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How do private equity fund performance, ESG integration, and external market factors influence LPs' investment decisions and outcomes?

par

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Abstract

This study investigates the short-term relationship between private equity (PE) fund performance and macroeconomic conditions, focusing on how internal rates of return (IRR) respond to shocks in market returns, interest rates, and GDP growth. Using a Vector Autoregressive (VAR) model framework, the research highlights the dynamic interactions between PE performance and external economic indicators. Early attempts to incorporate a broader set of private equity performance measures—such as DPI, TVPI, and ESG indicators—were limited by statistical challenges. The final model, focused on first-differenced IRR, revealed that macroeconomic shocks have statistically significant but economically modest effects on PE returns. The model indicates that short-term PE performance is largely shaped by internal fund dynamics rather than external economic shocks. These findings align with the view that PE is a path-dependent asset class influenced more by deal-specific outcomes and fund-level decisions than by contemporaneous economic shifts. The study also highlights the limitations of the model and current PE data sources and suggests that mixed-method approaches could enhance future research. The results are particularly relevant for institutional investors and LPs seeking to make private equity investment allocation decisions.

Keywords: ESG, private equity, internal rate of return, VARX model, VAR model, fund performance, market returns, interest rates, GDP, asset allocation

Research methods: Quantitative time series analysis using Vector Autoregressive (VAR) modeling

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1. Introduction

In the private equity (PE) investments industry, the majority of private equity funds are organized as limited partnerships, where private equity firms are called general partners (GPs), and the investors in such funds that commit capital are called limited partners (LPs). LPs include entities such as pension funds, endowments, foundations and multi/single family offices. LPs as capital allocators face the task of selecting capable and dedicated PE fund managers to diversify their investment portfolios and meet target returns (Beath, Flynn, & MacIntosh, 2014). GPs, on the other hand, are the front-line players. They are responsible for sourcing, acquiring, managing, and eventually exiting investments in those private companies. A typical private equity investment cycle involves acquiring underperforming mature companies or high performing growth-stage companies, actively improving operations and financial performance, and creating more value through an exit ultimately, often via a sale to a strategic buyer (i.e., other operating companies), another financial sponsor (i.e., other PE firms), or through an Initial Public Offering (IPO). At that point, capital gains are realized, and the returns are distributed to LPs according to the fund's distribution waterfall model, which is a predefined sequence outlining how cash flows are allocated—typically prioritizing the return of contributed capital and a preferred return (or "hurdle rate") to LPs before allocating carried interest to the GP (Metrick & Yasuda, 2010). In the past, the objective of GPs in private equity was relatively clear-cut: to maximize financial returns for LPs, primarily through achieving high Internal Rates of Return (IRR). Fund performance was assessed almost exclusively through traditional financial metrics, and the success of a PE strategy was measured in terms of its ability to outperform relative to public benchmarks and peer funds (Gredil et al, 2023).

However, in recent decades, fund managers' mission has become more complex and multidimensional. At the same time, the rise of Environmental, Social, and Governance (ESG) considerations has added new dimensions to investment decision-making, especially within PE. No longer focused solely on financial returns, fund managers are increasingly expected to account for ESG-related impacts in their strategies and operations (Schreane, 2023). The integration of ESG criteria introduces additional—and sometimes competing—objectives, also making it more challenging for investors to evaluate fund success using traditional financial metrics alone (Zaccone & Pedrini, 2020). This change signals a broader evolution in the role of finance—moving away from a narrow focus on profit maximization toward a more holistic approach that incorporates social and environmental impact (Revelli & Viviani, 2015). This broader shift has been reinforced by the growing influence of LPs—particularly institutional investors such as pension funds, endowments, and sovereign wealth funds—many of whom have fiduciary responsibilities that extend beyond short-term financial gains. These stakeholders encourage GPs to incorporate ESG considerations into their investment decisions, prompting a redefinition of the GP's mandate. In addition to generating attractive returns, GPs are now asked to demonstrate how their investment decisions align with sustainability goals, mitigate ESG-related risks, and in some cases deliver measurable impact (Jefferson et al., 2024). This shift has also led to the creation of dedicated ESG-focused funds, the development of ESG-linked due diligence frameworks, and portfolio-wide sustainability reporting initiatives (Jefferson et al., 2024). As a result, GPs must navigate a more complex investment landscape that balances financial performance with long-term responsibility and stakeholder accountability.

To better understand how ESG has come to shape investment mandates and fund evaluation practices, it is useful to trace the origins and evolution of the ESG concept (Schreane, 2023). The origin of ESG can be tracked back to the socially responsible investing (SRI) movements of the 1960s and 1970s, which primarily focused on negative screening—excluding investments in industries such as tobacco, alcohol, gambling, weapons manufacturing and nuclear power (Trinks & Scholtens, 2017). Since the early 2000s, however, ESG has evolved into a more proactive approach that seeks not only to passively avoid harm but also to actively generate positive outcomes from the environmental and social perspective alongside financial returns (Martini, 2021). This shift is also supported by growing evidence suggesting that ESG factors are financially material and can impact long-term risk-adjusted returns (Clark, Feiner, & Viehs, 2015). The term "ESG" was formally introduced in the 2004 UN-backed *Who Cares Wins* report, marking the inception of ESG's institutionalization within financial markets and asset management specifically (United Nations Global Compact, 2004).

By the 2010s, ESG considerations had gained widespread interest among institutional investors, including limited partners (LPs) such as pension funds and university endowments. However, most firms focused on ESG for due diligence to manage risks, rather than to generate new value. ESG integration in PE was still at an early stage and largely applied as risk management rather than strategic value creation (Zaccone & Pedrini, 2020). Between 2016 and 2018, global sustainable investing assets grew by 34%. Sustainable investments made up a significant share of asset management across regions—ranging from 18% in Japan, 42% in Canada, to 63% in Australia and New Zealand—highlighting strong investor interest worldwide (Global Sustainable Investment Alliance, 2018).

The growth of ESG slowed down during President Donald Trump's first term (2017–2021), as federal policies shifted toward deregulation and support for fossil fuel industries. Over 100 environmental regulations were rolled back, and federal guidance discouraged the use of ESG criteria in retirement investment portfolios (Michigan Journal of Economics, 2025). The second Trump administration has continued the concerns about potential regulatory obstacles for ESG and impact investing. This concern is underscored by recent legislative efforts, such as Congressman Andy Barr's introduction of a bill aimed at limiting ESG considerations in state pension fund investments (New York Post, 2025). These changes may influence LPs' confidence in ESG mandates, particularly in U.S.-based Private Equity funds.

In conclusion, the convergence of ESG integration, impact investing, concerns over purpose-washing and political influence creates a complex investing landscape for LPs. These factors influence how LPs evaluate the credibility of GP claims, assess alignment with their own mandates, and make allocation decisions in global private equity.

Through this thesis, I aim to empower LPs in their fund investment due diligence capabilities by providing comprehensive insights into the dynamics of PE fund performance, especially in track record analysis. I shed light on the relevance of previous performance records, the impact of ESG integration into investment decisions, and external factors on PE fund performance. More specifically, I use a quantitative model to analyze historical fund performance data through Vector Autoregression Methods and explore the dynamic relationships between PE fund performance indicators such as Internal Rate of Return (IRR), Distribution to Paid-in Capital (DPI), Total Value to Paid-in Capital (TVPI). I then demonstrate the effect of including ESG considerations in investment decisions on fund performance by accounting for the ESG orientation of a fund. Furthermore, other external macroeconomic factors may influence PE fund performance. The potential impact of some of external factors will be accounted by including variables such as Market Index Returns, GDP growth, and interest rates.

This research addresses a heated issue at the intersection of PE investment and ESG considerations. As PE continues to shape global economic activity by investing, driving innovation and evolving industries, researching the integration of ESG principles is more important than ever. My study seeks to explore effects of aligning with growing trends in ESG investing, which has implications for investors seeking both financial returns and responsible investment practices. By examining this topic, my research will generate valuable practical insights that may guide LPs' investment strategies, improve due diligence practices, and enhance risk management in the global PE industry.

This paper is organized as follows: Part 2 presents a review of the existing literature on the integration of ESG considerations into investment decision-making and its effects on firm and portfolio performance, drawing insights from studies on socially responsible investing (SRI), sustainable finance, and institutional investor behavior. Building on this general foundation, the section then narrows its focus to the PE context, reviewing empirical findings on ESG integration within PE fund strategies and its implications for fund performance, manager selection, and asset allocation decisions by LPs. This part will also examine the quantitative methodologies employed by other researchers in related studies and select one suitable methodology as the foundation for developing a regression model that incorporates key advantages from prior literature, with further enhancements. Part 3 presents the conceptual framework, which serves a guideline for building the quantitative model. Part 4 will present the research process, describe the data sources, introduce the model used in this research and detail the quantitative modelling process. Part 5 will present the regression model, list the results of all the statistical tests and interpret their meaning and implications. Lastly, Part 6 will draw the conclusions, highlighting the strengths and limitations of this research and suggesting directions for future studies.

2. Literature Review

This literature review begins by presenting the broader academic findings on the integration of Environmental, Social, and Governance (ESG) factors and socially responsible investing (SRI) in financial decision-making. Over the past decades, ESG and SRI have evolved from niche concerns into mainstream considerations within both public and private capital markets. Initially rooted in ethical exclusions—such as avoiding investments in tobacco or arms—the field has matured into a performance-linked strategy, with investors increasingly viewing ESG as a means of managing long-term risks and uncovering opportunities (Revelli & Viviani, 2015; Clark, Feiner, & Viehs, 2014).

This first subsection discusses key findings on the relationship between ESG/SRI and financial performance, including both firm-level and portfolio-level studies. A particular focus is placed on the financial materiality of ESG factors, the debate between risk mitigation and value creation, and the challenges posed by inconsistent ESG metrics and greenwashing. These foundational insights set the stage for examining the more specialized domain of PE investing.

Subsequently, the literature review narrows its focus to the private equity context, investigating how ESG considerations are being incorporated by GPs, and how LPs —especially those with fiduciary responsibilities such as pension funds and endowments—evaluate ESG-aligned strategies. While the broader literature on ESG in public markets is more mature, research in private markets remains fragmented and often inconclusive, particularly when it comes to quantifying ESG's impact on key performance measures like Internal Rate of Return (IRR), Total Value to Paid-In (TVPI), and Distributions to Paid-In (DPI).

The literature review also considers how external macroeconomic conditions such as interest rates, GDP growth, and public market trends influence PE fund performance, and why this matters for LP decision-making. Lastly, the investment process of LPs is explored in more detail, focusing on due diligence, fund selection, governance concerns, and the implications of ESG integration on capital allocation.

By synthesizing these streams of literature—ESG/SRI, private equity performance, macroeconomic influences, and LP behavior—this review identifies a key gap: the lack of empirical research quantifying the short-term effects of macroeconomic variables on ESG-integrated PE fund performance. The section concludes by formulating the research hypotheses that guide the empirical analysis in the following chapters.

2.1 ESG and SRI: Foundations and Performance Implications

The intersection of ESG considerations with financial performance has evolved into a field of empirical and theoretical inquiry. SRI, as a practice integrating ethical values into investment decisions, traces its roots back to exclusionary screening in the early 20th century and has since developed into a sophisticated investment philosophy including positive screening, ESG integration, and shareholder engagement (Revelli & Viviani, 2015).

The financial implications of ESG and SRI investments are based on several competing theoretical perspectives in finance history. The neoclassical view, rooted in modern portfolio theory (Markowitz, 1952), argues that ESG constraints reduce diversification and thus diminish portfolio efficiency (Revelli & Viviani, 2015). Other scholars, such as Friedman (1970), argued that incorporating non-financial goals imposes costs significant to shareholder value (Revelli & Viviani, 2015). Conversely, stakeholder theory (Freeman, 1984) and the Porter hypothesis (1991) propose that proactive ESG practices enhance long-term performance through closer stakeholder relationships and improved operational efficiency. These frameworks are supported by studies by Revelli & Viviani (2015), who argue that ESG integration can improve governance and reduce cost of capital. Bénabou & Tirole's (2010) typology, also cited in Revelli & Viviani's (2015) analysis, distinguishes between performance-enhancing ESG engagement, where socially responsible behavior is aligned with long-term shareholder value and firm competitiveness, and agency-driven forms, where managers pursue ESG initiatives based on personal preferences, reputational goals, or social pressure rather than economic rationale. While the former treats Corporate Social Responsibility (CSR) as an investment that can strengthen stakeholder relations and operational efficiency, the latter risks value destruction by diverting resources toward activities that may not reflect investor priorities or enhance firm performance.

Emerging conceptual models, such as Dupré et al.'s (2009) "transitional SRI effect," build on the broader debate around the financial implications of ESG by suggesting a two-stage equilibrium: In the initial stage, as socially responsible investing gains momentum, rising demand for ESG-compliant firms bids up their stock prices, which compresses their forward-looking return potential—resulting in lower expected returns for ethical investors compared to those in conventional portfolios. Over time this shift contributes to a new market equilibrium in which ESG compliance becomes widespread, and the performance differential between SRI and conventional investments narrows or disappears (Revelli & Viviani, 2015).

A large volume of empirical research has examined whether ESG criteria correlate with financial returns either positively, negatively, or not at all. Orlitzky, Schmidt, & Rynes (2003) conducted a meta-analysis of 52 studies and found a statistically significant, positive relationship between corporate social performance (CSP) and corporate financial performance (CFP), particularly when stakeholder management and accounting-based performance measures were emphasized. Similarly, Friede, Busch, & Bassen (2015), in the most comprehensive meta-analysis to date, aggregated over 2,000 empirical studies and found that approximately 90% showed a non-negative ESG–CFP relationship, with a predominant tendency toward positive correlation. This large-scale evidence foundation supports the view that ESG factors, when strategically managed, can enhance firm value. However, results vary depending on the specific ESG pillar considered. For example, Girerd-Potin et al. (2011), as cited in Revelli & Viviani (2015), argue that governance-focused SRI strategies tend to outperform environmental or social strategies due to lower diversification costs and greater investor familiarity. Additionally, methodological approaches significantly affect outcomes—as noted by Revelli & Viviani (2013) and by Flammer (2015), who uses a regression discontinuity design to identify a causal relationship between CSR shareholder proposal approvals and improved firm performance. Flammer (2015) finds that narrowly passed CSR proposals lead to statistically significant increases in both stock market reaction and operational performance (via sales growth and labor productivity).

Overall, the heterogeneity of findings is attributed to methodological diversity. Revelli and Viviani (2015) emphasize that investment horizon, geographic market, ESG focus area, and sample construction all moderate performance outcomes. Similarly, Orlitzky, Schmidt, & Rynes (2003) show that CSP–CFP correlations are stronger when using accounting-based financial measures and reputable CSP indicators. Revelli & Viviani (2013) also identify that data comparison methods, asset class (e.g., equity vs. bonds), and fund construction techniques (e.g., passive replication vs. active screening) contribute to varying results. Meanwhile, Friede et al. (2015) suggest that ESG performance is more consistently linked with positive financial returns in developed markets, particularly in equity investments, and that the strength of this relationship has increased over time. While many studies support a positive ESG–financial performance link, Flammer (2015) notes that such conclusions may not be universally applicable. Her research specifically focuses on "close-call" shareholder proposals—those that pass or fail by a narrow margin of votes—which serve as a quasi-random assignment of CSR initiatives to firms. By using this regression discontinuity design, Flammer (2015) isolates exogenous variation, thereby addressing the endogeneity concerns that often undermine causal interpretation in ESG research. As a result, Flammer (2015) warns against generalizing her findings to all CSR proposals, emphasizing that the performance-enhancing effects of ESG may depend heavily on proposal type, context, and baseline CSR levels.

From a practical point of view, investing in ESG doesn't have to mean giving up financial returns. The amount of money going into ESG investments is increasing, and empirical evidence continues to show that these investments can still perform well (Orlitzky et al., 2003; Revelli & Viviani, 2015; Friede et al., 2015; Flammer, 2015), supports the case for broader ESG adoption. The alignment between financial and ethical goals can be mutually reinforcing firms that adopt credible ESG practices can benefit from reputational advantages, lower capital costs, and enhanced stakeholder loyalty. Nonetheless, to realize these benefits, both investors and companies must avoid superficial compliance or symbolic CSR gestures —often referred to as "greenwashing" or "window dressing" (Delmas & Burbano, 2011; Findlay & Moran, 2019). As Revelli & Viviani (2015) argue, ESG initiatives must be material, transparent, and strategically integrated into business operations to generate value.

2.2 ESG vs. Impact Investing: Conceptual and Practical Distinctions

Although the primary focus of this thesis is ESG integration in private equity, it is also relevant to address impact investing, as it constitutes a related but distinct approach in which the pursuit of measurable social and environmental outcomes provides a clearer link to fund performance, whereas ESG factors often operate as contributory but less directly quantifiable influences. This inclusion is particularly important because the dataset analyzed in this thesis contains private equity funds that pursue impact investing strategies. Importantly, impact investing funds are nested within the broader ESG category: achieving intentional and measurable impact inherently satisfies ESG principles, whereas funds with ESG mandates do not necessarily meet the stricter criteria required to qualify as impact funds (Barber, Morse, & Yasuda, 2021). More broadly, ESG and impact investing are often grouped under the label of responsible investing, but they represent conceptually distinct approaches, shaped by different objectives, implementation strategies, and return expectations (Höchstädter & Scheck, 2015; Brest & Born, 2013). While ESG investing focuses on incorporating environmental, social, and governance factors into investment analysis to enhance risk-adjusted returns (Pedersen, Fitzgibbons, & Pomorski, 2021), impact investing is centered on achieving intentional and measurable social or environmental outcomes alongside financial returns (Brest & Born, 2013; Barber, Morse, & Yasuda, 2021).

The most fundamental difference lies in the intentionality of the investment mandate. ESG investing is usually applied in public markets, aiming to improve long-term risk-return profiles by taking into account the ESG-related material risks and opportunities (Pedersen et al., 2021; Heinz & Velamuri, 2024). In contrast, impact investing requires the explicit intent to generate positive social or environmental outcomes, which must be measurable and attributable to the specific investment (Brest & Born, 2013). To better clarify this difference, Brest & Born (2013) introduce a widely cited framework that differentiates among enterprise impact (impact created by the investee), investment impact (changes resulting from the investor's capital), and non-monetary impact (support services provided by the investor, such as governance or expertise). According to this view, impact investing must go beyond ESG screening to generate outcomes that would not otherwise occur, a concept known as additionality (Brest & Born, 2013). In this model, the "impact" objective is not incidental but core to the investment thesis, with investors actively seeking to address specific challenges such as climate change, poverty reduction, or access to healthcare. Measurement is a critical differentiator—impact investments typically require the use of standardized metrics or reporting frameworks (e.g., IRIS+, GIIRS) to assess progress toward stated impact goals (Brest & Born, 2013). While ESG strategies can be implemented without sacrificing financial returns, impact investing often involves a broader spectrum of return expectations, ranging from market-rate to concessional returns, depending on investor priorities and the nature of the social or environmental mission (Barber et al., 2021).

Despite this conceptual clarity in academic frameworks, the impact investing field continues to have terminological inconsistency and strategic ambiguity (Höchstädter & Scheck, 2015). In their comprehensive review of academic and practitioner literature, Höchstädter & Scheck (2015) identify four typologies of impact investing that reflect the internal distinctions. These typologies vary across several dimensions, including expected financial returns (e.g., market-rate vs. below-market), the intended social or environmental outcomes, the motivations of investors (such as values-based goals vs. strategic objectives), and the types of investees targeted (e.g., social enterprises vs. commercial ventures). Some definitions emphasize investing in mission-driven organizations that prioritize impact over profitability and accept below-market financial returns as a trade-off. This perspective is aligned with philanthropic approaches and is often referred to as "mission-first". In contrast, other interpretations focus on generating measurable impact without sacrificing financial performance, often by investing in scalable business models within mainstream sectors—an approach referred to as “finance-first” (Höchstädter & Scheck, 2015). The coexistence of these differing paths contributes to a lack of consensus about what truly qualifies as impact investing. It also raises questions about whether practices like ESG integration—which are typically grounded in risk-return optimization—should be considered part of the impact investing universe or treated as a separate category altogether (Höchstädter & Scheck, 2015). The authors argue that this fragmentation risks undermining the credibility and effectiveness of impact strategies.

Differences between ESG and impact investing are also evident in how institutional investors allocate capital. In a detailed analysis of LP commitments to private impact funds, Barber, Morse, & Yasuda (2021) find that impact funds do not significantly underperform traditional private equity funds. However, these funds are more frequently selected by non-profit-oriented LPs such as foundations, endowments, pension funds and development finance institutions—entities that often pursue core non-financial objectives. In contrast, wealth management firms and other return-constrained LPs show a lower propensity to invest in impact vehicles, due to fiduciary and regulatory limitations. The study highlights that willingness to trade financial return for impact outcomes is shaped by institutional investment mandates, which create clear boundaries between ESG integration (which is generally acceptable under fiduciary duty) and impact investing (which may be perceived as return-sacrificing).

In practice, ESG and impact investing differ not only in motivation but also in investment process and asset class focus. ESG strategies are most commonly implemented through public markets and involve techniques such as negative screening, best-in-class selection, or ESG factor integration into valuation models (Pedersen et al., 2021). These approaches often rely on third-party ESG ratings and do not necessarily require direct engagement or prove that capital flows result in real-world impact. Pedersen et al. (2021) introduce the concept of the ESG-efficient frontier, which quantifies how investors can optimize ESG alignment while minimizing both return sacrifice and tracking error. Their model suggests that investors can pursue ESG preferences at relatively low financial cost—making ESG integration compatible with modern portfolio theory. In contrast, impact investing usually takes place in private markets, often targeting early-stage venture companies, underserved sectors, or geographically marginalized communities where capital can play a catalytic role (Brest & Born, 2013; Barber et al., 2021).

These investments are more likely to involve non-financial value-add from investors and to rely on theory of change frameworks and impact measurement tools to evaluate outcomes. Measurement challenges remain a central issue in the field, as emphasized by Brest & Born (2013), who argue that many so-called impact strategies fail to demonstrate credible evidence of causality or additionality. While ESG may align with a firm's sustainability profile, it does not ensure that the investment caused the outcome.

2.3 ESG Integration in Private Equity

The integration of ESG factors into PE investment strategies has accelerated over the past decade, driven by growing institutional investor demand, evolving regulatory frameworks, and increased recognition of sustainability-related risks and opportunities. Although ESG adoption is now well-established in public markets, its application in private equity remains uneven due to the asset class's illiquidity, lack of transparency, and idiosyncratic governance structures. A growing amount of research highlights the distinct motivations, implementation models, and structural barriers shaping ESG integration in PE.

A recurring theme in the literature is the differentiated motivation for ESG integration between LPs and GPs. McCahery, Pudschedl, & Steindl (2023) conducted a comprehensive survey across 106 institutional investors and found that LPs are primarily motivated by their belief in ESG's link to financial performance. Approximately 48% of LPs ranked investment risk mitigation as a top reason for considering ESG, compared to only 13% citing diversification. GPs, by contrast, are more reactive—integrating ESG primarily in response to client demand and the broader shift toward responsible investing, rather than due to a proactive belief in ESG-driven value creation (McCahery et al., 2023).

ESG integration in PE is often characterized as a proactive strategy aligned with long-term value creation. However, empirical studies suggest that the primary drivers are external pressures—particularly from LPs, regulators, and reputational concerns—rather than internalized strategic commitment. Zaccone & Pedrini (2020) reinforce this finding through their qualitative interviews and survey of 23 international top-tier PE firms, find that ESG is most commonly embedded during the due diligence phase, often through standardized checklists, yet few firms maintain ESG oversight during ownership or link ESG outcomes to value creation or exit strategy. While firms recognize ESG as a reputational and risk-hedging tool, the broader integration into value-driving processes—such as operational improvements or pricing advantages at exit—is still underdeveloped. Thus, ESG remains more of a compliance response to LPs' expectations than a fully integrated investment lens (Zaccone & Pedrini, 2020). These findings also show that private equity firms respond to investor expectations rather than initiate ESG integration as a core value driver. Many GPs acknowledge ESG's relevance for risk mitigation, particularly reputational and regulatory risk, but remain skeptical of its short-term value-enhancing potential. This disconnect reflects a broader tension between the long-term nature of sustainability goals and the short- to medium-term incentive structures that dominate PE fund management.

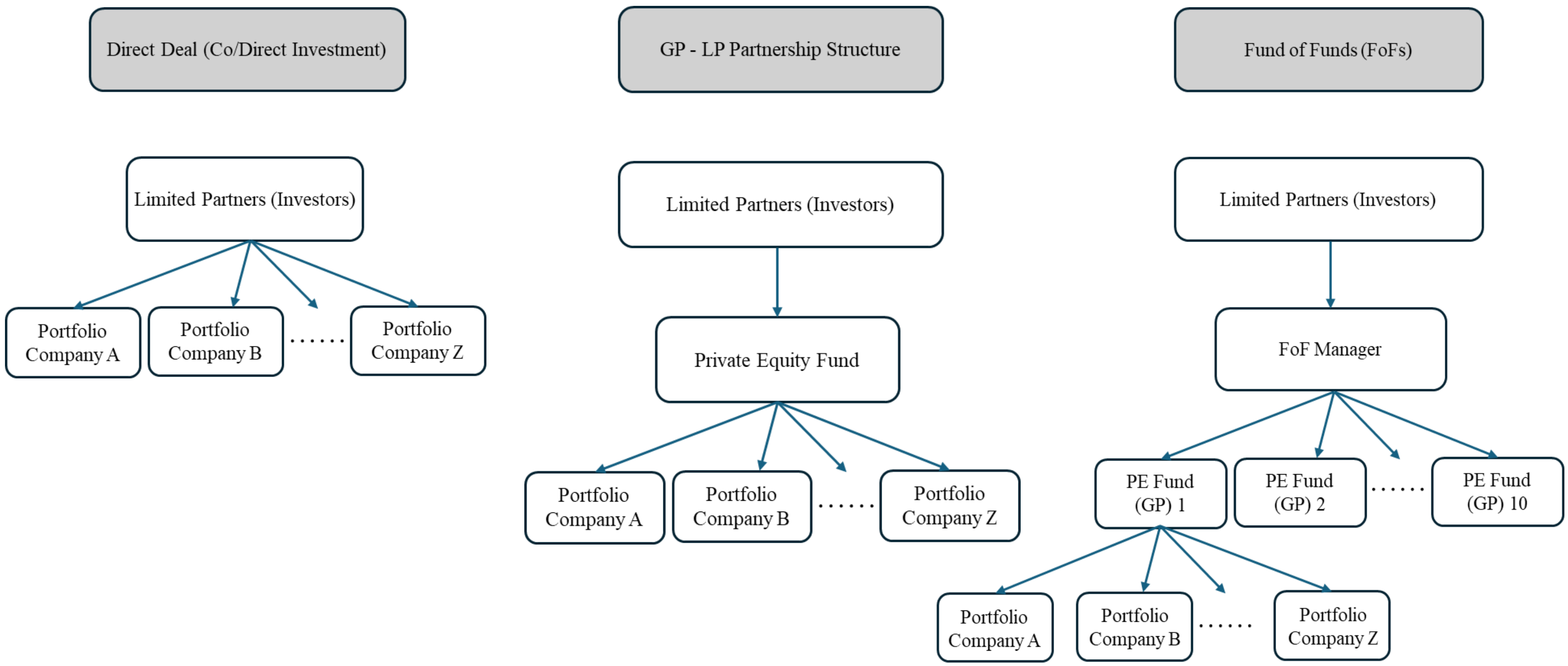
To formalize the financial implications of ESG integration in private markets, Bian et al. (2023) present a dynamic model that captures how LPs allocate capital based on both return objectives and ESG preferences. Using a continuous-time partnership valuation framework, they incorporate a variable called "ESG demand spending" to reflect LP willingness to pay for sustainability. The model reveals an inverted U-shaped relationship between ESG investment and LP utility: at low to moderate levels, ESG improves performance by reducing systemic and reputational risk, but beyond a certain threshold, ESG constraints erode returns by restricting investment flexibility and increasing idiosyncratic risk (Bian et al., 2023). This finding cautions against over-implementation and illustrates that ESG can be value-enhancing or value-dilutive depending on its intensity and context. Their findings also imply that ESG integration in PE must strike a balance between sustainability ambition and financial realism. LPs need to calibrate ESG demands not only based on their values but also on risk appetite and liquidity constraints. Importantly, Bian et al. (2023) also explore the implications of GP compensation and fund duration. They argue that traditional carried interest structures, focused on short-term IRR, often does not incentivize long-term ESG investments. Unless GPs are compensated for delivering ESG outcomes—through extra mechanisms like sustainability-linked carry or multi-layer performance fees—they may deprioritize ESG initiatives that do not align with fund economics. This creates a misalignment between ESG-oriented LPs and return-focused GPs, and limits ESG integration in practice.

