170)	(0.359)	(0.178)	(0.280)	(0.180)	(0.338)	(0.198)	(0.288)
SIZE	-0.007***	-0.002*	-0.001	-0.006***	-0.006***	-0.001	-0.002*	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
BEME	0.001	-0.053***	-0.006	-0.005	-0.005	-0.060***	-0.006	-0.001
	(0.009)	(0.010)	(0.010)	(0.009)	(0.009)	(0.010)	(0.011)	(0.010)
LEV	0.203***	-0.077	-0.013	-0.056	0.144***	-0.089*	-0.019	-0.067
	(0.047)	(0.053)	(0.052)	(0.050)	(0.047)	(0.052)	(0.055)	(0.052)
ROA	-0.005	-0.002	0.007*	0.006*	-0.003	0.004	0.006	0.006*
	(0.004)	(0.006)	(0.004)	(0.003)	(0.004)	(0.006)	(0.004)	(0.003)
LIQ	-0.010	0.062***	-0.035***	-0.023**	0.006	0.029**	-0.032***	-0.020*
	(0.009)	(0.013)	(0.012)	(0.011)	(0.010)	(0.014)	(0.012)	(0.011)
Mean CAR	-0.002	-0.001	-0.011	-0.003	-0.002	-0.001	-0.011	-0.003
N	2,723	2,723	2,723	2,723	2,723	2,723	2,723	2,723
Adj. R^2	0.110	0.126	0.093	0.035	0.125	0.211	0.097	0.036
F-statistic	26.235	46.124	24.511	6.737	13.987	41.790	14.186	5.477
IND FE	No	No	No	No	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses.

*Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.*

Table A.12.c. Excluding industry fixed effects: event-level regression, crisis 3 (2021–2024)

	Excluding Utility and Financial Firms: Event-Level Regression, Crisis 1 (2000 – 2006)							
Explanatory	Crisis 1, CAR (-3,+3), Full Sample				Crisis 1, CAR (-3,+3), Exclusion Sample			
Variable	Beginning	Crash	Trough	Recovery	Beginning	Crash	Trough	Recovery
Intercept	0.035	-0.312***	-0.111***	0.029	0.061	-0.342***	-0.170***	0.048
	(0.037)	(0.044)	(0.041)	(0.026)	(0.046)	(0.054)	(0.047)	(0.032)
BETA	0.008	-0.045***	0.011	0.000	0.001	-0.056***	0.004	-0.001
	(0.009)	(0.013)	(0.009)	(0.004)	(0.011)	(0.015)	(0.010)	(0.004)
VOL	-1.915***	-2.281***	-0.708***	-0.483*	-2.023***	-2.064***	-0.501*	-0.587*
	(0.205)	(0.288)	(0.244)	(0.266)	(0.239)	(0.332)	(0.284)	(0.300)
SIZE	0.000	0.019***	0.005**	-0.001	-0.000	0.020***	0.007***	-0.002
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
BEME	-0.011	0.039**	-0.060***	-0.005	-0.013	0.055***	-0.056***	-0.008
	(0.012)	(0.015)	(0.014)	(0.008)	(0.015)	(0.019)	(0.017)	(0.010)
LEV	0.067	0.211***	0.043	0.040	0.062	0.245***	0.039	0.023
	(0.059)	(0.080)	(0.062)	(0.064)	(0.062)	(0.086)	(0.064)	(0.067)
ROA	0.016***	0.028***	-0.004	0.011**	0.014**	0.027***	-0.001	0.011**
	(0.005)	(0.006)	(0.007)	(0.005)	(0.006)	(0.006)	(0.007)	(0.005)
LIQ	-0.058***	0.053**	-0.003	-0.024*	-0.059***	0.071***	0.005	-0.031**
	(0.018)	(0.021)	(0.018)	(0.012)	(0.019)	(0.023)	(0.020)	(0.013)
Mean CAR	-0.026	-0.027	-0.053	-0.007	-0.034	-0.041	-0.056	-0.007
N	2,050	2,050	2,050	2,050	1,636	1,636	1,636	1,636
Adj. R^2	0.150	0.268	0.048	0.023	0.142	0.241	0.046	0.024
F-statistic	32.744	69.434	11.913	3.758	27.828	56.603	10.668	3.605
IND FE	No	No	No	No	No	No	No	No

Note: Standard errors in parentheses.

Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.10.

