How large language models incorporate venture capital into investor portfolios[*]

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Abstract

This study examines whether large language models (LLMs) can effectively assist investors in incorporating venture capital (VC) investments into their portfolios. Using 48 hypothetical investor profiles that vary in VC focus, investor status, investment horizon, risk tolerance, and home country, we elicit portfolio recommendations from four reasoning LLMs. We find that LLMs incorporate VC preferences by increasing allocations to VC-like investment products and decreasing allocations to public equity and fixed income. LLMs recommend larger VC allocations to accredited investors than to retail investors. VC-focused prompts generate portfolios that mirror the more aggressive risk–return characteristics of VC investments. These portfolios exhibit higher exposure to the Fama–French size factor, lower exposure to the investment factor, higher historical excess returns and alphas, and additional risk that is primarily systematic. Overall, our results suggest that LLMs can incorporate nuanced investment objectives, potentially assisting investors with VC portfolio construction and broadening retail investors' access to VC-style investments.

Keywords: Large language models · venture capital · financial advice
JEL-Classification: G24 · G50

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1 Introduction

Retail investors' access to alternative asset classes has expanded, for example, through the provisions of the European Long-Term Investment Fund (ELTIF) regulation, which allows funds that invest in long-term and private market assets – including public venture capital (VC) investment funds – to be offered to retail buyers with lower barriers to entry (European Commission, 2024). Such developments have prompted several fund providers and brokers to introduce ELTIF products for retail investors (BlackRock, 2025; Bloomberg, 2025; S&P Global Market Intelligence, 2025). Despite this broader access, ELTIFs and similar investments continue to pose substantial challenges for investors. The assets underlying ELTIFs are often illiquid, with limited redemption options and extended capital lock-ups. The complexity and opacity of these investment structures make the assessment of risk, valuation, and performance difficult. In addition, high management and performance fees, often compounded by intermediary charges, can erode net returns. The assets underlying ELTIFs also tend to be concentrated, exposing investors to idiosyncratic project risks (e.g., BaFin, 2024; Cumming et al., 2023; Harrison and Mason, 2019).

Investor protection regulations, including EU's MiFID II (ESMA, 2023) and corresponding SEC mandates (SEC, 2019), require financial advisors to tailor recommendations to individual client circumstances. As advisory services evolve, large language models (LLMs) have emerged as innovative tools that can provide financial advice.[1] Previous studies suggest that LLMs can generate portfolio recommendations that account for broad investor characteristics, including risk tolerance, age, and investment horizon (e.g., Fieberg et al., 2024; Hens and Nordlie, 2025; Oehler and Horn, 2024). However, the question of whether LLMs can incorporate more specialized investment constraints and preferences remains underexplored.

The present article focuses on VC investments for three main reasons. First, gaining exposure to VC is operationally complex, especially for non-accredited investors. Retail investors typically gain access to VC through publicly traded VC vehicles or specialized funds, which

[1] Advancements in artificial intelligence (AI) enable LLMs to generate plausible research ideas, literature reviews, and empirical test designs (Dowling and Lucey, 2023). LLMs are expected to challenge business models across sectors (Stubbings and Wood, 2025). In public information-based domains, advanced AI may even replace established advisory services (Fieberg et al., 2023, 2024; Lopez-Lira and Tang, 2023).

differ from equities or bonds in terms of liquidity, fees, and disclosure (Cumming et al., 2023; Lerner and Nanda, 2020). Second, VC plays a distinctive role in the economy, financing innovation, supporting the professionalization of young firms, and shaping product–market strategies (Hellmann and Puri, 2000; Chemmanur et al., 2014). VC also fosters knowledge spillover through networks (González-Uribe, 2020) and relies on decision-making processes that differ from traditional asset management (Cumming et al., 2023), introducing risks not present in conventional investments. Third, VC has grown in economic importance and is increasingly accessible to retail investors (Harrison and Mason, 2019).[2] Against this backdrop, we examine whether LLMs can effectively assist investors in incorporating VC investments into their portfolios.

To answer our research question, we have requested portfolio recommendations for 48 hypothetical investor profiles from four reasoning LLMs: DeepSeek R1, Gemini 2.0 Flash Thinking, GPT-o1, and Grok-3. The profiles vary along five investor characteristics: (1) whether the prompt explicitly requests VC investments (yes or no), (2) investor status (accredited or retail), (3) risk tolerance (high or low), (4) investment horizon (5 or 20 years), and (5) home country (China, United Kingdom [UK], or United States [US]). We focus on reasoning LLMs because they improve accuracy and transparency through step-by-step problem-solving, generalize across domains, and reduce output errors by internally verifying consistency before finalizing answers (Gibney, 2025; Jones, 2025). To analyze the LLM-generated portfolio recommendations, we analyze two dimensions. First, we examine portfolio composition, including allocations across asset classes and market exposures. Second, we estimate factor exposures using the Fama–French six-factor model and assess performance based on historical monthly excess returns, total and idiosyncratic volatility, Fama–French six-factor alphas, annual Sharpe ratios, and total expense ratios.

We document three main findings. First, in terms of portfolio composition, VC-focused investment prompts lead LLMs to generate portfolios that differ markedly from those generated without such a focus. When prompted to include VC, LLMs incorporate VC preferences by increasing allocations to VC-like investment products and decreasing allocations to public equity

[2] VC investors are also central to the development of generative AI. For example, OpenAI's late-stage funding round in October 2024 raised USD 6.6 billion, with backing from Tiger Global and Khosla Ventures.

and fixed income. LLMs also recommend larger VC allocations to accredited investors than to retail investors. Second, for portfolios restricted to publicly traded assets, VC-focused prompts lead LLMs to recommend portfolios that mirror the more aggressive risk–return profile of VC (Cumming et al., 2023; Harrison and Mason, 2019).[3] Specifically, VC-focused investment prompts generate portfolios with increased exposure to the Fama–French size factor SMB (small minus big) and decreased exposure to the investment factor CMA (conservative minus aggressive), indicating a shift toward smaller firms and away from conservative, asset-heavy firms. LLMs generate higher historical excess returns and Fama–French six-factor alphas for a VC-focused prompt. However, these results may reflect look-ahead bias in backtested portfolios (Levy, 2024; Lopez-Lira et al., 2025) and return smoothing in private investments where providers have discretion over reported prices (Cao et al., 2017). VC-focused prompts result in portfolios with higher total volatility, while idiosyncratic volatility remains unchanged, suggesting that the additional risk is primarily systematic. Third, LLMs account for other investor characteristics. For example, investors with high risk tolerance receive higher equity allocations, resulting in higher performance measures (see e.g., Fieberg et al., 2023, 2024).

