# How resilient are PE/VC returns to real shocks?

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**Abstract**: This paper examines the resilience of private equity (PE) and venture capital (VC) returns to economic and market shocks, exploring their role as alternative asset classes within diversified institutional portfolios. Despite the increasing allocation to these illiquid and untransparent assets, little is understood about their shock resilience, econometric exogeneity, and diversification properties when combined with liquid assets such as equities, bonds, and commodities. We use a Vector Autoregression (VAR) framework to analyze PE and VC performance over thirty years, assessing their reactivity and adaptability to fluctuations in traditional asset classes and macroeconomic indicators. Our findings show that while PE and VC are sensitive to immediate market changes, they demonstrate substantial long-term resilience, regaining equilibrium aftershocks. This reveals that PE/VC is an ideal asset class for diversification within institutional portfolios as a buffer against market volatility without sacrificing returns.

**Keywords:** Private equity, Shock sensitivities, Institutional portfolio, Quantile vector autoregression, Impulse response

**JEL Classification:** C13; C32; C58; G1; G24; E14

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# 1 Introduction

Over the past 25 years, there has been a noticeable move in institutional portfolios from public market to private market investments. Institutional investors are particularly integrating Private Equity (PE) and Venture Capital (VC) into their portfolios, recognizing its diversification benefits due to its low correlation with traditional asset classes. It also aligns with the fundamental finance principle that diversification is crucial for optimizing risk-return profiles (Longin and Solnik, 2001). However, as Gompers and Lerner (2000) and Brown et al. (2021) note, diversifying in PE comes with its own set of challenges, including systematic liquidity shocks and the discretionary power of general partners (GPs). However, PE remains an attractive investment option. Despite these challenges, the potential of PE to enhance overall portfolio performance remains significant, especially when considered in the context of macroeconomic volatility and its impact on returns.

Recent crises that we witnessed in the financial market, including the global crisis and COVID-19, have forced many investors to question portfolio resilience and long-term persistence when faced with shocks and whether specific shocks carry structural or strategic implications on long-run persistence. This raised the question of the power of diversification in institutional investments. Additionally, we are moving into a structurally different interest rate environment. PE firms frequently employ leverage in their investment strategies. In an accommodative rate environment, investors are increasingly worried that if lack of easing leverage could challenge the high performance as it was in the last two decades.

Motivated by the growing interest in the diversification benefits of PE/VC, this paper examines how resilient PE and VC returns to real-world shocks, namely whether shocks of traditional assets and the macro economy coming from a range of factors have more or less persistence to PE and VC returns. The persistence of shocks on asset class behavior indicates how vulnerable the asset class is to volatility, either directly as a function of an exogenous shock or indirectly through a liquid asset class that impacts how PE and VC are financed. Specifically, we use a Vector Autoregression (VAR) framework to assess the reactivity and adaptability of PE and VC in the face of fluctuations in traditional asset classes and macroeconomic indicators.

As the economy experiences different states, implying a time-varying profile for such shocks, we apply models that allow the shock profile to change smoothly over time. The time-varying nature of these shocks and their impact on returns is not revealed when assuming stationary data. Hence, the treatment of non-stationarity will reveal alternative avenues for modeling and forecasting the impact these asset classes experience post-shock. A model that allows for the non-stationary nature of the data is essential to gain a meaningful appreciation of such shocks since it is unrealistic to assume that the behavior of a time series exhibits stability over the long run.

Given the sensitivity of asset return profiles to various shocks, we take into consideration the variety of modeling approaches and the assumptions therein. Hence, we generate impulse response functions from the following: (1) Unrestricted VAR (UVAR): a standard model with asset returns and all variables appearing in their differences. The problem here is that the long-run co-movements are ignored as the first difference filtering ignores underlying long-run properties and relationships. (2) Cointegrated Level VAR (CVAR) (Stock and Watson, 1990): As long as the system is cointegrated, variables appear in the level, preserving long-run dynamics. (3) Combing short and long run: Vector Error Correction Model (VECM): Allow both the short run and long run returns to coexist within the same system. Derive error correction term from underlying cointegrated model and embed within the model and generate Generalized Impulse Response Functions (GIRFs).

We begin by conducting unit root tests to explore the stationarity properties of the data, which is a prerequisite to ensure the validity of subsequent analyses. We run several unit root tests to examine whether the level and return of PE, VC and various indices are stationary. The results reveal that the level of PE, VC, S&P 500, Treasury bonds, commodities, and hedge funds generally show non-stationary behavior, indicating that their movements are more influenced by long-term factors than by short-term fluctuations. This non-stationarity suggests that predictions based solely on past data may not be dependable. In contrast, the liquidity and Purchasing Managers Index (PMI) demonstrate stationarity, often reverting to historical averages, which aligns with established financial theories. However, the indices appear stationary when looking at quarterly returns, supporting further analysis with VAR models to understand how PE and VC interact with other asset classes and economic factors.

Using a UVAR model with four lags[1], we use GIRFs to detect the effects of shock in PE and VC returns in response to one standard deviation shock in PE and VC returns on other asset classes, market liquidity and economic growth over the long run. The results show that while PE returns are influenced by immediate market and economic changes, they exhibit a solid ability to regain stability. It suggests an underlying robustness of PE against long-term market fluctuations, indicating that PE and VC are resilient to those shocks in the capital markets.

Under UVAR, we proceed with the Generalized Forecast Error Variance Decomposition (FEVD), which offers a detailed perspective on how shocks in PE and VC returns influence other financial series. It reveals a persistent correlation between PE returns and hedge funds, suggesting a shared influence or market strategy. Also, it suggests an increasing impact of S&P 500 on PE over extended periods, reflecting the sensitivity of PE to broader economic patterns. While also impacted by hedge funds and S&P 500, VC displays its distinct response curve. The results emphasize the importance of hedge funds as a proxy for alternative investments and the S&P 500's role in capturing long-term market trends affecting PE and VC returns.

[1]The selection of the number of lags is correlated to data frequency out of coincidence due to enough depth to determine correlated error structures. We choose a sufficient number of lags to achieve uncorrelated error structures within the VAR equations, ensuring that serial correlation is minimized. It also has to do with dynamic depth versus degrees of freedom so a ranking was used with serial correlation as primary with dynamic depth balanced with dimensionality to come up with an optimal choice of lag length.

CVAR combines variables in their levels (long-run content) and short-term dynamics, allowing for a comprehensive analysis of economic relationships. This approach addresses the limitations of the UVAR model, which traditionally focuses on individual time series without considering long-term equilibrium relationships. The CVAR results reveal an immediate and significant response to shocks in the PE/VC index level. However, these indices can adapt quickly to changes in market conditions, typically stabilizing within 10 quarters, with only a lasting effect on the price level from the initial shock. The CVAR model focuses on immediate impacts and extended market effects. Overall, the GIRF suggests that both PE and VC are influenced by immediate shocks in financial indicators but exhibit a strong capacity to regain equilibrium in the long term.

Furthermore, we conduct the persistence profiles for the effects of system-wide financial shocks on PE and VC. It illustrates the immediate and long-term impacts of hypothetical central disturbances in the financial system on PE and VC indices. PE shows an intense but brief reaction, recovering swiftly due to its association with more mature, diversified companies and the use of leveraged buyouts. This quick stabilization reflects PE's market resilience. In contrast, VC exhibits a less intense initial response but endures a more extended period of elevated impact, reflecting its investment focus on early-stage, high-growth companies. VC's extended recovery period is influenced by its limited use of leverage, high-risk investor tolerance, and dependence on growth and exit strategies, making it more sensitive to market and regulatory shifts.

Finally, we also conduct the GIRF analysis within the VECM framework. This analysis tracks the effects of a one-standard-deviation shock on each of the cointegrated variables in the system, considering both the short-term dynamics and the error correction mechanism. Consistent with the previous results, the VECM analysis shows that PE and VC markets are quite resilient to shocks.

Our study makes the following three contributions to the literature. First, we bridge a significant gap in existing research by exploring the relationship between private markets, public markets, and macroeconomic factors. While traditional assets have been extensively studied, the dynamics of their relationship with PE has received less attention. Our findings indicate that PE and VC, though impacted by short-term market fluctuations, exhibit long-term stability consistent with literature and policy reports (e.g., World Economic Forum, 2022; Kaplan and Schoar, 2005, etc). Specifically, the decomposition finding emphasizes the importance of hedge funds as a proxy for alternative investments and shares' role in capturing long-term market trends affecting PE and VC returns. This insight enhances our understanding of how these asset classes react to broader market dynamics and macroeconomic shifts, thereby enriching the current literature, which often overlooks these aspects.

Second, we address the less-explored role of PE and VC in institutional portfolios. By tracking the performance of major asset classes over 30 years, we examine the sensitivities of PE/VC to traditional financial market changes and macroeconomic variables. We find that although PE and VC are associated with high risk, they offer not only high returns but also significant resilience, providing another reason for institutional portfolios to select them. This study offers robust evidence that supports the inclusion of PE/VC in institutional portfolios and provides guidance on strategic asset allocation within a diversified portfolio.

Third, our study extends the existing literature on the relationship between illiquidity and resilience by providing empirical evidence on the resilience of PE/VC as an illiquid asset class faced with financial market shocks. Prior research has highlighted the varying resilience of different market segments, such as Anderson et al. (2018), who found that markets relying less on core intermediaries exhibit increased liquidity at the potential cost of reduced resilience, and Hua et al. (2020), who demonstrated that stocks with lower resiliency command higher expected returns. This work adds evidence from the private equity perspective and offers insights into how the illiquid nature of PE contributes to its ability to withstand market volatility, thereby enhancing our understanding of the intricate dynamics between asset illiquidity and resilience.

The remainder of the paper is organized as follows. Section 2 discusses the literature related to our studies. Section 3 details the data source and sample. Section 4 outlines the econometric models. Section 5 presents the empirical results. Section 6 concludes the studies and discusses the implications for the finance industry.

# 2 Literature Review

## 2.1 Private Equity and its Interplay with Other Asset Classes

There are two strands of literature related to our paper. The first strand is a large literature discussing asset allocation with private equity. Over the past twenty years, PE has increased significantly as an alternative investment asset class. Institutional investors increasingly integrate PE into their portfolios, recognizing its diversification benefits due to its low correlation with traditional asset classes.

However, determining the optimal allocation to PE is still debated. Some argue for a large allocation because of PE's high return potential, while others warn against excessive exposure due to the risks involved (Ang et al., 2018). The best allocation often depends on an investor's risk tolerance, investment horizon, and need for liquidity. Modeling PE returns can be challenging because they are generally "smoothed" due to appraisal-based reporting (Conner and Schmid, 2003; Couts et al., 2020). Ang and Chen (2002) and Phalippou and Gottschalg (2009) provide a balanced view, suggesting that while PE can enhance risk-adjusted returns in a diversified portfolio, its illiquidity is a key consideration. Therefore, investors must have a clear strategy to incorporate PE into their portfolios effectively.

Recent studies have also explored the connection between private and public equity. Evidence suggests that the movements of private and public equity markets are closely aligned (Gompers and Lerner, 2000; Gompers et al., 2008; Kaplan and Strömberg, 2009). High valuations in public markets often coincide with increased investments in PE funds and the creation of new funds (Kaplan and Schoar, 2005). This trend can lead to lower absolute returns for PE funds, potentially due to over-optimism among investors or natural market cycles. A key question is whether this cyclicality persists when adjusted for market conditions.

Asset prices are widely believed to react sensitively to economic factors, with the link between macroeconomic variables and financial market performance being a central focus for researchers. Earlier studies, such as Fama (1981) and Chen et al. (1986), emphasized the importance of macroeconomic variables like industrial production and inflation in predicting stock returns. Further research by Bekaert et al. (2014) and Koijen et al. (2017) highlighted the impact of global and transitory economic shocks on asset prices. Recent events like the Great Recession and the COVID-19 crisis have further demonstrated the heightened sensitivity of asset prices to macroeconomic shifts (Guerron-Quintana and Jinnai, 2019; Fromentin et al., 2022).

While there is extensive literature on how macroeconomic factors affect traditional asset classes, less research has focused on their impact on PE returns. Some studies, like Franzoni et al. (2012), have noted PE's exposure to liquidity risk but haven't deeply examined how economic conditions influence PE returns. Understanding this is crucial for effective diversification strategies, especially given the cyclical nature and resilience of PE returns.

## 2.2 Asset Performance Resilience

The second area of literature focuses on asset performance resilience, especially during economic downturns. (Bernstein et al., 2019) found that PE-backed companies tend to be more resilient during economic downturns, playing a stabilizing role in troubled times. Their research shows that PE-backed companies decrease their investments less than non-

PE-backed firms during financial crises, maintaining an investment rate 5-6% higher. This resilience is attributed to PE firms' better access to financial resources, strong banking relationships, long investment horizons, and the ability to redeploy human capital. These firms were more likely to interact frequently with portfolio companies during crises, leading to greater growth in their assets in subsequent years.

In contrast, research by Anand et al. (2013) focuses on institutional trading and stock resilience during the 2008 financial crisis. They find that liquidity suppliers, such as mutual and pension funds, withdrew from risky securities during the crisis and took an extended period to re-engage in risky assets as market conditions improved. This highlights how different asset classes exhibit varying levels of resilience and recovery patterns in response to economic shocks.

The connection between illiquidity and resilience is further explored. Anderson et al. (2018) argue that markets relying less on core intermediaries (e.g., equities) have increased normal liquidity levels at the potential cost of reduced resilience, whereas markets more dependent on intermediaries (e.g., corporate bonds) exhibit lower liquidity but greater resilience due to stronger intermediaries. Hua et al. (2020) find that stocks with lower resilience yield higher expected returns, suggesting that investors demand a premium for holding less resilient assets.

Regarding PE, Franzoni et al. (2012) challenge the idea that PE always provides diversification benefits. They argue that PE has significant exposure to liquidity risk, similar to public equities, and note a liquidity risk premium of about 6% per year for PE. When accounting for this premium, the additional returns (alpha) associated with PE diminish, raising questions about its true resilience during market stress.