In practice, the effectiveness and calibration of ESG integration—as modeled by Bian et al. (2023)—depend heavily on the heterogeneity of institutional investor preferences. While the theoretical framework identifies an optimal ESG intensity from a utility-maximizing standpoint, LPs differ significantly in their ESG motivations, constraints, and expectations. Renneboog, Horst, & Zhang (2008) demonstrate that socially responsible investment behavior differs substantially across investor types: public pension funds, churches, and foundations are more likely to prioritize ESG or ethical mandates as also pointed out by Barber, Morse, & Yasuda (2021), while commercial financial institutions tend to focus on performance and adopt ESG mainly for reputational reasons. These institutional differences shape the level of ESG scrutiny applied to GPs and the due diligence process and expectations embedded in limited partnership agreements. Building on this, impact funds are more frequently selected by these non-profit-oriented LPs. These LPs are more willing to commit capital to funds with ESG or impact mandates, even when this may entail trade-offs in terms of liquidity or investment constraints. Their behavior aligns with the upward-sloping part of Bian et al. (2023)'s curve, where ESG integration is seen as enhancing long-term value. Conversely, commercial LPs with strict fiduciary benchmarks may resist heavy ESG constraints, corresponding to the downward-sloping side of the utility curve, where the costs outweigh the perceived benefits (De Lucia et al., 2020). Taken together, this literature reinforces the notion that LP identity and mandate structure play a vital role in determining the level and nature of ESG integration in private equity. GPs, in turn, respond to these preferences—whether symbolically or substantively—depending on how ESG fits within their value-creation framework and investor base.

2.4 Private Equity Performance and Valuation

The performance and valuation of PE investments are shaped by a complex interplay of fund structures, valuation practices, and broader macroeconomic and industry-level dynamics. A critical first dimension relates to implementation style—that is, how LPs access PE: through direct internal management, traditional general partner-limited partner (GP-LP) structures, or fund-of-funds (FOFs), as demonstrated in Figure 2.4.1. In the internal management model, large institutional investors such as pension funds or sovereign wealth funds create in-house teams dedicated to sourcing, executing, and monitoring private equity investments directly. This structure removes the need to outsource these functions to external managers, which can significantly reduce total costs by avoiding management fees and carried interest (Beath, Flynn, & MacIntosh, 2014). It also gives the LP greater strategic control over investment pacing, sector targeting, and exit timing—allowing decisions to be more closely aligned with the fund's long-term objectives, such as matching liabilities or meeting sustainability goals. However, this approach is only practical for institutions with substantial scale, deep resources, and the ability to attract and retain specialized investment talent (Beath, Flynn, & MacIntosh, 2014). By contrast, the GP–LP model—the main structure in the PE industry—involves LPs committing capital to funds managed by external general partners. GPs are responsible for identifying attractive deals, conducting due diligence, overseeing portfolio companies, and ultimately driving value creation. In exchange, GPs typically charge a fixed annual management fee (often 1.5%–2% of committed capital) plus performance-based carried interest (commonly 20% of profits above a certain hurdle rate). While this model offers LPs access to experienced managers and specialized deal flow without building internal teams, it also introduces higher costs and less direct control over individual investment decisions (Beath et al., 2014). Finally, in FoFs structures, LPs allocate capital to intermediaries that invest in a diversified portfolio of underlying PE funds. While this approach offers built-in diversification and delegated selection expertise, it also introduces an additional fee layer and reduces transparency (Beath et al., 2014). Using a global sample from the CEM Benchmarking database, Beath, Flynn, & MacIntosh (2014) show that internal management tends to outperform GP-LP structures, while FOFs lag significantly in net performance. In comparison, internal management offers lower total costs and more direct control, while FOFs entail layered fees and limited transparency. Over a 17-year period, internally managed PE portfolios delivered an average net value added (NVA) of 3.52%, compared to just 0.28% for external LPs and –1.63% for FOFs. These disparities were largely cost-driven and exacerbated by underreporting of fees and carried interest in many fund disclosures (Beath et al., 2014). The findings emphasize that implementation style and full cost structure can materially skew performance metrics like IRR, DPI, and TVPI, making it imperative for LPs to consider these factors during due diligence.

Figure 2.4.1 Three Ways to Access Private Equity



Beyond cost and structure, PE valuation practices introduce additional noise into performance measurement. Czasonis, Kritzman, & Turkington (2019) argue that while private equity returns appear smoother than public markets due to quarterly reporting and appraisal-based valuations, this smoothness can mask true underlying volatility. They construct a model to align private equity returns with public equity benchmarks and find that illiquidity, smoothed valuations, and subjective judgment create a lag in private equity pricing, which in turn affects reported correlations and Sharpe ratios. This can lead to inflated perceptions of diversification benefits and risk-adjusted returns. The implications are significant for performance attribution: traditional IRR and TVPI measures may not fully reflect risk, particularly in times of market stress when valuation lags can be more pronounced (Czasonis et al., 2019). Another layer of complexity arises from the use of different commercial data sources, which often yield diverging conclusions about PE performance. Brown et al. (2015) compare datasets from Burgiss, Preqin, PitchBook, and Cambridge Associates, finding considerable heterogeneity in reported fund returns, quartile rankings, and persistence patterns. Although Burgiss is typically regarded as the most reliable due to its LP-sourced cash flow data, the discrepancies highlight the importance of data provenance, survivorship bias, and differences in vintage-year coverage when interpreting academic or practitioner research. As the authors note, LPs and consultants relying on any single database risk drawing skewed conclusions about manager skill or the predictive power of past performance (Brown et al., 2015).

Finally, zooming out from the fund-level perspective, Bernstein et al. (2017) examine the macroeconomic impact of private equity across industries and countries. Drawing on a comprehensive panel dataset from Capital IQ and OECD STAN covering 1991–2009, they find that industries with higher levels of PE activity—such as technology and manufacturing—experienced faster growth in output, value-added, wages, and employment. Crucially, these industries were not more volatile; if anything, PE-backed sectors showed reduced downside risk during downturns. These effects were not solely attributable to selection bias or pre-existing trends: results remained robust when controlling for lagged investment activity and using pension fund depth as an instrument. This suggests that PE plays a constructive role in enhancing industry-level productivity and resilience, potentially via active governance, capital reallocation, and managerial discipline (Bernstein et al., 2017).

In conclusion, evaluating private equity performance requires attention not only to consider return metrics but also to take into account the underlying structural factors, valuation methodologies, data sources, and macro-level effects. Fund formation—whether through internal platforms, GP-LP vehicles, or intermediated models—has different performance implications. Meanwhile, valuation discretion and database selection can also skew interpretations of alpha and persistence. Finally, on an aggregate level, PE can act as a stabilizing force in the economy, but this impact depends on investment timing, governance effectiveness, and industry context.

2.5 External Market Influences on Private Equity Performance

Building on the internal perspective that impact PE performance in Section 2.4, the analysis now considers external market influences — how macroeconomic and market environments constrain or amplify performance. The performance of PE investments is significantly influenced by broader market conditions, including public equity market cycles, credit availability, macroeconomic shocks, and liquidity dynamics. Unlike publicly traded assets, PE investments are illiquid, infrequently priced, and often less transparent in valuation. Franzoni, Nowak, & Phalippou (2012) challenge traditional methods of assessing private equity performance by using market prices of publicly traded private equity vehicles—such as business development companies (BDCs) and listed PE firms—to estimate systematic risk exposures and expected returns. This approach allows them to bypass the inherent biases in self-reported net asset values (NAVs), which are often subject to smoothing issue and valuation discretion by general partners. Unlike conventional IRR-based assessments, their methodology enables a more market-consistent evaluation of PE risk and return. Their results reveal that PE exhibits high beta exposure to public equity markets, meaning that PE values tend to decline sharply during market downturns. In addition, PE investments show significant exposure to liquidity risk, as their value declines disproportionately when market-wide liquidity tightens. These findings imply that the high historical average returns in private equity are not necessarily the result of superior manager skill (alpha), but rather compensation for bearing undiversifiable market and liquidity risks. The study fundamentally reframes the interpretation of PE excess returns, suggesting that they resemble a form of risk premium rather than persistent outperformance, thereby encouraging a more risk-adjusted evaluation of PE in portfolio construction. Complementing this perspective, Robinson & Sensoy (2016) examine the cyclicality dynamics of private equity cash flows using a large sample of buyout and venture capital funds spanning 1984 to 2010. They find that both capital calls and distributions exhibit strong procyclicality, with distributions responding more acutely to macroeconomic conditions than capital calls. This asymmetry results in cyclical net cash flow patterns, where LPs receive less liquidity precisely during downturns when other assets may also be distressed. The study shows that funds raised during “hot” markets tend to underperform, and that those with greater ability or willingness to call capital during downturns achieve superior performance. Moreover, venture capital funds display greater cyclicality than buyout funds, both in cash flow timing and in the strength of the relationship between market cycles and fund performance. These findings underscore the importance of viewing private equity not just as an illiquid asset, but as one whose performance and cash flow profile are highly sensitive to external macroeconomic conditions, especially during downturns (Robinson & Sensoy, 2016).

More research highlights that private equity is more deeply embedded in the macro-financial cycle than previously assumed. Jegadeesh, Kräussl, & Pollet (2015) demonstrate that PE returns—when assessed using market-based pricing such as secondary market transactions and listed PE vehicles—are significantly influenced by broad macroeconomic indicators. Their empirical results show that private equity performance is highly correlated with GDP growth, public equity indices (e.g., MSCI World), and credit spreads. In particular, widening credit spreads and deteriorating economic output are associated with lower PE returns, suggesting that the asset class is procyclical and exposed to systematic market and funding risk. These findings challenge the perception of private equity as a diversifier in institutional portfolios and instead frame it as a high-beta investment that compensates investors through illiquidity and risk premia. The apparent stability derived from GP-reported NAVs is largely an artifact of appraisal-based smoothing, which conceals underlying volatility and macro sensitivity. The role of external market factors is further explored by Gupta & Nieuwerburgh (2021), who argue that private equity valuations are influenced by shifts in market sentiment and economic conditions. For instance, rising interest rates increase the cost of leverage, which can weaken the net returns of private equity investments. This interplay between macroeconomic factors and fund performance underscores the need for LPs to adopt a holistic approach when evaluating potential investments, factoring in not only the historical performance of a fund but also its sensitivity to broader economic conditions.

However, at the firm level, the role of private equity during macroeconomic shocks is more nuanced. Bernstein, Lerner, & Mezzanotti (2019) explore how PE-backed firms responded to the 2008 global financial crisis, using a difference-in-differences approach to compare matched PE and non-PE-owned companies. Despite their reliance on leverage, PE-backed firms exhibited greater resilience during the crisis—they were less likely to default, more likely to sustain investment activity, and had better access to external financing. This resilience is attributed to active ownership, access to committed (but uncalled) capital, and better financial planning by PE sponsors. In fact, firms backed by larger and more experienced PE sponsors fared best, reinforcing the idea that not all private equity ownership is equal—sponsor reputation and scale play critical roles in managing through macro shocks.

Together, these studies underscore a central tension: while private equity as an asset class is vulnerable to external economic forces, private equity as a governance mechanism can serve to insulate firms from those very forces. This distinction is essential for investors and policymakers alike. For LPs, it suggests that while aggregate PE returns may decline during downturns, the underlying companies may still outperform their non-PE peers due to sponsor intervention.

2.6 LPs' Due Diligence and Investment Process

The due diligence and investment selection process by LPs in PE is multifaceted, shaped by information asymmetries, governance structures, and strategic alignment with fund managers (GPs). The bespoke nature of private equity investments and the opacity surrounding fund-level data create a complex decision environment in which LPs must carefully assess both risks and potential returns. Korteweg & Westerfield (2022) emphasize that LPs operate under constraints related to illiquidity, valuation opacity, and significant performance dispersion across funds. Illiquidity arises from long fund lock-up periods and uncertain capital call schedules, limiting LPs' flexibility to rebalance portfolios. Valuation opacity stems from infrequent, appraisal-based NAV reporting, which obscures real-time performance and complicates benchmarking. Besides, performance dispersion is unusually wide—top-quartile funds often outperform the median by several hundred basis points, making manager selection both crucial and difficult due to limited observable indicators of GP skills (Korteweg & Westerfield, 2022). These constraints heighten the importance of rigorous due diligence in identifying top-performing GPs and constructing resilient portfolios. Assessing GP skill is especially difficult due to the discretionary nature of capital calls and distributions, the absence of mark-to-market valuations, and performance manipulation risks—factors that prevent LPs from easily benchmarking one GP against another. On the governance side, Birdthistle & Henderson (2009) discuss the risks associated with "investment desegregation," where GPs invest across multiple asset classes (e.g., debt and equity) within the same issuer. This practice can create conflicts of interest, as GPs may prioritize one group of investors over another. This dynamic adds complexity to LPs' due diligence, as LPs must ensure that GPs manage these dual fiduciary responsibilities without compromising investor returns.

In response, institutional LPs have developed rigorous due diligence frameworks to mitigate adverse selection and governance risks. Cumming & Zambelli (2017) provide empirical evidence that greater time and effort spent on due diligence is positively associated with better future performance of investee firms, particularly when the process is conducted internally. Their study finds that internally conducted due diligence—typically involving deep investigation into management capabilities, financial projections, strategic fit, and industry risk—leads to more effective matching between investors and entrepreneurs. In contrast, when due diligence is outsourced to external consultants or law/accounting firms, the informational disadvantages may result in less optimal investment decisions. This suggests that internal due diligence not only enhances deal selection but also reduces agency costs stemming from delegated screening. Beyond investment selection, the legal and fiduciary obligations of LPs—as stewards of capital for pension beneficiaries, university endowments, and charitable foundations—introduce an additional layer of responsibility in the fund evaluation process. As fiduciaries, LPs are legally bound to act in the best interests of their beneficiaries, which entails both prudently maximizing returns and safeguarding assets against undue risk or opacity. Birdthistle & Henderson (2009) highlight the potential for role conflict, particularly when LP representatives serve dual functions—such as trustees of an institution and investment committee members allocating to private equity. In such cases, fiduciaries must navigate competing pressures between seeking high-yielding opportunities and maintaining transparency, liquidity, and accountability. They emphasize that trust and securities laws require LPs to conduct thorough due diligence, not only as a financial best practice but also as a legal duty tied to procedural care, loyalty, and oversight. Failure to rigorously evaluate GPs and fund structures may expose fiduciaries to liability, particularly in cases of underperformance, misalignment of interests, or governance failures. This legal framing highlights that due diligence goes beyond investment selection—it serves as a compliance mechanism to ensure LPs meet their regulatory and ethical responsibilities in a complex asset class (Birdthistle & Henderson, 2009). Ultimately, PE due diligence functions as both a screening tool and a strategic mechanism for enhancing alignment, improving portfolio management, and fulfilling fiduciary duties in an obscure, illiquid environment.

2.7 Literature Gaps and Research Motivation

The existing literature offers a broad foundation for understanding private equity (PE) performance, ESG integration, institutional behavior, and external market influences. Seminal studies such as Franzoni, Nowak, & Phalippou (2012), Jegadeesh, Kräussl, & Pollet (2015), and Robinson & Sensoy (2016) demonstrate that private equity returns exhibit sensitivity to public equity markets, liquidity conditions, and macroeconomic cycles. However, these analyses largely emphasize long-term performance trends or rely on market-based proxies and smoothed NAVs. While such approaches are valuable for identifying broad cyclical patterns, they often overlook the short-term responsiveness of actual, realized fund-level IRRs to macroeconomic shocks. This short-term dynamic—how returns respond within a few quarters to economic shifts—remains less understood, even though it is highly relevant for LPs' tactical allocation and liquidity planning.

Research on ESG integration in private equity has also expanded in recent years, reflecting the rising popularity of sustainable investing in alternative assets. Yet the majority of this work remains qualitative or conceptual in nature, often centered on frameworks, typologies, or case study analyses of ESG practices by GPs (Zaccone & Pedrini, 2020; McCahery, Pudschedl, & Steindl, 2023). Quantitative examinations of how ESG engagement interacts with macroeconomic volatility—for example, whether ESG-oriented funds are more resilient in downturns or more sensitive to shifts in interest rates are rare. Furthermore, the joint influence of sustainability preferences and macroeconomic shocks on PE performance has not been systematically tested within a time-series econometric framework. This leaves a conceptual and empirical gap in understanding the potentially nonlinear and interactive relationships between macro drivers, ESG considerations, and private equity outcomes.

In the area of performance measurement, Czasonis, Kritzman, & Turkington (2019) highlight that private equity valuations are closely tied to public equity markets, but important deviations arise due to illiquidity, appraisal-based pricing, and GP discretion in valuation inputs. These practices can be procyclical and are prone to biases—particularly during fundraising periods, when GPs may have incentives to present inflated valuations (Baik, 2024). This raises the possibility that reported fund performance may sometimes reflect public market sentiment and valuation conventions more than actual portfolio company fundamentals. Recognizing this linkage, the inclusion of public equity indices (e.g., S&P 500) as exogenous variables in a time-series model is not only methodologically defensible but also essential for disentangling true performance effects from valuation-driven artifacts.

Despite these insights, there remains limited empirical work that formally models the short-term dynamic relationship between private equity IRRs and macroeconomic indicators using tools like Vector Autoregressive (VAR) models. Most studies are either static in design, cross-sectional in focus, or rely on approximate fund-level proxies rather than observed IRR data. As such, the temporal feedback mechanisms between IRR and shocks to market returns, interest rates, or GDP growth remain underexplored.

This study addresses these gaps by applying a VAR framework to directly quantify the short-term relationships between PE fund performance and macroeconomic shocks, while accounting for public equity conditions and the valuation practices that link PE and public markets. In doing so, it contributes to the literature in three ways: Methodologically, by moving beyond static or cross-sectional designs toward a dynamic, time-series approach that captures temporal dependencies and feedback loops. Conceptually, by integrating insights from both the PE valuation literature and ESG discourse into a macro-financial performance framework. Practically, by providing LPs and asset allocators with a more nuanced understanding of how macroeconomic shocks affect short-term PE performance, which can inform commitment pacing, liquidity planning, and risk management.

2.8 Synthesis Table: ESG, Private Equity and LPs' Investment Process

Dimension	Concept	Description	Authors
2.1 ESG and SRI: Foundations and Performance Implications	**ESG as a Value Driver**	CSR adoption leads to significant positive abnormal returns and enhanced firm value, particularly for firms with lower baseline CSR performance.	Flammer (2015)
	Consolidated Evidence of CSP-CFP Link	There is a positive association between corporate social performance (CSP) and corporate financial performance (CFP) based on a meta-analysis of 52 studies.	Orlitzky, Schmidt & Rynes (2003)
	SRI Performance	Socially responsible investing (SRI) does not significantly underperform conventional investments, challenging traditional finance theories and suggesting SRI can be competitive	Revelli & Viviani (2015)
	ESG and Financial Performance: Broad Empirical Support	A second-order meta-analysis of over 2,000 empirical studies shows a broadly positive correlation between ESG criteria and corporate financial performance (CFP), especially in emerging markets and non-equity asset classes.	Friede, Busch & Bassen (2015)
	Moderators of SRI Outcomes	SRI's impact on financial performance varies, the average performance is statistically neutral, with positive and negative outcomes shaped heavily by methodological quality and observation periods based on 161 experimental observations from 75 papers.	Revelli & Viviani (2013)
2.2 ESG vs. Impact Investing: Conceptual and Practical Distinctions	**Impact in Practice**	Distinguishes between different types of impact (enterprise, investment, and non-monetary) and argues for greater rigor in evaluating how investments actually contribute to social or environmental outcomes. It provides a framework for assessing whether impact claims are substantiated.	Brest & Born (2013)
	Definitional Ambiguity in Impact Investing	Fragmented understanding of impact investing among scholars and professionals, highlighting four typologies and emphasizing the need for conceptual clarity in both research and practice.	Höchstädter & Scheck (2015)
	LP Preferences and Performance in	Impact funds do not significantly underperform traditional funds and are selected by LPs with non-pecuniary preferences (e.g., foundations,	Barber, Morse, & Yasuda (2021)

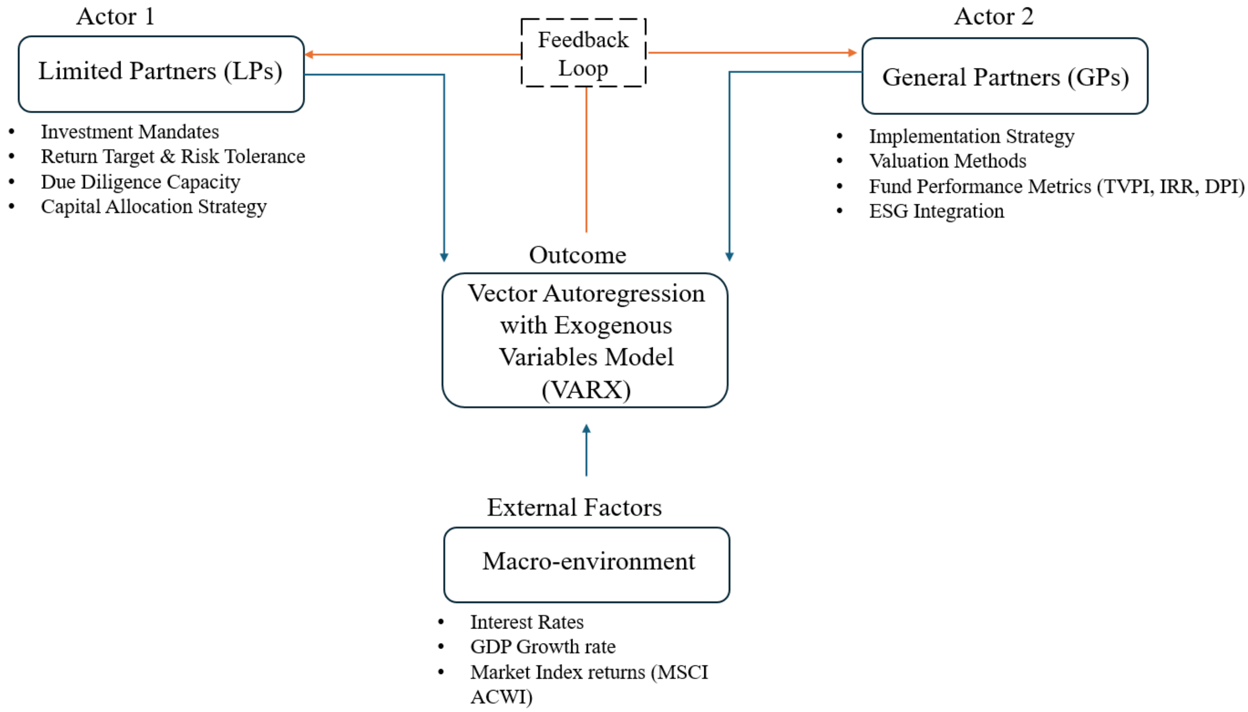
	Impact Investing	endowments). It highlights that institutional constraints, such as fiduciary duty, heavily influence LPs' willingness to sacrifice financial return for social impact.	
	Quantifying ESG Trade-Offs	Introduces the concept of the "ESG-efficient frontier" to show that investors can optimize ESG scores without significant sacrifice in financial returns, depending on their tolerance for ESG deviations and tracking error.	Pedersen, Fitzgibbons & Pomorski (2021)
2.3 ESG Integration in Private Equity (PE)	**ESG Integration and Financial Performance**	Funds that integrate ESG factors show enhanced long-term performance, although the effect can vary by sector and region. ESG integration in PE is increasingly demanded by LPs as part of their sustainability and risk management objectives.	Zaccone & Pedrini (2020); Revelli & Viviani (2015)
	Socially Responsible Investments (SRI)	SRI practices influence investment behavior, with varied performance outcomes. SRI strategies focus on ethical investments, but their financial performance compared to non-SRI funds has produced mixed results across different studies.	Renneboog et al. (2008)
	ESG Preferences of Institutional Investors	Institutional investors, especially those with long-term horizons, are increasingly prioritizing ESG-focused funds. These preferences are reshaping the private equity landscape, with more GPs adopting ESG mandates to attract LP commitments.	McCahery, Pudschedl, & Steindl (2023)
	Integrate ESG into PE valuation	A theoretical model is to assess LPs value PE investments when incorporating ESG objectives. It finds that ESG demand has an inverted U-shaped effect on LPs' certainty-equivalent wealth, implying that while ESG integration can enhance sustainable payoffs.	Bian, Gao, Wang, & Xiong (2023)
2.4 Private Equity Performance and Valuation	**Implementation Style and Costs**	The role of implementation strategies (e.g., internal management, fund-of-funds) in influencing PE fund performance, with costs affecting returns. Internal management generally outperforms other structures due to lower fees.	Beath, Flynn, & MacIntosh (2014)
	Fund Valuation Methods	The strip-by-strip valuation approach offers more accurate performance estimation by segmenting cash flows. PE valuations are	Gupta & Nieuwerburgh (2021);

		closely tied to public equity performance but differ due to liquidity and discretion in fund management.	Czasonis, Kritzman, & Turkington (2019)
	Industry Performance Linkages	Private equity drives industry-wide innovation and efficiency, enhancing overall performance, especially in sectors benefiting from PE investment, such as technology and manufacturing.	Bernstein et al. (2017)
	Performance Across Commercial Data Sets	Different commercial datasets provide varying insights into PE performance, though they align on key trends such as IRR and cash flow metrics. LPs must carefully select data sources for accurate benchmarking.	Brown et al. (2015)
2.5 External Market Influences on PE Performance	**Public Market Signals and PE Risk**	PE performance is closely tied to GDP growth, public equity indices, and credit spreads—demonstrating significant sensitivity to external market conditions.	Jegadeesh, Kräussl, & Pollet (2015)
	Macroeconomic Fragility in PE	PE-backed firms may contribute to systemic risk during downturns due to overleveraging in boom periods, leading to underperformance and fragility in crises.	Bernstein, Lerner, & Mezzanotti (2019)
	Strip PE Valuation and Systematic Exposure	Replicating portfolios of listed equity and bond strips, finding that average PE funds have negative risk-adjusted profits and that returns are sensitive to public market factors. It offers a decomposition of PE expected returns by risk exposures and investment horizon.	Gupta & Nieuwerburgh (2021)
	Liquidity Risk and PE Performance	PE returns are significantly exposed to liquidity risk, especially during credit tightening, and estimates a liquidity premium of about 3% per annum.	Franzoni, Nowak, & Phalippou (2012)
	PE Cash Flows and Economic Cyclicality	Cyclical macroeconomic factors impact the timing and measurement of PE cash flows, showing that performance metrics like IRR are sensitive to external market environments and internal liquidity dynamics.	Robinson & Sensoy (2016)
2.6 LP Investment Process	**Asset Allocation with Private Equity**	Allocating assets to private equity requires balancing illiquidity risks and returns. Larger LPs have more bargaining power to negotiate favorable terms with GPs, including access to top-performing funds, which significantly impacts returns.	Korteweg & Westerfield (2022)

	Conflicts of Interest in PE Structures	Investment desegregation, where GPs invest across various asset classes, can create conflicts of interest, leading to potential risks for LPs. Managing these conflicts is essential to maintaining transparency and fairness in fund management.	Birdthistle & Henderson (2009)
	Due Diligence	Thorough due diligence (DD), especially when conducted directly by fund managers rather than external agents, significantly improves investee performance in private equity.	Cumming & Zambelli (2017)

3. Conceptual framework

Figure 3.1 Conceptual Framework



The conceptual framework illustrates the dynamic relationships among LPs, GPs, and macroeconomic conditions in shaping PE fund performance. At the heart of the framework lies a Vector Autoregression with Exogenous Variables (VARX) model, which is employed to assess how short-term macroeconomic shocks—such as changes in market returns, interest rates, and GDP growth—affect IRR, the primary performance measure of interest in this study. The model situates IRR as the endogenous outcome, influenced by both external economic indicators and institutional decision-making within the PE ecosystem. This approach builds on calls from Jegadeesh, Kräussl, & Pollet (2015) and Franzoni, Nowak, & Phalippou (2012) to model private equity returns using dynamic market-sensitive tools, rather than relying solely on appraisal-based or smoothed performance data.