This study contributes to the literature on the capabilities of LLMs in financial advice (Ardekani et al., 2024; Beckmann and Hark, 2024; Boni, 2025; Dowling and Lucey, 2023; Ko and Lee, 2024; Oehler and Horn, 2024; Pelster and Val, 2024). Specifically, we expand the findings reported in Fieberg et al. (2023) and Fieberg et al. (2024) to the VC domain, in which investors may benefit particularly from LLMs due to the sparse information environment and the higher complexity compared to public markets. Our results provide some preliminary evidence that LLMs may help democratize access to private markets (e.g., Cumming et al., 2021) by offering recommendations of specific financial products to retail investors. Our study complements recent evidence that LLMs can support early-stage VC screening (Vismara et al., 2026) by suggesting that these models may also assist investors in portfolio construction.

[3] 47 out of 192 initial portfolio recommendations include at least one non-publicly traded asset without historical market price data. Because performance cannot be reliably evaluated using net asset values (NAVs) due to selection and measurement biases (e.g., Kaplan and Sensoy, 2015), we issued a follow-up prompt instructing each LLM to include only publicly traded assets for the risk–return analyses. See Section 3.2 for details.

The remainder of the paper is structured as follows: Section 2 describes the method and data collection process. Section 3 reports the findings on portfolio composition and risk–return characteristics. Section 4 concludes the study and provides a research outlook.

2 Method and data collection

To answer our research question, we constructed 48 hypothetical investor profiles, detailed in Table A1 in the Appendix.[4] To elicit portfolio recommendations from our chosen LLMs, a prompt was constructed for each profile reflecting five investor profile variables, the foremost being whether the investor explicitly requests VC-focused investments (yes or no). The remaining four attributes of the prompt correspond to established investor characteristics (Fieberg et al., 2024; ESMA, 2023; SEC, 2019). The investor status is either accredited or retail. The definition and implications of accredited investor status vary across jurisdictions (e.g., MiFID II in the EU, NI 45-106 in Canada, and SEC Rule 501 of Regulation D in the US). In general, accredited investors include high-net-worth individuals, banks, financial institutions, and certain large corporations. Many regulatory frameworks restrict specific financial offerings to accredited investors. For example, accredited investors are legally permitted to purchase unregistered securities and thus have privileged access to private-market opportunities such as VC, private equity (PE), hedge funds, and other complex or higher-risk investment instruments. We set the investment horizon at 5 or 20 years. Investors with shorter horizons typically hold less-volatile assets to meet liquidity needs at the end of their investment period (Merton, 1971). The investor's subjective risk tolerance is either high or low. Modern portfolio theory posits that risk tolerance is the primary determinant of an investor's allocation between risky and risk-free assets (Markowitz, 1952; Tobin, 1958). Finally, we vary the investor's home country between China, the UK, and the US to capture potential cross-country differences, such as regulatory regimes and product availability.

We elicited portfolio recommendations from four reasoning LLMs: DeepSeek R1, Gemini 2.0 Flash Thinking, GPT-o1, and Grok-3. Data collection occurred on March 18, 2025, with each model generating recommendations for all 48 investor profiles. We focus exclusively

[4] We adapt the hypothetical investor profiles from Fieberg et al. (2024).

on reasoning LLMs for four reasons. First, reasoning models improve accuracy on complex multi-step tasks by employing a chain-of-thought approach, which generates responses step-by-step in order to simulate human reasoning (Gibney, 2025). Such models consistently outperform traditional LLMs in fields such as science and mathematics (Jones, 2025). Second, reasoning LLMs can enhance transparency and explainability by revealing intermediate steps, allowing users to trace how outputs are derived (OpenAI, 2024). This advantage is particularly relevant in sensitive domains such as finance (Gennaioli et al., 2015; Litterscheidt and Streich, 2020). Third, reasoning LLMs demonstrate stronger generalization across domains, as their structured reasoning enables them to adapt to novel problems rather than merely replicating training patterns (Jones, 2025; Shojaee et al., 2025). Fourth, reasoning LLMs tend to generate fewer output errors, such as portfolio weights that do not sum up to 100% (Fieberg et al., 2024), because they perform internal consistency checks before producing a final answer (Patil and Jadon, 2025).

We set the temperature parameter to zero to obtain the most deterministic output from each LLM. Because LLMs are not designed to provide individual investment advice upon request, likely due to regulatory restrictions, we formulated the requests in a hypothetical scenario. We use the following prompt, replacing the placeholders with the investor characteristics of the respective profile as shown in Table A1 in the Appendix.

> *Forget all previous instructions. I am an [accredited / retail] investor in [China / UK / US]. My investment horizon is [5 / 20] years and I have a [low / high] risk tolerance.*
>
> > ***Version A: VC-focused prompt:*** *I am interested in investing in venture capital. Which specific public venture capital funds (including ticker and provider) or direct venture capital investments would a typical venture capital advisor or financial advisor recommend given my circumstances?*
> >
> > ***Version B: Non-VC-focused prompt:*** *Which specific financial products (including ticker and provider) would a typical financial advisor recommend given my circumstances?*

Please present the recommended portfolio in a table format, including each asset's ticker symbol, its corresponding allocation weight, and the provider. Please note, I will not consider your response personalized financial advice.

After the LLMs generated the portfolio recommendations, we found only a few errors in the LLM outputs. On average, 4% of the recommendations did not include a specific product, 2% had portfolio weights that did not sum up to 100%, and 3% suggested invalid tickers. To improve output quality, we applied prompt engineering (Fieberg et al., 2024; Lopez-Lira and Tang, 2023). Whenever an error occurred, we resubmitted the same prompt, along with the original output and a clarifying instruction that directly addressed the issue (e.g., "Please ensure that portfolio weights add up to 100%" or "Please ensure that you only recommend valid tickers"). As a result, the final dataset consists only of error-free LLM-generated recommendations.