## 2.3 Research Gap

Despite the growing body of literature on asset performance resilience, there is still a gap in understanding how PE and VC returns respond to macroeconomic shocks compared to other asset classes. While existing research has documented various macroeconomic factors affecting asset prices, it has yet to thoroughly explore how these factors interact with market conditions to influence PE returns. Given the unique nature of PE/VC as illiquid assets with potential for high returns, understanding their resilience to real economic shocks is important for institutional investors seeking to optimize portfolio diversification strategies.

To integrate PE/VC with traditional assets, this study will focus on two key areas. First, it will explore the relationship between PE/VC and traditional asset classes like stocks, bonds, commodities, and hedge funds. While the interactions between these traditional assets are well-studied, the connection between PE/VC and these assets remains a gap in the literature. Second, the study will consider how broader economic trends influence PE/VC performance. Although PE can diversify a portfolio, it is not completely insulated from the overall economy. A deeper understanding of these influences can help investors predict how PE/VC might respond to economic changes.

Our research aims to address the challenges of including PE/VC in institutional portfolios. We will identify major alternative asset classes, including public and private assets, and examine their performance over time. Using PE/VC index and return data, we will estimate how sensitive these assets are to macroeconomic factors and traditional market performance. We will also analyze how these investment strategies perform in different economic conditions to determine if PE/VC can offer protection against market volatility while still providing high returns.

# 3 Data: Construction and Basic Properties

## 3.1 Data Source

We collect data from the following four main sources: (1) PE and VC data from Preqin; (2) treasury bond prices and S&P 500 index from the Center for Research in Security Prices (CRSP); (3) commodity and hedge fund index from Datastream; (4) liquidity and economic growth data from Federal Reserve Economic Data (FRED).

The common way to assess fund performance is to look at the cash-flow stream between General Partners (GPs) and Limited Partners (LPs). Typically, performance is measured by the internal rate of return (IRR) of these cash flows (Kaplan and Schoar, 2005). We use the cash flow data from Preqin to construct the U.S. quarterly PE and VC indices. To be included in our sample for a specific time horizon, a fund must be active at both the beginning and end of the period, indicated by a residual value reported on both dates. Preqin addresses potential survivorship bias in its cash flow data by sourcing from diverse channels, including GP disclosures, public filings, and Freedom of Information Act (FOIA) requests. The risk of bias from GP-reported data is mitigated by leveraging substantial data from public LPs via FOIA. Moreover, data for each fund typically comes from an average of four sources, including LPs and GPs. This comprehensive approach allows for comparison and validation of fund performance data, effectively minimizing survivorship bias.

Specifically, we calculate the pooled IRR using the fund's net asset value (NAV) at the beginning of the period as a negative outflow, LP contributions as a negative outflow (treated as the initial investment), distributions as a positive inflow and the fund's NAV at the end of the period as a positive number.

$$IRR = \frac{NAV_{end} + Distributions}{NAV_{open} + Called} \tag{1}$$

Next, we value-weight the quarterly returns for the same year and quarter to get the time-series quarterly return for PE and VC. We then compute PE and VC index, setting the start of our sample period to 100. We define $I_{t1} = I_t * (1 + y_t)$, where $y_t$ is the quarterly return at quarter t. Other indices are collected directly. We compute quarterly returns as $y_t = ln(P_t/P_{t1})$, where $P_t$ represents the asset price or index at quarter t.

## 3.2 Sample Selection Procedures

Our sample data consist of quarterly return and index of (1) US Private Equity, (2) US Venture Capital, (3) S&P 500 index, (4) 10-year Treasury bond prices, (5) Goldman Sachs Commodity Index (GSCI), (6) Hedge Fund index (HFRI), (7) Chicago Fed National Financial Conditions Index (NFCI) and (8) U.S. ISM Manufacturing Purchasing Managers Index (PMI).

Our final sample covers the period from Q1 1990 to Q4 2022, totalling 132 quarterly returns and indices for each series.

## 3.3 Summary Statistics and Graph

Figures 1 and 2 plot the quarterly time series of return and index for PE and VC. PE returns have shown a pattern of relative stability, particularly since the early 1990s. There was a significant spike around the year 2000, influenced by the tech boom, and then a big drop in 2008 due to the global financial crisis reflecting the widespread impact of the economic downturn on asset values. Recovering from the crisis, the subsequent years have been returned to stability and went a gentle uptrend in quarterly returns suggesting a maturing market and possibly more conservative investment approaches. Similar to PE, VC returns have also been more stable since the 1990s, but the fluctuations were bigger here, especially with a huge jump around 2000 during the tech bubble and a noticeable crash in the

2008 economic crisis. After that, the post-crisis period for VC is characterized by resilience and growth, with a visible but gentle upward trend in the years following 2010. This period shows some fluctuations but lacks the extreme volatility of the early 2000s, possibly resulting from a more cautious investment climate and a diversification of the VC portfolio beyond the high-tech sector. The trend of PE and VC performance are consistent with Harris et al. (2014) and Ghai et al. (2014).

[Insert Figure 1-2 here]

Figure 3 plots the quarterly time series of indices for each of the eight assets or economic indicators that we examine from 1990 to 2022. Both PE and VC indices show a dramatic increase, especially notable after 2010, with PE index slightly outperforming the VC. This trend can be attributed to PE investments, which are often in more mature companies, demonstrating resilience to economic fluctuations and benefiting from a broader diversification across various sectors and geographies, thereby ensuring more stable performance. S&P500, which is a broad representation of the stock market, also climbs steadily, reflecting an overall exponential growth pattern with fewer fluctuations compared to PE and VC. The 10-year Treasury bond index also increases over time and does so at a much more modest pace, showing interest rates have been trending down. GSCI moves in a similar direction to S&P 500 but with more volatility, indicating periods of significant price changes in commodities. HFRI shows growth but levels off in the latter part of the sample, suggesting a phase of slower growth or stabilization in hedge fund performance. NFCI and PMI are more stable throughout the sample period, with NFCI showing slight upward movement and PMI remaining relatively flat, indicating consistent manufacturing conditions.

In summary, while all the assets and indicators show growth over the sample period, PE and VC indices exhibit the most pronounced increase, especially in recent years. The treasury bond index grows but remains stable, as expected for such assets. Commodity shows a similar upward trend to the S&P 500 but is more volatile, reflecting the dynamic nature of commodity markets. HFRI, NFCI, and PMI demonstrate more stability, with less pronounced changes over the period.

[Insert Figure 3 here]

Table 1 reports the summary statistics of the quarterly return and index for all 8 series for the 132 observations. PE shows an average return of 3.38% with a volatility of 5.89%, indicating a moderately stable investment compared to VC, which has similar average returns but higher volatility at 8.15%. The summary statistics of VC and PE are consistent with the US PE and VC 1-year pooled return from Cambridge Associated LLC from Datastream. The 10-year Treasury bond appears to be the most stable with the lowest volatility, as expected from such low-risk instruments. The S&P 500 has higher volatility similar to VC but with lower average returns, while the commodity index has the highest volatility at 13.40%, indicating a riskier investment. The hedge fund index provides a moderate return with lower volatility. The financial conditions index remains stable with zero average return and low volatility, while the PMI has a minimal average return with relatively high volatility.

Overall, PE and VC have provided higher returns with substantial growth in their index values, along with significant risk as shown by their volatility. Treasury bonds, while providing lower returns, offer stability, a contrast to the S&P 500 and GSCI, which present higher risk and return profiles. Hedge funds offer a middle ground with moderate returns and growth. The NFCI and PMI show stability in their respective economic conditions, with minimal fluctuations. Overall, the data indicates a varied performance across different asset classes and economic indicators, with higher returns generally associated with higher risk.

[Insert Table 1 here]

# 4 Underlying Model and Econometric Methodology

## 4.1 Unit Root Test

An important aspect of analyzing the time series process of asset returns is to have a unit root test that is able to identify a nonstationary property. Unit root tests are statistical methods used to determine whether a time series is stationary or non-stationary. Stationarity implies that the statistical properties of the series (like mean, variance, and autocorrelation) are constant over time, which is a key assumption in many time series analysis methods. A unit root in a time series signifies non-stationarity, meaning these properties change over time. Unit root tests are notoriously low-power tests. Therefore, we present five different unit root tests, which are: (1) Augmented Dickey-Fuller Generalized Least Squares (ADF-GLS) Test, (2) Augmented Dickey-Fuller Wavelet Spectrum (ADF-WS) Test, (3) Augmented Dickey-Fuller Maximum Value (ADF-MAX) Test, (4) Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test and (5) Phillips-Perron (PP) Test. Two of the most conventionally used unit root tests in the literature are the ADF and PP tests.

### 4.1.1 ADF Test

The ADF test is the most widely used. It checks for a unit root by estimating an autoregressive model and testing whether the lagged level of the series has a coefficient equal to one. The ADF test can be modified to include an intercept, a trend, or both, depending on the nature of the time series.

Consider the time series with serial correlation in errors described as:

$$y_t = a + \rho y_{t-1} + \varepsilon_t \tag{2}$$

and

$$\varepsilon_t = \phi\varepsilon_{t-1} + e_t + \theta e_{t-1} \tag{3}$$

The ADF test is carried out by estimating

$$\Delta y_t = a + \alpha y_{t-1} + \sum_{j=1}^{k} \beta_j \Delta y_{t-j} + \varepsilon_t \tag{4}$$

where $\alpha = 1$ and t = 1...,T. The augmented terms $y_t$ of higher order lags are included into equation (2) to correct the serial correlations of the disturbances $_t$. The number of k lags is selected by the SIC. The null hypothesis of a unit root ($\alpha = 0$) is tested against the alternative hypothesis of stationarity ($\alpha < 0$). The test statistic is evaluated using the conventional t-ratio for $\alpha$ and the critical value is obtained by MacKinnon's updated version of Dickey-Fuller critical values.

The ADF test reports a test statistic that is compared against critical values to determine the presence of a unit root. Lower test statistic values generally indicate stronger evidence against a unit root, suggesting stationarity. The test also includes additional lagged differences of the series to account for autocorrelation.

The ADF-GLS test is an enhancement of the traditional ADF test. The ADF test is one of the most used methods for unit root testing, but it has some limitations, especially in the presence of near-to-unit root processes or when the series has a large sample size. These limitations can lead to lower test power, meaning the ADF test might not always effectively differentiate between a stationary and a non-stationary series. To overcome these issues, the ADF-GLS test modifies the testing procedure by (1) Detrending the data: Before applying the ADF test, the series is transformed using a Generalized Least Squares (GLS) procedure to remove any deterministic trend. This detrending process enhances the power of the test, especially when the series is close to non-stationary; (2) Modified Test Equation: The test then applies the ADF test on this detrended series. The ADF test involves estimating an autoregressive model and testing whether the lagged level of the series has a coefficient equal to one (the unit root case).

The ADF-WS test aims to enhance the traditional ADF test by incorporating wavelet analysis into the unit root testing procedure. Wavelet analysis is a powerful tool in time series analysis, particularly for analyzing non-stationary data that exhibits variations at different frequencies or scales. Traditional time series methods often struggle with such data because they typically assume uniform properties over time. Therefore, this corporation allows the test to handle time series data that exhibits variations at different time scales, making it potentially more robust and informative, especially for non-stationary shows exhibiting certain types of non-linearities or time-varying properties.

The ADF-MAX test incorporates the possibility of structural breaks into the unit root testing procedure. This is important because ignoring such breaks can lead to incorrect conclusions about the presence of a unit root. The "MAX" refers to the maximum value of the test statistics obtained from these different breakpoints. This test is particularly useful when the underlying data-generating process of a time series is suspected to have experienced changes at unknown points in time. These changes could be in the form of level shifts, trend shifts, or other structural alterations.

### 4.1.2 PP Test

The PP test is an alternative non-parametric approach to deal with autocorrelation in the error term and allows for heterogeneity of variance. Rather than including extra lags of $y_t$ to ensure that the errors are white noise, the PP test estimates equation(1) and modifies the t-ratio of the  coefficient so that serial correlation does not affect the asymptotic distribution of the test statistic. The null and alternative hypotheses are the same as the ADF test. Phillips and Perron (1988) proposed the nonparametric test statistic as follows:

without a trend

$$Z_t = \frac{s_e}{s}\left(t_\alpha - \frac{1}{2s}\left(s^2 - s_e^2\right)\left(T - 2\sum_{t=1}^{T-1} y_t^2\right)^{-1/2}\right) \tag{5}$$

without a trend

$$Z_t = \frac{s_e}{s}\left(t_\alpha - \frac{1}{2s}\left(s^2 - s_e^2\right)\left[T - 2\sum_{t=1}^{T-1}(y_t - \bar{y}_{t-1})^2\right]^{-1/2}\right) \tag{6}$$

where $\alpha$ is the OLS estimate of $\alpha$, $t_\alpha$ is the t-ratio of $\alpha$, $s_e$ is the coefficient standard error, and $s^2$ is the consistent estimate of the error variance. We use a kernel sum-of-covariances estimator with Bartlett weights in combination with the Newey-West bandwidth selection method to obtain estimators of the residual spectrum at frequency zero. The asymptotic distribution of the PP-modified t-ratio is the same as that of the ADF statistic, so we report MacKinnon lower-tail critical values for this test.

#### 4.1.3 KPSS Test

The KPSS test is a statistical test used to analyze the stationarity of a time series. Unlike the Augmented Dickey-Fuller (ADF) test and other unit root tests, where the null hypothesis assumes the presence of a unit root (non-stationarity), the KPSS test has a null hypothesis that the series is stationary, which is y against the alternative hypothesis of a random walk.