On the left side of the framework, LPs represent the capital allocators whose behavior is defined by their investment mandates, risk-return preferences, due diligence capabilities, and capital allocation strategies. These institutional investors, such as pension funds and endowments, set the terms under which they engage with GPs, choosing which funds to back and imposing expectations around reporting, governance, and—where relevant—ESG integration (McCahery, Pudschedl, & Steindl, 2023). Their decisions feed directly into the dynamics modeled in the VARX framework, as LP preferences shape the flow of capital and the performance pressures imposed on GPs. As noted by Birdthistle & Henderson (2009), LPs also operate under fiduciary and legal obligations that require a balancing act between return objectives and risk governance, adding further scrutiny to the selection and monitoring of fund managers. On the right side, GPs are responsible for the implementation of the investment strategy, including the timing and structure of investments, valuation methods, reporting practices, and the integration of ESG considerations (Zaccone & Pedrini, 2020). Their actions have a direct impact on the observable fund performance metrics—IRR, TVPI, and DPI—which are often used by LPs to evaluate manager effectiveness. The framework recognizes that GP-reported outcomes may be influenced not only by real economic performance but also by discretionary decisions, such as the timing of capital calls and valuations, which can introduce biases during favorable public market cycles or fundraising periods (Czasonis, Kritzman, & Turkington, 2019; Baik, 2024). This justifies the inclusion of market-based indicators, such as public equity returns, as exogenous controls in the VARX model to isolate macro-driven fluctuations from manager discretion.

External macroeconomic factors are positioned at the base of the model and include variables such as interest rates, GDP growth rates, and market index returns (e.g., MSCI ACWI). These variables are treated as exogenous drivers that influence PE performance independently of fund-level or institutional behavior. For instance, rising interest rates increases the cost of leverage and reduce net returns, while GDP growth affects the timing and profitability of exits. Prior research has shown that PE returns are significantly exposed to credit and liquidity conditions, which tend to amplify in economic downturns (Franzoni et al., 2012; Jegadeesh et al., 2015; Robinson & Sensoy, 2016).

Importantly, the framework includes a feedback loop that acknowledges the recursive nature of the LP-GP relationship. LPs revise their future allocation strategies, risk tolerance, and ESG requirements based on observed fund outcomes and the macroeconomic climate. In turn, GPs adapt their implementation approaches, reporting transparency, and fundraising tactics in response to evolving LP expectations. This dynamic interaction reflects the co-evolution of capital providers and fund managers over time, where institutional learning and market performance jointly influence strategic behavior (Bian et al., 2023; Bernstein, Lerner, & Mezzanotti, 2019).

Altogether, the framework provides a structure for examining how PE fund performance responds to macroeconomic shocks in the short term. It does so by integrating econometric modeling with institutional behavior and governance considerations, contributing to the literature at the intersection of macro-finance, private equity, and sustainable investment practices.

Below is a list and a description of the main concepts that this research draws on:

Concept	***Description***
Private Equity Fund Performance	Private equity performance is measured through key metrics such as IRR, DPI, and TVPI, which reflect profitability, liquidity, and value creation over time. These metrics are essential for evaluating fund success and informing LPs' reinvestment decisions (McCahery et al., 2023).
ESG Integration	ESG represents Environmental, Social, and Governance. ESG integration in private equity reflects the adoption of sustainable investing principles. ESG consideration may either improve or disadvantage fund performance depending on the execution (Friede et al., 2015).
External Macro factors Influences	Public market returns (e.g., MSCI ACWI index), interest rates, and GDP growth impact private equity performance because the big investment environment is shaped by these factors. These factors play a significant role in assessing risks and rewards in private equity industry (Kaplan & Schoar, 2005).
Limited Partners Investment Due Diligence	LPs as capital allocators conduct due diligence and rely on performance record, risk tolerance, and ESG considerations to make investment decisions. Their investment mandates guide them for fund evaluation and allocation strategies (Gompers & Lerner, 1996).
VARX Model Application in Private Equity	The Vector Autoregression with Exogenous variables (VARX) model captures dynamic relationships between private equity performance metrics (IRR, DPI, TVPI) and external macroeconomic variables (Stock & Watson, 2001).

4. Methodology

4.1 Research protocol

The research adopts a quantitative strategy, employing a Vector Autoregression with Exogenous Variables (VARX) model to examine the dynamic relationship between private equity fund performance and macroeconomic conditions. As outlined in the conceptual framework, the VARX approach builds upon the traditional Vector Autoregression (VAR) model, which captures the interdependencies among multiple endogenous variables—in this case, performance metrics such as IRR, TVPI, DPI, and a binary ESG integration indicator. The VARX extension allows for the incorporation of external macroeconomic variables—including GDP growth, short-term interest rates, and MSCI ACWI Index returns—as exogenous drivers that may influence the endogenous performance dynamics. This time-series framework enables the analysis of short-term interactions and lagged effects between internal fund characteristics and broader economic conditions, offering a more granular understanding of how performance evolves in response to external shocks. The VARX model is particularly suited for this research, as it allows for the simultaneous modeling of feedback effects among fund-level indicators while isolating the impact of macroeconomic shocks (Stock & Watson, 2001).

However, in keeping with good econometric practice, model flexibility will be preserved. If preliminary diagnostics—such as stationarity tests, residual autocorrelation, or information criteria—suggest poor model fit or significant multicollinearity, alternative specifications may be considered. This includes the possibility of reverting to a standard VAR model, excluding exogenous variables, or reducing the number of endogenous indicators. These adjustments will be based on empirical evidence and aimed at preserving model robustness and interpretability. Further details will be presented in the model section.

4.2 Data Description

This research evaluates private equity fund performance using three core metrics—IRR, DPI and TVPI—which serve as the endogenous variables in the VARX. These measures are widely recognized in both scholarly research and industry practice as the principal indicators of private equity outcomes (Kaplan & Schoar, 2005; Phalippou & Gottschalg, 2009). Together, they capture complementary dimensions of performance, enabling a more comprehensive assessment than any single metric alone.

The IRR represents the annualized discount rate that equates the present value of a fund's capital inflows to its outflows. Within private equity, this metric accommodates the irregular timing of cash flows, thereby facilitating comparisons across funds with differing vintages and investment horizons (Phalippou, 2020). Because it is sensitive to the timing of both capital deployment and distributions, IRR is particularly informative in evaluating the efficiency with which managers convert committed capital into realized returns.

Whereas IRR captures the rate of return, DPI reflects the extent to which invested capital has been returned to limited partners. Defined as the ratio of cumulative distributions to total paid-in capital, DPI serves as a measure of realized liquidity (Brown et al., 2015). High DPI values indicate that a fund has successfully realized the gains and converted its investments into cash, while lower values—despite strong TVPI—may imply that much of the value remains tied up in unrealized holdings.

TVPI offers a broader measure of value creation by combining DPI with the residual value of unrealized investments, expressed as Residual Value to Paid-In Capital (RVPI). This comprehensive indicator captures both distributed and remaining value (Preqin, 2023), making it particularly relevant for ongoing funds where significant portions of the portfolio have yet to be realized. The joint consideration of IRR, DPI, and TVPI therefore provides a multidimensional view of performance, enabling the distinction between overall profitability, cash liquidity generation, and unrealized potential.

In addition to these core performance indicators, the analysis incorporates ESG integration as an additional explanatory variable. ESG orientation is coded as a binary variable (ESG_dummy) that equals one if a fund explicitly states that environmental, social, and governance principles are incorporated into its investment process, and zero otherwise. The classification is based on a systematic review of fund profiles and offering documents available on PitchBook, where information on ESG policies, sustainability mandates, PRI signatory status, or SDG alignment is disclosed. Where such information is absent, the fund is coded as non-ESG-oriented. This binary treatment reflects both data constraints and methodological considerations. Quantitative ESG scoring systems, such as weighted environmental, social, and governance sub-scores, are not consistently available for private equity funds, especially for smaller or emerging managers, funds in developing countries, or older vintage years. In many cases, ESG disclosure is qualitative or policy-based, making it difficult to assign a continuous or ordinal score that is comparable across the sample. Even where more granular ESG ratings exist, they are often proprietary, inconsistently updated, or use differing frameworks that would require extensive normalization before integration. From a modeling perspective, introducing heterogeneous scoring systems could lead to measurement error and bias in time-series estimations. The inclusion of this variable allows the study to assess whether ESG integration has a measurable impact—positive, negative, or neutral—on private equity performance. Prior research offers mixed findings: some studies report that ESG-oriented funds can enhance long-term value creation through improved risk management, operational efficiency, and reputational benefits (Bian et al., 2023), while others suggest that ESG mandates may introduce constraints that limit investment flexibility and potentially reduce returns (McCahery et al., 2023). This ambiguity in the empirical evidence makes it important to test ESG orientation as part of the model specification.

The exogenous variables in the model—market index returns, interest rates, and GDP growth—capture broader economic and financial conditions that influence private equity outcomes. Global public equity performance is represented by MSCI ACWI Index returns, sourced from Bloomberg, which serve as a proxy for prevailing equity market trends. These trends can affect portfolio company valuations, exit opportunities, and investor sentiment toward alternative assets. Interest rates are measured using the U.S. 10-Year Treasury yield from the Federal Reserve Economic Data (FRED, Series DGS10). Changes in interest rates affect the cost of leverage, which is a critical driver of buyout performance, and influence capital deployment decisions, thereby impacting overall fund profitability. GDP growth rates, drawn from the World Bank Open Data platform (Indicator NY.GDP.MKTP.KD.ZG), are based on U.S. data given that the majority of the private equity funds in the sample are U.S.-based. GDP growth reflects the pace of economic expansion or contraction, with strong growth generally supporting portfolio company revenue, exit valuations, and deal activity, while economic downturns can suppress earnings and delay exits.

4.3 Data Collection and Processing Method

The quantitative dataset for this study is primarily drawn from PitchBook, a widely recognized data platform used by both academic researchers and industry professionals for analyzing private capital markets (WRDS, 2021; Brown et al., 2015). The dataset includes detailed historical performance metrics for private equity funds, such as IRR, DPI, and TVPI. These indicators serve as the core dependent variables in modeling fund-level performance dynamics in this - model. PitchBook offers a range of fund-level data, including information on fund vintage year, size, strategy (e.g., buyout, growth, venture), geographic focus, and management firm characteristics. It also provides portfolio company coverage, cash flow data, dry powder levels, realized and unrealized deal performance, and quartile rankings based on peer fund comparisons. This coverage allows for a big picture of fund behavior across different macroeconomic conditions. In addition to quantitative performance indicators, data on ESG orientation is derived through a systematic qualitative review of individual fund profiles available within PitchBook. This involves manually screening fund descriptions, GP commentary, ESG-related fund labels (e.g., "sustainable," "impact," "responsible investing"), and any disclosed ESG integration strategies. While not all funds explicitly disclose ESG frameworks, this review aims to construct a binary variable reflecting the presence of ESG integration, which is considered in extended model specifications. The dataset is further refined to include only funds with sufficiently complete performance and macro-aligned time series data, ensuring compatibility with the requirements of VAR modeling. Data cleaning involves standardizing fund identifiers, aligning quarterly performance observations, and adjusting for currency where necessary. This structured approach to data collection ensures that the sample is both representative and methodologically reasonable for capturing the short-term dynamics between macroeconomic variables and private equity fund performance.

The dataset spans vintage years 2000 to 2018, with fund valuations tracked from 2000 through 2024, thereby covering at least two full private equity fund life cycles. In the private equity context, the vintage year refers to the year in which a fund officially begins making investments—effectively marking the start of its investment period and economic exposure. This temporal definition allows performance to be analyzed relative to the macroeconomic conditions prevailing during a fund's deployment and holding phases (Preqin, 2023). By including funds from multiple vintages, the dataset captures performance across different economic environments, including the early 2000s recession, the global financial crisis, and the post-COVID recovery. The data sample includes a range of fund strategies, specifically Buyout Funds, Growth Equity Funds, Opportunistic Funds, and Diversified Private Equity Funds, offering a representative view of the broader private equity market. To contextualize private equity performance within the broader macroeconomic environment, the analysis incorporates exogenous economic variables including quarterly GDP growth, short-term interest rates (e.g., 3-month or policy rates), and global equity market returns, proxied by MSCI World or MSCI

ACWI indices. These macroeconomic indicators are sourced from Bloomberg and official government databases (e.g., the U.S. Federal Reserve, OECD, and World Bank), ensuring consistency, reliability, and global comparability.

Besides, investment memos and fund performance reports are also referenced during the research process as supplementary qualitative sources of insight. These internal investment memos, typically prepared by institutional investors or consultants, outline the rationale behind private equity allocation decisions, including how performance metrics, macroeconomic conditions, and ESG factors are weighed in practice (Kaplan & Stromberg, 2004). While the focus of this thesis remains firmly quantitative, and investment memos are not incorporated into the dataset nor included in the VARX model, they are consulted to provide interpretive support for the empirical findings. By understanding how limited partners actually use indicators such as IRR, DPI, and TVPI in decision-making, investment memos help to triangulate results—that is, to compare and validate econometric evidence against professional practice. In this way, they strengthen the study's external validity without altering its quantitative orientation. The fund performance reports, typically issued on a quarterly or annual basis by general partners or consultants, provide aggregated updates on fund activities, realized and unrealized performance, and commentary on prevailing market conditions (Brown, Gredil, & Kaplan, 2019). While these documents are not included in the statistical dataset nor modeled within the VARX framework, they are used to enrich the interpretation of results by illustrating how performance indicators such as IRR, DPI, and TVPI are calculated, reported, communicated, and contextualized to investors. Similar to investment memos, performance reports contribute to triangulation, drawing on industry-standard reporting practices ensures that quantitative findings are interpreted in light of how fund performance is actually communicated and understood by practitioners. Their role is therefore interpretive rather than analytical, serving to align the quantitative analysis with the practical realities of performance evaluation and reporting in private equity industry. See Table 4.3.1 for a summary of all data collections.

Finally, the empirical analysis will be conducted using the R programming language within the Visual Studio Code environment, leveraging time-series packages such as vars, t-series to implement both the VAR and VARX models. Additional statistical processing, visualization, and diagnostics will also be performed in R to support tests, results and graphs. The detailed R scripts are provided in Appendix 1.

Table 4.3.1 Summary Table of Data Sources

Data source	Brief description	Period	Role in the project
PitchBook Database	Provides both quantitative data on PE metrics (IRR, DPI, TVPI) and qualitative information on ESG practices through fund profiles and offering documents.	Vintage Year 2000–2018 (quantitative); varied for ESG review (binary), depends on availability	Primary source for private equity fund performance and ESG-related insights. Used to construct both the VAR model and ESG classification variables.
World Bank Open Data	Provides annual U.S. GDP growth rates (%), sourced from the World Bank's publicly available dataset (Indicator code: NY.GDP.MKTP.KD.ZG)	2000-2024	Serves as a macroeconomic exogenous variable to capture the influence of economic expansion or contraction on PE performance.
Federal Reserve Economic Data (FRED) database	Provides interest rate data for U.S. Treasury Securities at 10-Year Constant Maturity.	2000-2024	Used as an exogenous variable – Interest rate in the VAR model to reflect long-term financing conditions and macroeconomic trends affecting PE performance.
Bloomberg Terminal	Provides historical price levels and total returns for the MSCI ACWI index as a proxy for global public equity performance.	2000-2024	Used as an exogenous variable to capture the influence of global public equity market trends on PE valuations and returns.
Investment Memos	Internal documents prepared by investors that record the rationale behind private equity investment decisions, including fundamental analysis, due diligence findings, and risk-return considerations.	Varied, depends on availability	Used qualitatively to contextualize and interpret quantitative findings by showing how LPs apply performance metrics in practice.
Fund Performance Reports	Reports summarizing historical and current performance of private equity funds.	Varied, depends on availability	Consulted to support interpretation and triangulation of results by illustrating how performance is reported and communicated in the industry.

4.4 Final Sample of Data

The unit of analysis in this study is annual observations of private equity fund at a specific valuation year, matched with corresponding macroeconomic and market data. The final dataset integrates quantitative fund-level metrics (IRR, DPI, TVPI) from the PitchBook database, macroeconomic indicators (U.S. GDP growth rates as GDP, interest rates as INT) from the World Bank and FRED, and public equity market performance (MSCI ACWI as MKT) from Bloomberg. Data preparation involved a multi-step cleaning and harmonization process. Observations with missing or clearly erroneous values, such as negative DPI or TVPI and IRRs beyond plausible ranges, were excluded to avoid distorting model estimation. Duplicates across overlapping sources were removed, and variable definitions were standardized to ensure comparability across years and datasets. The final cleaned dataset contains 19,764 fund-year observations across seven variables (IRR, DPI, TVPI, MKT, INT, GDP, ESG), spanning the period from 2000 to 2024. All variables are measured on an annual basis, allowing for consistent temporal matching between fund-level and macroeconomic data. The decision to use annual frequency reflects both data availability—particularly for private equity valuations, which are updated infrequently—and the objective of capturing macroeconomic effects over a relevant investment horizon for illiquid assets. This dataset structure ensures that each observation represents a coherent snapshot of a fund's performance metrics alongside the macro-financial conditions prevailing in the same year, thereby facilitating robust time-series and panel econometric analysis. To provide an overview of the dataset, Table 4.4.1 reports descriptive statistics of the main variables of interest, including averages, standard deviations, and observed ranges.

Table 4.4.1 Descriptive Statistics of Main Variables

	Mean	**Std. Dev.**	**Min**	**Max**
IRR	12.60%	16.55%	-59.50%	270.00%
DPI	0.92	0.8	0	9.61
TVPI	1.59	0.74	0.01	20
MKT	64.17%	64.19%	-45.55%	295.94%
INT	3.62%	1.25%	0.89%	6.03%
GDP	3.19%	1.45%	-2.93%	4.53%
ESG	19.10%	39.33%	0	1

4.5 Model Introduction

4.5.1 The Model

A Vector Autoregression with Exogenous Variables (VARX) method was selected. This model mathematically represents the relationships between the endogenous variables (IRR, DPI, TVPI, and ESG_dummy) and the exogenous variables (market index returns, interest rates, GDP growth).

Let:

Y_t: $vector\ of\ 4\ endogenous\ variables\ = (IRR_t, DPI_t, TVPI_t, ESG_{dummy_t})'$

X_t: $vector\ of\ 3\ exogenous\ variables\ = (Market\ Index_t, Interest\ Rate_t, GDP\ Growth_t)'$
$= (MKT_t, INT_t, GDP_t)'$

Here the model is established in Equation 4.1as:

$$Y_t = B_0 + \sum_{i=1}^{p} B_i Y_{t-i} + \sum_{j=0}^{q} C_j X_{t-j} + \varepsilon_t, \qquad \text{.............................. } 4.1$$

Component	Description	Dimensions
B_0	Intercepts	4 × 1
B_i	Endogenous lag coefficients (for each lag i)	4 × 4
C_j	Exogenous coefficients (for each exogenous lag) that measure the impact of exogenous macro variables on the endogenous private equity performance metrics. C_0: Coefficient Matrix for Contemporaneous Exogenous Variables. C_1: Coefficient Matrix for Lagged Exogenous Variables.	4 × 3
Y_t	Endogenous variables	4 × 1
X_t	Exogenous variables	3 × 1
ε_t	Error terms	4 × 1

For the C matrix, each column corresponds to: Col 1 = Market Index; Col 2 = Interest Rate; Col 3 = GDP Growth. Each row corresponds to an endogenous variable equation: IRR, DPI, TVPI, ESG_dummy. Here, *p* and *q* represent lag orders—*p* is the number of lags of endogenous variables, and *q* is the number of lags of exogenous variables. Both will be determined using the

Akaike Information Criterion (AIC) and Schwarz Criterion (SC). Section 4.5 will explain the lag order selection process in detail.

The expanded VAR matrix model can be presented as (assume p = 2, q = 1):

$$\begin{bmatrix} IRR_t \\ DPI_t \\ TVPI_t \\ ESG_{dummy_t} \end{bmatrix} = B_0 + B_1 \begin{bmatrix} IRR_{t-1} \\ DPI_{t-1} \\ TVPI_{t-1} \\ ESG_{dummy_{t-1}} \end{bmatrix} + B_1 \begin{bmatrix} IRR_{t-2} \\ DPI_{t-2} \\ TVPI_{t-2} \\ ESG_{dummy_{t-2}} \end{bmatrix} + C_0 \begin{bmatrix} MKT_t \\ INT_t \\ GDP_t \end{bmatrix} + C_1 \begin{bmatrix} MKT_{t-1} \\ INT_{t-1} \\ GDP_{t-1} \end{bmatrix} + \begin{bmatrix} e_{IRR,t} \\ e_{DPI,t} \\ e_{TVPI,t} \\ e_{ESG,t} \end{bmatrix}$$

Where $B_1 = \begin{bmatrix} B_{11} & B_{12} & B_{13} & B_{14} \\ B_{21} & B_{22} & B_{23} & B_{24} \\ B_{31} & B_{32} & B_{33} & B_{34} \\ B_{41} & B_{42} & B_{43} & B_{44} \end{bmatrix}$, $B_2 = \begin{bmatrix} B_{21} & B_{22} & B_{23} & B_{24} \\ B_{25} & B_{26} & B_{27} & B_{28} \\ B_{29} & B_{210} & B_{211} & B_{212} \\ B_{213} & B_{214} & B_{215} & B_{216} \end{bmatrix}$, $C_0 = \begin{bmatrix} C_{11} & C_{12} & C_{13} \\ C_{21} & C_{22} & C_{23} \\ C_{31} & C_{32} & C_{33} \\ C_{41} & C_{42} & C_{43} \end{bmatrix}$, $C_1 = \begin{bmatrix} C_{14} & C_{15} & C_{16} \\ C_{24} & C_{25} & C_{26} \\ C_{34} & C_{35} & C_{36} \\ C_{44} & C_{45} & C_{46} \end{bmatrix}$

Data will be analyzed using R. The first step includes data preparation and normality test. Secondly, testing for stationarity. Time series data will be tested for stationarity using tests such as the Augmented Dickey-Fuller (ADF) test. Non-stationary data will be transformed (e.g., differencing or logarithmic transformations) to meet the assumptions of the VARX model. Next, it would be lag selection. The optimal lag length for the VARX model will be determined using criteria such as the Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC). Further steps would be model estimation, which will estimate the regression coefficients in the standard VARX model. It examines the dynamic relationships between endogenous variables (e.g., IRR, DPI, TVPI, and ESG_dummy) and their interactions with exogenous variables (e.g., macroeconomic factors). Key metrics such as impulse response functions (IRFs) and variance decompositions will be used to interpret the relationships between variables. The final step of the quantitative data analysis is data validation. The tests for autocorrelation (e.g., Durbin-Watson test), heteroskedasticity, and stability will be conducted. Results will be compared against statistics theoretical expectations and benchmarks. The above will be detailed in Section 4.6 and Section 5.

4.6 Empirical Research Process

4.6.1 Data Examination and Pre-tests

Firstly, at the preparation stage, the dataset was organized in a excel CSV. file, with vintage years serving as the time index and including endogenous variables (IRR, DPI, TVPI, ESG_dummy) and exogenous variables (GDP growth, interest rates, and MSCI ACWI index returns).

Jarque-Bera test is used as a normality test, which is based on skewness and kurtosis of a dataset.

Hypothesis	**Meaning**
H_0 (Null Hypothesis)	The data follows a normal distribution (Skewness = 0, Kurtosis = 3)
H_1 (Alternative Hypothesis)	The data does not follow a normal distribution

Figure 4.5.1.1 Normality Test Result Table

Variable	Mean	SD	Skew	Kurt	JB.Stat.X-squared	JB.P
IRR	0.126	0.1655	2.5179	22.9713	455429.1379	0.0000
DPI	0.9249	0.8044	1.3687	4.0585	19734.8087	0.0000
TVPI	1.5945	0.74	4.557	65.067	3554871.6605	0.0000
ESG	0.1908	0.3929	1.5742	0.4782	8351.3159	0.0000
MKT	0.6417	0.6419	0.8115	0.2055	2203.9281	0.0000
INT	0.0362	0.0125	-0.0149	-0.9278	709.6319	0.0000
GDP	0.0319	0.0145	-2.1131	5.7173	41626.5441	0.0000

The above JB test statistic increases as skewness and kurtosis deviate from these ideal values. A low p-value (typically < 0.05) leads to the rejection of the null hypothesis, meaning that the data significantly deviates from normality. In this analysis, all variables exhibit p-values near zero, rejecting the H_0 assumption of normality. This result reflects the presence of heavy tails, skewed distributions, and outlier behavior, characteristics that are often observed in private equity fund performance and macroeconomic indicators.

4.6.2 Stationary Test

Stationarity of the variables was assessed using three complementary tests: the Augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) test, and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Hill et al., 2018). Each test is based on a different null hypothesis. The ADF and PP tests both have the null hypothesis (H_0) that the series contains a unit root (i.e., is non-stationary), whereas the KPSS test has the null hypothesis (H_0) that the series is stationary. Based on the results (see Figure 4.6.2), IRR is identified as non-stationary at the level data. Specifically, the ADF p-value for IRR is 0.99, which indicates a failure to reject the null hypothesis of a unit root, meaning the series is non-stationary. The KPSS test further supports this conclusion with a large test statistic (91.68) and a significant p-value (0.01), leading to the rejection of the null hypothesis of stationarity. In contrast, DPI, TVPI, ESG, MKT, INT, and GDP all exhibit low p-values (less than 0.05) under both the ADF and PP tests, which leads to the rejection of the unit root hypothesis and indicates that these variables are stationary. While the KPSS test also produces 0.01 p-values for these variables, the unit root tests generally take the majority results in practice as both ADF and PP tests align.

Although IRR_t variable indicates unit roots based on ADF tests, the process proceeds with a VARX model in levels. This is a common and well-accepted approach in large samples when the primary objective is to forecast or understand dynamic interactions, rather than to estimate structural causality, and this simplified approach avoids over-differencing and structural degradation. As emphasized by Sims (1980), differencing may lead to loss of information and distort long-run dynamics.

Figure 4.6.2 Stationarity Test Result Table

Variable	ADF.stat	ADF.p	PP.stat	PP.p	KPSS.stat	KPSS.p
IRR	5.9542	0.99	-388.0353	0.01	91.6809	0.01
DPI	-22.3265	0.01	-19,785.7742	0.01	75.1189	0.01
TVPI	-15.5434	0.01	-24,270.4083	0.01	96.2048	0.01
ESG	-25.2854	0.01	-15,534.0249	0.01	30.5452	0.01
MKT	-20.6749	0.01	-18,574.0563	0.01	8.5301	0.01
INT	-26.2721	0.01	-16,283.0673	0.01	20.0342	0.01
GDP	-25.5803	0.01	-17,709.4659	0.01	17.7305	0.01

4.6.3 Preliminary Analysis: Correlation among Variables

Correlation analysis is conducted to provide an initial understanding of the relationships between the variables before proceeding to more formal regression modeling. While correlation does not imply causation and does not account for dynamic interactions over time, it helps to reveal the potential linkages between private equity fund performance and external market factors. The results reveal several key patterns. As shown in Figure 4.6.3, Private equity fund performance metrics—IRR, DPI, and TVPI—are moderately to strongly correlated with each other, with the strongest observed between DPI and TVPI (0.7221), conforming the shared reliance on cash flow realizations and valuation updates. IRR shows a modest positive correlation with DPI (0.3626) and TVPI (0.5430), but negligible correlation with public market returns (MKT) at 0.0227, suggesting that private equity returns are not immediately sensitive to short-term public equity markets volatility. IRR also displays weak negative correlations with macroeconomic indicators such as interest rates (INT, -0.1724) and GDP growth (GDP, -0.1405). Overall, the correlation matrix supports the inclusion of market and macroeconomic variables in the VAR framework while confirming that private equity fund returns exhibit unique dynamics that are only partially connected to broader market trends.