To analyze the LLM-generated portfolio recommendations, we examine two dimensions: (1) portfolio composition and (2) risk–return characteristics. For portfolio composition, we evaluate the exposure to asset classes and markets. We calculate portfolio-level characteristics by aggregating each asset's characteristics with its recommended weight. We distinguish five asset classes: public equity, fixed income, alternative assets, cash, and VC-like investments. VC-like investments include traditional VC as well as business development companies (BDCs), crowdfunding, and PE.[5] Alternative assets encompass all remaining financial products, such as commodities, cryptocurrencies, and real estate (including REITs).[6] To examine market exposure, we group countries into developed, emerging, frontier, and standalone markets, following the market classification by MSCI Inc. (2025).

To examine risk–return characteristics, we analyze each portfolio's exposure to the six factors of the Fama–French model and a set of standard performance measures. We construct

[5] BDCs are US exchange-listed, closed-end investment companies created by Congress in 1980 (through amendments to the Investment Company Act of 1940) to expand capital access for small- and medium-sized private firms. By regulation, BDCs must invest at least 70% of their assets in non-publicly traded US companies with market values below USD 250 million.

[6] We are aware that alternative assets encompass investments outside traditional publicly traded equities, fixed income, and cash, including illiquid or non-standard asset classes such as commodities, hedge funds, PE, real estate, and VC (Cumming et al., 2014). For this study, we categorize the subset of VC, BDCs, crowdfunding, and PE into a composite category, referred to as VC-like investments.

a time series of monthly portfolio values using the recommended weights under the assumption of monthly rebalancing. For each recommended financial product, we use LSEG monthly total return values in US dollars from December 31, 2009, to March 31, 2025. To obtain the Fama–French alpha, factor betas, and idiosyncratic volatility, we estimate the following six-factor regression model:

$$
\begin{aligned}
r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{MKT}(R_{m,t} - r_{f,t}) + \beta_i^{SMB} \times SMB + \beta_i^{HML} \times HML \\
+ \beta_i^{RMW} \times RMW + \beta_i^{CMA} \times CMA + \beta_i^{WML} \times WML + \epsilon_{i,t} \quad (1)
\end{aligned}
$$

For each recommended portfolio $i = (m, p)$, defined by LLM m and investor profile p, we regress the monthly excess portfolio return $(r_{i,t} - r_{f,t})$ on the returns of the Fama–French six factors: market excess return (MKT), size (SMB, small minus big), value (HML, high minus low), profitability (RMW, robust minus weak), investment (CMA, conservative minus aggressive), and momentum (WML, winners minus losers). We obtain factor returns for developed markets from Kenneth French's data library. From these regressions, we extract estimates of risk-adjusted returns (α_i) as well as factor betas (β_i^{MKT}, β_i^{SMB}, β_i^{HML}, β_i^{RMW}, β_i^{CMA}, β_i^{WML}). Defined as the component of risk not explained by the six factors, idiosyncratic volatility is measured as the standard deviation of the regression residuals $\sigma(\epsilon_{i,t})$. We aggregate product-level total expense ratios (TERs) to the portfolio level to account for administrative and management costs.

3 Results

3.1 Portfolio composition

In this section, we examine the composition of the LLM-generated portfolios. Table 1 summarizes all portfolio recommendations for VC- and non-VC-focused prompts. On average, portfolios contain six assets. Public equity receives the highest average allocation (40%), followed by fixed income (25%), while cash holdings are minor (3%). VC accounts for an average portfolio allocation of 12%, typically through recommendations to invest in funds managed by firms such as Sequoia Capital, Andreessen Horowitz, or Qiming Venture Partners. Some LLMs assign substantially larger shares, reaching up to 100%.[7] The modest average VC allocation is not surprising because half of the 48 investor profiles do not receive a VC-focused prompt (median = 0%).[8] Crowdfunding receives only a small recommended share of the portfolio—on average 1% (with a maximum of 30%)—through platforms such as Crowdcube, Seedrs, and SeedInvest. Because crowdfunding is not a single investable product, investors must select individual campaigns themselves (Hornuf and Schwienbacher, 2018; Hornuf et al., 2022), and this selection process may be further supported by LLMs (e.g., Vismara et al., 2026). BDCs account for an average of 6% (with a maximum of 100%), including publicly traded firms such as Ares Capital Corporation and Hercules Capital. The average allocation of PE is 7% (with a maximum of 100%), either through direct exposure to buyout firms (e.g., Blackstone, Hg Capital, and KKR) or through publicly traded ETFs, such as the iShares Listed Private Equity UCITS ETF or the Invesco Global Listed Private Equity ETF. Finally, allocations to other alternative assets, including commodities, cryptocurrencies, and real estate, remain small at 2%.

Table 2 reports how investor characteristics determine the portfolio composition recommended by LLMs. When specifically prompted to include VC investments, LLMs allocate significantly less to traditional asset classes. Public equity decreases by 28 percentage points (pp.) ($p < 0.01$) and fixed income by 22 pp. ($p < 0.01$). VC-like investments increase by 52 pp. ($p < 0.01$). Within this composite category, VC allocations increase by 25 pp. ($p < 0.01$), BDC allocations by 13 pp. ($p < 0.01$), crowdfunding by 1 pp. ($p < 0.01$), and PE by 13 pp. ($p < 0.01$). Allocations to other alternative assets decrease slightly (-2 pp., $p < 0.01$). Overall, these results suggest that a VC-focused investment prompt shifts portfolios significantly toward VC-like investments across all subcategories. However, LLMs maintain a baseline allocation to traditional asset classes, consistent with standard diversification practices (Eun et al., 2010; Liu, 2016; Markowitz, 1952). The reduction in fixed income further suggests that LLMs interpret the VC-focused prompt as an additional proxy for higher investor risk toler-

[7] Please note that investing in VC funds typically requires meeting eligibility criteria such as accreditation, minimum investment sizes, and jurisdiction-specific regulations.

[8] For example, Fieberg et al. (2024), who do not provide any VC reference, find that portfolio allocations outside public equity, fixed income, and cash average only 2% in LLM-generated portfolios.