The KPSS test starts with

$$y_t = \delta t + \zeta_t + \varepsilon_t \tag{7}$$

where $_t$ is a stationary process and $_t$ is a random walk given by

$$\zeta_t = \zeta_{t-1} + u_t, \quad u \sim \mathrm{iid}(0, \sigma_u^2) \tag{8}$$

The null hypothesis of stationarity is formulated as

$$H_0 : \sigma_u^2 \quad \text{or} \quad \zeta_t \text{ is a constant} \tag{9}$$

and the alternative hypothesis is that the parameter follows a random walk. The test statistic for this hypothesis is given by

$$\text{LM} = \frac{\sum_{t=1}^{T} S_t^2}{\hat{\sigma}_e^2} \tag{10}$$

where $S_t = \sum_{i=1}^{t} e_i$, with $t = 1, \ldots, T$, is the cumulative residual function for $e_t$, which are the residuals from the regression of $y_t$ on a constant and a time trend. Here, $\hat{\sigma}_e^2$ is the residual variance. A Bartlett spectral window kernel-based estimator is used to obtain a consistent estimate of the variance, and the bandwidth is selected using the Newey-West method. The KPSS test is an upper-tailed test. Maddala and Kim (1998) do not recommend using the KPSS test since the KPSS test has low power, so test results can be very sensitive as shown by their Monte Carlo studies. However, we will report results from this test for the sake of completeness and because it is often used in empirical studies.

## 4.2 Unrestricted VAR model

The UVAR model analyzes the short-run dynamic interactions among variables by focusing solely on returns, thereby filtering out long-term information. Since UVAR requires all variables to be stationary, they are used in their first differences. While this approach is valid and widely used for examining short-run dynamics, it does not capture the long-term equilibrium relationships between variables.

### 4.2.1 Conceptual Implications

As a pre-requisite to an analysis of the relationship between two or more variables, it would seem reasonable to investigate whether there exists a long-run stable or equilibrium relationship between these variables in their levels. Alternatively, there is a need to check that the relationship between the variables is not spurious. There are theoretical grounds which also raise a number of interesting questions based on the validation of this proposition. Thus, given its importance for economic theory and econometric modelling purposes, many studies have employed cointegration based techniques to address the issue of the estimation and long-run relationship between variables. The concept of cointegration was introduced by Granger (1981). A formal definition considers two variables $x_t$ and $y_t$, that are both $I(1)$. Then $x_t$ and $y_t$ are said to be cointegrated if there exists a $\beta$ such that $y_t - \beta x_t$ is $I(0)$. Intuitively, this implies that there exists a long-run equilibrium relationship between $x_t$ and $y_t$. If these variables were not cointegrated, then the relationship between them would be spurious.

Starting off with an underlying, unrestricted VAR model, we briefly review the VAR model concerning its functional specification. The popular Johansen procedure is discussed among the various tests employed for cointegration, considering its advantages and limitations. Building on this, we then turn to the concept behind testing for causality, whether this be short-run or long-run causality, and consider the implications for causality testing in VAR and VEC models. We pay attention to what issues confront the applied researcher in testing hypotheses in the absence and presence of cointegration. Finally, we present the methodology associated with an alternative potential approach for application in testing whether the finance-growth relationship shares a long-run relationship and also to what extent these variables are 'long-run forcing.'

### 4.2.2 Model

Drawing upon the exposition provided by Pesaran and Smith (1998), consider a basic $p$-th order structural vector autoregressive distributed lag (VARDL) model, where $y_t$ is a column vector of $m_y$ endogenous variables and $x_t$ is a column vector of $m_x$ strictly exogenous variables, specified as:

$$A_0 y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + B_0 x_t + B_1 x_{t-1} + \cdots + B_p x_{t-p} + D d_t + \varepsilon_t \tag{11}$$

where $t = 1, 2, \ldots, T$ and $d_t$ is a $q$-dimensional vector of deterministic variables such as intercept, trends and seasonal dummies. The errors, $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t}, \ldots, \varepsilon_{m_y t})'$, are assumed to be a serially uncorrelated column vector of errors distributed independently of the strictly exogenous variables $x_t$ with mean zero and variance-covariance matrix $\Omega = (\omega_{ij})$. The stability of this system is ensured if all roots of the determinant equation fall strictly outside the unit circle. This implies that long-run relationships may exist between $x_t$ and $y_t$ as long as one of the elements of $x_t$ contains a unit root.

The additional feature of this model is that, by allowing for contemporaneous interactions between the endogenous variables through the coefficient matrix $A_0$, it can be termed as 'structural'. Alternatively, by making use of the lag operator $Ly_t = y_{t-1}$, the model can also be written as:

$$A(L) y_t = B(L) x_t + D d_t + \varepsilon_t \tag{12}$$

where

$$A(L) = A_0 - A_1 L - \cdots - A_p L^p$$

$$B(L) = B_0 - B_1 L - \cdots - B_p L^p$$

The long-run effects of exogenous variables $x_t$ of the system on the endogenous variables $y_t$ are given by:

$$A(1)^{-1}B(1) = \left(A_0 - \sum_{i=1}^{p} A_i\right)^{-1} \sum_{i=1}^{p} B_i \tag{13}$$

In the absence of exogenous variables, $B_i = 0$ for $i = 0, 1, \ldots, p$ and the VARDL model reduces to a VAR($p$) model. This restricted model has provided a basis from which much of the cointegration literature has expanded from and become an essential part of the time series econometrician's toolkit. While this model can also be employed to analyse situations where Bayesian priors and more detailed structural forms are used in macroeconometrics, the next section builds on this model in demonstrating the implications of cointegration.

## 4.3 Cointegrated Level VAR

The CVAR model addresses the limitations of the UVAR model by incorporating both long-run equilibrium relationships and short-term dynamics among variables. Unlike UVAR, which filters out long-term information by using only the first differences of variables, CVAR allows variables to appear in their levels. This inclusion provides a more comprehensive analysis of economic relationships by capturing both the long-term content and short-run interactions. As a modern econometric approach, CVAR offers a more comprehensive understanding of how variables co-move over time, making it particularly useful for analyzing complex financial and economic systems.

### 4.3.1 Conceptual Implications

The concept of the long run is linked to the notion of equilibrium in economics, as many economic theories are concerned with equilibrium relationships in which one or more series are expected to act as attractors to each other. In contrast, the concept of short-run is mainly associated with the temporal dynamics surrounding the path to the long-run relationship.

For example, short-run dynamics could be due to adjustment costs, unfilled expectations, etc. In this respect, it is not surprising that theory typically has little to say about short-run relationships, since asset prices and other financial instruments in the immediate to short-run are mainly governed by noise, technical or purely non-fundamental phenomena. In econometric modeling, the long-run and short-run have traditionally been treated as part of separate models, but nowadays procedures can allow both the short-run and long-run to be incorporated into the same model.

Pesaran (1997) places special emphasis on this issue in applied econometric modeling and argues that theory is often more informative about long-run relationships rather than short-run dynamics. A closer link between theory and empirical evidence is called for and an alternative theory-based procedure is proposed. One suggestion is that one formulates long-run relations as the steady-state solution of intertemporal economic optimization problems. If a stable steady-state solution exists, such long-run relations will be the steady-state solution of the particular model under consideration. An example of a model for practical purposes is a VAR model, which enables one to incorporate theory-consistent long-run relations in a suitably specified multivariate dynamic model. The question of how the short-run dynamics can also be accounted for is still unsolved. Using this framework, the adjustment to the long-run equilibrium can be restricted by examining the nature of the underlying optimization problem. This approach links the modeling of long-run relations in economics and the intertemporal equilibrium concept from economic theory.

### 4.3.2 Model

In the context of the VAR(p) model discussed above where $A_0 = I_m$ and $B_i = 0$ for all $i$, consider the case where only endogenous I(1) variables are included along with linear deterministic trends. This leads to:

$$z_t = \Phi_1 z_{t-1} + \ldots + \Phi_p z_{t-p} + a_0 + a_1 T + e_t \quad (11)$$

where $a_0$ and $a_1$ are $m \times 1$ column vectors of estimable parameters, and the lag length $p$ is assumed to be sufficiently large enough to ensure $e_t$ is serially uncorrelated, distributed as with mean zero and a positive definite variance-covariance matrix. In empirical analysis, normality of $e_t$ is also assumed for the purposes of maximum likelihood estimation, although this is not necessary asymptotically.

## 4.4 Vector Error Correction Model (VECM)

The VECM extends both the UVAR and CVAR models by incorporating short-term dynamics and long-term equilibrium relationships into a single framework. It derives an error correction term from the cointegrated model, allowing the system to adjust to shocks while maintaining equilibrium over time. By capturing the effects of one-standard-deviation shocks on both short- and long-run dynamics, VECM helps indicate a robust nature of the interactions between PE/VC returns and other financial indicators.

### 4.4.1 Conceptual Implications

As the VAR(p) model stands, no assumptions have so far been made regarding the stochastic properties of $z_t$. We now introduce a reparametrized version of the VAR(p) model where the implications of cointegration may be discussed. Engle and Granger (1987) show that in the presence of cointegration, there always exists a corresponding error-correction representation which implies that changes in the dependent variable are a function of the level of disequilibrium in the cointegrating relationship (captured by the error-correction term), as well as changes in other explanatory variable(s). If we exploit the idea that there may exist co-movements between alternative measures of asset returns and growth, and possibilities that they will trend together in finding a long-run stable equilibrium, using the Granger representation theorem, we may specify a relationship which constitutes our $p$-th order vector error-correction model (VECM(p)).

### 4.4.2 Model

Pesaran et al. (2000) essentially partition the $m$-vector of random variables $z_t = (y_t', x_t')'$, $t = 1, 2, \ldots$ constituting an $n$-dimensional vector of $y_t$ and $k$-vector of $x_t$, where $k = m - n$. This framework allows structural modeling of the vector of $y_t$ conditional upon historical or lagged values of $y_t$ as well as contemporary and past values of random variables $x_t$. Both PSS (2000b) as well as Harbo et al. (1998) consider the problem of structural modeling and inference using this framework. Hence consider a $(k-1)$ vector random process $\{z_t\}_{t=1}^{\infty}$ whose data generating process is given by

$$\Delta z_t = a_0 + a_1 t + \sum_{i=1}^{p-1} \Gamma_i \Delta z_{t-i} + \Pi z_{t-1} + e_t, \quad t = 1, 2, \ldots, T \quad (12)$$

where $\Delta \equiv 1 - L$ is the difference operator

$$\Pi = -(I_m - \sum_{i=1}^{p} \Phi_i); \Gamma_i = -\sum_{j=i+1}^{p} \Phi_j, \quad i = 1, \ldots, p-1 \quad (13)$$

Note that the short-run response matrices $\{\Gamma_i\}_{i=1}^{p-1}$ and the long-run multiplier matrix $\Pi$ are defined above. Along with $z_t$, the error term $e_t$ is also partitioned as $e_t = (e_{yx}', e_{xt}')$ with a positive-definite variance-covariance matrix specified as:

$$\Omega = \begin{pmatrix} \Omega_{yy} & \Omega_{yx} \\ \Omega_{xy} & \Omega_{xx} \end{pmatrix} \quad (14)$$

and this allows $e_{yt}$ to be expressed conditionally in terms of $e_{xt}$ as:

$$e_{yt} = \Omega_{yx}\Omega_{xx}^{-1}e_{xt} + u_t \quad (15)$$

where $u_t \sim IN(0, \Omega_{uu}), \Omega_{uu} \equiv \Omega_{yy} - \Omega_{yx}\Omega_{xx}^{-1}\Omega_{xy}$ and $u_t$ is independent of $e_{xt}$. Substitution of the above into the expression for $\Delta z_t$ and partitioning the parameter vectors and matrices $a_0 = (a'_{y0}, a'_{x0}), a_1 = (a'_{y1}, a'_{x1}), \Pi = (\Pi'_y, \Pi'_x)', \Gamma = (\Gamma'_y, \Gamma'_x)', \Gamma_i = (\Gamma'_{yi}, \Gamma'_{xi})', i = 1, \ldots, p-1,$ leads to the following conditional model for $\Delta y_t$ as a function of $z_{t-1}, \Delta x_t, \Delta z_{t-1}, \Delta z_{t-2}, \ldots$.

# 5 Empirical Analysis

## 5.1 Unit Root Test

Tables 2 and 3 present the results of the unit root test, which is organized into five panels. Each panel shows the results from a suite of unit root tests conducted on financial market and economic time series variables: ADF-GLS, ADF-WS, ADF-MAX, KPSS and PP test. These tests are essential in proving the stationarity of the time series, examining the null hypothesis that a series is stationary around a mean (level stationarity) or a trend (trend stationarity). These tests check for stationarity, a key characteristic that implies a time series has consistent properties over time, which is important for making accurate forecasts and informed financial decisions.

Table 2 provides a comprehensive look at the unit root test results for a variety of indices. The * in the table indicates the rejection of the null hypothesis at a 5% significance level. The results suggest that indices of PE, VC, shares, bonds, commodities, and hedge funds generally exhibit non-stationary behavior. This implies that their movements are likely to be influenced by long-term factors rather than short-term, random fluctuations, which suggests that their future behaviors are less predictable based on historical averages.

By contrast, for NFCI and PMI, we can reject the null of a unit root at 5% significance level across the various tests, which consistently show signs of stationarity. This implies a tendency for these indices to revert to their historical average over time. The finding is consistent with foundational financial market principles. For NFCI, this could indicate a stable long-term trend in financial conditions despite short-term variability in liquidity. PMI, on the other hand, suggests that while industrial production may vary, it tends to stabilize around a consistent baseline, reinforcing its utility for accurate production forecasting and economic assessment.

[Insert Table 2 here]

Table 3 revisits the unit root tests, this time focusing on the quarterly returns of the same set of financial and economic indices, presenting a contrasting picture to the level data. For example, the ADF-GLS, ADF-WS, and ADF-MAX tests across all indices show significant negative values at the 5% level, suggesting stationarity in the quarterly returns. The PP test results align with this, also displaying significant negative values, further supporting the stationarity hypothesis. Moreover, the KPSS test results align with these findings, with no asterisks present, indicating a failure to reject the null hypothesis of stationarity for these series.