Figure 4.6.3 Correlation Table

Variable	IRR	DPI	TVPI	ESG	MKT	INT	GDP
IRR	1.0000						
DPI	0.3626	1.0000					
TVPI	0.5430	0.7221	1.0000				
ESG	0.2114	-0.2351	0.0335	1.0000			
MKT	0.0227	0.4535	0.2128	-0.1918	1.0000		
INT	-0.1724	0.2351	-0.0392	-0.5747	-0.1722	1.0000	
GDP	-0.1405	0.0611	-0.0180	-0.2036	-0.1572	0.4624	1.0000

5. Regression Analysis

5.1 Sample Regression – From VARX to VAR

The initial objective of the empirical analysis is to evaluate how private-equity performance indicators move together over time and how they respond to shifts in macroeconomic conditions. To that end, a Vector Autoregressive model with exogenous variables (VARX) was first considered. Although VARX is not commonly used in the field of international business, it is a standard tool in finance and macro-finance whenever the goal is to study dynamic co-movement and shock transmission across variables over multiple horizons (Kilian, 2006). Existing research in macroeconomics treats VAR-based impulse responses as a standard way to trace the effects of monetary and real shocks through financial and real variables over multiple horizons, with careful discussion of exogeneity and identification of shocks. Within finance, VAR/VARX frameworks quantify how asset prices and returns respond to policy and macroeconomic shocks and trace shock transmission dynamics, with uncertainty summarized by bootstrap confidence bands. Related business fields have also used VARX where a small system of outcomes is driven by both internal dynamics and outside forces; for example, Horváth, et al. (2005) analyze competitive reaction and feedback using a VARX with fixed effects in pooled market data, illustrating the model's suitability for business questions with dynamic feedback and exogenous drivers.

The performance measures (e.g., IRR, DPI, TVPI) evolve together and influence one another. A VAR/VARX treats them as a system of endogenous variables, allowing feedback across horizons; a single-equation panel regression fixes one outcome as dependent and treats others as controls, constraining feedback by design (Lütkepohl, 2005; Enders, 2015). Market and macro variables (MKT, INT, GDP) enter as shocks whose effects unfold over time. VARX is built to recover impulse responses and forecast-error variance decompositions; panel regression models typically deliver average partial effects at one horizon without the full propagation path (Kilian & Lütkepohl, 2017). Besides, the strong serial dependence typical of fund outcomes is handled directly by the VAR's lag structure and evaluated with system-level diagnostics (stability via companion-matrix roots, residual serial-correlation tests, and Granger causality), while panel regressions require instruments and added assumptions to mitigate bias from lagged outcomes.

The following null hypothesis (H_0) was specified to guide the model setup:

H_0: The dynamics of the endogenous variables (IRR, DPI, TVPI, ESG_dummy) can be explained by their own lags and the lags of a set of exogenous macroeconomic variables (Market Index Return, Interest Rate, GDP Growth). This assumes temporal dependence in the system, and that the selected macroeconomic variables influence the private equity indicators without being influenced by them (i.e., true exogeneity).

Although VARX is appealing in theory, attempts to estimate VARX models across a grid of endogenous and exogenous lag orders did not yield an admissible specification. First, the Feasibility heatmap shows very large positive degrees-of-freedom margins in every (p,m) cell (≈ 19,745 to 19,759 per equation); see Figure 5.1.1 Feasibility heatmap), so the failures are not due to limited sample size. The Companion-roots plot confirms the core system is dynamically stable as all roots strictly inside the unit circle, see Figure 5.1.2 Stability Check: Roots of Companion Matrix, and stability is determined by the endogenous lag polynomial rather than by exogenous regressors, so VAR model is stable. However, once lagged macro variables are added, the design matrix becomes ill-conditioned: condition numbers rise from ≈15 at (p=1, m=0) to the high hundreds or thousands for most other cells (see Figure 5.1.3 Conditioning heatmap), large κ (e.g., > 30–50) reflecting near-duplication/collinearity among lagged regressors from stacked endogenous and exogenous lags, which can cause estimation failure. Consistent with this, every VARX attempt terminates before information criteria can be computed: the AIC surface consists entirely of "Fail" tiles, and the attempts table reports Fit_OK = FALSE with the same input-length error across all (p,m) combinations, see Figure 5.1.4 Information Criteria Surface and VARX Model Attempt Summary. Taken together, the results show that the VARX specification is not estimable in a reliable way for this dataset. Accordingly, a stable VAR without exogenous lags is retained, and the incremental value of the macro block is evaluated via a system-wide joint Wald test. Specifically, the joint null hypothesis that all coefficients on the lagged macro variables {MKT, INT, GDP} are zero in every equation (IRR, DPI, TVPI), conditional on the endogenous dynamics with p=5 lags, is tested. The test rejects the null, as $\chi2(9)=400.91$, $p<0.001$, see Figure 5.1.5, indicating that one or more lagged macro variables provide incremental predictive content beyond the variables' own lags. The system-wide Wald test shows that lagged macro variables are jointly relevant, but this does not justify adopting a fully parameterized VARX: in this dataset, combining macro and endogenous lags produces severe ill-conditioning and unstable estimation.

Figure 5.1.1 Feasibility Heatmap

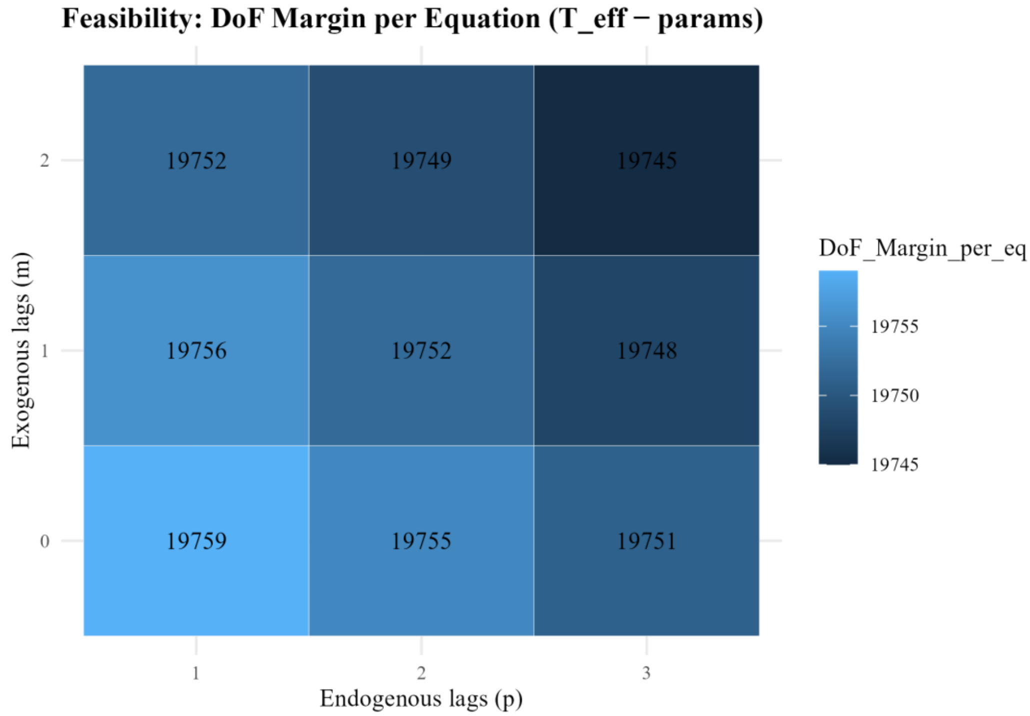


Figure 5.1.2 Stability Check: Roots of Companion Matrix

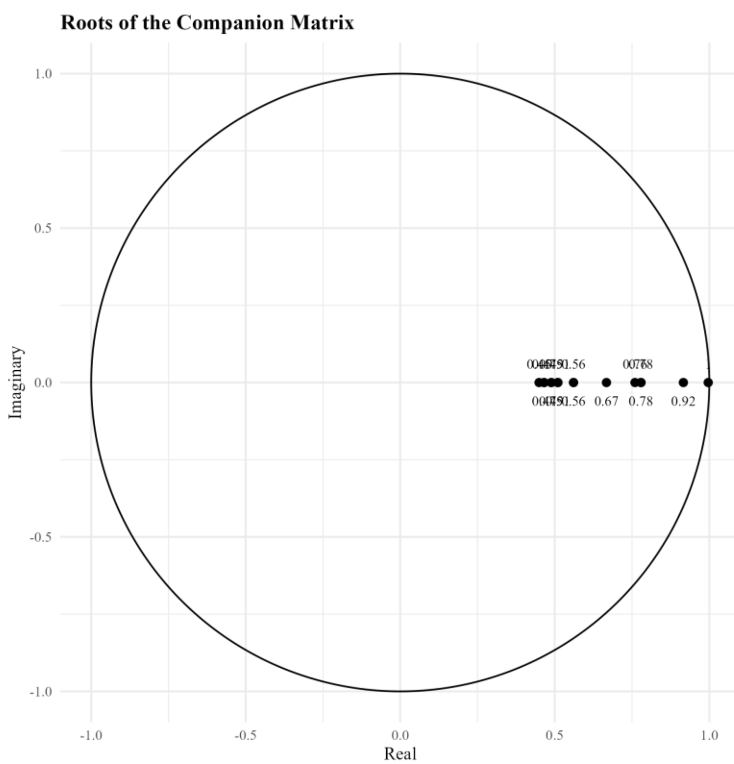


Figure 5.1.3 Conditioning Heatmap (Collinearity Check)

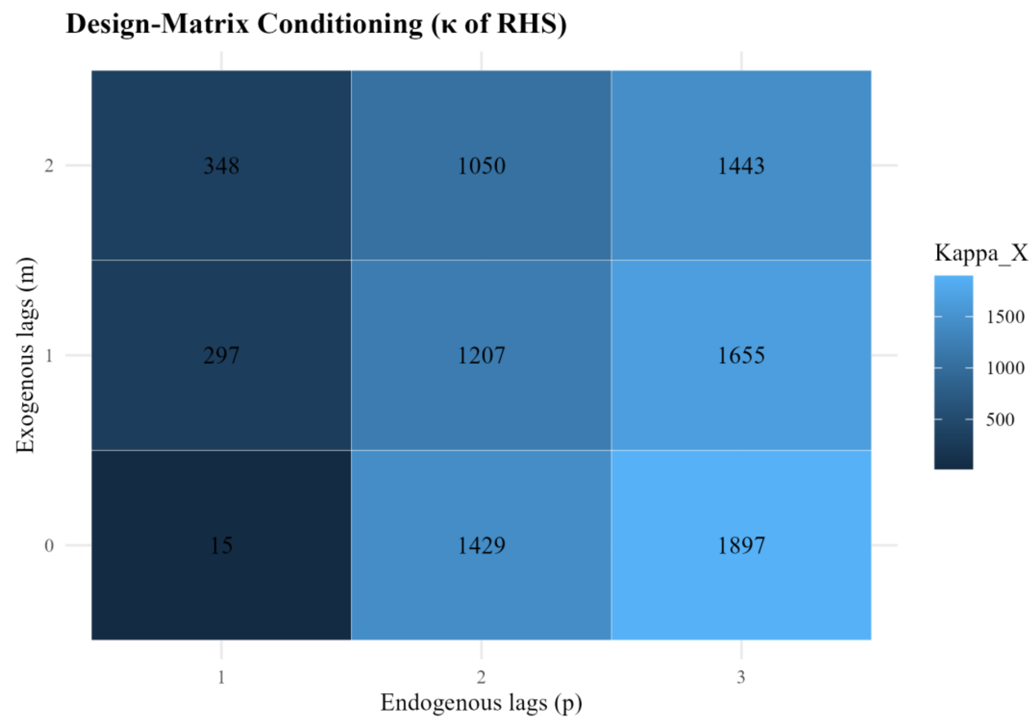


Figure 5.1.4 (i) Information Criteria Surface

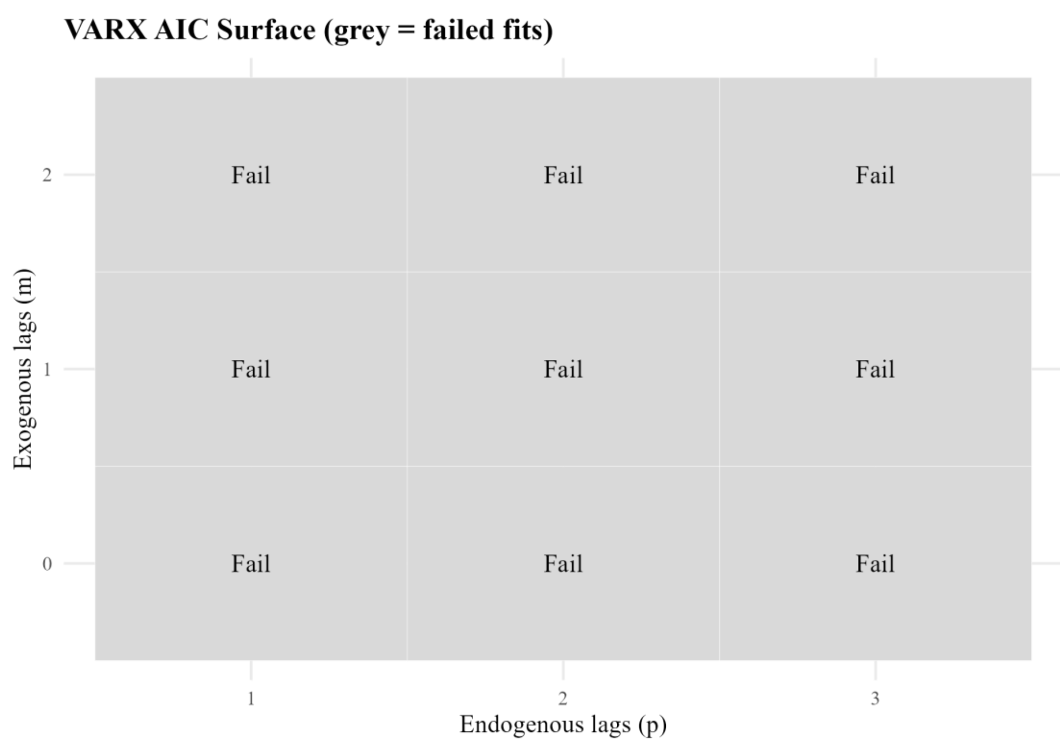


Figure 5.1.4 (ii) VARX Model Attempt Summary

p	m	T_eff	Params_per_eq	DoF_Margin_per_eq	Kappa_X	Fit_OK
1	0	19,763	4	19,759	15.12	FALSE
1	1	19,763	7	19,756	296.56	FALSE
1	2	19,762	10	19,752	348.02	FALSE
2	0	19,762	7	19,755	1,429.48	FALSE
2	1	19,762	10	19,752	1,207.31	FALSE
2	2	19,762	13	19,749	1,050.09	FALSE
3	0	19,761	10	19,751	1,897.11	FALSE
3	1	19,761	13	19,748	1,655.15	FALSE
3	2	19,761	16	19,745	1,443.36	FALSE

Figure 5.1.5 System-wide Joint Wald Test

Test	Lags_endogenous_p	Lags_exogenous_m	Num_Params	Wald_ChiSq	DF	P_Value
H0: Lagged MKT, INT, GDP jointly zero across IRR, DPI, TVPI	5	1	9	400.9073	9	0.0000

In light of these results, moving to simpler VAR specifications is warranted. Here, “simpler models” means specifications with fewer parameters (for example, a pure VAR without exogenous lags or a lower lag order) that achieved better AIC/BIC/Hannan–Quinn values because the penalty for added parameters outweighed the small gains in fit. These outcomes match the canonical failure modes highlighted in the VAR/VARX and model-selection literature (Lütkepohl, 2006; Enders, 2015; Kilian & Lütkepohl, 2017). Because potential redundancy within the endogenous block can amplify such problems—especially once multiple lags are included—the next step was to test for overlap among the private-equity variables themselves.

Therefore, multicollinearity diagnostics were performed to assess whether the endogenous private equity variables (IRR, DPI, TVPI, ESG_dummy) contributed redundant information. A Variance Inflation Factor (VIF) test was used to evaluate linear relationships among these variables. Although typically applied in regression settings, VIF is a useful indicator in multivariate time series for identifying overlapping signals among predictors (Gujarati et al., 2009). The results showed that both DPI and TVPI had VIF values of 2.0898, indicating moderate collinearity (see Table 5.1.8). These values suggest that DPI and TVPI behave in similar ways, since both are cumulative measures that are closely related to IRR over time. Including both variables has caused problems for the model and made the results impractical to interpret.

As a result, I simplified the model and proceeded the analysis with a standard VAR model using only IRR (in first differences) as the private equity return variable, while treating the macroeconomic variables—MKT, INT, and GDP—as jointly endogenous. To preserve the thesis's ESG focus while avoiding the instability encountered with fully parameterized VARX specifications, the ESG dimension is retained as an ESG-conditioned variant estimated in which the annual ESG intensity—the share of ESG-classified observations—enters exogenously with one lag. The simplified VAR (1) model can be presented as (assume lag length =1):

$$\begin{bmatrix} IRR_{diff,t} \\ MKT_t \\ INT_t \\ GDP_t \end{bmatrix} = B_0 + B_1 \begin{bmatrix} IRR_{diff,t-1} \\ MKT_{t-1} \\ INT_{t-1} \\ GDP_{t-1} \end{bmatrix} + \text{C*}ESG\_Share_{t-1} + \begin{bmatrix} e_{IRR,t} \\ e_{MKT,t} \\ e_{INT,t} \\ e_{GDP,t} \end{bmatrix} \text{......................with ESG}$$

Where B_0 $is\ a$ 4x1 vector of intercepts, $B_1 = \begin{bmatrix} B_{11} & B_{12} & B_{13} & B_{14} \\ B_{21} & B_{22} & B_{23} & B_{24} \\ B_{31} & B_{32} & B_{33} & B_{34} \\ B_{41} & B_{42} & B_{43} & B_{44} \end{bmatrix}$, C= $\begin{bmatrix} C_{IRR} \\ C_{MKT} \\ C_{INT} \\ C_{GDP} \end{bmatrix}$, e_t is a 4x1 vector

of noise error terms. ESG_Share_{t-1} is the annual share of ESG-classified observations. Because ESG_Share_{t-1} is treated as exogenous, it affects the conditional mean but does not enter the stability polynomial; stability is governed only by B_1. The stability test (companion-matrix roots) reported in Figure 5.1.6 that roots lie strictly inside the unit circle (moduli $\approx$ 0.00, 0.02, 0.23, 0.90), confirming that the VAR(1) is dynamically stable. A system-wide joint Wald test is then conducted and revealed that the four ESG loadings are jointly zero across all equations yields $X^2(4) = 1.66$, with p=0.8 (see Figure 5.1.7). This result fails to reject H_0 indicating that at the annual frequency and over this sample, adding the ESG intensity as a conditioning variable does not improve the model's fit beyond what is captured by the system's own dynamics. Importantly, the joint test is sensitive to any non-zero effect in any equation; failure to reject at the system level therefore constitutes a finding that the ESG block as implemented here has no incremental predictive content. The limitations section in Section 6.2 therefore notes that identifying ESG mechanisms likely requires richer micro data. And this finding is also compared to existing literature in Section 5.6. Therefore, the VAR (1) without ESG is further examined in the following:

$$\begin{bmatrix} IRR_{diff,t} \\ MKT_t \\ INT_t \\ GDP_t \end{bmatrix} = B_0 + B_1 \begin{bmatrix} IRR_{diff,t-1} \\ MKT_{t-1} \\ INT_{t-1} \\ GDP_{t-1} \end{bmatrix} + \begin{bmatrix} e_{IRR,t} \\ e_{MKT,t} \\ e_{INT,t} \\ e_{GDP,t} \end{bmatrix} \text{...without ESG}$$

Before estimating the VAR model, stationarity testing was again performed using Augmented Dickey-Fuller (ADF) tests. The results showed that IRR was non-stationary at level (see Table 5.1.9) and required first differencing to achieve stationarity (see Table 5.1.10), while MKT, INT, and GDP were stationary in levels. Accordingly, the final VAR model was estimated using IRR_diff, with MKT, INT, and GDP in levels. According to Enders (2015), if the variables are of different orders of integration, a VAR model can still be estimated provided as long as all variables are stationary in their used form—whether in levels or first differences. This revised VAR structure allows for dynamic interaction among private equity returns and macroeconomic indicators and serves as the foundation for all subsequent regression and diagnostic analysis.

Figure 5.1.6 Stability Check: Roots of Companion Matrix

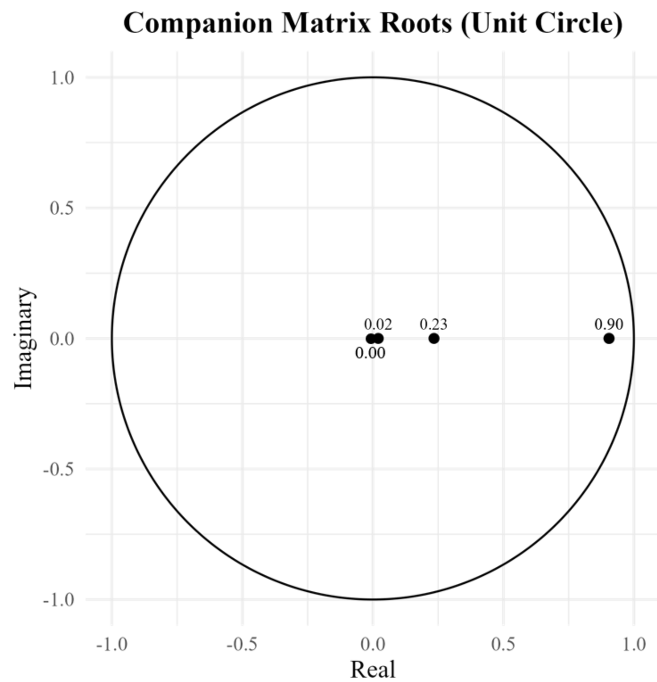


Figure 5.1.7 System-wide joint Wald on ESG_share_{t−1}

Test	Lag_p	DF	Wald_ChiSq	P_Value
H0: ESG_share_{t-1} jointly zero across all equations	1	4	1.6609	0.7978

Table 5.1.8 Multicollinearity Test: Exogenous Variables (VIF)

Variable	**VIF**	**Variable**	**VIF**
DPI	2.0898	**INT**	1.272
TVPI	2.0898	**GDP**	1.272

Table 5.1.9 Stationarity Test Results (Level):

Statistic	**P_Value**	**Variable**
5.9542	0.99	IRR
-20.6749	0.01	MKT
-26.2721	0.01	INT
-25.5803	0.01	GDP

Table 5.1.10 Stationarity Test of IRR after First-Differencing:

Variable	Statistic	P_Value
IRR_diff	-27.6863	0.01

5.2 Lag Analysis and Model Estimation

The lag length was determined using four common information criteria: Akaike Information Criterion (AIC), Hannan–Quinn Criterion (HQ), Schwarz Criterion (SC), and Final Prediction Error (FPE). Per standard best-fit criteria, the optimal lag length is selected by identifying the column with the lowest value for each information criterion, so all four criteria accordantly selected lag order 5 as optimal (see Table 5.2.1), suggesting a VAR (5) model.

After estimating the VAR (5) model, the residuals were tested for serial autocorrelation using the Portmanteau test. The test yielded a Chi-squared statistic of 9,143.92 with 176 degrees of freedom, and a p-value of 0.0000 (see Table 5.2.2)—indicating the presence of residual autocorrelation. While the Portmanteau test identified statistically significant residual autocorrelation in the estimated VAR(5) model—the model VAR (5) is retained for the purposes of this analysis. The decision is based on both practical and methodological reasons. First, the primary objective of the VAR model in this study is not point forecasting, but rather the analysis of dynamic interactions through impulse response functions (IRFs) and forecast error variance decomposition (FEVD), which are further analyzed in Section 5.5. These tools are subject to certain violations of the white noise assumption, particularly when inference is based on bootstrapped confidence intervals, as applied here (Lütkepohl, 2006). Second, the sample size is relatively large, which mitigates small-sample biases and reduces the impact of residual autocorrelation (Stock & Watson, 2015). Finally, increasing the lag length to address serial correlation would increase the overfitting risk and reduce model interpretability—particularly given the limited number of variables retained after differencing and transformation. Therefore, the VAR (5) specification is sufficient to capture the main dynamic relationships while maintaining practicability and analytical clarity.

Table 5.2.1 VAR Lag Selection Results

1	2	3	4	**5**	Criterion
-30.5653	-30.5971	-30.8847	-30.9710	**-30.9763**	AIC(n)
-30.5627	-30.5924	-30.8779	-30.9621	**-30.9653**	HQ(n)
-30.5573	-30.5827	-30.8640	-30.9439	**-30.9427**	SC(n)
0.0000	0.0000	0.0000	0.0000	**0.0000**	FPE(n)

Table 5.2.2 Residual Serial Correlation Test (Portmanteau Test)

Test_Type	Chi_Squared	DF	P_Value
Portmanteau (asymptotic)	9,143.928	176	0

5.3 Equation-by-Equation Summary

Each equation of the VAR model reveals how current values are influenced by lagged endogenous variables. The IRR_diff equation indicates that changes in private equity returns are overwhelmingly driven by their own past values, with evidence of short-run persistence (positive and significant effects of lags 1, 3, and 4) but also mean reversion at longer horizons (negative coefficients at lags 2 and 5) (see Figure 5.3.1). While macroeconomic variables—such as GDP growth, interest rates, and equity market returns—occasionally appear with positive or negative significant coefficients, their explanatory power is small relative to the autoregressive dynamics of IRR. In contrast, the equations for MKT, INT, and GDP display strong self-dependence and persistence, reflecting the stability of macroeconomic time series, with limited evidence that private equity performance feeds back into these variables (see Figure 5.3.2, Figure 5.3.3 and Figure 5.3.4).

For the macroeconomic block, the MKT equation indicates strong autoregressive behavior and significant contributions from both interest rates and GDP growth. The INT and GDP equations also display clear self-dependence, with additional cross-effects: GDP responds to interest rates and, to a lesser extent, market returns, while INT dynamics are influenced by past GDP growth and equity market performance. These interactions confirm that macroeconomic variables are not independent of each other, though they remain largely exogenous with respect to private equity performance.