Table 1: Summary statistics of LLM-generated recommendations

	N	Mean	Median	SD	Min	Max
***Panel A**: Portfolio composition*						
Number of assets	192	6.35	6.00	2.13	2.00	13.00
Public equity	192	0.42	0.34	0.32	0.00	1.00
Fixed income	192	0.25	0.10	0.30	0.00	0.99
Cash	192	0.03	0.00	0.08	-0.11	0.60
Alternative assets	192	0.02	0.00	0.05	-0.03	0.30
VC-like investments	192	0.28	0.05	0.37	0.00	1.00
VC	192	0.13	0.00	0.23	0.00	0.95
BDCs	192	0.06	0.00	0.17	0.00	1.00
Crowdfunding	192	0.01	0.00	0.03	0.00	0.30
PE	192	0.07	0.00	0.16	0.00	1.00
***Panel B**: Geographic allocation*						
Chinese securities	192	0.20	0.03	0.31	0.00	1.00
UK securities	192	0.13	0.02	0.21	0.00	0.94
US securities	192	0.48	0.42	0.33	-0.00	1.00
Developed markets	192	0.75	0.88	0.30	0.00	1.00
Emerging markets	192	0.25	0.12	0.30	0.00	1.00
Frontier markets	192	0.00	0.00	0.00	0.00	0.01
Standalone markets	192	0.00	0.00	0.00	0.00	0.00

Note: The table reports summary statistics at the LLM-profile level (4 LLMs $\times$ 48 profiles). We refer to VC-like investments as a composite including VC, BDCs, crowdfunding, and PE. Alternative assets include all remaining financial products outside the other asset classes, such as commodities, cryptocurrencies, and real estate (including REITs). Chinese, UK, and US securities denote the shares of each portfolio invested in financial products listed in the respective countries. Developed markets are defined according to MSCI Inc. (2025), with the addition of Luxembourg and Liechtenstein. Emerging, frontier, and standalone markets follow the definitions provided by MSCI Inc. (2025).

Table 2: Regression on portfolio composition

	Asset class exposure					VC-like investments				Geographical exposure	
	(1) Public equity	(2) Fixed income	(3) Cash	(4) Alternative assets	(5) VC-like investments	(6) VC	(7) BDCs	(8) Crowd-funding	(9) PE	(10) Developed markets	(11) Emerging markets
VC prompt	-0.278***	-0.224***	-0.001	-0.017**	0.519***	0.253***	0.128***	0.013***	0.126***	0.088***	-0.088***
	(0.036)	(0.026)	(0.010)	(0.007)	(0.034)	(0.024)	(0.020)	(0.005)	(0.020)	(0.026)	(0.026)
Accredited investor	-0.085**	0.001	-0.009	0.013*	0.080**	0.070***	0.014	-0.006	0.002	0.044*	-0.044*
	(0.036)	(0.026)	(0.010)	(0.007)	(0.034)	(0.024)	(0.020)	(0.005)	(0.020)	(0.026)	(0.026)
20-year horizon	0.049	-0.032	-0.014	0.005	-0.009	-0.023	-0.009	0.005	0.017	0.020	-0.020
	(0.036)	(0.026)	(0.010)	(0.007)	(0.034)	(0.024)	(0.020)	(0.005)	(0.020)	(0.026)	(0.026)
High risk tolerance	0.274***	-0.414***	-0.048***	0.011	0.177***	0.096***	0.019	0.010**	0.051**	-0.018	0.018
	(0.036)	(0.026)	(0.010)	(0.007)	(0.034)	(0.024)	(0.020)	(0.005)	(0.020)	(0.026)	(0.026)
UK investor	-0.043	-0.022	0.028**	0.006	0.030	0.108***	-0.166***	0.011	0.077***	-0.090***	0.089***
	(0.043)	(0.031)	(0.012)	(0.008)	(0.040)	(0.030)	(0.029)	(0.007)	(0.024)	(0.020)	(0.020)
Chinese investor	0.037	0.008	0.045***	0.010	-0.101**	0.041	-0.146***	-0.004	0.008	-0.541***	0.541***
	(0.046)	(0.033)	(0.011)	(0.008)	(0.044)	(0.027)	(0.029)	(0.003)	(0.021)	(0.035)	(0.035)
Constant	0.423***	0.534***	0.049***	0.031***	-0.037	-0.126***	0.115***	-0.010	-0.016	0.831***	0.168***
	(0.052)	(0.046)	(0.015)	(0.012)	(0.050)	(0.034)	(0.036)	(0.006)	(0.028)	(0.038)	(0.038)
LLM FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	192	192	192	192	192	192	192	192	192	192	192
Adj. R^2	0.387	0.641	0.140	0.084	0.598	0.476	0.312	0.074	0.238	0.644	0.644

Note: The table reports OLS regression coefficients of portfolio shares allocated to public equity, fixed income, cash, alternative assets, and VC-like investments as broad asset classes, as well as on the individual components of VC-like investments on investor characteristics. We calculate VC-like investments as the sum of the portfolio weights invested in VC, BDCs, crowdfunding, and PE. Alternative assets include all financial products outside the preceding categories, such as commodities, cryptocurrencies, hedge funds, and real estate. Developed markets follow the MSCI classification with the addition of Luxembourg and Liechtenstein. Emerging markets follow the MSCI definition. We omit frontier and standalone markets due to negligible portfolio weights. Omitted reference categories are: "5 years" (investment horizon), "low" (risk tolerance), "US" (home country), "no" (VC prompt), and "retail investor" (investor status). All regressions include LLM fixed effects. Heteroskedasticity-robust standard errors are reported in parentheses ($^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$).

ance. In addition, such a prompt increases exposure to developed markets (+9 pp., $p < 0.01$) and decreases exposure to emerging markets (−9 pp., $p < 0.01$). Accredited investors receive higher allocations to VC-like investments (+8 pp., $p < 0.01$), particularly to VC (+7 pp., $p < 0.01$). Public equity allocations decrease (−8 pp., $p < 0.05$), while other alternative assets increase modestly (+1 pp., $p < 0.10$). All remaining asset classes do not show significant differences.