[Insert Table 3 here]

To summarize, the unit root tests applied to the quarterly returns of the indices suggest a general trend of stationarity, with characteristics such as mean and variance remaining constant over time. This stationarity contrasts with the non-stationary behavior inferred from the level data and aligns with expectations that the indices' returns may exhibit mean-reverting characteristics. These results, indicating stationarity in returns, justify proceeding with VAR testing to explore the interactions between PE and VC performance with other asset classes and economic factors, providing a logical next step in the analysis.

## 5.2 Unrestricted VAR

### 5.2.1 The Generalized Impulse Response Functions

The GIRFs provide a comprehensive analysis of how a shock, or unexpected change, in the returns of PE and VC impacts the returns of other asset classes over time in the long run. These graphs illustrate how a sudden change in other asset classes, market liquidity, and economic growth affects the returns of private equity and venture capital funds over time. The generalised indicates that the impulse responses are not sensitive to the order of variables in the system, which can be an issue with traditional impulse responses.

We employ a VAR model with an order of four, meaning that each equation in the system includes four lags of all the variables as predictors. Each graph represents the response of PE or VC returns to a one standard deviation shock in other variables. They typically display the response over quarters with lines representing different statistical measures like the mean or median response, as well as confidence intervals to indicate the statistical significance of the responses.

The immediate and pronounced response to an S&P 500 shock suggests PE's sensitivity to equity market dynamics, with a positive market shift translating into a swift, though temporary, rise in PE returns. This temporary effect mirrors the reaction observed when PE returns face shocks from hedge funds, suggesting a shared sensitivity to broader equity market movements given their similar investment categories. PE's integration into the wider market explains this rapid response to equity changes.

Conversely, PE's response to a 10-year bond return shock is initially negative, signifying a potential inverse relationship between bond market performance and PE returns. However, this impact is short-lived, pointing to a swift PE market adjustment to changes in bond yields, which indicates a complex interplay between fixed-income markets and PE investments, where yield fluctuations momentarily influence PE but do not result in sustained effects. PE's sensitivity to interest rate changes due to its leveraged nature. This structure makes them sensitive to interest rate changes, which is why a shock in bond yields, reflecting interest rate movements, impacts PE returns.

When shocks come from the commodity market, as indicated by the GSCI, PE returns dip initially, hinting at an adverse reaction to rising commodity prices. This response quickly reaches equilibrium, reflecting PE's ability to absorb and adapt to shifts in commodity pricing without enduring consequences. This resilience is also apparent in the reaction to market liquidity, as captured by the NFCI. Here, the initial negative response of PE returns to liquidity and stability challenges is notably short-term, with a rapid return to baseline levels. Market liquidity impacts investment strategies. The NFCI shock showing a quick but short-lived impact on PE returns might be due to PE firms' ability to secure or release capital in response to changing financial conditions, displaying efficient liquidity management.

The reaction of PE returns to shocks in economic growth, as measured by the PMI, is initially positive, highlighting the sector's favorable response to promising economic indicators. However, similar to other observed reactions, this boost in PE returns is short-lived, suggesting that while PE is adapted to immediate economic changes, its long-term pattern is not significantly affected by such fluctuations. The positive response to an economic growth shock results from PE's resilience to short-term economic variations.

In summary, these impulse responses show how PE returns react to shocks from other asset classes and economic signals. While PE returns are affected by immediate market and economic changes, they show a strong ability to regain stability, suggesting PE's resilience to long-term market fluctuations. As a result, PE is a useful asset class for diversification within institutional portfolios. The observed sensitivity highlights the need for active risk management and emphasizes the importance of a long-term view in investment strategies, making PE a valuable part of a diversified approach that helps reduce exposure to market volatility.

[Insert Figure 4 here]

The impulse response in Figure 5 demonstrates how venture capital returns react to a standard deviation shock across various financial indicators. Like PE, VC returns exhibit an immediate response to shifts in the S&P 500, hedge funds, commodities, and liquidity, as illustrated by the initial peaks in the graphs. This reflects a shared market sensitivity and a capacity for quick recovery from immediate market disturbances, indicating agility in adapting to financial market fluctuations.

The response of VC to a 10-year bond yield shock initially dips, suggesting an inverse reaction to rising bond yields, which often reflect increased interest rates. This initial reaction is less pronounced for VC than PE, hinting at VC's lower sensitivity to interest rate changes, which may be attributed to VC's investment in early-stage companies whose valuations are less directly tied to interest rates and more to growth potential and sector-specific dynamics.

VC's response to the PMI shock, while initially rising, is less pronounced compared to PE. This is because VC investments, which are often in high-growth sectors, are not as directly affected by the health of the manufacturing sector as more mature PE investments. The quick return to normal for VC shows only brief sensitivity to economic indicators, followed by a return to pre-shock conditions, highlighting the resilience of VC investments to short-term economic changes.

Overall, the generalized impulse responses suggest that both PE and VC are influenced by immediate shocks in financial indicators but exhibit a strong capacity to regain equilibrium. For investors, this pattern focuses on the need for dynamic risk management that can capitalize on quick market shifts while maintaining a strategic, long-term investment outlook. The observed resilience also positions VC as a component of diversified portfolios, capable of weathering short-term market volatilities without compromising long-term growth prospects.

[Insert Figure 5 here]

#### 5.2.2 Generalised Forecast Error Variance Decomposition

Table 4 illustrates the percentage of movements in various financial indices and economic indicators that can be explained by shocks to private equity returns (Panel A) and venture capital returns (Panel B), respectively. The output from a Generalized Forecast Error Variance Decomposition (FEVD) using an UVAR model with an order of 4.

Panel A shows the decomposition for PE return, which starts with 100% variance explained by its own shock in the first quarter, which is expected as the shock to private equity return is the variable's own innovation. For one quarter, hedge funds have a considerable impact on PE returns, with a 39.06% contribution, suggesting a strong correlation or perhaps shared market influences between PE and hedge fund performance. As the investment horizon lengthens to 10 years, the contribution of HFRI to PE returns remains consistent at 26.39%, indicating a sustained relationship over time. Differently, The S&P 500's influence on PE returns is relatively smaller at 0.35% for one quarter but increases substantially over longer horizons, aligning closely with PE returns at a 20.37% contribution for both 5 and 10-year periods. This increasing influence suggests that as an aggregate measure of the stock market, the S&P 500 captures broader economic trends that PE returns may also respond to over longer investment horizons. In comparison, other variables like the 10-year Treasury bonds (BOND10), commodities (GSCI) have less influence on PE returns. Their contributions, while notable, do not exhibit the same level of consistent explanatory power as the HFRI and S&P 500, especially over extended periods.

As the horizon extends, the percentage attributable to PE_R 's own shock decreases, indicating that other variables in the system begin to explain more of the variance in PE_R. The explanatory power of SP500_R, BOND10_R, HFRI_R, and GSCI_R on the variance of PE_R converges to a consistent range after approximately three years and maintains this stability through to the ten-year horizon. For instance, by the two-year mark, PE_R 's own variance explanation has reduced to 70.90%, while S&P 500_R explains 20.64%, and the Hedge Fund Research Index accounts for 26.47%. Notably, the variance explained by other variables remains relatively stable across longer horizons (3, 5, and 10 years), showing the persistent influence of these other asset classes on the variance of PE_R. This suggests that the financial markets may integrate and adjust to the information contained in PE shocks, settling into a state where the contributions of these variables to PE_R 's variance remain relatively constant.

The marginal impacts from NFCI_R and PMI_R are small but slightly increased over time, pointing to a growing but limited connection between these broader economic indicators and PE returns. Panel B shows a similar composition for VC returns, with HFRI and S&P 500 also being significant contributors. The HFRI's influence starts at 32.62% for one quarter and slightly decreases over a 10-year horizon to 16.43%, while the S&P 500's contribution increases from 0.45% in one quarter to 21.75% over 10 years. The pattern suggests that, like PE, VC returns are significantly influenced by market performance represented by HFRI and the broader market trends captured by the S&P 500.

Also, similar with PE return, VC return initially explains 100% of its own variance. As time progresses, the impact of VC_R's own shock diminishes, and the explanatory power of other variables such as the S&P 500 and HFRI_R increases. In this panel, by two years, the variance explained by $VC_R$ has decreased significantly to 67.97%, with the S&P 500 explaining 21.56%, and HFRI_R accounting for 16.44%. This pattern is consistent over the longer horizons, indicating a lasting interplay between venture capital returns and these indices.

The consistent explanatory power of HFRI for both PE and VC returns across all horizons suggests that hedge fund returns could be a proxy for alternative investment strategies, which are closely related to the strategies employed in private equity and venture capital. Additionally, the increasing explanatory power of the S&P 500 over longer horizons reinforces the idea that PE and VC returns are not only affected by the alternative investment space but also by the same long-term economic factors that drive the broader stock market. Both panels also suggest that while PE and VC returns can largely explain their own variance in the short term, other asset classes and economic indicators become significant in explaining their movements over time.

The relatively consistent explanatory power of other variables at longer horizons suggests that the financial markets may assimilate information from PE and VC returns and reflect it in these asset classes over time. This decomposition explains how shocks in PE and VC returns influence broader market dynamics and helps understand the diversification benefits or risks associated with these asset classes in the context of a mixed-asset portfolio.

[Insert Table 4 here]

## 5.3 Cointegrating VAR

### 5.3.1 The Generalized Impulse Response Functions

The exploration of how shocks in PE and VC returns influence other financial assets and economic factors over the long term has been detailed in previous sections. Modern econometric models, such as the CVAR model, seamlessly blend short-term and long-term dynamics, allowing for a comprehensive analysis of economic relationships. These models move beyond the UVAR approach, which traditionally focuses on individual time series without considering the long-term equilibrium relationships between them. Utilizing the CVAR model, we can examine the ripple effects of a one standard deviation shock in PE/VC on various asset classes. The main line in these graphs—typically blue—depicts the median response of PE/VC to these shocks, highlighting the typical reaction one might expect in the short run.

The shock to the S&P 500 shows an immediate and sharp response in PE/VC returns, reflecting the close ties between PE investments and broader equity market performance. This indicates that PE and VC investments, being equity-based, are sensitive to stock market movements. When shocks occur in the 10-year bond yields, PE/VC's initial negative response suggests its vulnerability to interest rate fluctuations. This is particularly relevant for PE investments that are leveraged, as changes in interest rates directly affect their cost of capital. Similarly, shocks in hedge fund returns elicit a response from PE that suggests overlapping strategies or market exposures, underlining the interconnected nature of these alternative investments. The reaction to a hedge fund shock indicates a shared exposure between PE/VC and hedge funds, which may arise from overlapping investment strategies or market exposures. This similarity in response suggests that shocks affecting hedge funds can have parallel effects on PE.

Regarding market factors, responses to commodity index shocks and NFCI reveal PE/VC's capacity to quickly adjust to changing market conditions. A negative response to commodity shocks could reflect PE/VC's exposure to sectors sensitive to raw material costs, while the NFCI response suggests PE/VC's ability to navigate financial stability and liquidity conditions. Additionally, the PMI response highlights PE/VC's sensitivity to economic health indicators, with an initial positive reaction suggesting optimism in response to positive developments in PE/VC markets.

In summary, these GIRFs reveal that PE/VC is sensitive to a range of economic and financial shocks. The patterns observed suggest that while PE/VC is influenced by immediate changes in the market, it also can stabilize over time. This resilience is crucial for investors considering both short-term volatility and long-term trends when making investment decisions. The CVAR model's integration of both short-run and long-run dynamics into a single model is particularly beneficial in finance, where understanding the fundamental economic forces driving an asset is essential for making informed investment choices.

In contrast to the CVAR's comprehensive approach, UVAR models may fail to capture the full scope of these complex relationships, particularly for those that pertain to long-run equilibrium states. The insights provided by the CVAR model underline the importance of dynamic risk management and a sustained investment perspective. By accommodating both short-run and long-run perspectives, the CVAR model helps to aid in more nuanced decision-making in finance, recognizing that while PE/VC investments may react to immediate market sentiments, fundamental economic drivers.

[Insert Figure 6,7 here]

### 5.3.2 Persistence Profile of the effect of a system-wide shock to CV

Figures 8 and 9 show two persistence profiles for the effects of system-wide shocks on PE and VC respectively. Each profile measures the impact of a hypothetical shock on the cardiovascular (CV) systems, which is likely a metaphor for a central component or driving factor in the financial system, not an actual medical reference. The persistence profile analysis is from a VAR model with a single lag (order of VAR = 1), using a cointegrating vector that includes various financial indices and a trend component.

Figure 8 suggests that the effect of the shock on private equity is strong but short-lived. At the initial horizon, the response to a system-wide shock (a widespread financial disturbance, which could range from a fiscal crisis to a sudden market adjustment) to the PE is complete, with a value of 1, indicating a significant immediate impact of the shock, which then quickly trends downward, becoming relatively negligible. When we reach the long-term horizons, such as 10 years and beyond, the persistence of the shock is minimal, suggesting that the system's response to the shock has largely stabilized and the impact is no longer significant. This pattern suggests that while the private equity market may be sensitive to shocks with some resilience, it experiences a swift initial reaction followed by a steady return to equilibrium.

[Insert Figure 8 here]

Figure 9, corresponding to the VC index, shows a similar pattern of response to the shock with a sharp initial reaction followed by a rapid decline. However, the peak in the VC index graph is less pronounced compared to the PE index graph. This indicates that the venture capital index itself has a slightly less volatile reaction to its own shocks yet follows a similar pattern of quick recovery and stabilization.

Both profiles demonstrate that the systems eventually absorb the shocks, but the paths to stabilization differ, reflecting the unique response dynamics of each index to systemic shocks. Compared to the PE index. The VC index response to the shock also approaches zero, but it maintains a slightly elevated level longer than the private equity before settling down, implying a longer-lasting effect of the shock in the venture capital system.

The differential shock response between PE and VC performance is mainly due to their distinct market characteristics and investor profiles. PE typically deals with more established firms and leveraged buyouts, leading to an immediate but short-lived shock response due to better liquidity, diversification, and market depth. In contrast, VC's focus on early-stage, high-growth companies results in a stronger initial shock impact and a longer adjustment period, as these companies are less diversified and require more time to adapt to market changes.