Figure 5.3.1 Equation for: IRR_diff

IRR_diff ~ + 0.1729 * IRR_diff.l1 + 1e-04 * MKT.l1 + 0.0013 * INT.l1 + 0.0062 * GDP.l1 - 0.0173 * IRR_diff.l2 + 0 * MKT.l2 - 0.0014 * INT.l2 + 0.0024 * GDP.l2 + 0.3832 * IRR_diff.l3 + 0 * MKT.l3 - 9e-04 * INT.l3 - 5e-04 * GDP.l3 + 0.2626 * IRR_diff.l4 + 0 * MKT.l4 - 0.0015 * INT.l4 + 0.0014 * GDP.l4 - 0.0535 * IRR_diff.l5 + 0 * MKT.l5 + 0.0014 * INT.l5 - 6e-04 * GDP.l5 – 0.0003

term	estimate	std.error	statistic	p.value
IRR_diff.l1	0.1729	0.0071	24.3866	0.0000
MKT.l1	0.0001	0.0000	1.9993	0.0456
INT.l1	0.0013	0.0015	0.8329	0.4049
GDP.l1	0.0062	0.0012	5.0747	0.0000
IRR_diff.l2	-0.0173	0.0069	-2.5241	0.0116
MKT.l2	0.0000	0.0000	1.0125	0.3113
INT.l2	-0.0014	0.0016	-0.8543	0.3929
GDP.l2	0.0024	0.0012	1.9336	0.0532
IRR_diff.l3	0.3832	0.0060	63.3665	0.0000
MKT.l3	0.0000	0.0000	-0.8227	0.4107
INT.l3	-0.0009	0.0016	-0.5725	0.5670
GDP.l3	-0.0005	0.0012	-0.4288	0.6681
IRR_diff.l4	0.2626	0.0063	41.4648	0.0000
MKT.l4	0.0000	0.0000	0.8698	0.3844
INT.l4	-0.0015	0.0016	-0.9147	0.3604
GDP.l4	0.0014	0.0012	1.1293	0.2588
IRR_diff.l5	-0.0535	0.0065	-8.2792	0.0000
MKT.l5	0.0000	0.0000	0.4308	0.6666
INT.l5	0.0014	0.0015	0.9234	0.3558
GDP.l5	-0.0006	0.0012	-0.4617	0.6443
const	-0.0003	0.0001	-3.8218	0.0001

Figure 5.3.2 Equation for: MKT

MKT ~ + 1.6215 * IRR_diff.l1 + 0.2038 * MKT.l1 + 3.6872 * INT.l1 - 1.5764 * GDP.l1 + 2.8229 * IRR_diff.l2 + 0.0626 * MKT.l2 + 1.1455 * INT.l2 - 0.2152 * GDP.l2 + 0.9801 * IRR_diff.l3 + 0.0346 * MKT.l3 + 0.5955 * INT.l3 - 0.3307 * GDP.l3 + 0.2189 * IRR_diff.l4 + 0.0183 * MKT.l4 + 0.6685 * INT.l4 - 0.6502 * GDP.l4 - 0.3345 * IRR_diff.l5 + 0.0328 * MKT.l5 + 1.4225 * INT.l5 - 0.6953 * GDP.l5 + 0.255

term	estimate	std.error	statistic	p.value
IRR_diff.l1	1.6215	2.0371	0.7960	0.4261
MKT.l1	0.2038	0.0073	27.9221	0.0000
INT.l1	3.6872	0.4387	8.4048	0.0000
GDP.l1	-1.5764	0.3520	-4.4790	0.0000
IRR_diff.l2	2.8229	1.9719	1.4316	0.1523
MKT.l2	0.0626	0.0074	8.4051	0.0000
INT.l2	1.1455	0.4620	2.4793	0.0132
GDP.l2	-0.2152	0.3573	-0.6021	0.5471
IRR_diff.l3	0.9801	1.7381	0.5639	0.5728
MKT.l3	0.0346	0.0075	4.6442	0.0000
INT.l3	0.5955	0.4624	1.2877	0.1979
GDP.l3	-0.3307	0.3575	-0.9252	0.3549
IRR_diff.l4	0.2189	1.8204	0.1202	0.9043
MKT.l4	0.0183	0.0074	2.4658	0.0137
INT.l4	0.6685	0.4622	1.4464	0.1481
GDP.l4	-0.6502	0.3574	-1.8192	0.0689
IRR_diff.l5	-0.3345	1.8557	-0.1803	0.8570
MKT.l5	0.0328	0.0072	4.5310	0.0000
INT.l5	1.4225	0.4402	3.2315	0.0012
GDP.l5	-0.6953	0.3525	-1.9727	0.0485
const	0.2550	0.0250	10.2048	0.0000

Figure 5.3.3 Equation for: INT

INT ~ - 0.0538 * IRR_diff.l1 - 1e-04 * MKT.l1 + 0.3356 * INT.l1 - 0.0219 * GDP.l1 + 0.0618 * IRR_diff.l2 - 2e-04 * MKT.l2 + 0.0688 * INT.l2 + 0.0036 * GDP.l2 + 0.0596 * IRR_diff.l3 - 1e-04 * MKT.l3 + 0.0548 * INT.l3 + 0.0039 * GDP.l3 + 0.0439 * IRR_diff.l4 - 4e-04 * MKT.l4 + 0.0568 * INT.l4 + 0.0073 * GDP.l4 - 0.0181 * IRR_diff.l5 - 3e-04 * MKT.l5 + 0.0229 * INT.l5 + 0.0112 * GDP.l5 + 0.0173

term	estimate	std.error	statistic	p.value
IRR_diff.l1	-0.0538	0.0374	-1.4394	0.1501
MKT.l1	-0.0001	0.0001	-0.9205	0.3573
INT.l1	0.3356	0.0080	41.7024	0.0000
GDP.l1	-0.0219	0.0065	-3.3971	0.0007
IRR_diff.l2	0.0618	0.0362	1.7084	0.0876
MKT.l2	-0.0002	0.0001	-1.5633	0.1180
INT.l2	0.0688	0.0085	8.1206	0.0000
GDP.l2	0.0036	0.0066	0.5485	0.5833
IRR_diff.l3	0.0596	0.0319	1.8681	0.0618
MKT.l3	-0.0001	0.0001	-0.7445	0.4566
INT.l3	0.0548	0.0085	6.4542	0.0000
GDP.l3	0.0039	0.0066	0.5975	0.5502
IRR_diff.l4	0.0439	0.0334	1.3141	0.1888
MKT.l4	-0.0004	0.0001	-2.6581	0.0079
INT.l4	0.0568	0.0085	6.6985	0.0000
GDP.l4	0.0073	0.0066	1.1149	0.2649
IRR_diff.l5	-0.0181	0.0340	-0.5309	0.5955
MKT.l5	-0.0003	0.0001	-2.0072	0.0447
INT.l5	0.0229	0.0081	2.8370	0.0046
GDP.l5	0.0112	0.0065	1.7320	0.0833
const	0.0173	0.0005	37.6555	0.0000

Figure 5.3.4 Equation for: GDP

GDP ~ + 0.0039 * IRR_diff.l1 - 5e-04 * MKT.l1 + 0.058 * INT.l1 + 0.1568 * GDP.l1 + 0.0881 * IRR_diff.l2 - 1e-04 * MKT.l2 + 0.0248 * INT.l2 + 0.0354 * GDP.l2 + 0.1218 * IRR_diff.l3 - 2e-04 * MKT.l3 + 0.0121 * INT.l3 + 0.0152 * GDP.l3 + 0.0403 * IRR_diff.l4 - 2e-04 * MKT.l4 + 0.0332 * INT.l4 + 0.0127 * GDP.l4 - 0.0541 * IRR_diff.l5 + 0 * MKT.l5 + 0.0173 * INT.l5 - 0.0097 * GDP.l5 + 0.0206

term	estimate	std.error	statistic	p.value
IRR_diff.l1	0.0039	0.0461	0.0850	0.9323
MKT.l1	-0.0005	0.0002	-3.0445	0.0023
INT.l1	0.0580	0.0099	5.8397	0.0000
GDP.l1	0.1568	0.0080	19.6732	0.0000
IRR_diff.l2	0.0881	0.0447	1.9727	0.0485
MKT.l2	-0.0001	0.0002	-0.7465	0.4554
INT.l2	0.0248	0.0105	2.3707	0.0178
GDP.l2	0.0354	0.0081	4.3774	0.0000
IRR_diff.l3	0.1218	0.0394	3.0948	0.0020
MKT.l3	-0.0002	0.0002	-1.1277	0.2595
INT.l3	0.0121	0.0105	1.1511	0.2497
GDP.l3	0.0152	0.0081	1.8786	0.0603
IRR_diff.l4	0.0403	0.0412	0.9783	0.3279
MKT.l4	-0.0002	0.0002	-1.1807	0.2378
INT.l4	0.0332	0.0105	3.1678	0.0015
GDP.l4	0.0127	0.0081	1.5729	0.1158
IRR_diff.l5	-0.0541	0.0420	-1.2866	0.1982
MKT.l5	0.0000	0.0002	-0.0848	0.9324
INT.l5	0.0173	0.0100	1.7320	0.0833
GDP.l5	-0.0097	0.0080	-1.2103	0.2262
const	0.0206	0.0006	36.4434	0.0000

5.4 Model Assessment

The estimated VAR(5) summarizes short-run dynamics between private equity returns and macro indicators. Because IRR_diff is the first difference of IRR, coefficients capture changes rather than levels. The ESG series employed in VAR with ESG is a coarse, annual intensity proxy that aggregates substantial cross-sectional heterogeneity in fund-level ESG quality and timing; with a short annual sample ($T \approx 20$), such aggregation and measurement error weaken estimated effects and widen intervals. VAR (1) Without ESG: In the IRR_diff equation (see Figure 5.3.1), own lags dominate the dynamics of private equity returns. Positive and significant coefficients at IRR_diff.l1 = 0.1729 ($p < 0.001$), IRR_diff.l3 = 0.3832 ($p < 0.001$), and IRR_diff.l4 = 0.2626 ($p < 0.001$) provide clear evidence of short-run persistence, meaning that increases or decreases in returns tend to reinforce themselves in the near term. By contrast, IRR_diff.l2 = –0.0173 ($p = 0.0116$) and IRR_diff.l5 = –0.0535 ($p < 0.001$) are negative and significant, pointing to longer-term mean reversion. This combination of momentum and delayed correction is consistent with cyclical dynamics in private equity valuations. By comparison, the influence of macroeconomic variables is limited. GDP.l1 = 0.0062 ($p < 0.001$) is statistically meaningful but small in magnitude, while MKT.l1 = 0.0001 ($p = 0.0456$) is statistically detectable yet economically negligible. Interest rates do not enter significantly, with INT.l1 = 0.0013 ($p = 0.4049$). The intercept is near zero (const = –0.0003, $p = 0.0001$), implying negligible drift in the series. Taken together, the IRR_diff equation shows that fluctuations in private equity returns are shaped primarily by internal return dynamics—short-run momentum followed by longer-run mean reversion—while macroeconomic shocks play a secondary role.

The MKT equation (see Figure 5.3.2) displays strong autoregressive behavior, confirming that equity market returns are heavily influenced by their own past values. All five lags are significant (MKT.l1 = 0.2038, $p < 0.001$; MKT.l2 = 0.0626, $p < 0.001$; MKT.l3 = 0.0346, $p < 0.001$; MKT.l4 = 0.0183, $p = 0.0137$; MKT.l5 = 0.0328, $p < 0.001$), underscoring the persistence of equity market dynamics. In addition, lagged interest rates contribute systematically, with INT.l1 = 3.6872 ($p < 0.001$), INT.l2 = 1.1455 ($p = 0.0132$), and INT.l5 = 1.4225 ($p = 0.0012$) all significant, while GDP growth enters negatively at GDP.l1 = –1.5764 ($p < 0.001$) and GDP.l5 = –0.6953 ($p = 0.0485$). These results suggest that equity markets are not only driven by their own history but also respond to macroeconomic conditions—interpreting strong GDP growth as coinciding with tighter monetary policy or reduced risk premia, while higher past interest rates reflect changing discount-rate environments. By contrast, private equity performance (IRR_diff) does not appear to feed back into market returns, as coefficients on its lags are insignificant (e.g., IRR_diff.l1 = 1.6215, $p = 0.4261$).

The INT equation (see Figure 5.3.3) is likewise dominated by autoregression, with highly significant own lags including INT.l1 = 0.3356 ($p < 0.001$), INT.l2 = 0.0688 ($p < 0.001$), INT.l3 = 0.0548 ($p < 0.001$), INT.l4 = 0.0568 ($p < 0.001$), and INT.l5 = 0.0229 ($p = 0.0046$). Output growth influences interest rates, with GDP.l1 = –0.0219 ($p = 0.0007$) entering negatively and GDP.l4 = 0.0073 ($p = 0.0833$) weakly positive. Equity market conditions also feed into monetary dynamics at longer horizons, as indicated by MKT.l4 = –0.0004 ($p = 0.0079$) and MKT.l5 = –0.0003 ($p = 0.0447$). These results indicate that while interest rates are primarily self-driven, they also respond to broader macroeconomic and financial variables. By contrast, IRR_diff terms remain insignificant, showing that changes in private equity returns do not drive monetary conditions.

The GDP equation (see Figure 5.3.4) highlights the autoregressive structure typical of output growth. Own lags are highly significant, with GDP.l1 = 0.1568 ($p < 0.001$) and GDP.l2 = 0.0354 ($p < 0.001$), confirming persistence in economic activity. Monetary conditions exert clear influence, with INT.l1 = 0.0580 ($p < 0.001$), INT.l2 = 0.0248 ($p = 0.0178$), and INT.l4 = 0.0332 ($p = 0.0015$) all positive and significant, consistent with the transmission of interest rates to real activity. Market returns also contain predictive information, with MKT.l1 = –0.0005 ($p = 0.0023$) negative and significant, consistent with the idea that financial markets anticipate real economic fluctuations. Interestingly, some IRR_diff terms enter positively but less significantly as P value is higher than 0.001, notably IRR_diff.l2 = 0.0881 ($p = 0.0459$) and IRR_diff.l3 = 0.1218 ($p = 0.0020$). However, their magnitudes are small relative to GDP's own lags, suggesting that these associations are reduced-form correlations rather than evidence of structural causality.

Two cautions guide interpretation. First, large and significant own-lag coefficients in MKT, INT, and GDP confirm the strong serial dependence typical of macro-financial time series, while the autoregressive structure of IRR_diff demonstrates that private equity return changes are largely self-driven, displaying both short-run persistence and long-run mean reversion. Second, although the VAR framework treats all variables as endogenous, the economic plausibility of feedback from IRR_diff to macro variables is weak. For instance, IRR_diff lags are insignificant in the MKT and INT equations, and the small coefficients in the GDP equation are unlikely to reflect structural effects. This supports the reduced-form endogeneity assumption in the VAR but should not be interpreted as structural causality, which is better assessed through IRFs, which are discussed in Section 5.5.

Overall, the economically material movements in IRR_diff are driven by its own lag structure and, to a smaller extent, by GDP growth. Market and interest-rate effects are either negligible or statistically insignificant in the IRR equation. The macro block, by contrast, is highly persistent and exhibits meaningful cross-effects among MKT, INT, and GDP. The direction of influence in the system appears to run predominantly from macroeconomic conditions toward private equity returns, rather than the reverse. Despite residual autocorrelation flagged by the Portmanteau test, the system provides a clear and interpretable summary of near-term dynamics. Inference on timing and direction is therefore best assessed using impulse response functions (IRFs) and forecast error variance decompositions (FEVD), which scale effects across shocks and horizons. Both are examined in detail in the following section.

5.5 FEVD and IRF Analysis

To complement the coefficient-based interpretation of the VAR, two post-estimation tools are employed—impulse response functions (IRFs) and forecast-error variance decompositions (FEVDs)—because they reveal the time path of effects that static coefficients cannot (Lütkepohl, 2006). In a VAR, IRFs trace the expected trajectory of each variable after a one-unit shock at a time hits another variable, period by period; this shows the sign, timing, build-up, and persistence of the effect, and here the bands around the paths are obtained with bootstrap confidence intervals. IRFs are the standard way economists and finance scholars study how monetary, real, or financial shocks spread through systems, and their use and implementation are documented in core references and applications (Enders, 2015; Kilian & Lütkepohl, 2017; Lütkepohl, 2006) as well as in business contexts such as marketing dynamics and panel-VAR studies (Abrigo & Love, 2016; Dekimpe & Hanssens, 1999; Love & Zicchino, 2006). FEVD complements IRFs by partitioning forecast uncertainty: at each horizon it attributes the share of a variable’s forecast-error variance to shocks from each equation, thereby ranking which shocks matter most for variability rather than showing their time profile (Enders, 2015; Lütkepohl, 2006). In this study, IRFs quantify the direction, timing, and persistence of the response of ΔIRR to shocks in MKT, INT, and GDP (and the reverse responses) over 1–10 periods, using orthogonalization via a Cholesky factor (a standard way to 'uncorrelate' the shocks in a VAR so it can shock one variable at a time) under the maintained ordering and 95% bootstrapped bands; FEVD reports, over the same horizons, how much of the variability in ΔIRR is explained by its own innovations versus macro shocks, providing an interpretable measure of economic importance that is comparable across variables and horizons.

IRFs from this model (see Figure 5.5.1) show how private equity return changes (IRR_diff) react over time to a one-standard-deviation shock in macroeconomic indicators—specifically, GDP growth (GDP), interest rates (INT), and market returns (MKT). GDP shock causes an immediate jump in IRR_diff, followed by ups and downs that fade quickly. INT shocks also trigger a short-lived positive response in IRR_diff, back-and-forth movement around zero. MKT shocks show a similarly unstable and low-magnitude pattern. All responses tend to decline toward zero by horizon 5–6. The wide confidence intervals, particularly for MKT and INT, indicate a high degree of uncertainty in the estimated impulse responses. These findings suggest that short-term macroeconomic shocks can trigger an initial directional response in changes to private equity returns, but the effects are modest and statistically weak.

Figure 5.5.1 Impulse Response Functions for IRR_diff

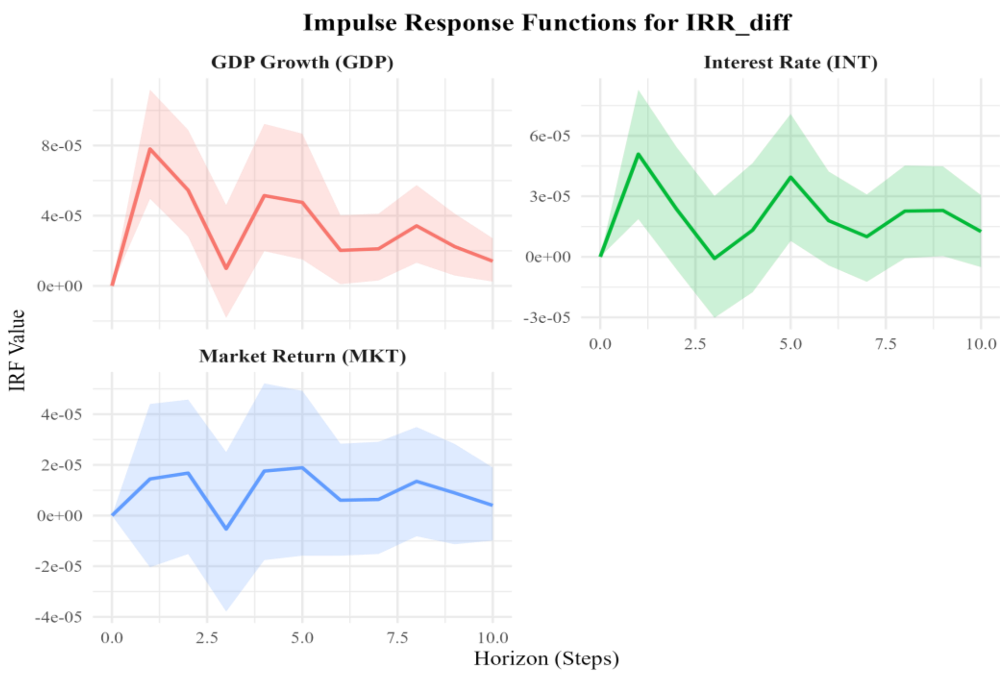
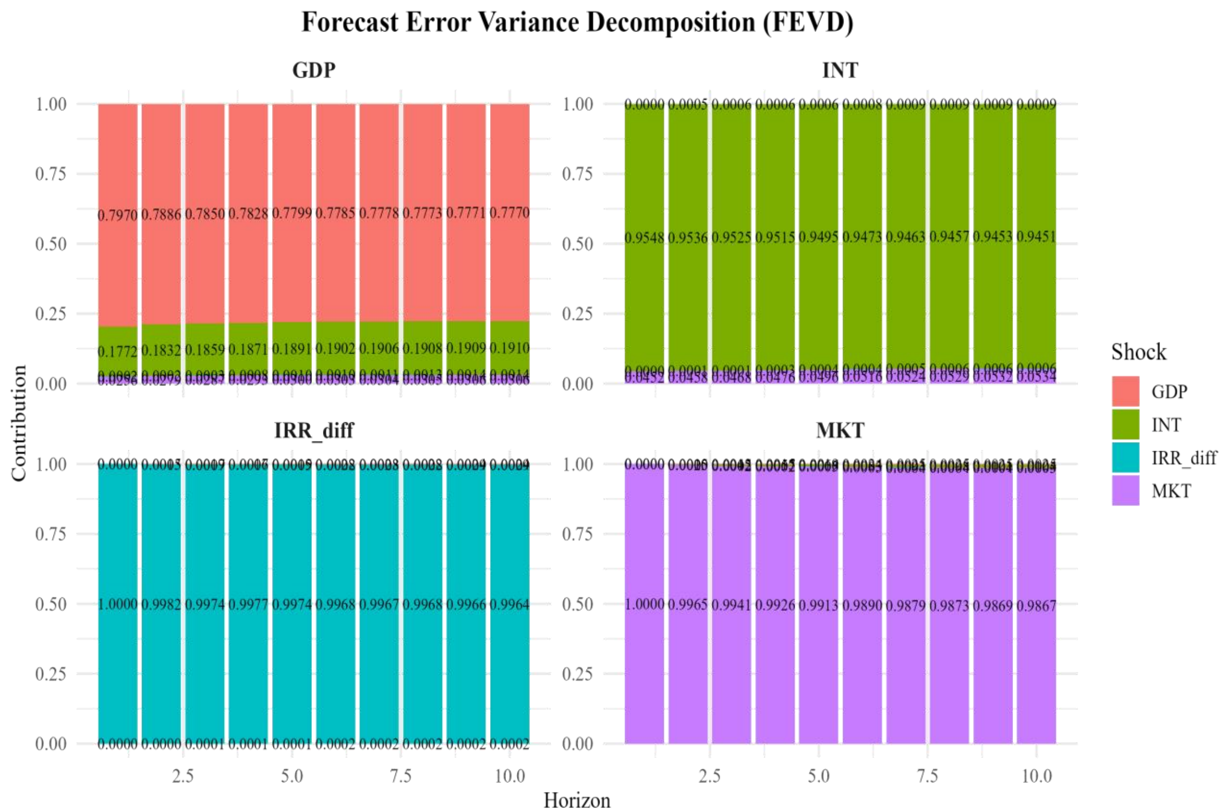


Figure 5.5.2 Forecast Error Variance Decomposition



The FEVD plots (see Figure 5.5.2) support this conclusion from the impulse response analysis: although macroeconomic shocks generate some initial movement in IRR_diff, their overall impact is limited. Over a 10-step horizon, IRR_diff's forecast error variance is almost entirely explained by its own past shocks (over 99.6%), with negligible contribution from macroeconomic variables. This confirms that private equity return changes are largely self-driven in the short term and not meaningfully influenced by exogenous macro conditions within the structure of the VAR model. In contrast, GDP shows some external influence: around 18–19% of its variance is attributed to interest rate shocks, which reflects known macroeconomic linkages between GDP growth and monetary policy. INT and MKT are mostly self-explanatory, with over 94% and nearly 99% of their respective variances accounted for by their own shocks.

Taken together, the IRF and FEVD analyses suggest that private equity return dynamics—as represented by IRR_diff—respond weakly and inconsistently to macroeconomic shocks, and that their predictability is driven primarily by their own historical behavior. This finding supports the view that private equity returns are relatively unaffected by short-term macroeconomic disturbances, with a substantial portion of performance variation likely driven by idiosyncratic, fund-specific, or deal-level factors not captured within the VAR model. Private equity performance is often highly traceable to a manager's historical track record, which is why asset allocators place significant emphasis on analyzing past deals and performance history during the due diligence process.

5.6 Robustness Check

Before turning to the discussion of how these results align with the existing literature, it is important to establish whether the conclusions are sensitive to the particular performance metric chosen for private equity. While DPI and TVPI are cumulative measures that capture cash-on-cash outcomes and total value creation, respectively, they tend to move slowly and often exhibit high persistence due to their construction. By contrast, IRR (in first differences) provides a flow-based measure of private equity performance that better reflects time-varying shocks and cyclical movements. Using IRR_diff as the baseline therefore emphasizes short-run dynamics and allows for more meaningful interactions with macroeconomic variables, which was the central focus of this thesis.

To assess robustness, two additional VAR specifications were estimated, replacing IRR_diff with DPI (in levels) and TVPI (in levels), given that both series were found to be stationary in the stationarity tests (see Figure 4.6.2). Full estimation output, including lag-selection tables, equation-by-equation results, and the corresponding IRFs and FEVDs, is presented in Appendices 2 (TVPI) and 3 (DPI).

The overall picture is highly consistent with the baseline model. Both DPI and TVPI display strong autoregressive dynamics, mirroring the persistence seen in IRR_diff, and the macroeconomic variables continue to exhibit the expected self-dependence and cross-linkages. Importantly, in all specifications, feedback from private equity metrics into the macro block remains negligible, indicating that causality runs primarily from macroeconomic conditions toward private equity outcomes rather than in the opposite direction.

While some differences in coefficient magnitudes and horizon-specific impulse responses appear across the specifications, the qualitative conclusions remain unchanged: private equity performance is driven mainly by its own dynamics and by macro shocks, but does not exert meaningful influence on macroeconomic aggregates. These similarities across models reinforce the robustness of the findings and validate the choice of IRR_diff as the most appropriate baseline for capturing dynamic return behavior.

5.7 Findings Compared to the Existing Literature

The empirical findings of this study—particularly the impulse response function (IRF) and forecast error variance decomposition (FEVD) analyses—indicate that PE return dynamics, as represented by IRR_diff, exhibit weak and inconsistent responses to macroeconomic shocks. The overwhelming explanatory power of a fund's own historical performance over macroeconomic factors aligns with the argument that PE returns are primarily driven by idiosyncratic, fund-level characteristics, timing decisions, and operational strategies rather than short-term fluctuations in GDP growth, public market indices, or interest rates. This finding is broadly consistent with strands of the prior literature that emphasize the structural and operational determinants of PE performance. Beath, Flynn, & MacIntosh (2014) stress that implementation style, fee structures, and GP skill materially shape outcomes—factors inherently internal to the fund and unlikely to be captured by macro variables in short-horizon models. Similarly, Bernstein et al. (2017) note that PE's contribution to industry performance is realized through innovation and efficiency gains over multi-year horizons, which naturally dilutes short-term macro sensitivities. Besides, the lagged ESG (ESG_Share_{t-1}) does not add incremental explanatory power once endogenous macro dynamics are controlled for (seen in system-wide Wald test) is consistent with what prior research highlights about measurement, horizon, and design. Studies reporting positive or non-negative ESG–performance links—such as meta-analyses (Orlitzky, Schmidt & Rynes, 2003; Friede, Busch & Bassen, 2015) and event-style evidence on CSR initiatives (Flammer, 2015)—typically rely on micro-level variation and detailed ESG metrics. By contrast, the present analysis employs a coarse incidence proxy (annual share classified as ESG) over a relatively short sample, which plausibly weakens effects toward zero and aligns with the heterogeneous or neutral average outcomes emphasized by Revelli & Viviani (2013, 2015).

The results also partially converge with research on external market influences. Studies such as Jegadeesh, Kräussl, & Pollet (2015) and Gupta & Nieuwerburgh (2021) identify measurable links between PE performance and public market signals, GDP growth, and credit spreads. However, while these works often find stronger correlations, this study's weaker and more unstable macroeconomic coefficients suggest that such relationships may attenuate when using quarterly, fund-level aggregated IRR data—especially when focused on short-run dynamics. This divergence may be due to differences in measurement horizons (long-term IRRs vs. quarterly IRR changes), data granularity, and the aggregation of multiple vintage years, which can mask cyclical effects.

From a risk and liquidity perspective, the finding that interest rates exert only a marginal and unstable influence on changes in private equity fund IRRs diverges from Franzoni, Nowak, & Phalippou's (2012) evidence of a persistent liquidity premium in PE. Since IRR incorporates both the scale and the timing of cash flows, it is expected to be sensitive to financing conditions—higher interest rates increase the cost of leverage (debt), potentially delay exits, and reduce the present value of future distributions. The weak and unstable effect observed here suggests that this transmission mechanism is less visible in the short-term dynamics captured by the VAR model. One plausible explanation is that the liquidity channel manifests most strongly during credit tightening episodes, when exit markets seize up and distributions fall sharply, effects which are smoothed out in the present sample due to aggregation across multiple strategies, vintages, and relatively stable periods.