Relative to a 5-year horizon, a 20-year horizon does not significantly alter asset allocations, although the coefficient signs align with theory. Longer horizons can bear more risk, implying higher public equity and lower fixed income allocations (Merton, 1971). Investors high in risk tolerance receive riskier portfolios. Public equity increases by 27 pp. ($p < 0.01$), fixed income decreases by 41 pp. ($p < 0.01$), cash decreases by 5 pp. ($p < 0.01$), and VC-like investments increase by 18 pp. These changes are consistent with modern portfolio theory (Markowitz, 1952; Tobin, 1958). Compared to US investors, UK investors receive higher VC allocations (+11 pp., $p < 0.01$), higher PE allocations (+8 pp., $p < 0.01$), and lower BDC allocations (−17 pp., $p < 0.01$). Chinese investors also receive lower BDC allocations (−15 pp., $p < 0.01$). The allocation reduction to BDCs likely reflects that LLMs recognize BDCs as US-specific investment vehicles to which non-US investors may have limited access (e.g., Kallenos and Nishiotis, 2023).

Table 3 analyzes whether the VC-focused prompt generates different portfolio allocations across investor characteristics. Panel A reports the interaction with high risk tolerance. For low-risk investors, the VC-focused prompt increases VC allocations by 17 pp. ($p < 0.01$), BDC allocations by 11 pp. ($p < 0.01$), and PE allocations by 10 pp. ($p < 0.01$). We find no statistically significant influence of high risk tolerance on portfolio composition for VC-like investments. The interaction term, however, reveals an additional increase of 16 pp. in VC ($p < 0.01$) and 2 pp. in crowdfunding ($p < 0.05$). These results indicate that LLMs tilt portfolios more strongly toward VC-style investments when a VC-focused investment prompt interacts with high risk tolerance. Panel B examines how the VC-focused investment prompt interacts with accredited investor status. Consistent with the baseline results, the VC-focused prompt significantly increases allocations to VC (+20 pp., $p < 0.01$), BDCs (+12 pp., $p < 0.01$), crowdfunding (+2 pp., $p < 0.05$), and PE (+14.6 pp., $p < 0.01$). Investor

Table 3: Interaction of VC prompt with risk tolerance and accreditation

	(1) VC	(2) BDCs	(3) Crowd-funding	(4) PE
***Panel A:** Interaction of VC prompt and high risk tolerance*				
VC prompt	0.171***	0.111***	0.003	0.095***
	(0.032)	(0.031)	(0.002)	(0.023)
High risk tolerance	0.015	0.002	-0.000	0.020
	(0.019)	(0.016)	(0.002)	(0.012)
VC prompt ×	0.164***	0.034	0.020**	0.063
High risk tolerance	(0.047)	(0.041)	(0.009)	(0.040)
Constant	-0.085***	0.124***	-0.005	-0.001
	(0.031)	(0.034)	(0.005)	(0.024)
LLM FE	✓	✓	✓	✓
Profile controls	✓	✓	✓	✓
Obs.	192	192	192	192
Adj. R^2	0.506	0.310	0.093	0.244
***Panel B:** Interaction of VC prompt and investor status*				
VC prompt	0.197***	0.116***	0.019**	0.146***
	(0.030)	(0.028)	(0.009)	(0.032)
Accredited investor	0.015	0.002	-0.000	0.022*
	(0.020)	(0.016)	(0.002)	(0.013)
VC prompt ×	0.110**	0.024	-0.012	-0.040
Accredited investor	(0.048)	(0.041)	(0.009)	(0.041)
Constant	-0.098***	0.121***	-0.013*	-0.026
	(0.033)	(0.037)	(0.008)	(0.030)
LLM FE	✓	✓	✓	✓
Profile controls	✓	✓	✓	✓
Obs.	192	192	192	192
Adj. R^2	0.488	0.309	0.077	0.238

Notes: This table reports OLS regressions of portfolio shares allocated to alternative investment categories on investor characteristics and interaction terms. Panel A reports the interaction between the VC-focused prompt and high risk tolerance. Panel B reports the interaction between the VC-focused prompt and accredited investor status. Profile controls include investment horizon, home country, and risk tolerance (in Panel B) or accreditation status (in Panel A). All regressions include LLM fixed effects. Standard errors are heteroskedasticity-robust. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

status has a minor influence. Accredited investors receive slightly higher PE exposure (+2 pp., $p < 0.10$), while all other differences are statistically insignificant. The interaction between the VC-focused prompt and accredited investor status results in a significant increase in VC exposure only (+11 pp., $p < 0.05$). These findings suggest that LLMs account for regulatory access rules by recommending more VC to accredited investors.

3.2 Risk–return characteristics

An analysis of the risk–return characteristics of initial portfolio recommendations is not feasible because many of the proposed financial products are not publicly traded and therefore lack historical price data.[9] This limitation is well known in research on private markets. Because valuations typically rely on accounting-based NAVs rather than market prices, performance measurement is susceptible to selection biases (e.g., Cao et al., 2017; Kallenos and Nishiotis, 2023). For example, Gornall and Strebulaev (2020) document substantial overvaluation in VC, and Brown et al. (2019) show evidence of NAV manipulation by PE fund managers. As a result, practitioners and academics generally avoid NAV-based factor-model performance evaluation for PE and VC (Kaplan and Sensoy, 2015). To facilitate an analysis of risk–return characteristics, we submitted the original prompt along with the LLMs' output and added an explicit instruction: "Please provide only publicly traded venture capital products (including ticker and provider) for which historical price data exist." We applied this adjustment only to recommendations that included non-publicly traded assets.[10]

Table 4 analyzes how investor characteristics determine the probability that an LLM recommends any non-publicly traded assets and the portfolio share allocated to such assets. A non-publicly traded asset is defined as a financial product that is not listed and lacks historical market price data (e.g., Jegadeesh et al., 2015). Column (1) reports average marginal effects from a logit model in which the dependent variable equals one if the recommendation includes at least one non-publicly traded asset. Column (2) estimates the same binary outcome using a linear probability model. Columns (3) and (4) present OLS estimates where the dependent

[9] 47 out of 192 initial portfolio recommendations include at least one non-publicly traded asset.