Furthermore, PE's use of debt boosts shock effects but also facilitates a quicker recovery through well-established financial mechanisms. VC, being less leveraged and more equity-oriented, faces longer-term challenges post-shock, exacerbated by the high-risk tolerance of its investors and reliance on growth and exit strategies that are sensitive to market sentiment and regulatory changes. These factors collectively contribute to the observed differences in shock absorption and recovery paths between PE and VC investments.

[Insert Figure 9 here]

## 5.4 Vector Error Correction Model

After detailing the generalized impulse response functions and the forecast error variance decomposition using unrestricted VAR models, the next step in the analysis involves applying the Vector Error Correction Model (VECM). This model allows for a nuanced analysis of the cointegrated relationship between non-stationary financial time series. The VECM considers the long-run equilibrium relationships between the series while still capturing their short-run dynamics.

The VECM analysis has provided substantial insights into the dynamic behavior of PE and VC returns in response to various economic and financial shocks. The results of the VECM, which incorporate both the short-term dynamics and the long-term equilibrium relationships between the variables, exhibit a strong resemblance to the findings obtained from the UVAR model. This indicates that the inclusion of the long-term equilibrium constraints into the VECM does not substantially alter the fundamental nature of the relationship between PE/VC returns and the other financial indicators.

Consistent with the UVAR results, the VECM analysis shows that PE and VC markets are quite resilient to shocks. Despite the initial fluctuations in response to shocks from different financial indices and economic indicators, the PE/VC returns demonstrate a rapid reversion toward the equilibrium state. This resilience is reflected in the error correction terms, which capture the speed of adjustment back to the long-run equilibrium following short-term disturbances. The relatively quick adjustment processes highlight the robustness of PE/VC as investment classes and underscore their potential for stability in the face of market volatility. The VECM's confirmation of the UVAR findings lends further credence to the view that PE/VC investments are capable of withstanding shocks and suggests they may serve as a stabilizing force within a diversified portfolio.

[Insert Figure 10,11 here]

## 5.5 Summary of Results

Our findings offer a comprehensive view of how PE and VC response to traditional asset classes and economic shocks, highlighting their resilience and adaptability.

Firstly, under the UVAR model, the GIRFs show that PE and VC are sensitive to fluctuations in the S&P 500, hedge funds, bond yields, commodities, and market liquidity. The analysis indicates that PE aligns closely with broader equity market dynamics, as evidenced by its immediate and significant response to shocks in the S&P 500 and hedge funds. Conversely, the inverse reaction of PE to bond yield fluctuations highlights its vulnerability to interest rate changes, reflecting its leveraged nature. Both PE and VC demonstrate the ability to quickly adapt to changes in market conditions, such as shifts in commodity prices and liquidity challenges. Their returns initially react to these shocks but tend to stabilize quickly, indicating a robustness against long-term market fluctuations. Overall, PE exhibits a more pronounced response to these variables than VC. The differential responses of PE and VC to shocks are attributed to their unique market characteristics. PE's immediate but short-lived response is due to its focus on more established firms and leveraged buyouts, while VC's longer adjustment period is linked to its investment in early-stage, high-growth companies.

The Decomposition offers a detailed perspective on how shocks in PE and VC returns influence other financial series. It reveals a persistent correlation between PE returns and hedge funds, suggesting a shared influence or market strategy. Additionally, it highlights an increasing impact of the S&P 500 on PE over extended periods, reflecting the sensitivity of PE to wider economic patterns.VC, while also impacted by hedge funds and the S&P 500, displays its own distinct response curve, which emphasize the importance of hedge funds as a proxy for alternative investments and the S&P 500's role in capturing long-term market trends affecting PE and VC returns.

The UVAR models show the immediate effects of shocks followed by gradual adjustments that disappear over time. The CVAR model, focusing on the short run, shows a similar but sharper response as the market adjusts, with the shock's impact being smoothed out by the market's long-term trends. There are some slight differences in the initial reactions. For instance, in response to an S&P 500 shock, the UVAR model shows that PE has a quick positive reaction that soon wanes, whereas the CVAR model indicates a slight initial negative response before correcting upwards. Also, the confidence intervals in the CVAR model are wider, suggesting greater variability in the short-term reaction to the shock. Comparing the two, the CVAR suggests significant adjustments to shocks in the short run, while in the long run, the UVAR indicates that the effects of shocks are temporary and eventually revert to the baseline. The CVAR results are robust compared to the UVAR findings and reinforce that while PE and VC are sensitive to immediate market changes, they can stabilize over time.

Moreover, the persistence profiles show the effects of system-wide financial shocks on PE and VC. PE shows an intense but brief reaction, recovering rapidly due to its association with more mature, diversified companies and the use of leveraged buyouts. This quick stabilization reflects PE's market resilience. VC, while exhibiting a similar pattern, displays a slightly less volatile but more prolonged response to shocks.

Finally, we also do the GIRF analysis within the VECM framework. This analysis tracks the effects of a one-standard-deviation shock to each of the cointegrated variables on the system, considering both the short-term dynamics and the error correction mechanism. Consistent with the UVAR results, the VECM analysis shows that PE and VC markets are quite resilient to shocks.

# 6 Implication

This study offers several practical implications for institutional investing, particularly within the field of PE and VC. The study's findings suggest that both PE and VC demonstrate an inherent resilience to economic and market shocks, which is valuable for portfolio management, especially during heightened volatility.

For institutional investors, the ability of PE and VC to quickly stabilize after initial shocks is particularly significant. This resilience makes these assets strong foundations for portfolios that can withstand and recover from market downturns. Furthermore, the distinct response patterns of PE and VC to market shocks, as opposed to traditional assets like stocks and bonds, emphasized their value in diversification strategies. By including PE and VC, fund managers can potentially smooth out the overall volatility of the portfolio, as these assets often do not move in lockstep with broader market indices.

Furthermore, PE/VC investments could be particularly compelling for fund managers, especially those fund managers overseeing superannuation funds and other long-term investment vehicles. The ability of PE/VC to act as a counterbalance during market downturns—not merely surviving but providing an avenue for risk mitigation—is a powerful characteristic. This may lead to an increased allocation to PE/VC in mixed-asset portfolios, as fund managers seek to leverage their shock-absorbing properties while pursuing superior returns.

The study also contributes to the ongoing discussion on the connections of private and public markets. The findings regarding the shared market influences between PE returns and hedge fund performance, as well as the S&P 500's longer-term influence on PE, suggest that private market investments are not isolated from broader economic trends. This has implications for asset allocation decisions, as it points to the potential benefits of integrating private market insights into the broader investment strategy, beyond mere diversification.

Considering these insights, institutional investors may need to review their risk management frameworks to account for the distinct dynamics of PE/VC investments. By doing so, they can better capitalize on the inherent resilience of these asset classes, strategically positioning their portfolios to navigate both bear and bull market conditions.

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Table 1. Summary statistics

| Variables | N | Mean | Std.dev | Skewness | Kurtosis | p1 | Median | p99 |
|---|---|---|---|---|---|---|---|---|
| Panel A: Return | | | | | | | | |
| PE_r | 132 | 3.38 | 5.89 | 0.71 | 6.67 | -10.70 | 3.08 | 23.90 |
| VC_r | 132 | 3.28 | 8.15 | 1.33 | 8.46 | -16.10 | 2.21 | 30.90 |
| Bond10_r | 132 | 1.34 | 3.86 | 0.35 | 2.97 | -6.41 | 0.78 | 11.30 |
| S&P 500_r | 132 | 1.76 | 8.11 | −0.90 | 4.13 | -22.30 | 2.70 | 18.20 |
| GSCI_r | 132 | 0.47 | 13.40 | −1.28 | 8.46 | -55.10 | 2.07 | 28.60 |
| HFRI_r | 132 | 2.17 | 4.04 | −0.53 | 5.93 | -10.00 | 1.90 | 12.70 |
| NFCI_r | 132 | 0.00 | 0.27 | 0.93 | 11.06 | -0.80 | -0.01 | 0.96 |
| PMI_r | 132 | 0.05 | 7.37 | 0.06 | 4.65 | -20.40 | -0.09 | 19.80 |
| Panel B: Level | | | | | | | | |
| PE_index | 132 | 1433 | 1649.00 | 2.02 | 6.71 | 100 | 864 | 7135 |
| VC_index | 132 | 1221 | 1240.00 | 2.04 | 7.16 | 100 | 819 | 5728 |
| Bond10 | 132 | 364 | 171.40 | 0.16 | 1.69 | 103 | 330 | 681 |
| S&P 500 | 132 | 419 | 277.70 | 1.32 | 4.45 | 93 | 351 | 1282 |
| GSCI | 132 | 193 | 84.22 | 1.33 | 5.06 | 87 | 171 | 434 |
| HFRI | 132 | 840 | 487.60 | 0.17 | 1.99 | 104 | 848 | 1823 |
| NFCI | 132 | 100 | 0.50 | 2.90 | 13.96 | 99 | 99 | 102 |
| PMI | 132 | 111 | 10.80 | −0.71 | 3.61 | 82 | 111 | 129 |

Panel A provides summary statistics related to returns on different investment types or indices. The investments or indices analyzed are PE (Private Equity), VC (Venture Capital), Bond10, SP500 (an indicator likely representing the S&P 500), GSCI (Goldman Sachs Commodity Index), HFRI (Hedge Fund Research Index), NFCI (National Financial Conditions Index), and PMI (Purchasing Managers' Index). For each of these, several statistical measures are presented, including the number of observations (N), the mean, standard deviation, skewness, kurtosis, the first percentile (p1), median, and the 99th percentile (p99). Panel B presents data related to the indices of these investment types or benchmarks. The statistical measures remain the same as in Panel A, providing a comprehensive view of both return and level across a substantial dataset.

Table 2. Root unit test on Index level

| | (1) PE_index | (2) VC_index | (3) Bond10 | (4) S&P 500 | (5) GSCI | (6) HFRI | (7) NFCI | (8) PMI |
|---|---|---|---|---|---|---|---|---|
| ADF-GLS test: | | | | | | | | |
| With no drift term | −0.598 72 | −1.5995 | 0.808 07 | 1.008 | −1.3824 | 2.1795 | −2.9108 * | −3.7716 * |
| Lagged terms | 1 | 1 | 1 | 1 | 4 | 1 | 1 | 1 |
| With a drift term | −0.254 07 | −0.988 52 | −2.4736 | −1.5582 | −1.753 | −2.621 | −3.292 | −5.053 * |
| Lagged terms | 4 | 4 | 1 | 1 | 4 | 1 | 1 | 1 |
| ADF-WS test: | | | | | | | | |
| With no drift term | −1.1293 | −0.681 44 | 0.052 165 | 0.136 98 | −2.0416 | 1.1781 | −3.5788 * | −4.932 * |
| Lagged terms | 1 | 3 | 1 | 1 | 4 | 1 | 1 | 1 |
| With a drift term | −0.7054 | −1.0895 | −2.5464 | −1.8275 | −2.0881 | −3.8295 * | −3.5687 * | −5.2103 * |
| Lagged terms | 3 | 4 | 1 | 1 | 4 | 1 | 1 | 1 |
| ADF-MAX test: | | | | | | | | |
| With no drift term | −0.896 08 | −0.394 39 | −0.794 23 | −0.055 838 | −1.7579 | 0.061 275 | −3.3661 * | −4.8635 * |
| Lagged terms | 1 | 3 | 1 | 1 | 4 | 1 | 1 | 1 |
| With a drift term | −1.4351 | −1.8495 | −2.3711 | −1.6207 | −1.8443 | −3.8844 | −3.3551 * | −5.0759 * |
| Lagged terms | 2 | 3 | 1 | 1 | 4 | 1 | 1 | 1 |
| Phillips-Perron test: | | | | | | | | |
| With no drift term | 5.0602 | 1.5236 | −1.1722 | 0.330 12 | −2.365 | 1.1255 | −2.8285 | −3.3540 * |
| With a drift term | 1.7922 | −0.240 62 | −1.7418 | −1.6377 | −2.2900 | −2.4601 | −2.8033 | −3.1394 * |
| KPSS test: | | | | | | | | |
| No Trend | 0.5927 | 0.5610 | 0.6773 | 0.6171 | 0.1655 | 0.6973 | 0.1001 | 0.4941 |
| Linear Trend | 0.1702 | 0.1471 | 0.1122 | 0.1480 | 0.1509 | 0.1011 | 0.0837 | 0.0884 |

* indicates rejection of the null hypothesis at a 5% significance level. Critical values for the ADF and PP tests are -2.8835 and -3.4445 without and with a drift term, respectively. If the ADF or PP statistic is greater than the critical value, it suggests that the null hypothesis can be rejected, indicating that the time series is stationary. The critical values for the KPSS test are 0.463 and 0.146 without and with a drift term. If the KPSS statistics is lower than the critical value, it suggests that the null hypothesis cannot be rejected, indicating that the time series is stationary.