The dominance of own-lag effects in IRR_diff also reinforces LP due diligence practices described by Cumming & Zambelli (2017), where historical GP performance is considered the single most important predictor of future returns. LPs often view macroeconomic variables as relevant for pacing commitments or sector allocation, but not as decisive for manager selection in established fund strategies.

By focusing on short-term macro-PE interactions, this study extends the literature in two ways. First, it complements valuation-linked research (e.g., Czasonis, Kritzman, & Turkington, 2019; Gupta & Nieuwerburgh, 2021) by isolating and quantifying the limited role of macro shocks in explaining near-term IRR variation. Second, it bridges the performance literature with LP investment process insights, illustrating empirically why LPs place greater emphasis on qualitative and historical performance metrics during fund selection.

Overall, while the findings converge with the broader consensus that PE performance is relatively insulated from short-term macroeconomic volatility, they diverge from certain empirical works that report stronger market linkages—likely due to differences in methodology, measurement frequency, and variable specification. This suggests that future studies could benefit from disaggregating performance by fund type, sector exposure, and macro regime to reconcile these differences.

5.8 Summary: Results and Interpretations

The empirical results provide insight into how private equity fund performance relates to broader macroeconomic conditions. An initial attempt to estimate a VARX model—including IRR, DPI, TVPI, and an ESG dummy variable—proved unsuccessful. The model could not be statistically validated, and moderate multicollinearity between DPI and TVPI highlighted a key limitation: cumulative private equity performance metrics are not well suited for capturing short-term responses to macroeconomic fluctuations. Their high correlation with IRR reduced model interpretability and pointed to the need for a more focused, dynamic measure.

The refined VAR model, centered on IRR_diff, offered a clearer—though still limited—view of macro-financial interactions. Lagged GDP growth and public market returns had statistically significant but economically modest effects on changes in IRR, while the interest rate variable showed a weak and unstable influence. These findings suggest that macroeconomic shocks have only a limited short-term impact on private equity performance. This is consistent with the view that private equity returns are primarily driven by illiquidity premiums, operational improvements, and fund-specific timing decisions, rather than by short-term market movements.

More revealing is the result from the variance decomposition: over 99% of the variation in IRR_diff is explained by its own past values. This indicates that even though macroeconomic variables are economically relevant in theory, they contribute very little to explaining short-term volatility in private equity returns over the observed period. This outcome is consistent with the nature of private equity, where valuation adjustments occur infrequently and macroeconomic influences tend to be reflected through long-term capital cycles rather than short-term market movements.

The VAR model's diagnostic limitations, including residual autocorrelation, do require caution. However, these statistical imperfections are common in financial time series analysis, especially when constrained to low-order lags and a limited number of aggregate variables (Lütkepohl, 2006). Despite these limitations, the model provided bootstrapped inference and interpretable impulse response and variance decomposition results.

In summary, the regression results indicate that private equity performance—captured through IRR—is only modestly responsive to macroeconomic variables and not significantly shaped by them in the short term. The findings supported the view that while macro shocks may influence investor sentiment or fundraising dynamics, the realized return path of private equity funds is largely shaped by internal factors, deal-specific outcomes, and timing decisions, rather than by contemporaneous economic trends.

6. Conclusions

6.1 Research Summary

This study examines the dynamic relationship between private equity fund performance and external macroeconomic conditions, with a particular focus on the sensitivity of IRR to shocks in market returns, interest rates, and GDP growth. Using a Vector Autoregressive framework, the analysis sheds light on how broader financial conditions influence private equity return dynamics—an area of increasing importance in a world of rising interest rate volatility and heightened macroeconomic uncertainty.

The findings indicate that short-term macroeconomic shocks have only modest effects on PE returns, with performance being driven largely by fund-specific and historical factors. For practitioners, this has several tangible implications. For institutional investors, asset allocators, and LPs, the results suggest that strategic emphasis should remain on assessing GP track records, deal selection quality, operational value creation capabilities, and alignment of interest, rather than relying heavily on macro-timing strategies for commitment pacing. Since macro conditions play a limited short-term role, commitment and re-up decisions should be based more on the structural characteristics of a GP's investment process and historical value creation patterns than on transient economic forecasts. For portfolio construction, the limited macro sensitivity reinforces PE's value as a long-term diversifier in multi-asset portfolios. However, given PE's illiquidity, practitioners should continue to stress-test portfolios for extreme macro events (e.g., credit crunches, deep recessions) that, while infrequent, can disrupt exit markets and delay distributions. This is particularly relevant for LPs managing large, multi-vintage programs where overlapping fund life cycles may amplify liquidity demands. For liquidity planning, the weak short-term macro link implies that cash flow modeling and distribution forecasts should place greater weight on historical fund pacing, GP exit behavior, and portfolio company maturity profiles rather than near-term market indicators such as GDP or equity index volatility. This means that internal data—such as prior distribution waterfalls and capital call patterns—can be more predictive for managing liquidity buffers than public market benchmarks. Finally, for risk management and governance, these results suggest that macroeconomic monitoring, while important, should be complemented with deep, ongoing qualitative due diligence on GPs' operational performance, sector focus, and ability to navigate idiosyncratic challenges at the deal level. In practice, this could translate into enhancing investment committee materials with scenario analysis based on historical GP behavior, rather than relying primarily on macro-driven stress cases.

This paper also responds to a timely and globally relevant issue: bridging the gap between the non-quantitative private market characteristics and empirical macroeconomic analysis. By converting often qualitative aspects—such as deal pacing and exit timing (which influence IRR), and macro sentiment—into a structured statistical framework, the study offers an approach that can be adapted by investors and consultants to enhance due diligence, scenario analysis, and long-term allocation decisions.

From a methodological perspective, the research began with a VARX model incorporating IRR, DPI, and TVPI, but empirical limitations such as multicollinearity and model instability led to a simplified approach. The final model adopted a standard VAR specification, focusing on IRR in first differences and treating macroeconomic variables as endogenous. Diagnostic testing, impulse response functions and forecast error variance decomposition were conducted to provide both statistical validity and interpretive meanings.

The study is based on a time frame that includes two complete private equity cycles, strengthening the generalizability of the results across market regimes. The results indicate that IRR reacts weakly to macroeconomic shocks. Most variation in IRR is internally driven, highlighting the idiosyncratic and path-dependent nature of private equity returns, which are less influenced by short-term macroeconomic fluctuations and more by fund-specific dynamics. Overall, this study offers two key contributions. First, it quantifies the limited but non-negligible impact of macroeconomic variables on short-term private equity performance. Second, it proposes a framework for applying empirical discipline to the evaluation of opaque, long-duration investments—providing investors with a method to interpret performance not just statically, but also dynamically and in relation to broader macroeconomic conditions.

6.2 Limitations of This Research Project

Several limitations should be noted in interpreting the results of this study. First, while the analysis aimed to explore the influence of macroeconomic factors on private equity performance using a structured time series approach, empirical constraints limited the scope of modeling. Early attempts to estimate a VARX model—intended to incorporate IRR, DPI, TVPI, and an ESG dummy—were unsuccessful due to multicollinearity and model instability. These issues ultimately necessitated a shift toward a simplified VAR framework, which focused on IRR in first differences alongside endogenous macro variables. Second, the ESG information available is coarse and likely attenuates effects toward zero: ESG is recorded as a binary indicator at the observation level and used only through an annual share as a conditioning regressor. This proxy captures compliance incidence rather than intensity or quality; it is not fund-weighted, offers limited time variation over a short annual sample ($T \approx 20$), and may embed classification inconsistencies, survivorship bias, and measurement error. Treating this ESG share as exogenous further abstracts from possible feedback between performance and ESG adoption. Taken together, these features reduce statistical power and make it harder to detect economically meaningful ESG effects. Even within the VAR model, diagnostic testing identified residual autocorrelation, as flagged by the Portmanteau test. While this suggests the model may not fully capture all serial dependencies, the issue was judged acceptable given the study's objectives. The primary aim was to assess dynamic relationships through impulse response functions and variance decomposition, rather than to generate forecasts. Finally, while the model captures short-term interactions, it does not incorporate structural breaks, regime shifts (e.g., ESG policies), or fund-level heterogeneity (e.g., strategy drift) that can also influence private-equity performance. The limitations therefore stress that identifying ESG mechanisms likely requires richer micro data (e.g., fund-level ESG scores or exposures), longer panels, or designs that exploit policy-driven regime changes and interactions. Within these constraints, the present strategy keeps ESG explicitly in the empirical design—by conditioning on ESG_Share_{t-1} and testing its joint contribution—while maintaining a parsimonious and statistically reliable dynamic specification. Future research could expand the framework by incorporating longer lags, richer ESG measures (e.g., fund-level ESG scores/intensity, policy-based regime indicators) and weights, additional explanatory variables, or case-study designs that capture manager-specific factors.

6.3 Recommendations for Further Research

While this study offers useful insights into how private equity performance responds to macroeconomic conditions, there are several areas where further research could add depth and practical relevance. First, incorporating more fund-specific variables—such as fund size, vintage year, sector, strategy, or geographic focus—would allow for a more granular analysis. These attributes are likely to influence how different funds react to economic shocks, which aggregate IRR figures alone may not capture. However, collecting these data points at the necessary scale and frequency was beyond the scope of this master's thesis due to both data availability constraints and time limitations inherent in the program. Many of these variables are available through industry databases; however, integrating them into the model was not practical within the scope of this thesis. Several methodological challenges arise. Variables such as vintage year, fund size, and strategy are not naturally suited to time-series econometric modeling, as they are often categorical or static attributes rather than continuous measures that vary over time. Quantifying their influence on an annual or quarterly basis would require complex transformations and the creation of interaction terms that could substantially reduce degrees of freedom in a relatively short sample. Besides, the number of funds represented in each period varies significantly, which complicates the construction of a consistent aggregate series. This issue is amplified when considering strategic focus or sector breakdowns, where some categories—particularly emerging managers or funds in developing markets—have incomplete or irregular reporting. Incorporating these variables robustly would therefore require advanced panel data methods, additional adjustments for sampling bias, and possibly separate sub-models, all of which extend beyond the feasible scope of a master's thesis.

Second, future work could apply a mixed-method approach, integrating both qualitative (e.g. case-study, semi-structured interviews) and quantitative methodologies. This would allow researchers to control fund-specific effects and account for variation that cannot be observed in a single time series. It would also improve the reliability of results and make findings more applicable for LPs comparing managers or strategies. Third, while this study focuses on short-term dynamics using a VAR model, there is value in exploring longer-term relationships. Techniques such as cointegration analysis or a Vector Error Correction Model (VECM) could help identify equilibrium trends and how short-term deviations are corrected over time.

There is also room to better integrate qualitative and ESG-related factors into empirical models. Elements like ESG policies, governance practices, or manager reputation are often assessed qualitatively, but translating them into measurable indicators would support more robust analysis. Developing hybrid models that combine these proxies with macroeconomic inputs could improve how investors evaluate fund alignment with long-term goals.

Lastly, better access to more frequent and detailed private equity data would improve model accuracy and responsiveness. Since data from sources like PitchBook is typically delayed by at least one quarter—and often incomplete due to managers' reluctance to disclose information, more transparent and timely data sharing between LPs and fund managers would help support more effective portfolio monitoring and quicker responses to macroeconomic developments. Incorporating a mixed-method approach—such as interviews with fund managers to obtain first-hand performance data—could help address data quality and accuracy issues.

Overall, while this study provides a starting point, further research is needed to refine the methods, expand the dataset, and build more practical tools. These advances will be critical for investors seeking to integrate private equity into portfolios with a more rigorous, macro-aware approach to allocation and risk management.

References

Abrigo, M. R. M., & Love, I. (2016). Estimation of panel vector autoregression in Stata. *The Stata Journal, 16*(3), 778–804. https://doi.org/10.1177/1536867X1601600314

Baik, B. K. (2024). *Private equity fund valuation management during fundraising*. Harvard Business School.

Barber, B. M., Morse, A., & Yasuda, A. (2021). Impact investing. *Journal of Financial Economics, 139*(1), 162–185. https://doi.org/10.1016/j.jfineco.2020.07.008

Beath, A., Flynn, C., & MacIntosh, J. (2014). How implementation style and costs affect private equity performance. *Rotman International Journal of Pension Management, 7*(1), 50–54. https://doi.org/10.3138/ripjm.7.1.50

Bénabou, R., & Tirole, J. (2010). Individual and corporate social responsibility. *Economica, 77*(305), 1–19.

Bernstein, S., Lerner, J., & Mezzanotti, F. (2019). Private equity and financial fragility during the crisis. *The Review of Financial Studies, 32*(4), 1309–1373.

Bernstein, S., Lerner, J., Sorensen, M., & Strömberg, P. (2017). Private equity and industry performance. *Management Science, 63*(4), 1198–1213. https://doi.org/10.1287/mnsc.2015.2404

Bian, Y., Gao, H., Wang, R., & Xiong, X. (2023). Sustainable development for private equity: Integrating environment, social, and governance factors into partnership valuation. *Business Strategy and the Environment, 32*(6), 3359–3370. https://doi.org/10.1002/bse.3304

Birdthistle, W. A., & Henderson, M. T. (2009). One hat too many? Investment desegregation in private equity. *The University of Chicago Law Review, 76*(1), 45–82.

Brest, P., & Born, K. (2013). Unpacking the impact in impact investing. *Stanford Social Innovation Review* (Fall). https://ssir.org/articles/entry/unpacking_the_impact_in_impact_investing

Brown, G. W., Gredil, O. R., & Kaplan, S. N. (2019). Do private equity funds manipulate reported returns? *Journal of Financial Economics, 132*(2), 267–297. https://doi.org/10.1016/j.jfineco.2018.10.011

Brown, G. W., Harris, R. S., Jenkinson, T., Kaplan, S. N., & Robinson, D. T. (2015). What do different commercial data sets tell us about private equity performance? *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2701317

Clark, G. L., Feiner, A., & Viehs, M. (2014). From the stockholder to the stakeholder: How sustainability can drive financial outperformance. *SSRN Electronic Journal*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2508281

Cumming, D., & Zambelli, S. (2017). Due diligence and investee performance. *European Financial Management, 23*(2), 211–253. https://doi.org/10.1111/eufm.12100

Czasonis, M., Kritzman, M., & Turkington, D. (2019). Private equity valuations and public equity performance. *The Journal of Alternative Investments, 22*(1), 8–19.

De Lucia, C., Pazienza, P., & Bartlett, M. (2020). Does good ESG lead to better financial performances by firms? Machine learning and logistic regression models of public enterprises in Europe. *Sustainability, 12*, Article 5317.

Dekimpe, M. G., & Hanssens, D. M. (1999). Sustained spending and persistent response: A new look at long-term marketing profitability. *Journal of Marketing Research, 36*(4), 397–412. https://doi.org/10.2307/3151996

Dupré, D., Girerd-Potin, I., Jimenez-Garces, S., & Louvet, P. (2009). Influence de la notation éthique sur l'évolution du prix des actions Un modèle théorique. *Revue Économique, 60*(1), 5. https://doi.org/10.3917/reco.601.0005

Enders, W. (2015). *Applied econometric time series* (4th ed.). Wiley.

Findlay, S., & Moran, M. (2019). Purpose-washing of impact investing funds: Motivations, occurrence and prevention. *Social Responsibility Journal, 15*(7), 853–873. https://doi.org/10.1108/SRJ-11-2017-0260

Flammer, C. (2015). Does corporate social responsibility lead to superior financial performance? A regression discontinuity approach. *Management Science, 61*(11), 2549. https://doi.org/10.1287/mnsc.2014.2038

Franzoni, F., Nowak, E., & Phalippou, L. (2012). Private equity performance and liquidity risk. *The Journal of Finance, 67*(6), 2341.

Friede, G., Busch, T., & Bassen, A. (2015). ESG and financial performance: Aggregated evidence from more than 2000 empirical studies. *Journal of Sustainable Finance & Investment, 5*(4), 210–233. https://doi.org/10.1080/20430795.2015.1118917

Friedman, M. (1970). The social responsibility of business is to increase its profits. *The New York Times Magazine*.

Global Sustainable Investment Alliance (GSIA). (2018). *Global sustainable investment review*. http://www.gsi-alliance.org/trends-report-2018/

Gompers, P., & Lerner, J. (1996). The use of covenants: An empirical analysis of venture partnership agreements. *The Journal of Law and Economics, 39*(2), 463–498. https://doi.org/10.1086/467356

Gredil, O. R., Griffiths, B., & Stucke, R. (2023). Benchmarking private equity: The direct alpha method. *Journal of Corporate Finance, 81*, Article 102360. https://doi.org/10.1016/j.jcorpfin.2023.102360

Gujarati, D. N., & Porter, D. C. (2009). *Basic econometrics* (5th ed.). McGraw-Hill.

Gupta, A., & Nieuwerburgh, S. (2021). Valuing private equity investments strip by strip. *The Journal of Finance, 76*(6), 3255–3307. https://doi.org/10.1111/jofi.13073

Heinz, D. C., & Velamuri, V. K. (2024). Intentionality and decision-making in impact investing—Understanding investment motivation and selection criteria of impact investors. *Sustainability, 16*(11), 4497. https://doi.org/10.3390/su16114497

Hill, R. C., Griffiths, W. E., & Lim, G. C. (2018). *Principles of econometrics* (5th ed.). Wiley.

Höchstädter, A. K., & Scheck, B. (2015). What's in a name: An analysis of impact investing understandings by academics and practitioners. *Journal of Business Ethics, 132*(2), 449–475. https://doi.org/10.1007/s10551-014-2327-0

Horváth, C., Leeflang, P. S. H., Wieringa, J. E., & Wittink, D. R. (2005). Competitive reaction- and feedback effects based on VARX models of pooled store data. *International Journal of Research in Marketing, 22*(4), 415–426. https://doi.org/10.1016/j.ijresmar.2005.09.007

Jefferson, A., Olbert, M., & Vasvari, F. (2024). ESG disclosures in the private equity industry. *Journal of Accounting Research, 62*(5), 1611–1660. https://doi.org/10.1111/1475-679X.12570

Jegadeesh, N., Kräussl, R., & Pollet, J. M. (2015). Risk and expected returns of private equity investments: Evidence based on market prices. *The Review of Financial Studies, 28*(12), 3269.

Kaplan, S. N., & Stromberg, P. (2004). Characteristics, Contracts, and Actions: Evidence from Venture Capitalist Analyses. *The Journal of Finance*, *59(5),* 2177–2210.

Kaplan, S. N., & Schoar, A. (2005). Private equity performance: Returns, persistence, and capital flows. *The Journal of Finance, 60*(4), 1791–1823. https://doi.org/10.1111/j.1540-6261.2005.00780.x

Kilian, L. (2006). New introduction to multiple time series analysis, by Helmut Lütkepohl, Springer, 2005. *Econometric Theory, 22*(5), 961–967. https://doi.org/10.1017/S0266466606000442

Kilian, L., & Lütkepohl, H. (2017). Structural vector autoregressive analysis. *Cambridge University Press*. https://doi.org/10.1017/9781108164818

Korteweg, A., & Westerfield, M. M. (2022). Asset allocation with private equity. *Foundations and Trends® in Finance, 13*(2), 95–204.

Love, I., & Zicchino, L. (2006). Financial development and dynamic investment behavior: Evidence from panel VAR. *Quarterly Review of Economics and Finance, 46*(2), 190–210.

Lütkepohl, H. (2006). *New introduction to multiple time series analysis* (1st ed.). Springer.

Markowitz, H. (1952). Portfolio selection. *The Journal of Finance, 7*(1), 77–91.

Martini, A. (2021). Socially responsible investing: From the ethical origins to the sustainable development framework of the European Union. *Environment, Development and Sustainability, 23*(11), 16874–16890. https://doi.org/10.1007/s10668-021-01375-3

Delmas, M. A., & Burbano, V. C. (2011). The drivers of greenwashing. *California Management Review, 54*(1), 64–87. https://doi.org/10.1525/cmr.2011.54.1.64

McCahery, J. A., Pudschedl, P. C., & Steindl, M. (2023). Institutional investors, alternative asset managers, and ESG preferences. *European Business Organization Law Review, 23*(4), 821–868. https://doi.org/10.1007/s40804-022-00264-0

Metrick, A., & Yasuda, A. (2010). The economics of private equity funds. *The Review of Financial Studies, 23*(6), 2303–2341.

Michigan Journal of Economics. (2025, January 10). The future of ESG under the Trump administration. *Michigan Journal of Economics*. https://sites.lsa.umich.edu/mje/2025/01/10/the-future-of-esg-under-the-trump-administration/

New York Post. (2025, March 26). Congressman Andy Barr to introduce bill to curb 'woke' ESG investing by state pension funds. *New York Post*. https://nypost.com/2025/03/26/business/congressman-andy-barr-to-introduce-bill-to-curb-woke-esg-investing-by-state-pension-funds/

Orlitzky, M., Schmidt, F. L., & Rynes, S. L. (2003). Corporate social and financial performance: A meta-analysis. *Organization Studies, 24*(3), 403–441.

Patton, M. Q. (2002). Qualitative interviewing. In *Qualitative research and evaluation methods* (pp. 339–422). Sage.

Pedersen, L. H., Fitzgibbons, S., & Pomorski, L. (2021). Responsible investing: The ESG-efficient frontier. *Journal of Financial Economics, 142*(2), 572. https://doi.org/10.1016/j.jfineco.2020.11.001

Phalippou, L., & Gottschalg, O. (2009). The Performance of Private Equity Funds. *The Review of Financial Studies*, *22*(4), 1747–1776. https://doi.org/10.1093/rfs/hhn014

Phalippou, L. (2020). Better Alignment of Financial Interest in Private Equity. *Journal of Investing*, *30*(1), 101–108. https://doi.org/10.3905/joi.2020.1.156

Porter, M. E. (1991). America's green strategy. *Scientific American, 264*(4), 168.

Preqin. (2023). *Preqin global private equity report 2023*. Preqin Ltd.

Renneboog, L., Ter Horst, J., & Zhang, C. (2008). Socially responsible investments: Institutional aspects, performance, and investor behavior. *Journal of Banking and Finance, 32*(9), 1723–1742.

Revelli, C., & Viviani, J.-L. (2013). The link between SRI and financial performance: Effects and moderators. *Management International, 17*(2), 105–122. https://doi.org/10.7202/1015403ar

Revelli, C., & Viviani, J.-L. (2015). Financial performance of socially responsible investing (SRI): What have we learned? A meta-analysis. *Business Ethics: A European Review, 24*(2), 158–185. https://doi.org/10.1111/beer.12076

Robinson, D. T., & Sensoy, B. A. (2016). Cyclicality, performance measurement, and cash flow liquidity in private equity. *Journal of Financial Economics, 122*(3), 521–543. https://doi.org/10.1016/j.jfineco.2016.09.008

Schreane, K. C. (2023). *Gambling on green: Uncovering the balance among revenues, reputations, and ESG*. John Wiley & Sons, Inc. https://search.ebscohost.com/login.aspx?direct=true&scope=site&db=nlebk&db=nlabk&AN=3384645

Sims, C. A. (1980). Macroeconomics And Reality. *Econometrica (Pre-1986)*, *48*(1), 1.

Stock, J. H., & Watson, M. W. (2001). Vector autoregressions. *The Journal of Economic Perspectives, 15*(4), 101–115. https://doi.org/10.1257/jep.15.4.101

Stock, J. H., & Watson, M. W. (2015). *Introduction to econometrics* (3rd ed., update). Pearson.

Trinks, P. J., & Scholtens, B. (2017). The opportunity cost of negative screening in socially responsible investing. *Journal of Business Ethics, 140*(2), 193–208. https://doi.org/10.1007/s10551-015-2684-3

United Nations Global Compact, Global Compact, & Swiss Federal Department of Foreign Affairs. (2004). *Who cares wins: Connecting financial markets to a changing world: Recommendations by the financial industry to better integrate environmental, social and governance issues in analysis, asset management and securities*.