[10] For the non-VC-focused prompt, we used an analogous instruction: "Please provide only publicly traded financial products (including ticker and provider) for which historical price data exist."

variable is the portfolio share of non-publicly traded assets. LLMs are significantly more likely to recommend non-publicly traded assets and allocate a larger share to them when prompted to include VC. Accredited investors are also more likely than retail investors to receive non-publicly traded assets in their recommended portfolios. Specifically, the interaction term in column (4) indicates that accredited investors giving a VC-focused prompt are allocated an additional 11 pp. higher non-publicly traded share. High risk tolerance also significantly increases the probability and the share of non-publicly traded assets. We find no significant results for investment horizon or being from the UK, while Chinese investors receive a slightly higher allocation to non-publicly traded assets than do US investors. Overall, the VC-focused prompt and accredited investor status significantly increase the incidence and extent of non-publicly traded assets in LLM-generated portfolios.

Next, we examine the risk–return characteristics of the portfolios containing only publicly traded assets.[11] Table 5 reports summary statistics for the resulting Fama–French six-factor betas and performance measures.[12] On average, portfolios exhibit moderate market exposure ($\beta^{\mathrm{MKT}} = 0.58$) and a small-cap tilt ($\beta^{\mathrm{SMB}} = 0.27$). The betas for value, profitability, and momentum are close to zero on average, while the loading of the investment factor is negative ($\beta^{\mathrm{CMA}} = -0.29$). Considering performance measures, the portfolios earn an average excess monthly return of 0.48%, with a monthly volatility of 3.61% and an idiosyncratic volatility of 0.62%. The mean Sharpe ratio is 0.42, the mean alpha is close to zero, and the mean total expense ratio is 0.26%.

Table 6 reports the estimated regression coefficients of investor characteristics on the Fama–French six-factor betas. The VC-focused investment prompt loads more heavily on the market factor ($\Delta\beta^{\mathrm{MKT}} = 0.189,\ p < 0.01$) and the value factor ($\Delta\beta^{\mathrm{HML}} = 0.095,\ p < 0.01$). Momentum exposure increases modestly ($\Delta\beta^{\mathrm{WML}} = 0.026,\ p < 0.01$), while profitability differences remain insignificant. Most notably, VC-focused investment prompts generate a pronounced small-cap tilt ($\Delta\beta^{\mathrm{SMB}} = 0.251,\ p < 0.01$) and a more negative investment loading

[11] Tables A2 and A3 in the Appendix show that the main results of the VC-focused investment prompt on portfolio composition remain qualitatively similar when restricting recommendations to publicly traded assets.

[12] Point estimates for Fama–French six-factor alpha and betas are set to zero if they are not statistically significant at the 10% level.

Table 4: Determinants of non-publicly traded recommendations

	Recommendation of non-publicly traded assets (1/0)		Portfolio share of non-publicly traded assets (%)	
	(1)	(2)	(3)	(4)
VC prompt	0.343***	0.365***	0.126***	0.071***
	(0.037)	(0.050)	(0.018)	(0.017)
Accredited investor	0.175***	0.177***	0.077***	0.022
	(0.043)	(0.050)	(0.018)	(0.015)
20-year horizon	-0.010	-0.010	0.000	0.000
	(0.045)	(0.050)	(0.018)	(0.018)
High risk tolerance	0.214***	0.219***	0.075***	0.075***
	(0.042)	(0.050)	(0.018)	(0.018)
UK investor	-0.033	-0.031	-0.008	-0.008
	(0.056)	(0.061)	(0.019)	(0.018)
Chinese investor	0.060	0.063	0.047*	0.047**
	(0.053)	(0.064)	(0.024)	(0.024)
VC prompt × Accredited investor				0.110***
				(0.036)
LLM FE	✓	✓	✓	✓
Obs.	192	192	192	192
Pseudo R^2	0.450			
Adj. R^2		0.351	0.351	0.380
Model	Logit	OLS	OLS	OLS

Note: Column (1) reports average marginal effects from a logit regression where the dependent variable equals 1 if the initial LLM-generated portfolio recommendation contains at least one non-publicly traded asset. Column (2) reports OLS estimates using the same binary dependent variable (linear probability model). Columns (3) and (4) report OLS coefficients where the dependent variable is the portfolio share (in pp.) allocated to non-publicly traded assets. Omitted reference categories are: "5 years" (investment horizon), "low" (risk tolerance), "US" (home country), "no" (VC prompt), and "retail investor" (investor status). All regressions include LLM fixed effects and an intercept. Heteroskedasticity-robust standard errors are shown in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5: Summary statistics of risk–return characteristics

	N	Mean	Median	SD	Min	Max
***Panel A**: Fama–French six-factor betas*						
FF6 β_{MKT}	192	0.58	0.57	0.28	0.03	1.39
FF6 β_{SMB}	192	0.27	0.22	0.23	-0.27	0.97
FF6 β_{HML}	192	0.01	0.00	0.21	-1.14	1.04
FF6 β_{RMW}	192	0.10	0.00	0.35	-2.35	0.92
FF6 β_{CMA}	192	-0.29	0.00	0.42	-1.63	0.23
FF6 β_{WML}	192	-0.03	0.00	0.05	-0.24	0.00
***Panel B**: Performance*						
Excess monthly return (%)	192	0.48	0.43	0.36	-0.13	1.36
Monthly volatility (%)	192	3.61	3.69	1.61	0.64	9.57
Idiosyncratic volatility (%)	192	0.62	0.67	0.24	0.08	0.97
Annual Sharpe ratio	192	0.42	0.50	0.29	-0.55	0.98
FF6 α (%)	192	0.05	0.00	0.22	-0.41	0.95
Total expense ratio (%)	192	0.26	0.22	0.20	0.00	0.99

Note: The table reports summary statistics at the LLM-profile level (4 LLMs × 48 profiles). The six Fama–French factors are: MKT (market excess return), SMB (small minus big, size), HML (high minus low, value), RMW (robust minus weak, profitability), CMA (conservative minus aggressive, investment), and WML (winners minus losers, momentum). Idiosyncratic volatility is measured as the standard deviation of residuals from a regression using historical monthly price data from LSEG (December 31, 2009–March 31, 2025). Total expense ratios are calculated as weighted averages of product-level expense ratios.