Table A.13.a. Excluding utility and financial firms: event-level regression, crisis 1 (2000–2006)

	Excluding Utility and Financial Firms: Event-Level Regression, Crisis 2 (2007 – 2012)							
Explanatory	Crisis 2, CAR (-3,+3), Full Sample				Crisis 2, CAR (-3,+3), Exclusion Sample			
Variable	Beginning	Crash	Trough	Recovery	Beginning	Crash	Trough	Recovery
Intercept	-0.085	-0.021	-0.038	-0.022	-0.106	-0.101**	-0.069	-0.012
	(0.060)	(0.053)	(0.044)	(0.022)	(0.075)	(0.043)	(0.052)	(0.028)
BETA	-0.020**	0.075***	0.024**	0.004	-0.020**	0.061***	0.012	0.002
	(0.008)	(0.006)	(0.010)	(0.004)	(0.008)	(0.007)	(0.012)	(0.005)
VOL	0.946	-1.104***	-0.086	0.086	1.000	-0.791**	0.023	-0.208
	(0.732)	(0.308)	(0.289)	(0.215)	(0.833)	(0.322)	(0.338)	(0.252)
SIZE	0.004	-0.000	-0.000	-0.001	0.005	0.004**	0.002	-0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)
BEME	-0.006	-0.035**	-0.008	0.016**	-0.004	-0.022	-0.019	0.038***
	(0.009)	(0.014)	(0.019)	(0.008)	(0.010)	(0.014)	(0.024)	(0.009)
LEV	-0.066	-0.073	0.005	0.006	-0.090	-0.063	-0.010	0.011
	(0.115)	(0.065)	(0.055)	(0.047)	(0.121)	(0.073)	(0.058)	(0.051)
ROA	0.010	-0.001	0.018***	0.019***	0.015	-0.016**	0.016**	0.018***
	(0.009)	(0.007)	(0.006)	(0.003)	(0.011)	(0.008)	(0.007)	(0.004)
LIQ	0.009	-0.069***	0.044***	0.029***	0.009	-0.033**	0.040**	0.045***
	(0.010)	(0.014)	(0.016)	(0.009)	(0.011)	(0.015)	(0.019)	(0.011)
Mean CAR	-0.002	-0.004	-0.005	-0.004	-0.002	-0.013	-0.007	-0.006
N	2,379	2,379	2,379	2,379	1,828	1,828	1,828	1,828
Adj. R^2	0.025	0.087	0.013	0.043	0.026	0.087	0.008	0.031
F-statistic	2.368	31.788	4.028	11.438	1.642	23.152	2.335	6.189
IND FE	No	No	No	No	No	No	No	No

Note: Standard errors in parentheses.

Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.10.

Table A.13.b. Excluding utility and financial firms: event-level regression, crisis 2 (2007–2012)

	Excluding Utility and Financial Firms: Event-Level Regression, Crisis 3 (2021 – 2024)							
Explanatory	Crisis 3, CAR (-3,+3), Full Sample				Crisis 3, CAR (-3,+3), Exclusion Sample			
Variable	Beginning	Crash	Trough	Recovery	Beginning	Crash	Trough	Recovery
Intercept	0.167***	-0.006	0.071***	0.132***	0.169***	-0.000	0.059**	0.149***
	(0.027)	(0.031)	(0.020)	(0.028)	(0.033)	(0.038)	(0.025)	(0.036)
BETA	0.023***	0.035***	-0.008	0.019***	0.021***	0.032***	-0.014*	0.017**
	(0.005)	(0.008)	(0.006)	(0.006)	(0.006)	(0.009)	(0.007)	(0.007)
VOL	-1.433***	0.630*	-1.245***	-1.086***	-1.567***	0.535	-1.103***	-1.211***
	(0.170)	(0.359)	(0.178)	(0.280)	(0.193)	(0.428)	(0.216)	(0.325)
SIZE	-0.007***	-0.002*	-0.001	-0.006***	-0.006***	-0.003*	-0.001	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
BEME	0.001	-0.053***	-0.006	-0.005	0.004	-0.036***	-0.005	0.005
	(0.009)	(0.010)	(0.010)	(0.009)	(0.012)	(0.013)	(0.014)	(0.013)
LEV	0.203***	-0.077	-0.013	-0.056	0.208***	-0.019	-0.004	-0.058
	(0.047)	(0.053)	(0.052)	(0.050)	(0.051)	(0.052)	(0.057)	(0.054)
ROA	-0.005	-0.002	0.007*	0.006*	0.000	0.000	0.008	0.005
	(0.004)	(0.006)	(0.004)	(0.003)	(0.006)	(0.007)	(0.005)	(0.004)
LIQ	-0.010	0.062***	-0.035***	-0.023**	-0.004	0.079***	-0.033**	-0.020
	(0.009)	(0.013)	(0.012)	(0.011)	(0.011)	(0.014)	(0.014)	(0.012)
Mean CAR	-0.002	-0.001	-0.011	-0.003	-0.004	0.005	-0.018	-0.005
N	2,723	2,723	2,723	2,723	2,153	2,153	2,153	2,153
Adj. R^2	0.110	0.126	0.093	0.035	0.112	0.115	0.069	0.031
F-statistic	26.235	46.124	24.511	6.737	25.145	37.438	16.575	5.063
IND FE	No	No	No	No	No	No	No	No