Wharton Research Data Services (WRDS). (2021, October 21). *WRDS adds PitchBook private equity data to its offerings*. University of Pennsylvania. https://wrds-www.wharton.upenn.edu/pages/news/wrds-adds-pitchbook-private-equity-data-to-its-offerings/

Zaccone, M. C., & Pedrini, M. (2020). ESG factor integration into private equity. *Sustainability, 12*(14), 5725. https://doi.org/10.3390/su12145725

Appendices

Appendix 1. R code

```
# =====================
# VARX IRR_diff VAR MODEL
# =====================
# Load libraries
library(vars)
library(tseries)
library(readr)
library(officer)
library(flextable)
library(ggplot2)
library(tidyr)
library(dplyr)
library(reshape2)
library(broom)
library(car)

# ----------------------
# 1. Read Data
# ----------------------
df <- read_csv("C:/Users/BB/Desktop/HEC Thesis/Data Test2.csv", show_col_types =
FALSE)
data_VAR <- df[, c("IRR", "DPI", "TVPI", "MKT", "INT", "GDP")]
doc <- read_docx()

# ----------------------
# 2. Stationarity Test (Level Data)
# ----------------------
adf_test_results <- lapply(data_VAR, function(x) {
  adf_test <- adf.test(x)
  data.frame(
    Statistic = round(adf_test$statistic, 4),
    P_Value = round(adf_test$p.value, 4)
  )
})
adf_test_table <- do.call(rbind, adf_test_results)
adf_test_table$Variable <- rownames(adf_test_table)
rownames(adf_test_table) <- NULL

doc <- body_add_par(doc, "1. Stationarity Test Results (Level Data)", style =
"heading 1")
```

```
doc <- body_add_flextable(doc, flextable(adf_test_table))

# ----------------------
# 2b. Multicollinearity Test: VIF (Endogenous Variables)
# ----------------------

vif_model_endo <- lm(IRR ~ DPI + TVPI, data = data_VAR)
vif_values_endo <- vif(vif_model_endo)
vif_table_endo <- data.frame(
  Variable = names(vif_values_endo),
  VIF = round(as.numeric(vif_values_endo), 4)
)

doc <- body_add_par(doc, "Multicollinearity Test: Endogenous Variables (VIF)",
style = "heading 1")
doc <- body_add_flextable(doc, flextable(vif_table_endo))
doc <- body_add_break(doc)

# ----------------------
# 2c. Multicollinearity Test: VIF (Exogenous Variables)
# ----------------------
vif_model_exog <- lm(MKT ~ INT + GDP, data = data_VAR)
vif_values_exog <- vif(vif_model_exog)
vif_table_exog <- data.frame(
  Variable = names(vif_values_exog),
  VIF = round(as.numeric(vif_values_exog), 4)
)

doc <- body_add_par(doc, "Multicollinearity Test: Exogenous Variables (VIF)",
style = "heading 1")
doc <- body_add_flextable(doc, flextable(vif_table_exog))
doc <- body_add_break(doc)

# ----------------------
# 3. First-Difference IRR Only
# ----------------------
data_VAR$IRR_diff <- c(NA, diff(data_VAR$IRR))
data_VAR_final <- data_VAR[, c("IRR_diff", "MKT", "INT", "GDP")] %>% na.omit()

# ----------------------
# 4. Stationarity Test of IRR_diff
# ----------------------
adf_diff_IRR <- adf.test(data_VAR_final$IRR_diff)
adf_diff_table <- data.frame(
  Variable = "IRR_diff",
```

```r
  Statistic = round(adf_diff_IRR$statistic, 4),
  P_Value = round(adf_diff_IRR$p.value, 4)
)
doc <- body_add_par(doc, "2. Stationarity Test of IRR after First-Differencing",
style = "heading 1")
doc <- body_add_flextable(doc, flextable(adf_diff_table))
doc <- body_add_break(doc)

# ----------------------
# 5. VAR Lag Selection
# ----------------------
lag_selection <- VARselect(data_VAR_final, lag.max = 5, type = "const")
best_p <- lag_selection$selection["AIC(n)"]
lag_table <- as.data.frame(round(lag_selection$criteria, 4))
lag_table$Criterion <- rownames(lag_table)
rownames(lag_table) <- NULL
doc <- body_add_par(doc, "3. VAR Lag Selection Results", style = "heading 1")
doc <- body_add_flextable(doc, flextable(lag_table))
doc <- body_add_break(doc)

# ----------------------
# 6. Fit VAR Model
# ----------------------
var_model <- VAR(data_VAR_final, p = best_p, type = "const")
doc <- body_add_par(doc, paste0("4. VAR(", best_p, ") Model Summary"), style =
"heading 1")

for (eqn in names(var_model$varresult)) {
  tidy_eqn <- tidy(var_model$varresult[[eqn]]) %>%
    mutate(across(where(is.numeric), ~ round(., 4)))

  eqn_text <- paste0(
    eqn, " ~ ", paste(
      paste0(ifelse(tidy_eqn$estimate >= 0, "+ ", "- "),
             abs(tidy_eqn$estimate), " * ", tidy_eqn$term),
      collapse = " ")
  )
  eqn_text <- sub("^\\+ ", "", eqn_text)

  doc <- body_add_par(doc, paste0("Equation for: ", eqn), style = "heading 2")
  doc <- body_add_par(doc, eqn_text, style = "Normal")
  doc <- body_add_flextable(doc, flextable(tidy_eqn))
  doc <- body_add_break(doc)
}
```

```
# ----------------------
# 7. Residual Serial Correlation (Portmanteau Test)
# ----------------------
serial_result <- serial.test(var_model, lags.pt = 12, type = "PT.asymptotic")
serial_test_table <- data.frame(
  Test_Type = "Portmanteau (asymptotic)",
  Chi_Squared = round(serial_result$serial$statistic, 4),
  DF = serial_result$serial$parameter,
  P_Value = round(serial_result$serial$p.value, 4)
)
doc <- body_add_par(doc, "5. Residual Serial Correlation Test", style = "heading
1")
doc <- body_add_flextable(doc, flextable(serial_test_table))
doc <- body_add_break(doc)

# ----------------------
# 8. Impulse Response Functions (IRFs)
# ----------------------
irf_result <- irf(var_model, impulse = c("MKT", "INT", "GDP"), response =
"IRR_diff", boot = TRUE, ci = 0.95, runs = 500)
steps <- 0:(length(irf_result$irf$MKT)-1)
irf_df <- data.frame(
  Step = rep(steps, 3),
  IRF = c(irf_result$irf$MKT, irf_result$irf$INT, irf_result$irf$GDP),
  Lower = c(irf_result$Lower$MKT, irf_result$Lower$INT, irf_result$Lower$GDP),
  Upper = c(irf_result$Upper$MKT, irf_result$Upper$INT, irf_result$Upper$GDP),
  Shock = rep(c("Market Return (MKT)", "Interest Rate (INT)", "GDP Growth
(GDP)"), each = length(steps))
)

irf_plot <- ggplot(irf_df, aes(x = Step, y = IRF, group = Shock, color = Shock,
fill = Shock)) +
  geom_ribbon(aes(ymin = Lower, ymax = Upper), alpha = 0.2, color = NA) +
  geom_line(size = 1) +
  facet_wrap(~Shock, scales = "free_y", ncol = 2) +
  labs(
    title = "Impulse Response Functions for IRR_diff",
    x = "Horizon (Steps)",
    y = "IRF Value"
  ) +
  theme_minimal(base_size = 13, base_family = "Times New Roman") +
  theme(
    plot.title = element_text(hjust = 0.5, face = "bold", family = "Times New
Roman"),
    axis.title = element_text(family = "Times New Roman"),
```

```
    axis.text = element_text(family = "Times New Roman"),
    strip.text = element_text(size = 12, face = "bold", family = "Times New
Roman"),
    legend.text = element_text(family = "Times New Roman"),
    legend.title = element_text(family = "Times New Roman"),
    legend.position = "none"
  )

ggsave("IRF_plot_custom.png", plot = irf_plot, width = 8, height = 6)
doc <- body_add_par(doc, "6. Impulse Response Functions (with 95% CI)", style =
"heading 1")
doc <- body_add_img(doc, src = "IRF_plot_custom.png", width = 6, height = 4)
doc <- body_add_break(doc)

# ----------------------
# 9. Forecast Error Variance Decomposition (FEVD)
# ----------------------
fevd_result <- fevd(var_model, n.ahead = 10)
fevd_long <- bind_rows(lapply(names(fevd_result), function(var) {
  temp <- as.data.frame(fevd_result[[var]])
  temp$Horizon <- 1:nrow(temp)
  temp$Response <- var
  temp
}))

fevd_long_melt <- pivot_longer(fevd_long, cols = -c(Horizon, Response), names_to
= "Shock", values_to = "Contribution")

fevd_plot <- ggplot(fevd_long_melt, aes(x = Horizon, y = Contribution, fill =
Shock)) +
  geom_bar(stat = "identity", position = "stack") +
  geom_text(
    aes(label = sprintf("%.4f", Contribution)),
    position = position_stack(vjust = 0.5),
    size = 3,
    color = "black",
    family = "Times New Roman"
  ) +
  facet_wrap(~Response, ncol = 2, scales = "free_y") +
  labs(
    title = "Forecast Error Variance Decomposition (FEVD)",
    x = "Horizon",
    y = "Contribution",
    fill = "Shock"
  ) +
```

```
  theme_minimal(base_size = 13, base_family = "Times New Roman") +
  theme(
    plot.title = element_text(hjust = 0.5, face = "bold", family = "Times New
Roman"),
    axis.title = element_text(size = 12, family = "Times New Roman"),
    axis.text = element_text(family = "Times New Roman"),
    strip.text = element_text(size = 12, face = "bold", family = "Times New
Roman"),
    legend.text = element_text(family = "Times New Roman"),
    legend.title = element_text(family = "Times New Roman")
  )

ggsave("FEVD_plot_custom.png", plot = fevd_plot, width = 10, height = 6)
doc <- body_add_par(doc, "7. Forecast Error Variance Decomposition (FEVD)", style
= "heading 1")
doc <- body_add_img(doc, src = "FEVD_plot_custom.png", width = 6, height = 4)

# ----------------------
# 10. Save Word Document
# ----------------------
out_path <- "C:/Users/BB/Desktop/HEC Thesis/IRR_VARX_Results.docx"
if (file.exists(out_path)) file.remove(out_path)
print(doc, target = out_path)

# ----------Additional Edits (Including ESG Data series)------------
# - Companion roots plot (stability)
# - VAR(1) conditioned on ESG_share_{t-1} + system-wide Wald

# ----- Libraries -----
library(readr);    library(dplyr);  library(tidyr);  library(tseries)
library(vars);     library(officer); library(flextable); library(ggplot2)
library(broom);    library(systemfit); library(MASS)
library(sandwich); library(lmtest)
# optional: for non-overlapping labels on roots plot
have_repel <- requireNamespace("ggrepel", quietly = TRUE)

# ----- Paths -----
in_path  <- "C:/Users/BB/Desktop/HEC Thesis/Data Test3.csv"
out_path <- "C:/Users/BB/Desktop/HEC Thesis/IRR_ESG_FINAL.docx"


# ----- Helpers -----
tnr_theme <- theme_minimal(base_size = 13, base_family = "Times New Roman") +
  theme(plot.title = element_text(hjust = 0.5, face = "bold", family = "Times New
Roman"),
```

```
        strip.text  = element_text(size = 12, face = "bold", family = "Times New 
Roman"))

add_ft <- function(doc, df) {
  ft <- flextable(df)
  ft <- font(ft, fontname = "Times New Roman", part = "all")
  flextable::body_add_flextable(doc, value = ft)
}

log_doc <- function(doc, ...) {
  msg <- paste0(...)
  message(msg)
  officer::body_add_par(doc, msg, style = "Normal")
}

# ======================================
# 0) Read & aggregate to annual series
# ======================================
df <- readr::read_csv(in_path, show_col_types = FALSE) |>
  dplyr::mutate(Year = as.integer(Year)) |>
  dplyr::arrange(Year)

doc <- officer::read_docx()
doc <- officer::body_add_par(doc, "Empirical Appendix: VAR(1) with ESG 
Conditioning + LP IRFs", style = "heading 1")
doc <- log_doc(doc, sprintf("Loaded %d rows. Year range: %s-%s.", nrow(df), 
min(df$Year, na.rm=TRUE), max(df$Year, na.rm=TRUE)))
doc <- officer::body_add_break(doc)

annual <- df |>
  dplyr::group_by(Year) |>
  dplyr::summarise(
    IRR = mean(IRR, na.rm = TRUE),
    DPI = mean(DPI, na.rm = TRUE),
    TVPI = mean(TVPI, na.rm = TRUE),
    MKT = mean(MKT, na.rm = TRUE),
    INT = mean(INT, na.rm = TRUE),
    GDP = mean(GDP, na.rm = TRUE),
    ESG_share = mean(ESG, na.rm = TRUE),
    .groups = "drop"
  ) |>
  dplyr::arrange(Year) |>
  dplyr::mutate(
    IRR_diff = c(NA, diff(IRR)),
    ESG_share_L1 = dplyr::lag(ESG_share, 1)
```

```
  )
# Clean sample for models
A <- annual |>
  tidyr::drop_na(IRR_diff, MKT, INT, GDP)
Tn <- nrow(A)
doc <- log_doc(doc, sprintf("Annual VAR sample size after differencing: T = %d
years.", Tn))
doc <- officer::body_add_break(doc)

# --- Stability: companion roots plot (unit circle) ---
rts <- vars::roots(var1)
roots_df <- data.frame(
  Real = Re(rts),
  Imag = Im(rts),
  Mod  = round(Mod(rts), 2),
  Lab  = sprintf("%.2f", round(Mod(rts), 2))
)

roots_plot <- ggplot(roots_df, aes(x = Real, y = Imag)) +
  geom_point(size = 2) +
  { if (have_repel) ggrepel::geom_text_repel(aes(label = Lab), size = 3, family =
"Times New Roman")
    else geom_text(aes(label = Lab), vjust = -0.8, size = 3) } +
  annotate("path", x = cos(seq(0, 2*pi, length.out = 400)),
                   y = sin(seq(0, 2*pi, length.out = 400)),
           color = "black") +
  coord_equal() +
  labs(title = "Companion Matrix Roots (Unit Circle)", x = "Real", y =
"Imaginary") +
  tnr_theme

img_roots <- tempfile(fileext = ".png")
ggsave(img_roots, roots_plot, width = 5.5, height = 5, dpi = 300)
doc <- officer::body_add_par(doc, "Stability Check: Roots of Companion Matrix",
style = "heading 3")
doc <- officer::body_add_img(doc, src = img_roots, width = 5.5, height = 5)
doc <- officer::body_add_par(doc,
  if (all(Mod(rts) < 1)) "All roots are inside the unit circle: the VAR(1) is
stable."
  else "At least one root lies on/outside the unit circle: treat dynamic
interpretations with caution.",
  style = "Normal")
doc <- officer::body_add_break(doc)

# ======================================
```

```
# 2) VAR(1) conditioned on ESG_share_{t-1} (exogenous)
#    + system-wide joint Wald on ESG block
# =======================================
AX <- annual |>
  dplyr::select(Year, IRR_diff, MKT, INT, GDP, ESG_share_L1) |>
  tidyr::drop_na()

doc <- officer::body_add_par(doc, "3. VAR(1) conditioned on ESG intensity
(ESG_share_{t-1})", style = "heading 2")
if (nrow(AX) >= 8) {
  Y_blk  <- AX[, c("IRR_diff","MKT","INT","GDP")]
  X_exog <- as.matrix(AX$ESG_share_L1); colnames(X_exog) <- "ESG_share_L1"
  var1x  <- try(vars::VAR(Y_blk, p = 1, type = "const", exogen = X_exog), silent
= TRUE)

  if (!inherits(var1x, "try-error")) {
    for (eqn in names(var1x$varresult)) {
      tab <- broom::tidy(var1x$varresult[[eqn]]) |>
        dplyr::mutate(across(where(is.numeric), ~ round(., 4)))
      doc <- officer::body_add_par(doc, paste0("Equation: ", eqn), style =
"heading 3")
      doc <- add_ft(doc, tab)
      doc <- officer::body_add_break(doc)
    }
  } else {
    doc <- log_doc(doc, "VAR(1)+ESG_share_L1 could not be estimated (small
T/collinearity).")
    doc <- officer::body_add_break(doc)
  }
} else {
  doc <- log_doc(doc, "Too few annual observations to add ESG_share_L1
exogenously in VAR(1).")
  doc <- officer::body_add_break(doc)
}

# --- System-wide joint Wald test on ESG_share_L1 across all equations (SUR; OLS
fallback) ---
regd <- annual |>
  dplyr::mutate(
    IRR_diff_L1 = dplyr::lag(IRR_diff, 1),
    MKT_L1      = dplyr::lag(MKT, 1),
    INT_L1      = dplyr::lag(INT, 1),
    GDP_L1      = dplyr::lag(GDP, 1)
  ) |>
```

```
  dplyr::select(IRR_diff, MKT, INT, GDP, IRR_diff_L1, MKT_L1, INT_L1, GDP_L1,
ESG_share_L1) |>
  tidyr::drop_na()

doc <- officer::body_add_par(doc, "System-wide joint Wald on ESG_share_{t-1}",
style = "heading 3")
wald_tab <- NULL
if (nrow(regd) >= 8) {
  f_IRR <- IRR_diff ~ IRR_diff_L1 + MKT_L1 + INT_L1 + GDP_L1 + ESG_share_L1
  f_MKT <- MKT      ~ IRR_diff_L1 + MKT_L1 + INT_L1 + GDP_L1 + ESG_share_L1
  f_INT <- INT      ~ IRR_diff_L1 + MKT_L1 + INT_L1 + GDP_L1 + ESG_share_L1
  f_GDP <- GDP      ~ IRR_diff_L1 + MKT_L1 + INT_L1 + GDP_L1 + ESG_share_L1

  fit_sur <- try(systemfit::systemfit(list(IRR=f_IRR, MKT=f_MKT, INT=f_INT,
GDP=f_GDP),
                                      data = regd, method = "SUR"),
                 silent = TRUE)
  if (!inherits(fit_sur, "try-error")) {
    b  <- coef(fit_sur); V <- vcov(fit_sur); cn <- names(b)
    idx <- match(paste0(c("IRR","MKT","INT","GDP"), "_ESG_share_L1"), cn); idx <-
idx[!is.na(idx)]
    if (length(idx) > 0) {
      R <- matrix(0, nrow=length(idx), ncol=length(b)); R[cbind(seq_along(idx),
idx)] <- 1
      Rb <- as.numeric(R %*% b); RVRT <- R %*% V %*% t(R)
      Vinv <- try(solve(RVRT), silent = TRUE); if (inherits(Vinv, "try-error"))
Vinv <- MASS::ginv(RVRT)
      W <- as.numeric(t(Rb) %*% Vinv %*% Rb); dfW <- qr(R)$rank; pW <- pchisq(W,
df=dfW, lower.tail=FALSE)
      wald_tab <- data.frame(Test = "H0: ESG_share_{t-1} jointly zero across all
equations",
                             Lag_p = 1, DF = dfW, Wald_ChiSq = round(W,4),
                             P_Value = formatC(pW, format="f", digits=4))
    }
  } else {
    # OLS fallback
    fit_e <- lm(f_IRR, data = regd); fit_m <- lm(f_MKT, data = regd)
    fit_i <- lm(f_INT, data = regd); fit_g <- lm(f_GDP, data = regd)
    b  <- c(coef(fit_e), coef(fit_m), coef(fit_i), coef(fit_g))
    Ve <- vcov(fit_e); Vm <- vcov(fit_m); Vi <- vcov(fit_i); Vg <- vcov(fit_g)
    cn_e <- names(coef(fit_e)); cn_m <- names(coef(fit_m))
    cn_i <- names(coef(fit_i)); cn_g <- names(coef(fit_g))
    idx <- c(match("ESG_share_L1", cn_e),
             length(cn_e)+match("ESG_share_L1", cn_m),
             length(cn_e)+length(cn_m)+match("ESG_share_L1", cn_i),
```

```
              length(cn_e)+length(cn_m)+length(cn_i)+match("ESG_share_L1", cn_g))
    idx <- idx[!is.na(idx)]
    V <- matrix(0, nrow=length(b), ncol=length(b))
    V[1:length(cn_e), 1:length(cn_e)] <- Ve
    V[(length(cn_e)+1):(length(cn_e)+length(cn_m)),
      (length(cn_e)+1):(length(cn_e)+length(cn_m))] <- Vm
    off3 <- length(cn_e)+length(cn_m)
    V[(off3+1):(off3+length(cn_i)), (off3+1):(off3+length(cn_i))] <- Vi
    off4 <- off3+length(cn_i)
    V[(off4+1):(off4+length(cn_g)), (off4+1):(off4+length(cn_g))] <- Vg
    R <- matrix(0, nrow=length(idx), ncol=length(b)); R[cbind(seq_along(idx),
idx)] <- 1
    Rb <- as.numeric(R %*% b); RVRT <- R %*% V %*% t(R)
    Vinv <- try(solve(RVRT), silent=TRUE); if (inherits(Vinv, "try-error")) Vinv
<- MASS::ginv(RVRT)
    W <- as.numeric(t(Rb) %*% Vinv %*% Rb); dfW <- qr(R)$rank; pW <- pchisq(W,
df=dfW, lower.tail=FALSE)
    wald_tab <- data.frame(Test = "H0: ESG_share_{t-1} jointly zero across all
equations (OLS fallback)",
                           Lag_p = 1, DF = dfW, Wald_ChiSq = round(W,4),
                           P_Value = formatC(pW, format="f", digits=4))
  }
  if (!is.null(wald_tab)) {
    doc <- add_ft(doc, wald_tab)
    doc <- officer::body_add_par(doc,
      if (as.numeric(wald_tab$P_Value) < 0.05)
        "Decision (5%): Reject H0 — ESG intensity adds incremental explanatory
power, conditional on VAR lags."
      else
        "Decision (5%): Fail to reject H0 — ESG intensity does not add
explanatory power beyond VAR lags.",
      style = "Normal")
  } else {
    doc <- officer::body_add_par(doc, "Wald test could not be computed (singular
covariance).", style = "Normal")
  }
} else {
  doc <- officer::body_add_par(doc, "Too few aligned observations for the SUR-
based Wald test.", style = "Normal")
}
doc <- officer::body_add_break(doc)


# ======================================
# Save Word document
```

```r
# ========================================
if (file.exists(out_path)) file.remove(out_path)
print(doc, target = out_path)
message("Done. Results written to: ", out_path)


# ======================
# TVPI (LEVEL) VAR MODEL
# ======================

# Load libraries
library(vars)
library(tseries)
library(readr)
library(officer)
library(flextable)
library(ggplot2)
library(tidyr)
library(dplyr)
library(reshape2)
library(broom)
library(car)

set.seed(123)  # for IRF bootstraps

# ----------------------
# 1. Read Data
# ----------------------
df <- read_csv("C:/Users/BB/Desktop/HEC Thesis/Data Test2.csv", show_col_types =
FALSE)

# Keep variables of interest
data_VAR <- df[, c("IRR", "DPI", "TVPI", "MKT", "INT", "GDP")]
doc <- read_docx()

# ----------------------
# 2. Stationarity Test (Level Data for all variables)
# ----------------------
adf_test_results <- lapply(data_VAR, function(x) {
  adf_test <- adf.test(x)
  data.frame(
    Statistic = round(adf_test$statistic, 4),
    P_Value = round(adf_test$p.value, 4)
  )
})
```

```
adf_test_table <- do.call(rbind, adf_test_results)
adf_test_table$Variable <- rownames(adf_test_table)
rownames(adf_test_table) <- NULL
adf_test_table <- adf_test_table[, c("Variable", "Statistic", "P_Value")]

doc <- body_add_par(doc, "1. Stationarity Test Results (Levels)", style =
"heading 1")
doc <- body_add_flextable(doc, flextable(adf_test_table))
doc <- body_add_break(doc)

# ----------------------
# 2b. Multicollinearity Test: VIF (Fund-level endogenous block)
#     TVPI is the focus; check collinearity with IRR & DPI (fund metrics)
# ----------------------
vif_model_endo <- lm(TVPI ~ IRR + DPI, data = data_VAR)
vif_values_endo <- vif(vif_model_endo)
vif_table_endo <- data.frame(
  Variable = names(vif_values_endo),
  VIF = round(as.numeric(vif_values_endo), 4)
)

doc <- body_add_par(doc, "Multicollinearity Test: Fund Metrics (VIF)", style =
"heading 1")
doc <- body_add_flextable(doc, flextable(vif_table_endo))
doc <- body_add_break(doc)

# ----------------------
# 2c. Multicollinearity Test: VIF (Macro block)
# ----------------------
vif_model_exog <- lm(MKT ~ INT + GDP, data = data_VAR)
vif_values_exog <- vif(vif_model_exog)
vif_table_exog <- data.frame(
  Variable = names(vif_values_exog),
  VIF = round(as.numeric(vif_values_exog), 4)
)

doc <- body_add_par(doc, "Multicollinearity Test: Macro Variables (VIF)", style =
"heading 1")
doc <- body_add_flextable(doc, flextable(vif_table_exog))
doc <- body_add_break(doc)

# ----------------------
# 3. VAR in LEVELS (TVPI, MKT, INT, GDP)
#    Note: We keep TVPI in levels as requested
# ----------------------
```

```r
data_VAR_final <- data_VAR[, c("TVPI", "MKT", "INT", "GDP")] %>% na.omit()

# ----------------------
# 4. VAR Lag Selection
# ----------------------
lag_selection <- VARselect(data_VAR_final, lag.max = 5, type = "const")
best_p <- lag_selection$selection["AIC(n)"]
lag_table <- as.data.frame(round(lag_selection$criteria, 4))
lag_table$Criterion <- rownames(lag_table)
rownames(lag_table) <- NULL

doc <- body_add_par(doc, "2. VAR Lag Selection Results", style = "heading 1")
doc <- body_add_flextable(doc, flextable(lag_table))
doc <- body_add_break(doc)

# ----------------------
# 5. Fit VAR Model (Levels)
# ----------------------
var_model <- VAR(data_VAR_final, p = best_p, type = "const")

doc <- body_add_par(doc, paste0("3. VAR(", best_p, ") Model Summary – Levels"),
style = "heading 1")
for (eqn in names(var_model$varresult)) {
  tidy_eqn <- tidy(var_model$varresult[[eqn]]) %>%
    mutate(across(where(is.numeric), ~ round(., 4)))

  eqn_text <- paste0(
    eqn, " ~ ", paste(
      paste0(ifelse(tidy_eqn$estimate >= 0, "+ ", "- "),
             abs(tidy_eqn$estimate), " * ", tidy_eqn$term),
      collapse = " ")
  )
  eqn_text <- sub("^\\+ ", "", eqn_text)

  doc <- body_add_par(doc, paste0("Equation for: ", eqn), style = "heading 2")
  doc <- body_add_par(doc, eqn_text, style = "Normal")
  doc <- body_add_flextable(doc, flextable(tidy_eqn))
  doc <- body_add_break(doc)
}

# ----------------------
# 6. Residual Serial Correlation (Portmanteau Test)
# ----------------------
serial_result <- serial.test(var_model, lags.pt = 12, type = "PT.asymptotic")
serial_test_table <- data.frame(
```

```
  Test_Type = "Portmanteau (asymptotic)",
  Chi_Squared = round(serial_result$serial$statistic, 4),
  DF = serial_result$serial$parameter,
  P_Value = round(serial_result$serial$p.value, 4)
)

doc <- body_add_par(doc, "4. Residual Serial Correlation Test", style = "heading 
1")
doc <- body_add_flextable(doc, flextable(serial_test_table))
doc <- body_add_break(doc)

# ----------------------
# 7. Impulse Response Functions (IRFs) — response = TVPI (level)
# ----------------------
irf_result <- irf(
  var_model,
  impulse = c("MKT", "INT", "GDP"),
  response = "TVPI",
  boot = TRUE, ci = 0.95, runs = 500
)

steps <- 0:(length(irf_result$irf$MKT)-1)
irf_df <- data.frame(
  Step = rep(steps, 3),
  IRF = c(irf_result$irf$MKT, irf_result$irf$INT, irf_result$irf$GDP),
  Lower = c(irf_result$Lower$MKT, irf_result$Lower$INT, irf_result$Lower$GDP),
  Upper = c(irf_result$Upper$MKT, irf_result$Upper$INT, irf_result$Upper$GDP),
  Shock = rep(c("Market Return (MKT)", "Interest Rate (INT)", "GDP Growth 
(GDP)"), each = length(steps))
)

irf_plot <- ggplot(irf_df, aes(x = Step, y = IRF, group = Shock, color = Shock, 
fill = Shock)) +
  geom_ribbon(aes(ymin = Lower, ymax = Upper), alpha = 0.2, color = NA) +
  geom_line(size = 1) +
  facet_wrap(~Shock, scales = "free_y", ncol = 2) +
  labs(
    title = "Impulse Response Functions for TVPI (Levels)",
    x = "Horizon (Steps)",
    y = "IRF Value"
  ) +
  theme_minimal(base_size = 13, base_family = "Times New Roman") +
  theme(
    plot.title = element_text(hjust = 0.5, face = "bold", family = "Times New 
Roman"),
```

```r
    axis.title = element_text(family = "Times New Roman"),
    axis.text = element_text(family = "Times New Roman"),
    strip.text = element_text(size = 12, face = "bold", family = "Times New
Roman"),
    legend.text = element_text(family = "Times New Roman"),
    legend.title = element_text(family = "Times New Roman"),
    legend.position = "none"
  )

ggsave("IRF_plot_TVPI_levels.png", plot = irf_plot, width = 8, height = 6, dpi =
300)
doc <- body_add_par(doc, "5. Impulse Response Functions (with 95% CI)", style =
"heading 1")
doc <- body_add_img(doc, src = "IRF_plot_TVPI_levels.png", width = 6, height = 4)
doc <- body_add_break(doc)

# ----------------------
# 8. Forecast Error Variance Decomposition (FEVD)
# ----------------------
fevd_result <- fevd(var_model, n.ahead = 10)
fevd_long <- bind_rows(lapply(names(fevd_result), function(var) {
  temp <- as.data.frame(fevd_result[[var]])
  temp$Horizon <- 1:nrow(temp)
  temp$Response <- var
  temp
}))

fevd_long_melt <- pivot_longer(fevd_long, cols = -c(Horizon, Response), names_to
= "Shock", values_to = "Contribution")

fevd_plot <- ggplot(fevd_long_melt, aes(x = Horizon, y = Contribution, fill =
Shock)) +
  geom_bar(stat = "identity", position = "stack") +
  geom_text(
    aes(label = sprintf("%.4f", Contribution)),
    position = position_stack(vjust = 0.5),
    size = 3,
    color = "black",
    family = "Times New Roman"
  ) +
  facet_wrap(~Response, ncol = 2, scales = "free_y") +
  labs(
    title = "Forecast Error Variance Decomposition (FEVD) – Levels",
    x = "Horizon",
    y = "Contribution",
```

```
    fill = "Shock"
  ) +
  theme_minimal(base_size = 13, base_family = "Times New Roman") +
  theme(
    plot.title = element_text(hjust = 0.5, face = "bold", family = "Times New
Roman"),
    axis.title = element_text(size = 12, family = "Times New Roman"),
    axis.text = element_text(family = "Times New Roman"),
    strip.text = element_text(size = 12, face = "bold", family = "Times New
Roman"),
    legend.text = element_text(family = "Times New Roman"),
    legend.title = element_text(family = "Times New Roman")
  )

ggsave("FEVD_plot_TVPI_levels.png", plot = fevd_plot, width = 10, height = 6, dpi
= 300)
doc <- body_add_par(doc, "6. Forecast Error Variance Decomposition (FEVD)", style
= "heading 1")
doc <- body_add_img(doc, src = "FEVD_plot_TVPI_levels.png", width = 6, height =
4)

# ----------------------
# 9. Save Word Document (TVPI in levels)
# ----------------------
out_path <- "C:/Users/BB/Desktop/HEC Thesis/TVPI_VAR_Results.docx"
if (file.exists(out_path)) file.remove(out_path)
print(doc, target = out_path)
```