($\Delta\beta^{\text{CMA}} = -0.417,\ p < 0.01$). These results indicate that recommendations from a VC-focused investment prompt tilt toward smaller firms and away from conservative, asset-heavy firms, consistent with the characteristics of VC (e.g., Chemmanur et al., 2014; Kallenos and Nishiotis, 2023). Relative to retail investors, we do not observe any significant differences for accredited investors across the six factors when restricting portfolios to publicly traded assets. A longer investment horizon of 20 years leads to a modest increase in market exposure ($\Delta\beta^{\text{MKT}} = 0.063,\ p < 0.05$), with no significant differences for the remaining factors at the 5% level. Relative to those with low risk tolerance, investors high in risk tolerance exhibit significantly higher market exposure ($\Delta\beta^{\text{MKT}} = 0.308,\ p < 0.01$) and a stronger small-cap tilt ($\Delta\beta^{\text{SMB}} = 0.079,\ p < 0.01$). In contrast, loadings on profitability and investment factors decrease ($\Delta\beta^{\text{RMW}} = -0.149,\ p < 0.01$; $\Delta\beta^{\text{CMA}} = -0.258,\ p < 0.01$), while exposures to value and momentum remain statistically indistinguishable from zero.

Before evaluating the historical performance of LLM-generated portfolios, we first acknowledge that the measures may be affected by look-ahead bias. This bias occurs when

Table 6: Fama–French six-factor model loadings

	(1) β_{MKT}	(2) β_{SMB}	(3) β_{HML}	(4) β_{RMW}	(5) β_{CMA}	(6) β_{WML}
VC prompt	0.189***	0.251***	0.095***	-0.043	-0.417***	0.026***
	(0.025)	(0.026)	(0.029)	(0.045)	(0.047)	(0.007)
Accredited investor	0.020	0.027	0.035	0.024	-0.030	-0.002
	(0.025)	(0.026)	(0.029)	(0.045)	(0.047)	(0.007)
20-year horizon	0.063**	-0.050*	-0.013	-0.038	0.038	0.001
	(0.025)	(0.026)	(0.029)	(0.045)	(0.047)	(0.007)
High risk tolerance	0.308***	0.079***	0.015	-0.149***	-0.258***	0.011
	(0.025)	(0.026)	(0.029)	(0.045)	(0.047)	(0.007)
UK investor	-0.114***	0.118***	-0.065	0.219***	0.154***	-0.040***
	(0.032)	(0.030)	(0.040)	(0.063)	(0.054)	(0.007)
Chinese investor	-0.308***	0.029	-0.092**	-0.094	0.290***	-0.017**
	(0.031)	(0.034)	(0.042)	(0.060)	(0.062)	(0.008)
Constant	0.435***	0.130***	0.017	0.293***	-0.143**	-0.025***
	(0.045)	(0.037)	(0.045)	(0.059)	(0.064)	(0.008)
LLM FE	✓	✓	✓	✓	✓	✓
Obs.	192	192	192	192	192	192
Adj. R^2	0.621	0.413	0.070	0.219	0.418	0.146

Note: The table reports OLS regression coefficients of factor loadings on investor characteristics. The dependent variables are the Fama–French six-factor betas: MKT (market excess return), SMB (small minus big, size), HML (high minus low, value), RMW (robust minus weak, profitability), CMA (conservative minus aggressive, investment), and WML (winners minus losers, momentum). Omitted reference categories are: “5 years” (investment horizon), “low” (risk tolerance), “US” (home country), “no” (VC prompt), and “retail investor” (investor status). All regressions include LLM fixed effects. Heteroskedasticity-robust standard errors are reported in parentheses ($^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$).

LLMs recommend portfolios using information about historical performance embedded in their training data, potentially overstating future performance (Levy, 2024; Lopez-Lira et al., 2025). Because our analysis necessarily relies on historical price data, we cannot avoid this bias. A genuine out-of-sample evaluation for a 20-year investment horizon would, by definition, require waiting 20 years (e.g., Alonso, 2024). To mitigate concerns about look-ahead bias, we focus on relative performance comparisons between VC- and non-VC-focused investment prompts. Because LLM-generated recommendations from both prompt types are likely affected by look-ahead bias to a similar degree, the historical performance results still provide a basis for comparing relative differences.

Table 7 reports regression coefficients of investor characteristics on the performance measures. For a VC-focused prompt, LLMs recommend portfolios with higher excess monthly returns (+0.23 pp., $p < 0.01$), greater total monthly volatility (+1.57 pp., $p < 0.01$), and a modest increase in the Sharpe ratio (+0.06, $p < 0.10$). Portfolio recommendations for a VC-focused prompt also generate higher Fama–French six-factor alphas (+0.14 pp., $p < 0.01$) and slightly higher total expense ratios (+0.04 pp., $p < 0.10$). Idiosyncratic volatility does not change significantly, indicating that the additional risk associated with the VC-focused prompt is primarily systematic. Overall, the results indicate that the portfolios generated by LLMs for VC-focused prompts mirror the more aggressive risk–return profiles characteristic of VC investments (Cumming et al., 2023; Harrison and Mason, 2019). For accredited investors, we do not find any significant differences at the 5% level. Compared to investors with a 5-year horizon, investors with a 20-year horizon earn higher excess monthly returns (+0.07 pp., $p < 0.05$), have higher Sharpe ratios (+0.08, $p < 0.05$), and are exposed to higher idiosyncratic volatility (+0.08 pp., $p < 0.01$). For investors high in risk tolerance, LLMs recommend portfolios with higher excess returns (+0.35 pp., $p < 0.01$), higher total monthly volatility (+1.77 pp., $p < 0.01$), higher idiosyncratic volatility (+0.11 pp., $p < 0.01$), higher Sharpe ratios (+0.16, $p < 0.01$), higher FF6 alphas (+0.12 pp., $p < 0.01$), and higher total expense ratios (+0.12 pp., $p < 0.01$). Relative to US investors, UK investors earn lower excess returns (-0.35 pp., $p < 0.01$), have lower Sharpe ratios (-0.32, $p < 0.01$), and have lower FF6 alphas (-0.26 pp., $p < 0.01$). Chinese investors also underperform US investors, with lower excess returns (-0.43 pp., $p < 0.01$), lower Sharpe ratios (-0.42, $p < 0.01$), and lower alphas

(-0.11 pp., $p < 0.01$). However, Chinese investors have to pay higher total expense ratios (+0.18 pp., $p < 0.01$). These findings align with Fieberg et al. (2024).