Note: Standard errors in parentheses.

Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.13.c. Excluding utility and financial firms: event-level regression, crisis 3 (2021–2024)

9. References

Davis, S. M., & Madura, J. (2012). *How the shift to quality distinguished winners from losers during the financial crisis*. Journal of Behavioral Finance, 13(2), 81–92. https://doi.org/10.1080/15427560.2012.657506

Fauzi, R., & Wahyudi, I. (2016). *The effect of firm and stock characteristics on stock returns: Stock market crash analysis*. Journal of Finance and Data Science, 2(2), 112–124. https://doi.org/10.1016/j.jfds.2016.07.001

Financial Crisis Inquiry Commission. (2011). *The financial crisis inquiry report*. https://www.govinfo.gov/content/pkg/GPO-FCIC/pdf/GPO-FCIC.pdf

Federal Reserve Bank of St. Louis. (2023, January 12). *The many interest rates in 2022*. https://www.stlouisfed.org/on-the-economy/2023/jan/many-interest-rates-2022

Board of Governors of the Federal Reserve System. (2023, April 28). *Review of the Federal Reserve's supervision and regulation of Silicon Valley Bank.* https://www.federalreserve.gov/publications/review-of-the-federal-reserves-supervision-and-regulation-of-silicon-valley-bank.htm

Hayes, A. (2025, August 10). *Understanding the dotcom bubble: Causes, impact, and lessons*. Investopedia. Retrieved November 20, 2025, from https://www.investopedia.com/terms/d/dotcom-bubble.asp

Johansen, A., & Sornette, D. (2010). *Shocks, crashes and bubbles in financial markets*. Brussels Economic Review, 53(2), 201–253.

Mishkin, F. S., & White, E. N. (2002). *U.S. stock market crashes and their aftermath: Implications for monetary policy*. (NBER Working Paper 8992). https://doi.org/10.3386/w8992

Miyajima, H., & Yafeh, Y. (2007). *Japan's banking crisis: An event-study perspective*. Journal of Banking & Finance, 31(9), 2866–2885. https://doi.org/10.1016/j.jbankfin.2007.03.006

OECD. (2001). *OECD Economic Outlook No. 69*. https://www.oecd.org/content/dam/oecd/en/publications/reports/2001/06/oecd-economic-outlook-volume-2001-issue-1_g1ghg821/eco_outlook-v2001-1-en.pdf

Patel, S. A., & Sarkar, A. (1998). *Stock market crises in developed and emerging markets*. Financial Analysts Journal, 54(6), 50–61. https://doi.org/10.2469/faj.v54.n6.2225

Ramelli, S., & Wagner, A. F. (2020). *Feverish stock price reactions to COVID-19*. Review of Corporate Finance Studies, 9(3), 622–655. https://doi.org/10.1093/rcfs/cfaa012

U.S. Bureau of Labor Statistics. (2023, January 17). *Consumer Price Index: 2022 in review*. https://www.bls.gov/opub/ted/2022/consumer-prices-up-9-1-percent-over-the-year-ended-june-2022-largest-increase-in-40-years.htm

Wang, J., Meric, G., Liu, Z., & Meric, I. (2009). *Stock market crashes, firm characteristics, and stock returns*. Journal of Banking & Finance, 33(9), 1563–1574. https://doi.org/10.1016/j.jbankfin.2009.03.002

Wang, J., Meric, G., Liu, Z., & Meric, I. (2011). *The determinants of stock returns in the October 9, 2007–March 9, 2009 bear market*. The Journal of Investing, 20(3), 18–24. https://doi.org/10.3905/joi.2011.20.3.018

Zouaoui, M., Nouyrigat, G., & Beer, F. (2011). *How does investor sentiment affect stock market crises? Evidence from panel data*. Financial Review, 46(4), 723–747. https://doi.org/10.1111/j.1540-6288.2011.00316.x