Appendix 2. TVPI_VAR Results

Figure A2.1 Multicollinearity Test: Fund Metrics (VIF)

Variable	VIF
IRR	1.151
DPI	1.151
INT	1.272
GDP	1.272

Figure A2.2 VAR Lag Selection Results

1	2	3	4	5	Criterion
-19.5875	-19.7046	-19.7610	-19.7972	-19.8161	AIC(n)
-19.5849	-19.6999	-19.7542	-19.7883	-19.8051	HQ(n)
-19.5796	-19.6902	-19.7402	-19.7701	-19.7825	SC(n)
0.0000	0.0000	0.0000	0.0000	0.0000	FPE(n)

Figure A2.3 VAR(5) Model Summary — Levels

Figure A2.3.1 Equation for: TVPI

TVPI ~ + 0.206 * TVPI.l1 + 0.0021 * MKT.l1 + 2.3429 * INT.l1 - 2.0371 * GDP.l1 + 0.1656 * TVPI.l2 - 0.0186 * MKT.l2 - 0.9485 * INT.l2 - 0.7806 * GDP.l2 + 0.1413 * TVPI.l3 - 0.027 * MKT.l3 - 1.3308 * INT.l3 - 0.2918 * GDP.l3 + 0.1418 * TVPI.l4 - 0.0236 * MKT.l4 - 0.0894 * INT.l4 - 1.1653 * GDP.l4 + 0.1257 * TVPI.l5 - 0.0369 * MKT.l5 - 1.3469 * INT.l5 - 0.951 * GDP.l5 + 0.6328

term	estimate	std.error	statistic	p.value
TVPI.l1	0.2060	0.0073	28.1743	0.0000
MKT.l1	0.0021	0.0072	0.2962	0.7671
INT.l1	2.3429	0.4239	5.5275	0.0000
GDP.l1	-2.0371	0.3381	-6.0253	0.0000
TVPI.l2	0.1656	0.0074	22.3883	0.0000
MKT.l2	-0.0186	0.0074	-2.5267	0.0115
INT.l2	-0.9485	0.4458	-2.1279	0.0334
GDP.l2	-0.7806	0.3433	-2.2740	0.0230
TVPI.l3	0.1413	0.0074	19.0336	0.0000
MKT.l3	-0.0270	0.0074	-3.6612	0.0003
INT.l3	-1.3308	0.4461	-2.9832	0.0029
GDP.l3	-0.2918	0.3435	-0.8496	0.3956
TVPI.l4	0.1418	0.0074	19.1641	0.0000
MKT.l4	-0.0236	0.0074	-3.2020	0.0014
INT.l4	-0.0894	0.4459	-0.2005	0.8411
GDP.l4	-1.1653	0.3434	-3.3932	0.0007
TVPI.l5	0.1257	0.0073	17.1931	0.0000
MKT.l5	-0.0369	0.0072	-5.1367	0.0000
INT.l5	-1.3469	0.4250	-3.1692	0.0015
GDP.l5	-0.9510	0.3388	-2.8070	0.0050
const	0.6328	0.0280	22.6168	0.0000

Figure A2.3.2 Equation for: MKT

MKT ~ + 0.0039 * TVPI.l1 + 0.2025 * MKT.l1 + 3.8586 * INT.l1 - 1.5047 * GDP.l1 + 0.0124 * TVPI.l2 + 0.0595 * MKT.l2 + 1.2125 * INT.l2 - 0.166 * GDP.l2 + 0.0146 * TVPI.l3 + 0.0313 * MKT.l3 + 0.6365 * INT.l3 - 0.2621 * GDP.l3 + 0.0166 * TVPI.l4 + 0.0145 * MKT.l4 + 0.6864 * INT.l4 - 0.5853 * GDP.l4 + 0.0025 * TVPI.l5 + 0.0329 * MKT.l5 + 1.5759 * INT.l5 - 0.5854 * GDP.l5 + 0.1539

term	estimate	std.error	statistic	p.value
TVPI.l1	0.0039	0.0076	0.5109	0.6094
MKT.l1	0.2025	0.0075	26.8932	0.0000
INT.l1	3.8586	0.4412	8.7460	0.0000
GDP.l1	-1.5047	0.3519	-4.2760	0.0000
TVPI.l2	0.0124	0.0077	1.6129	0.1068
MKT.l2	0.0595	0.0077	7.7481	0.0000
INT.l2	1.2125	0.4640	2.6134	0.0090
GDP.l2	-0.1660	0.3573	-0.4646	0.6422
TVPI.l3	0.0146	0.0077	1.8955	0.0580
MKT.l3	0.0313	0.0077	4.0707	0.0000
INT.l3	0.6365	0.4643	1.3709	0.1704
GDP.l3	-0.2621	0.3575	-0.7332	0.4635
TVPI.l4	0.0166	0.0077	2.1543	0.0312
MKT.l4	0.0145	0.0077	1.8935	0.0583
INT.l4	0.6864	0.4641	1.4790	0.1392
GDP.l4	-0.5853	0.3575	-1.6375	0.1015
TVPI.l5	0.0025	0.0076	0.3278	0.7431
MKT.l5	0.0329	0.0075	4.3989	0.0000
INT.l5	1.5759	0.4424	3.5624	0.0004
GDP.l5	-0.5854	0.3526	-1.6600	0.0969
const	0.1539	0.0291	5.2853	0.0000

Figure A2.3.3 Equation for: INT

INT ~ - 4e-04 * TVPI.l1 + 0 * MKT.l1 + 0.3307 * INT.l1 - 0.0221 * GDP.l1 - 4e-04 * TVPI.l2 - 1e-04 * MKT.l2 + 0.0662 * INT.l2 + 0.0023 * GDP.l2 - 5e-04 * TVPI.l3 + 0 * MKT.l3 + 0.0531 * INT.l3 + 0.0033 * GDP.l3 - 5e-04 * TVPI.l4 - 2e-04 * MKT.l4 + 0.0552 * INT.l4 + 0.007 * GDP.l4 - 2e-04 * TVPI.l5 - 2e-04 * MKT.l5 + 0.017 * INT.l5 + 0.0091 * GDP.l5 + 0.0207

term	estimate	std.error	statistic	p.value
TVPI.l1	-0.0004	0.0001	-2.7341	0.0063
MKT.l1	0.0000	0.0001	0.1395	0.8890
INT.l1	0.3307	0.0081	40.9937	0.0000
GDP.l1	-0.0221	0.0064	-3.4412	0.0006
TVPI.l2	-0.0004	0.0001	-3.0665	0.0022
MKT.l2	-0.0001	0.0001	-0.5914	0.5542
INT.l2	0.0662	0.0085	7.7979	0.0000
GDP.l2	0.0023	0.0065	0.3453	0.7299
TVPI.l3	-0.0005	0.0001	-3.4384	0.0006
MKT.l3	0.0000	0.0001	0.2947	0.7682
INT.l3	0.0531	0.0085	6.2559	0.0000
GDP.l3	0.0033	0.0065	0.5099	0.6102
TVPI.l4	-0.0005	0.0001	-3.5143	0.0004
MKT.l4	-0.0002	0.0001	-1.5405	0.1235
INT.l4	0.0552	0.0085	6.4999	0.0000
GDP.l4	0.0070	0.0065	1.0654	0.2867
TVPI.l5	-0.0002	0.0001	-1.2645	0.2061
MKT.l5	-0.0002	0.0001	-1.5935	0.1111
INT.l5	0.0170	0.0081	2.1001	0.0357
GDP.l5	0.0091	0.0064	1.4063	0.1596
const	0.0207	0.0005	38.9526	0.0000

Figure A2.3.4 Equation for: GDP

GDP ~ - 1e-04 * TVPI.l1 - 4e-04 * MKT.l1 + 0.0523 * INT.l1 + 0.1568 * GDP.l1 - 3e-04 * TVPI.l2 + 0 * MKT.l2 + 0.0213 * INT.l2 + 0.0349 * GDP.l2 - 4e-04 * TVPI.l3 + 0 * MKT.l3 + 0.0106 * INT.l3 + 0.0155 * GDP.l3 - 5e-04 * TVPI.l4 + 0 * MKT.l4 + 0.0322 * INT.l4 + 0.0136 * GDP.l4 - 4e-04 * TVPI.l5 + 1e-04 * MKT.l5 + 0.013 * INT.l5 - 0.01 * GDP.l5 + 0.0237

term	estimate	std.error	statistic	p.value
TVPI.l1	-0.0001	0.0002	-0.6244	0.5324
MKT.l1	-0.0004	0.0002	-2.4231	0.0154
INT.l1	0.0523	0.0100	5.2385	0.0000
GDP.l1	0.1568	0.0080	19.6879	0.0000
TVPI.l2	-0.0003	0.0002	-1.9755	0.0482
MKT.l2	0.0000	0.0002	-0.0576	0.9541
INT.l2	0.0213	0.0105	2.0331	0.0421
GDP.l2	0.0349	0.0081	4.3157	0.0000
TVPI.l3	-0.0004	0.0002	-2.5664	0.0103
MKT.l3	0.0000	0.0002	-0.2782	0.7808
INT.l3	0.0106	0.0105	1.0088	0.3131
GDP.l3	0.0155	0.0081	1.9159	0.0554
TVPI.l4	-0.0005	0.0002	-2.8952	0.0038
MKT.l4	0.0000	0.0002	-0.2240	0.8228
INT.l4	0.0322	0.0105	3.0675	0.0022
GDP.l4	0.0136	0.0081	1.6754	0.0939
TVPI.l5	-0.0004	0.0002	-2.5082	0.0121
MKT.l5	0.0001	0.0002	0.6468	0.5178
INT.l5	0.0130	0.0100	1.2987	0.1941
GDP.l5	-0.0100	0.0080	-1.2548	0.2096
const	0.0237	0.0007	35.9301	0.0000

Figure A2.4 Impulse Response Functions (with 95% CI)

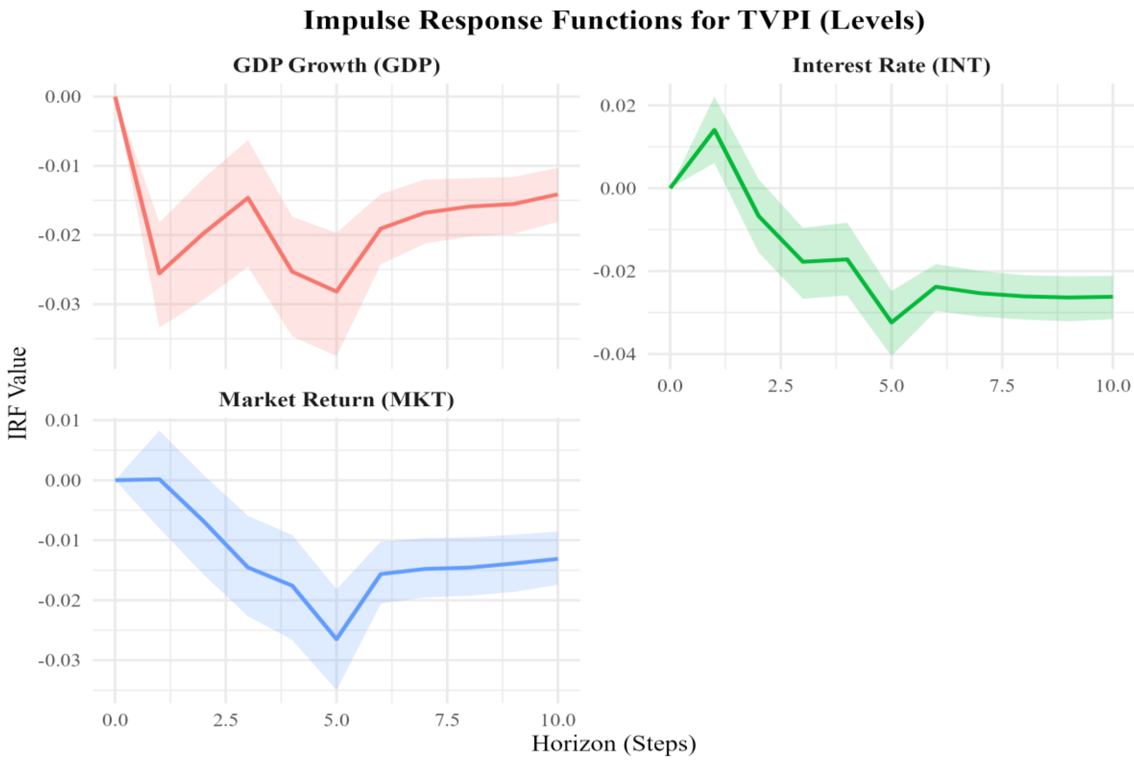
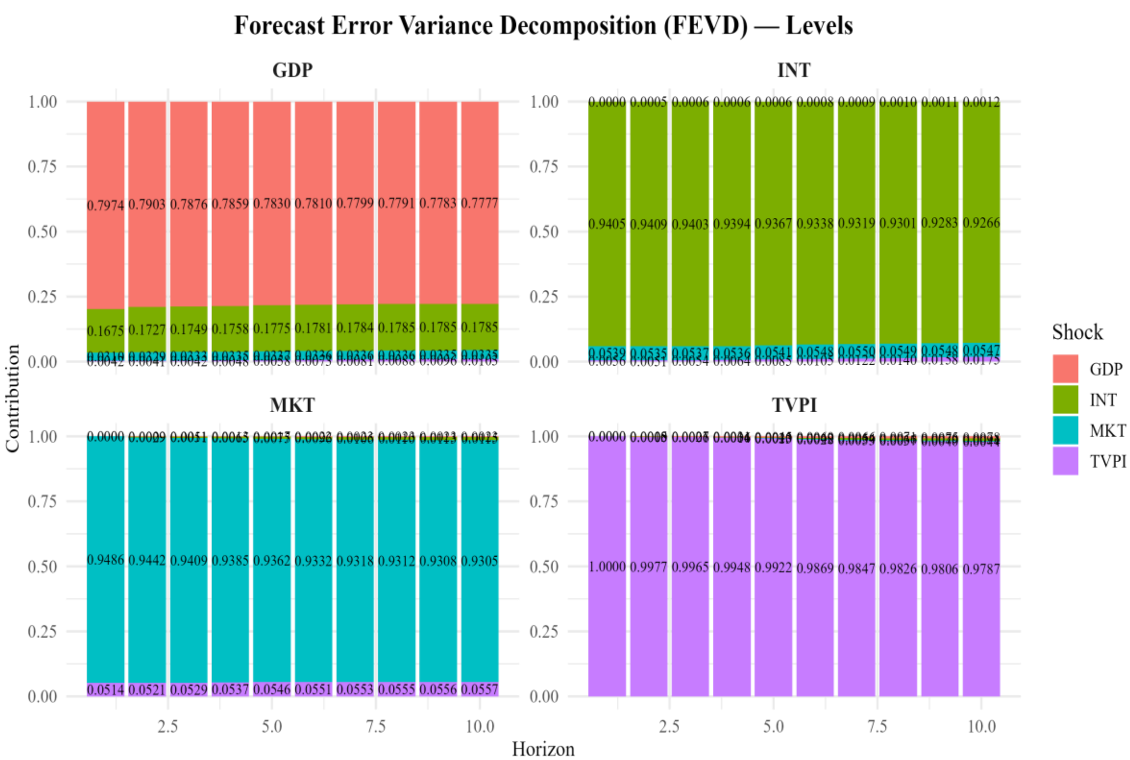


Figure A2.5 Forecast Error Variance Decomposition (FEVD)



Appendix 3. DPI_VAR Results

Figure A3.1 Multicollinearity Test: Fund Metrics (VIF)

Variable	VIF
IRR	1.418
TVPI	1.418
INT	1.272
GDP	1.272

Figure A3.2 VAR Lag Selection Results

1	2	3	4	5	Criterion
-19.6747	-19.7671	-19.8153	-19.8431	-19.8604	AIC(n)
-19.6720	-19.7624	-19.8085	-19.8342	-19.8494	HQ(n)
-19.6667	-19.7528	-19.7946	-19.8159	-19.8269	SC(n)
0.0000	0.0000	0.0000	0.0000	0.0000	FPE(n)

Figure A3.3 VAR(5) Model Summary — Levels

Figure A3.3.1 Equation for: DPI

DPI ~ + 0.2164 * DPI.l1 + 0.0042 * MKT.l1 + 5.4039 * INT.l1 - 2.3182 * GDP.l1 + 0.1486 * DPI.l2 - 0.0543 * MKT.l2 - 2.2781 * INT.l2 - 0.604 * GDP.l2 + 0.127 * DPI.l3 - 0.0572 * MKT.l3 - 2.5245 * INT.l3 - 0.4237 * GDP.l3 + 0.1141 * DPI.l4 - 0.0645 * MKT.l4 - 0.9799 * INT.l4 - 1.2852 * GDP.l4 + 0.1114 * DPI.l5 - 0.07 * MKT.l5 - 2.1562 * INT.l5 - 1.1486 * GDP.l5 + 0.6924

term	estimate	std.error	statistic	p.value
DPI.l1	0.2164	0.0089	24.1832	0.0000
MKT.l1	0.0042	0.0101	0.4179	0.6760
INT.l1	5.4039	0.5510	9.8077	0.0000
GDP.l1	-2.3182	0.4028	-5.7557	0.0000
DPI.l2	0.1486	0.0091	16.3272	0.0000
MKT.l2	-0.0543	0.0103	-5.2698	0.0000
INT.l2	-2.2781	0.5765	-3.9514	0.0001
GDP.l2	-0.6040	0.4087	-1.4779	0.1394
DPI.l3	0.1270	0.0091	13.9301	0.0000
MKT.l3	-0.0572	0.0103	-5.5525	0.0000
INT.l3	-2.5245	0.5770	-4.3749	0.0000
GDP.l3	-0.4237	0.4089	-1.0361	0.3002
DPI.l4	0.1141	0.0091	12.5483	0.0000
MKT.l4	-0.0645	0.0103	-6.2797	0.0000
INT.l4	-0.9799	0.5767	-1.6990	0.0893
GDP.l4	-1.2852	0.4089	-3.1432	0.0017
DPI.l5	0.1114	0.0089	12.4621	0.0000
MKT.l5	-0.0700	0.0100	-6.9831	0.0000
INT.l5	-2.1562	0.5520	-3.9063	0.0001
GDP.l5	-1.1486	0.4033	-2.8477	0.0044
const	0.6924	0.0284	24.3969	0.0000

Figure A3.3.2 Equation for: MKT

MKT ~ - 0.0085 * DPI.l1 + 0.209 * MKT.l1 + 4.0262 * INT.l1 - 1.5232 * GDP.l1 + 0.0057 * DPI.l2 + 0.0592 * MKT.l2 + 1.0918 * INT.l2 - 0.1881 * GDP.l2 + 0.0145 * DPI.l3 + 0.0259 * MKT.l3 + 0.3 * INT.l3 - 0.2877 * GDP.l3 + 0.021 * DPI.l4 + 0.0053 * MKT.l4 + 0.201 * INT.l4 - 0.595 * GDP.l4 + 0.0122 * DPI.l5 + 0.0254 * MKT.l5 + 1.2391 * INT.l5 - 0.6267 * GDP.l5 + 0.2464

term	estimate	std.error	statistic	p.value
DPI.l1	-0.0085	0.0078	-1.0944	0.2738
MKT.l1	0.2090	0.0088	23.6898	0.0000
INT.l1	4.0262	0.4809	8.3724	0.0000
GDP.l1	-1.5232	0.3515	-4.3332	0.0000
DPI.l2	0.0057	0.0079	0.7188	0.4723
MKT.l2	0.0592	0.0090	6.5878	0.0000
INT.l2	1.0918	0.5032	2.1699	0.0300
GDP.l2	-0.1881	0.3567	-0.5273	0.5980
DPI.l3	0.0145	0.0080	1.8186	0.0690
MKT.l3	0.0259	0.0090	2.8756	0.0040
INT.l3	0.3000	0.5036	0.5957	0.5514
GDP.l3	-0.2877	0.3569	-0.8061	0.4202
DPI.l4	0.0210	0.0079	2.6424	0.0082
MKT.l4	0.0053	0.0090	0.5895	0.5555
INT.l4	0.2010	0.5034	0.3993	0.6896
GDP.l4	-0.5950	0.3568	-1.6673	0.0955
DPI.l5	0.0122	0.0078	1.5635	0.1180
MKT.l5	0.0254	0.0088	2.9045	0.0037
INT.l5	1.2391	0.4818	2.5720	0.0101
GDP.l5	-0.6267	0.3520	-1.7804	0.0750
const	0.2464	0.0248	9.9478	0.0000

Figure A3.3.3 Equation for: INT

INT ~ + 2e-04 * DPI.l1 - 2e-04 * MKT.l1 + 0.328 * INT.l1 - 0.0218 * GDP.l1 - 2e-04 * DPI.l2 - 1e-04 * MKT.l2 + 0.0713 * INT.l2 + 0.0034 * GDP.l2 - 5e-04 * DPI.l3 + 3e-04 * MKT.l3 + 0.0664 * INT.l3 + 0.0044 * GDP.l3 - 5e-04 * DPI.l4 + 0 * MKT.l4 + 0.0666 * INT.l4 + 0.0077 * GDP.l4 - 4e-04 * DPI.l5 + 0 * MKT.l5 + 0.0296 * INT.l5 + 0.0106 * GDP.l5 + 0.0171

term	estimate	std.error	statistic	p.value
DPI.l1	0.0002	0.0001	1.1200	0.2627
MKT.l1	-0.0002	0.0002	-1.1488	0.2506
INT.l1	0.3280	0.0088	37.2325	0.0000
GDP.l1	-0.0218	0.0064	-3.3800	0.0007
DPI.l2	-0.0002	0.0001	-1.4791	0.1391
MKT.l2	-0.0001	0.0002	-0.3955	0.6925
INT.l2	0.0713	0.0092	7.7327	0.0000
GDP.l2	0.0034	0.0065	0.5267	0.5984
DPI.l3	-0.0005	0.0001	-3.6937	0.0002
MKT.l3	0.0003	0.0002	1.5537	0.1203
INT.l3	0.0664	0.0092	7.2018	0.0000
GDP.l3	0.0044	0.0065	0.6659	0.5055
DPI.l4	-0.0005	0.0001	-3.2188	0.0013
MKT.l4	0.0000	0.0002	-0.2447	0.8067
INT.l4	0.0666	0.0092	7.2255	0.0000
GDP.l4	0.0077	0.0065	1.1712	0.2416
DPI.l5	-0.0004	0.0001	-3.1370	0.0017
MKT.l5	0.0000	0.0002	0.2008	0.8409
INT.l5	0.0296	0.0088	3.3562	0.0008
GDP.l5	0.0106	0.0064	1.6467	0.0996
const	0.0171	0.0005	37.7238	0.0000

Figure A3.3.4 Equation for: GDP

GDP ~ + 6e-04 * DPI.l1 - 8e-04 * MKT.l1 + 0.0391 * INT.l1 + 0.1573 * GDP.l1 + 0 * DPI.l2 - 1e-04 * MKT.l2 + 0.0204 * INT.l2 + 0.0362 * GDP.l2 - 5e-04 * DPI.l3 + 1e-04 * MKT.l3 + 0.0224 * INT.l3 + 0.017 * GDP.l3 - 6e-04 * DPI.l4 + 2e-04 * MKT.l4 + 0.0485 * INT.l4 + 0.0147 * GDP.l4 - 9e-04 * DPI.l5 + 6e-04 * MKT.l5 + 0.0356 * INT.l5 - 0.0088 * GDP.l5 + 0.0203

term	estimate	std.error	statistic	p.value
DPI.l1	0.0006	0.0002	3.5148	0.0004
MKT.l1	-0.0008	0.0002	-4.1965	0.0000
INT.l1	0.0391	0.0109	3.5883	0.0003
GDP.l1	0.1573	0.0080	19.7627	0.0000
DPI.l2	0.0000	0.0002	0.1971	0.8437
MKT.l2	-0.0001	0.0002	-0.6599	0.5093
INT.l2	0.0204	0.0114	1.7897	0.0735
GDP.l2	0.0362	0.0081	4.4813	0.0000
DPI.l3	-0.0005	0.0002	-2.5579	0.0105
MKT.l3	0.0001	0.0002	0.5922	0.5537
INT.l3	0.0224	0.0114	1.9619	0.0498
GDP.l3	0.0170	0.0081	2.1097	0.0349
DPI.l4	-0.0006	0.0002	-3.5734	0.0004
MKT.l4	0.0002	0.0002	1.1800	0.2380
INT.l4	0.0485	0.0114	4.2594	0.0000
GDP.l4	0.0147	0.0081	1.8254	0.0679
DPI.l5	-0.0009	0.0002	-5.0443	0.0000
MKT.l5	0.0006	0.0002	2.9180	0.0035
INT.l5	0.0356	0.0109	3.2632	0.0011
GDP.l5	-0.0088	0.0080	-1.0994	0.2716
const	0.0203	0.0006	36.1209	0.0000

Figure A3.4 Impulse Response Functions (with 95% CI)

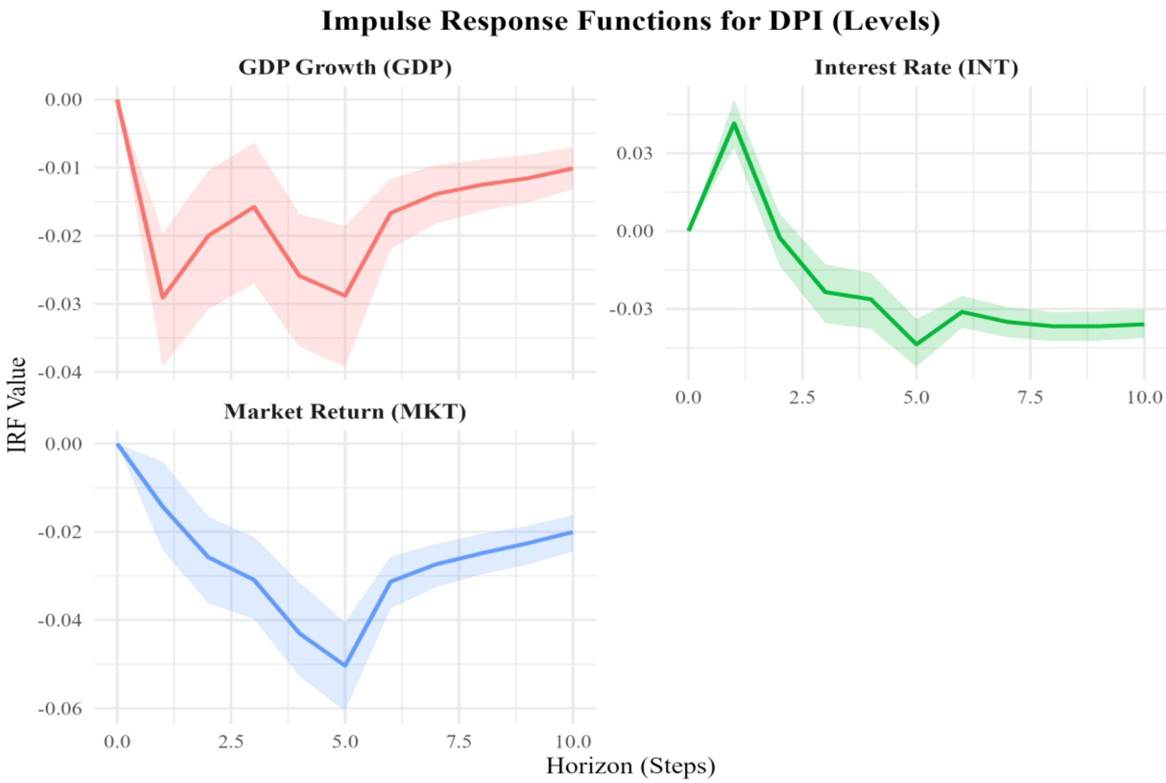


Figure A3.5 Forecast Error Variance Decomposition (FEVD)