Table 3. Root unit test on Return

| | (1) PE_r | (2) VC_r | (3) Bond10_r | (4) S&P 500_r | (5) GSCI_r | (6) HFRI_r | (7) NFCI_r | (8) PMI_r |
|---|---|---|---|---|---|---|---|---|
| ADF-GLS test: | | | | | | | | |
| With no drift term | −4.0421* | −4.4294* | −5.2192* | −6.6356* | −7.9343* | −5.4652* | −4.3897* | −8.9209* |
| Lagged terms | 3 | 3 | 1 | 1 | 1 | 1 | 1 | 1 |
| With a drift term | −4.7504* | −4.6119* | −6.6356* | −7.2882* | −7.9299* | −6.125 * | −6.5897* | −8.9193* |
| Lagged terms | 3 | 3 | 1 | 1 | 1 | 1 | 1 | 1 |
| ADF-WS test: | | | | | | | | |
| With no drift term | −5.2622* | −4.9211* | −7.3311* | 7.5171* | −8.2762* | −6.9709* | −7.8185* | −8.9439* |
| Lagged terms | 3 | 3 | 1 | 1 | 1 | 1 | 1 | 1 |
| With a drift term | −5.2425* | −4.9116* | −9.012 * | −7.4934* | −8.2757* | −7.7082* | −7.8212* | −8.9439* |
| Lagged terms | 3 | 3 | 1 | 1 | 1 | 1 | 1 | 1 |
| ADF-MAX test: | | | | | | | | |
| With no drift term | −5.0585* | −4.7281* | −8.3462* | −7.3438* | −7.9028* | −6.6263* | −7.6558* | −8.8063* |
| Lagged terms | 3 | 3 | 1 | 1 | 1 | 1 | 1 | 1 |
| With a drift term | −5.0452* | −4.7107* | −8.9051* | −7.3308* | −7.8835* | −7.2998* | −7.6313* | −8.7709* |
| Lagged terms | 3 | 3 | 1 | 1 | 1 | 1 | 1 | 1 |
| Phillips-Perron test: | | | | | | | | |
| With no drift term | −4.4224* | −4.411 * | −10.7203* | −11.2702* | −10.9946* | −10.4226* | −11.5875* | −15.2791* |
| With a drift term | −4.3734* | −4.3539* | −12.7022* | −11.2300* | −11.1633* | −10.6820* | −11.5324* | −15.2569* |
| KPSS test: | | | | | | | | |
| No Trend | 0.0833 | 0.089 56 | 0.5670 | 0.092 71 | 0.1597 | 0.5314 | 0.1279 | 0.1252 |
| Linear Trend | 0.0838 | 0.082 33 | 0.1172 | 0.087 12 | 0.0895 | 0.1279 | 0.0838 | 0.091 30 |

* indicates rejection of the null hypothesis at a 5% significance level. Critical values for the ADF and PP tests are -2.8835 and -3.4445 without and with a drift term, respectively. If the ADF or PP statistic is greater than the critical value, it suggests that the null hypothesis can be rejected, indicating that the time series is stationary. The critical values for the KPSS test are 0.463 and 0.146 without and with a drift term. If the KPSS statistics is lower than the critical value, it suggests that the null hypothesis cannot be rejected, indicating that the time series is stationary.

Figure 1. PE Quarterly Return

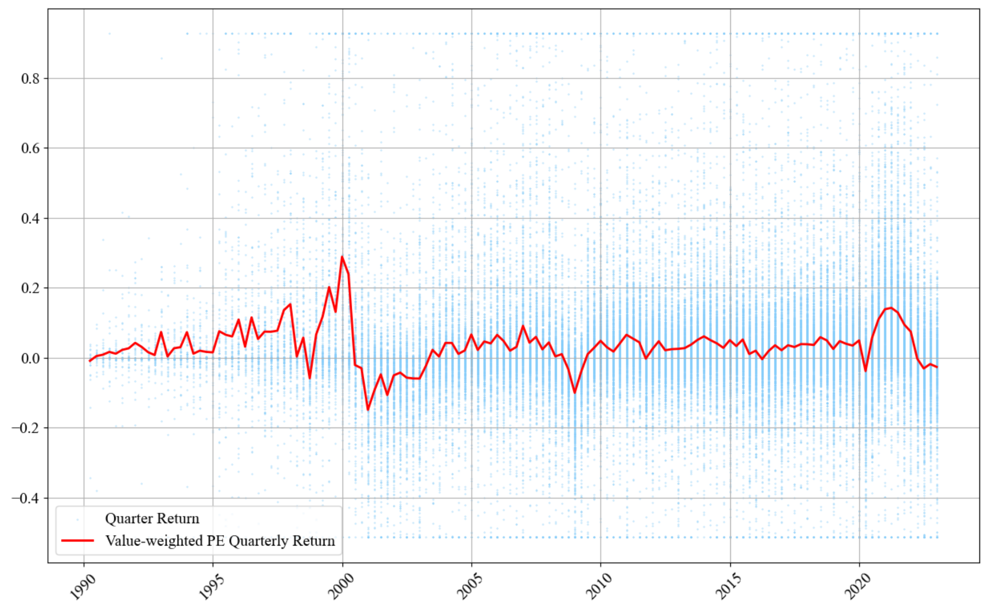



Figure 2. VC Quarterly Return

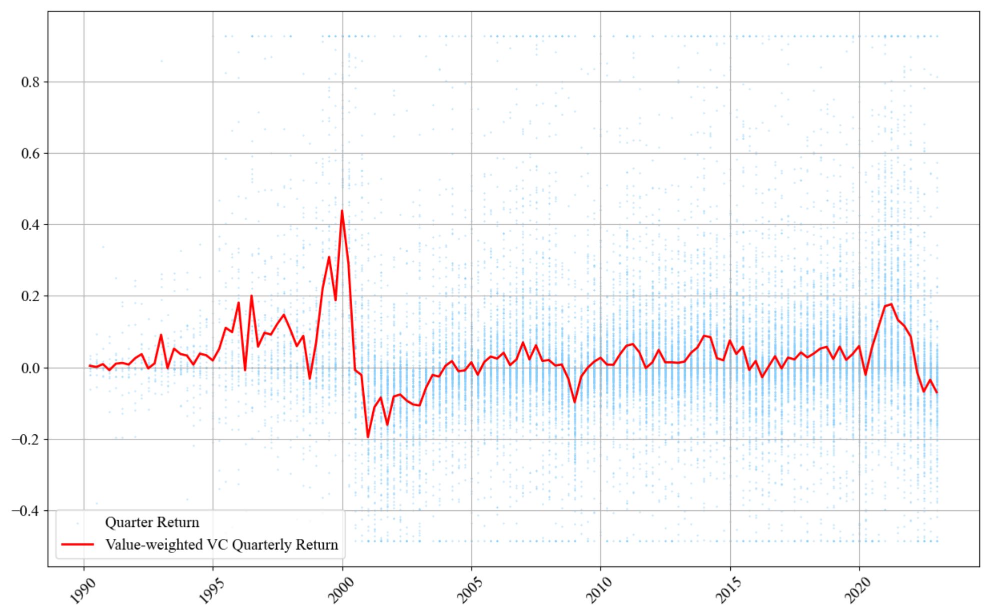


Figure 3. Comparative Index Level of Various Assets and Econ Factors

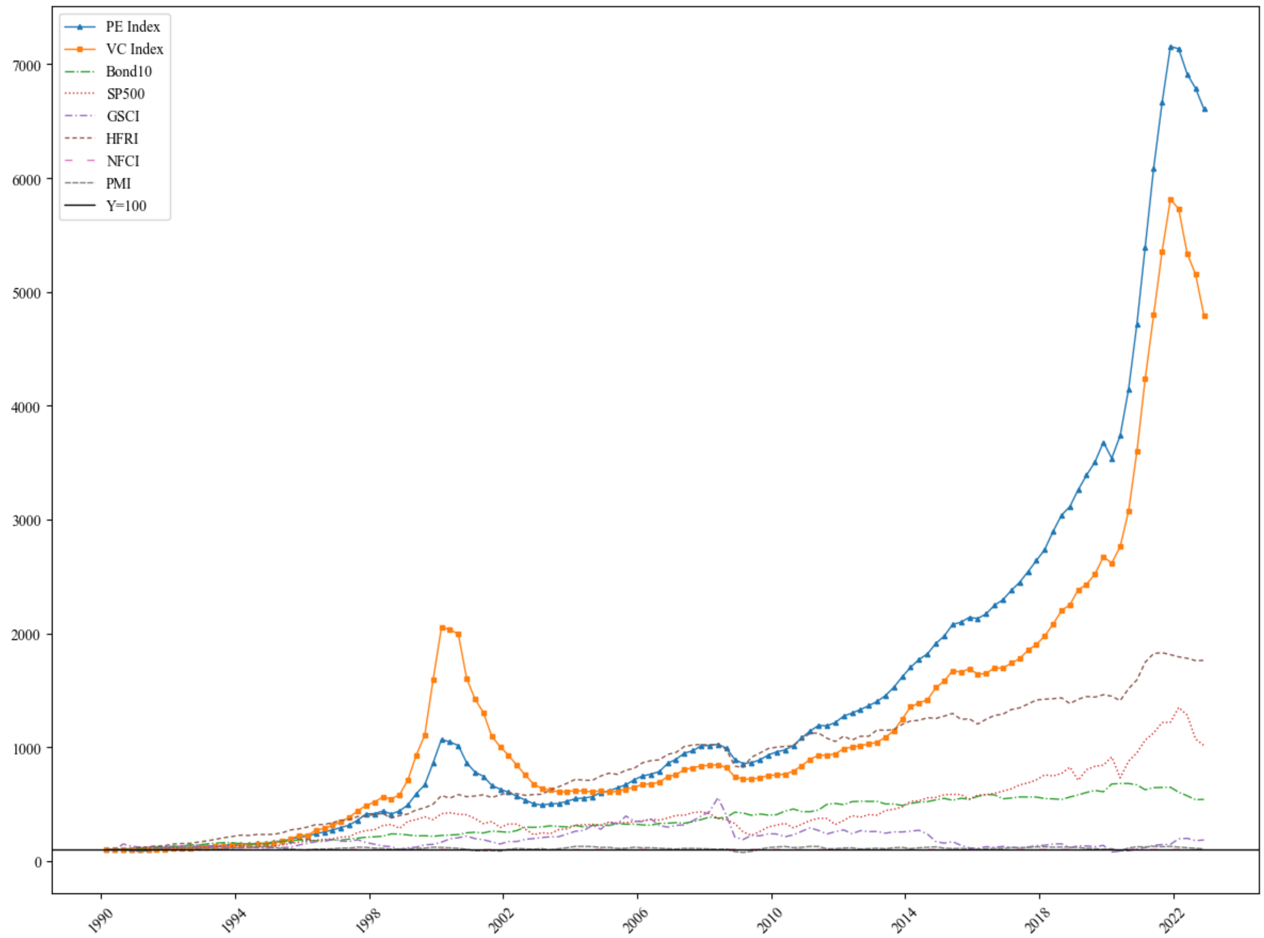


Table 4. Generalised Forecast Error Variance Decomposition

**Panel A: Private equity return**

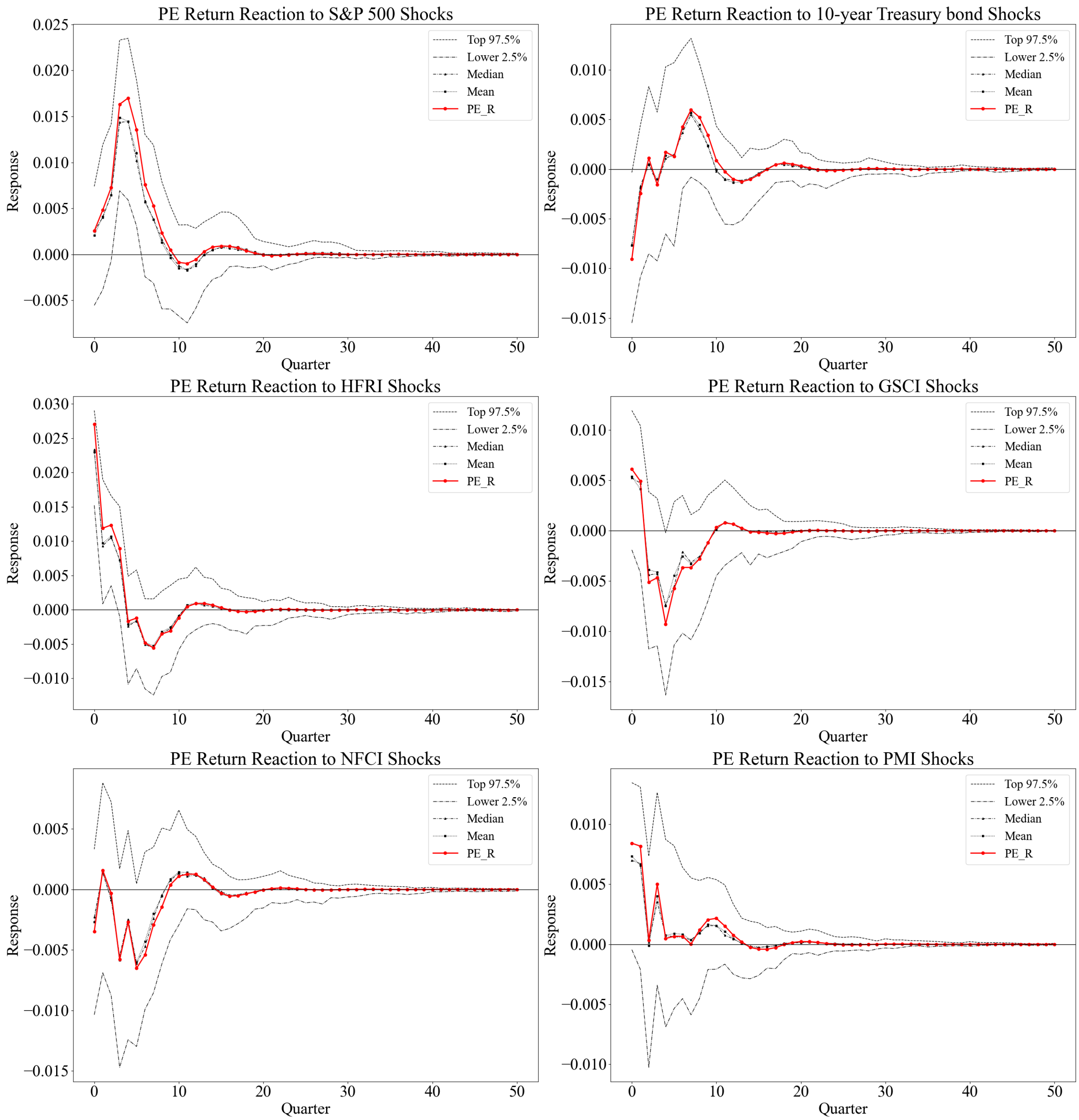
| Horizon | PE_r | S&P 500_r | BOND10_r | HFRI_r | GSCI_r | NFCI_r | PMI_r |
|---|---|---|---|---|---|---|---|
| One quarter | 100.00 | 0.35 | 4.37 | 39.06 | 2.00 | 0.64 | 3.77 |
| Half year | 96.92 | 1.19 | 3.53 | 35.10 | 2.48 | 0.58 | 5.53 |
| 1 year | 86.69 | 9.84 | 2.58 | 31.16 | 3.09 | 1.36 | 4.58 |
| 2 years | 70.90 | 20.64 | 3.41 | 26.47 | 5.80 | 3.09 | 3.72 |
| 3 years | 69.76 | 20.39 | 4.23 | 26.45 | 5.91 | 3.14 | 3.93 |
| 5 years | 69.58 | 20.37 | 4.32 | 26.39 | 5.90 | 3.19 | 3.94 |
| 10 years | 69.57 | 20.37 | 4.32 | 26.39 | 5.90 | 3.19 | 3.94 |

**Panel B: Venture capital return**

| Horizon | VC_r | S&P 500_r | BOND10_r | HFRI_r | GSCI_r | NFCI_r | PMI_r |
|---|---|---|---|---|---|---|---|
| One quarter | 100.00 | 0.45 | 3.08 | 32.62 | 0.85 | 1.67 | 3.36 |
| Half year | 96.53 | 0.97 | 2.64 | 28.42 | 0.67 | 1.41 | 5.45 |
| 1 year | 86.34 | 8.32 | 2.04 | 20.83 | 2.98 | 1.52 | 4.03 |
| 2 years | 67.97 | 21.56 | 4.24 | 16.44 | 7.67 | 3.16 | 3.27 |
| 3 years | 66.91 | 21.69 | 5.02 | 16.45 | 7.73 | 3.24 | 3.38 |
| 5 years | 66.73 | 21.75 | 5.07 | 16.43 | 7.74 | 3.30 | 3.39 |
| 10 years | 66.73 | 21.75 | 5.07 | 16.43 | 7.74 | 3.30 | 3.39 |

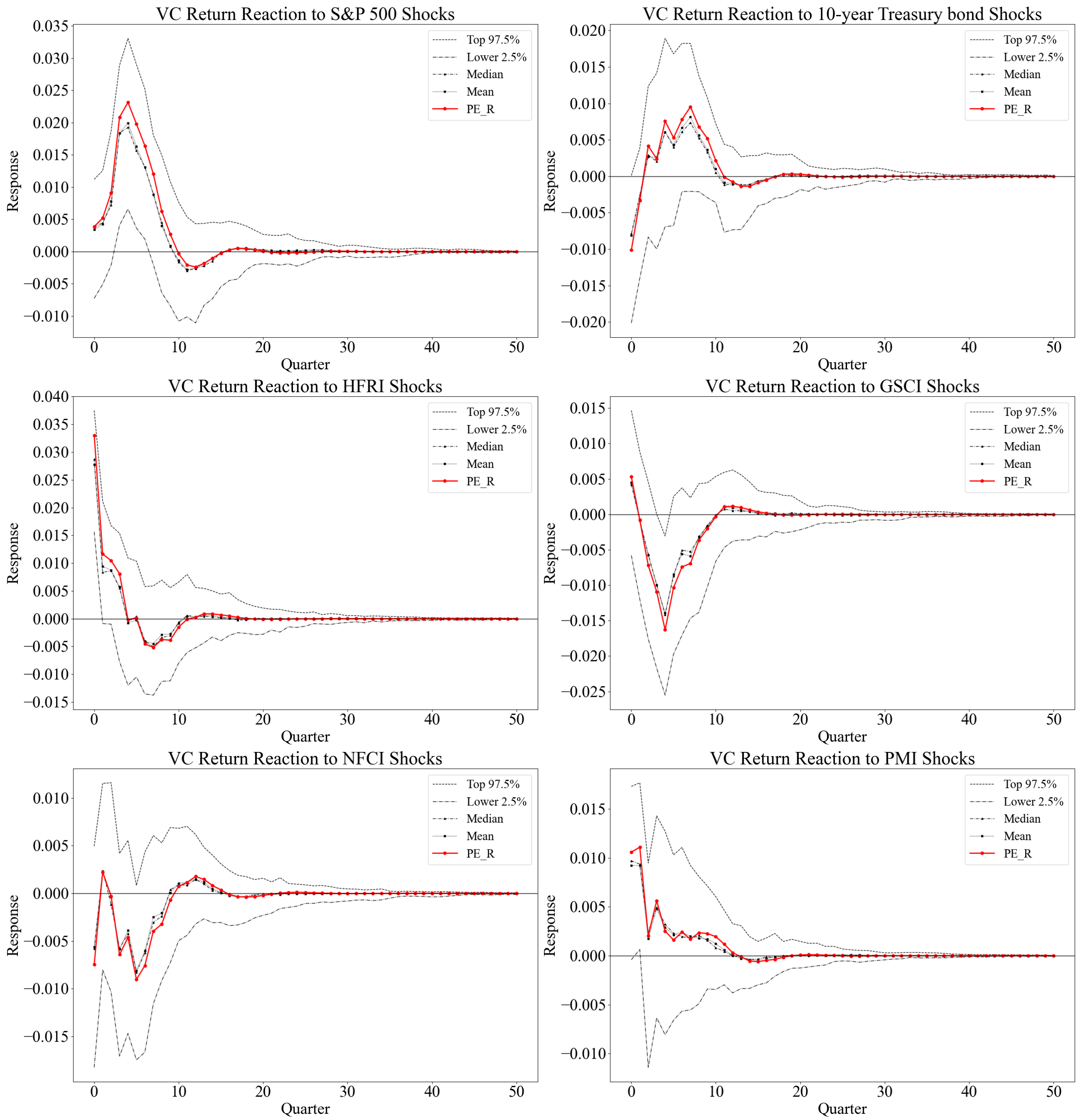
Table 4 illustrates the percentage of movements in various financial indices and economic indicators that can be explained by shocks to private equity returns (Panel A) and venture capital returns (Panel B), respectively. The output from a Generalized Forecast Error Variance Decomposition (FEVD) using an unrestricted Vector Autoregressive (VAR) model with an order of 4.

Figure 4. UVAR: GIRFs of PE return to shocks



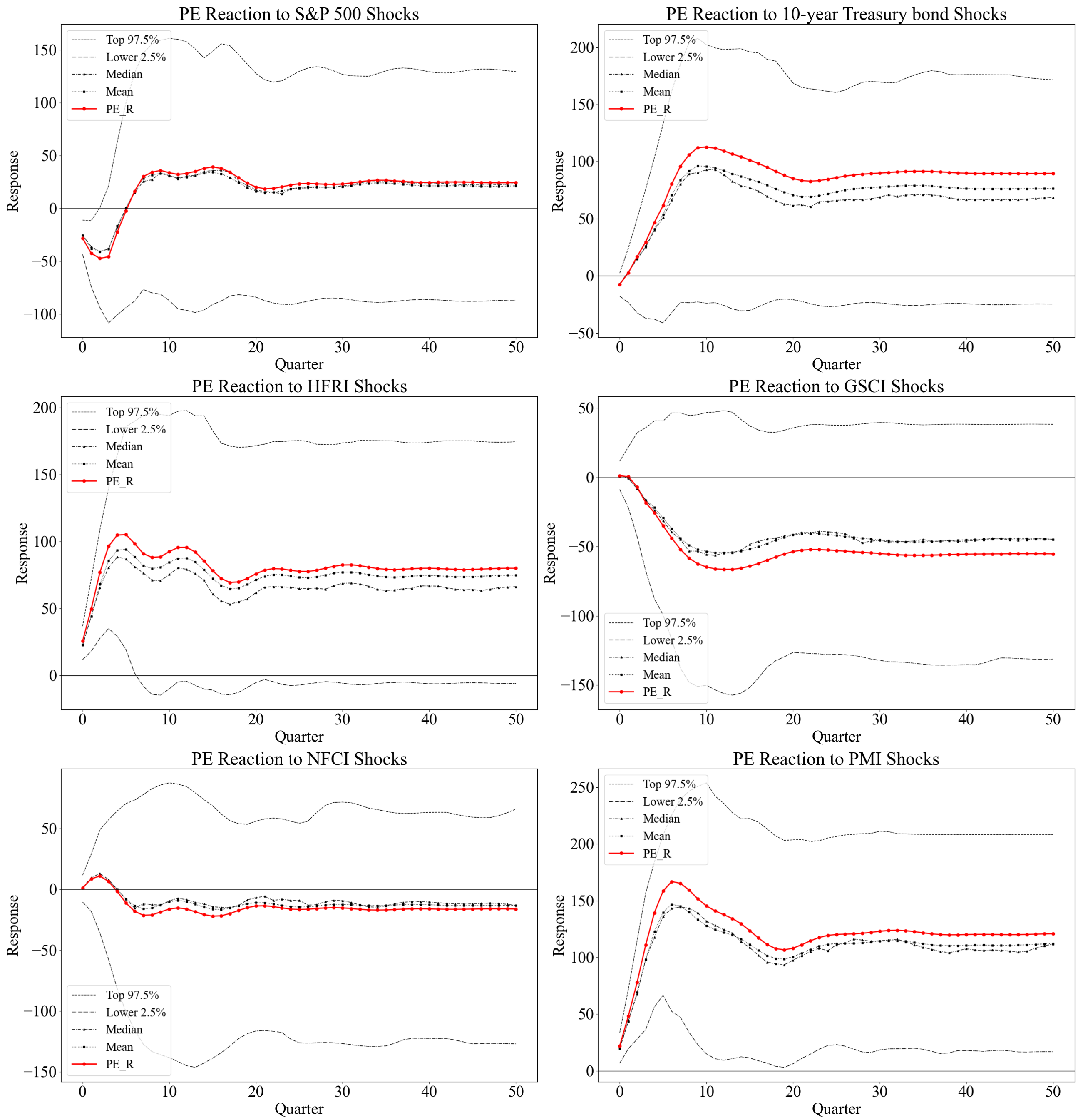

Note: We employ a UVAR model with an order of four, meaning that each equation in the system includes four lags of all the variables as predictors. Each graph represents the Generalized Impulse response functions of PE return to a one standard deviation shock on other asset classes and econ factors(i.e., stock, Bond, Hedge fund, Commodity, Financial condition and PMI). They typically display the response over quarters with lines representing different statistical measures like the mean or median response, as well as confidence intervals to indicate the statistical significance of the responses.

Figure 5. UVAR: GIRFs of VC return to shocks



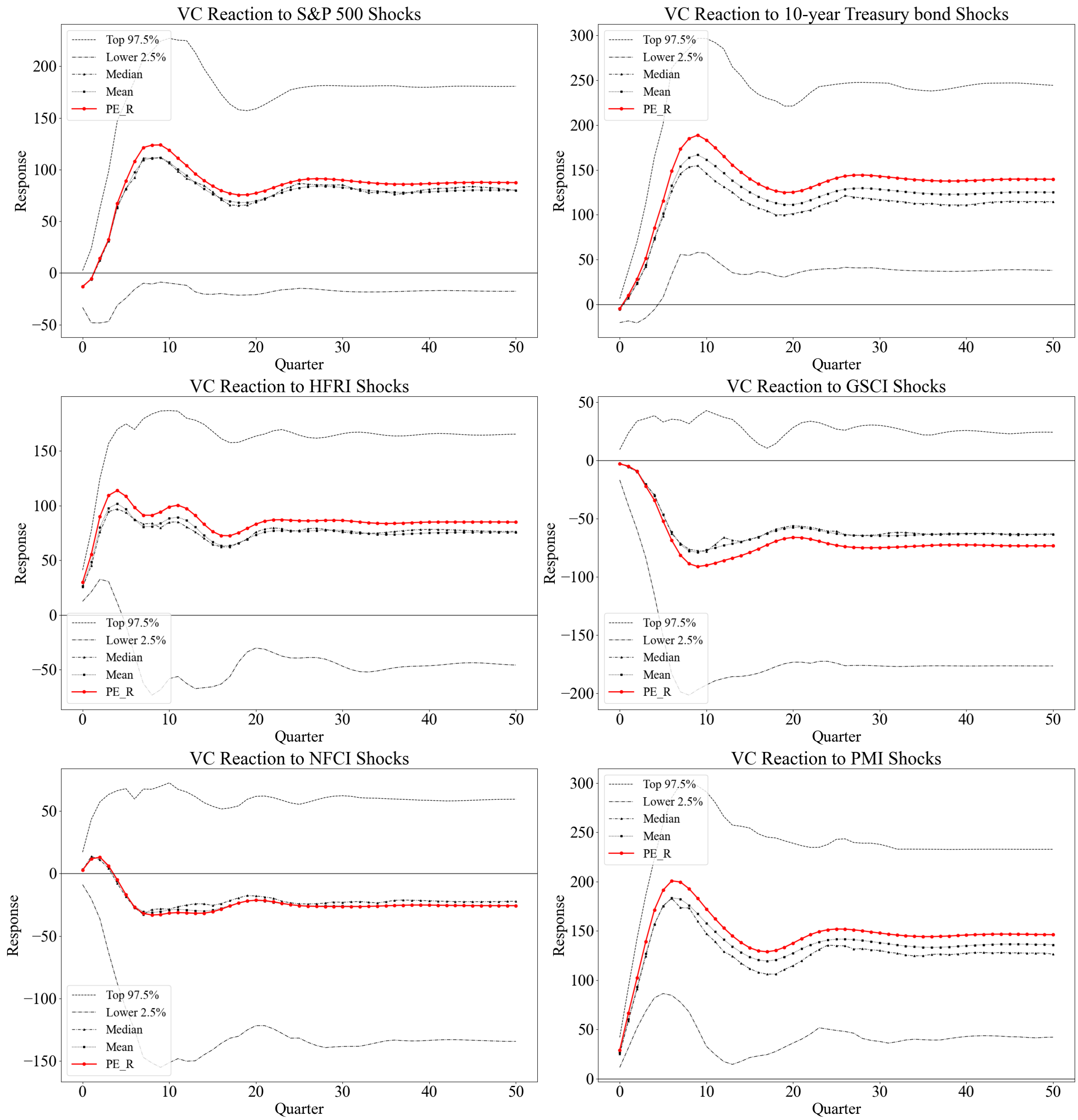

Note: We employ a UVAR model with an order of four, meaning that each equation in the system includes four lags of all the variables as predictors. Each graph represents the Generalized Impulse response functions of VC return to a one standard deviation shock on other asset classes and econ factors(i.e., stock, Bond, Hedge fund, Commodity, Financial condition and PMI). They typically display the response over quarters with lines representing different statistical measures like the mean or median response, as well as confidence intervals to indicate the statistical significance of the responses.

Figure 6. CVAR: GIRFs of PE return to shocks



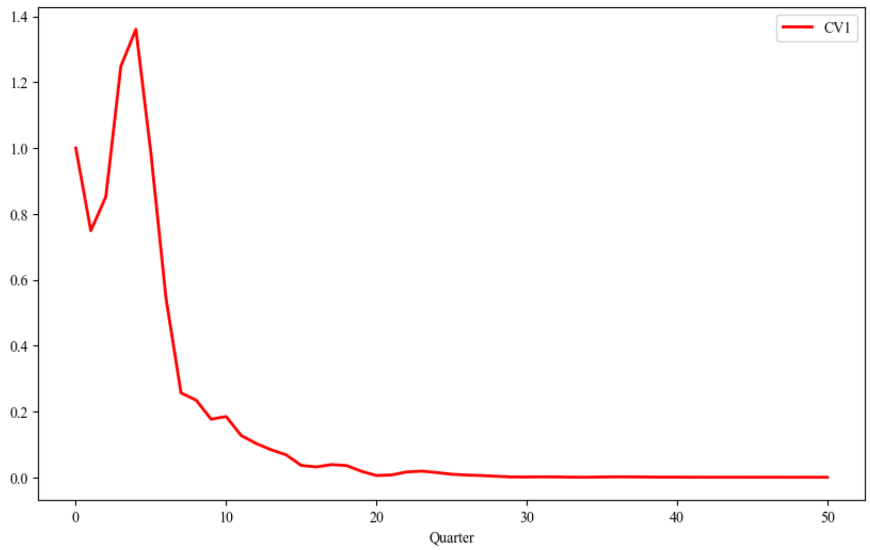

Note: We employ a CVAR model with an order of four, meaning that each equation in the system includes four lags of all the variables as predictors. Each graph represents the Generalized Impulse response functions of PE return to a one standard deviation shock on other asset classes and econ factors(i.e., stock, Bond, Hedge fund, Commodity, Financial condition and PMI). They typically display the response over quarters with lines representing different statistical measures like the mean or median response, as well as confidence intervals to indicate the statistical significance of the responses.

Figure 7. CVAR: GIRFs of VC return to shocks



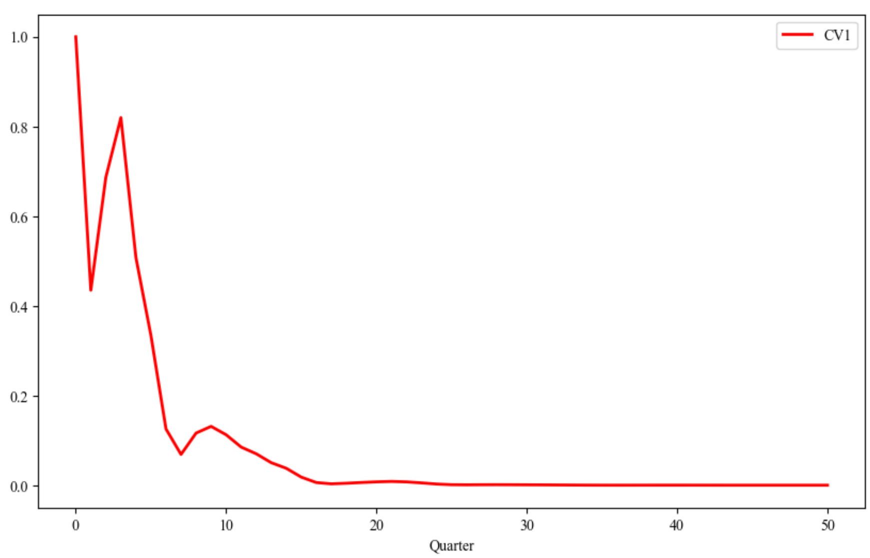

Note: We employ a CVAR model with an order of four, meaning that each equation in the system includes four lags of all the variables as predictors. Each graph represents the Generalized Impulse response functions of VC return to a one standard deviation shock on other asset classes and econ factors(i.e., stock, Bond, Hedge fund, Commodity, Financial condition and PMI). They typically display the response over quarters with lines representing different statistical measures like the mean or median response, as well as confidence intervals to indicate the statistical significance of the responses.

Figure 8. Persistence Profile of the effect of a system-wide shock on PE returns



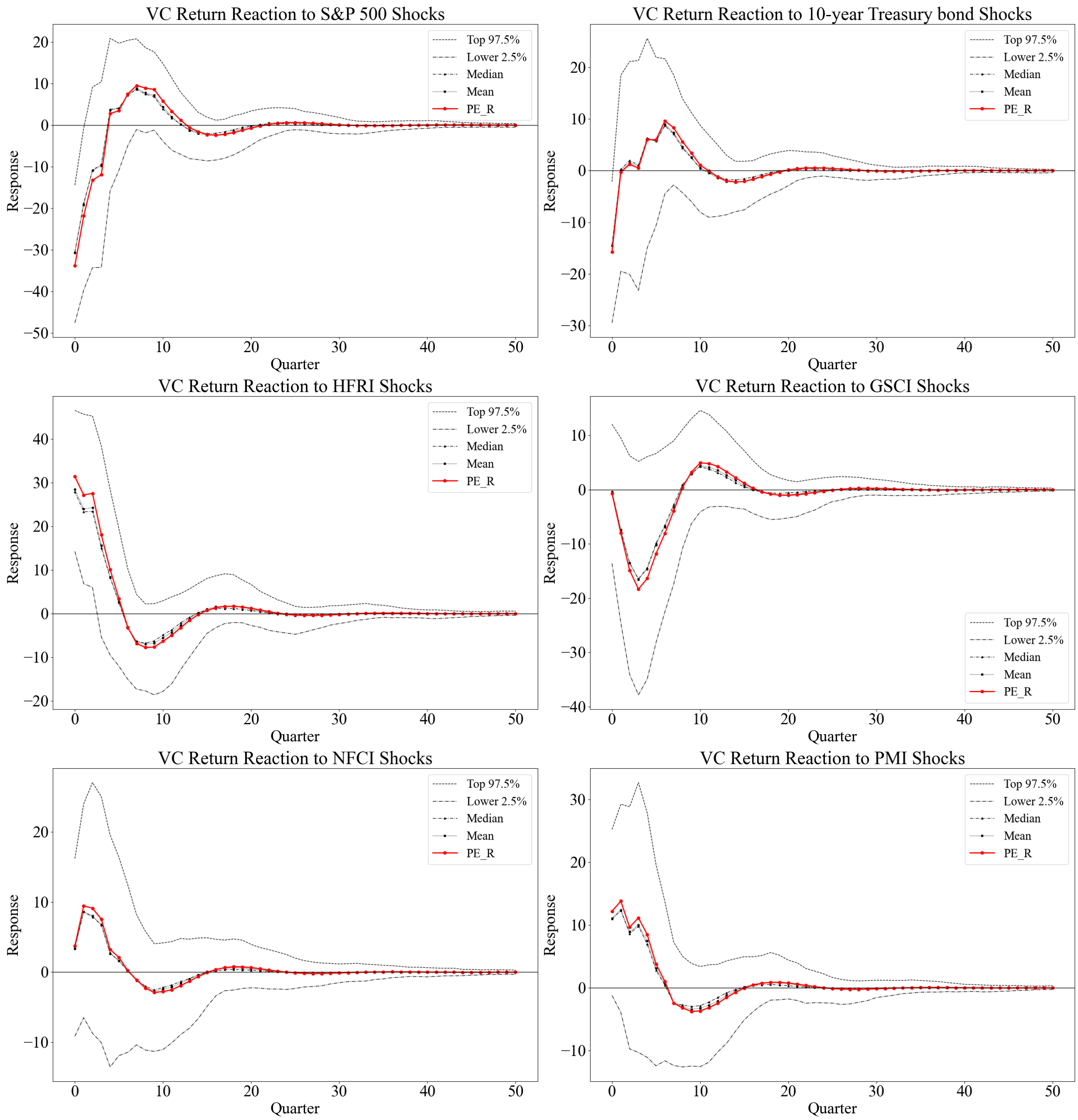

Note: This graph shows the persistence profile for the effects of system-wide shocks on PE. The persistence profile analysis is from a VAR model with a single lag (order of VAR = 1), using a cointegrating vector that includes various financial indices and a trend component.

Figure 9. Persistence Profile of the effect of a system-wide shock on VC returns



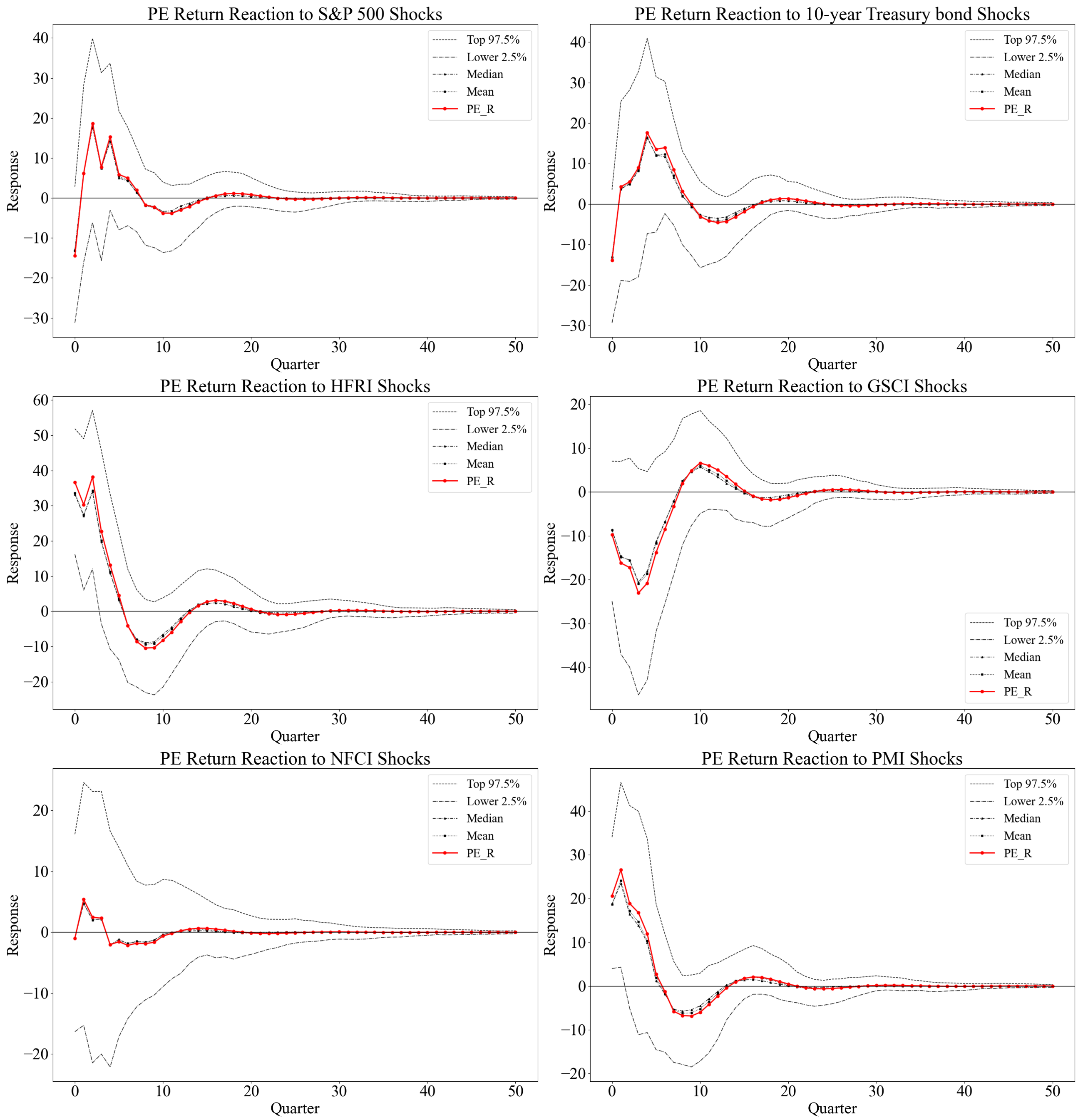

Note: This graph shows the persistence profile for the effects of system-wide shocks on VC. The persistence profile analysis is from a VAR model with a single lag (order of VAR = 1), using a cointegrating vector that includes various financial indices and a trend component

Figure 10. VECM: GIRFs of PE return to shocks




Note: We employ a VECM model with an order of four, meaning that each equation in the system includes four lags of all the variables as predictors. Each graph represents the Generalized Impulse response functions of PE return to a one standard deviation shock on other asset classes and econ factors(i.e., stock, Bond, Hedge fund, Commodity, Financial condition and PMI). They typically display the response over quarters with lines representing different statistical measures like the mean or median response, as well as confidence intervals to indicate the statistical significance of the responses.

Figure 11. VECM: GIRFs of VC return to shocks




Note: We employ a VECM model with an order of four, meaning that each equation in the system includes four lags of all the variables as predictors. Each graph represents the Generalized Impulse response functions of VC return to a one standard deviation shock on other asset classes and econ factors(i.e., stock, Bond, Hedge fund, Commodity, Financial condition and PMI). They typically display the response over quarters with lines representing different statistical measures like the mean or median response, as well as confidence intervals to indicate the statistical significance of the responses.