Table 7: Performance

	(1) Excess return (%)	(2) Monthly vola. (%)	(3) Idios. vola. (%)	(4) Sharpe ratio	(5) FF6 α (%)	(6) Total exp. ratio (%)
VC prompt	0.228***	1.567***	-0.003	0.058*	0.139***	0.042*
	(0.033)	(0.148)	(0.023)	(0.031)	(0.023)	(0.023)
Accredited investor	0.021	0.125	-0.001	0.002	-0.044*	0.016
	(0.033)	(0.148)	(0.023)	(0.031)	(0.023)	(0.023)
20-year horizon	0.074**	0.100	0.075***	0.077**	0.006	-0.016
	(0.033)	(0.148)	(0.023)	(0.031)	(0.023)	(0.023)
High risk tolerance	0.346***	1.767***	0.106***	0.160***	0.122***	0.123***
	(0.033)	(0.148)	(0.023)	(0.031)	(0.023)	(0.023)
UK investor	-0.349***	-0.458**	-0.111***	-0.321***	-0.258***	-0.036
	(0.042)	(0.195)	(0.025)	(0.033)	(0.030)	(0.028)
Chinese investor	-0.425***	-0.655***	-0.388***	-0.418***	-0.113***	0.176***
	(0.041)	(0.184)	(0.031)	(0.040)	(0.031)	(0.031)
Constant	0.403***	2.358***	0.658***	0.496***	0.031	0.182***
	(0.055)	(0.248)	(0.032)	(0.048)	(0.033)	(0.040)
LLM FE	✓	✓	✓	✓	✓	✓
Obs.	192	192	192	192	192	192
Adj. R^2	0.598	0.594	0.540	0.468	0.447	0.336

Note: This table reports OLS regressions of portfolio performance measures on investor characteristics. The dependent variables are six performance measures: excess monthly return (%), monthly volatility (%), idiosyncratic volatility (%), Sharpe ratio, Fama–French six-factor alpha (FF6 α (%)), and total expense ratio (%). Omitted reference categories are: "5 years" (investment horizon), "low" (risk tolerance), "US" (home country), "no" (VC prompt), and "retail investor" (investor status). All regressions include LLM fixed effects. Heteroskedasticity-robust standard errors are reported in parentheses ($^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$).

For a supplementary overview of the results, Table 8 compares portfolios generated with and without a VC-focused investment prompt using unconditional Wilcoxon rank-sum tests. The results are consistent with our earlier findings. VC-focused prompts lead to significant shifts in Fama–French six-factor betas and performance measures. The most economically meaningful differences arise in the size (SMB) and investment (CMA) factors; portfolios exhibit a stronger small-cap tilt and a more negative investment loading. Monthly excess returns and total volatility are significantly higher, whereas Sharpe ratios and idiosyncratic volatility do not differ significantly, indicating that the additional risk is primarily systematic. VC-

Table 8: Wilcoxon rank-sum test of VC-focused vs. non-VC-focused prompts

	(1) VC-focused prompts			(2) Non-VC-focused prompts			(3) Wilcoxon rank-sum test	
	N	Mean	SD	N	Mean	SD	Δ	z-score
***Panel A**: Fama–French six-factor betas*								
FF6 β_{MKT}	96	0.67	0.26	96	0.49	0.27	0.19	4.57 ***
FF6 β_{SMB}	96	0.40	0.25	96	0.15	0.13	0.25	6.81***
FF6 β_{HML}	96	0.06	0.28	96	-0.04	0.07	0.09	4.11***
FF6 β_{RMW}	96	0.08	0.46	96	0.12	0.19	-0.04	-0.76
FF6 β_{CMA}	96	-0.50	0.49	96	-0.08	0.18	-0.42	-6.55***
FF6 β_{WML}	96	-0.01	0.05	96	-0.04	0.05	0.03	4.83***
***Panel B**: Performance*								
Excess monthly return (%)	96	0.59	0.37	96	0.37	0.32	0.23	4.34***
Monthly volatility (%)	96	4.39	1.60	96	2.82	1.19	1.57	7.00***
Idiosyncratic volatility (%)	96	0.62	0.20	96	0.62	0.28	0.00	-0.94
Sharpe ratio	96	0.45	0.25	96	0.40	0.33	0.06	0.95
FF6 α (%)	96	0.12	0.23	96	-0.02	0.18	0.14	4.28***
Total exp. ratio (%)	96	0.28	0.22	96	0.24	0.17	0.04	1.19

Note: Column (1) reports summary statistics for the LLM-generated recommendations for profiles with a VC-focused investment prompt. Column (2) reports summary statistics for the LLM-generated recommendations for profiles without a VC-focused investment prompt. Column (3) reports the difference in means and the z-scores for the non-parametric Wilcoxon rank-sum test for differences in means ($^{*}p < 0.1$,$^{**}p < 0.05$,$^{***}p < 0.01$).

focused prompts also yield higher Fama–French alphas, while differences in total expense ratios remain insignificant.

4 Conclusion and outlook

This article examines whether LLMs can effectively assist investors in incorporate VC investments into their portfolios. To address our research question, we designed 48 hypothetical investor profiles and elicited portfolio recommendations from four reasoning LLMs.

We document three main findings. First, in terms of portfolio composition, LLMs incorporate VC preferences by increasing allocations to VC-like investment products and decreasing allocations to public equity and fixed income. LLMs recommend higher VC allocations to accredited investors than to retail investors. Second, for portfolios restricted to publicly traded assets, VC-focused prompts generate portfolios with higher exposure to the Fama–French size factor and lower exposure to the investment factor, indicating a tilt toward smaller firms and away from conservative, asset-heavy firms. These portfolios also exhibit higher historical excess returns, six-factor alphas, and total volatility, while idiosyncratic volatility remains unchanged, suggesting that the additional risk is primarily systematic. However, these performance measures require caution due to potential look-ahead bias (Levy, 2024; Lopez-Lira et al., 2025). Third, LLMs account for other investor characteristics. For example, investors with high risk tolerance receive higher equity allocations (e.g., Fieberg et al., 2024).

Our study has several limitations that constitute avenues for future research. First, the risk–return analyses are restricted to publicly traded assets. These products can differ substantially from private VC investments, which are characterized by illiquidity, capital calls, and pronounced J-curve dynamics (Cumming et al., 2023). Consequently, we cannot directly generalize our results to private markets. Future research could investigate the potential of LLMs to support the selection of private VC investments (e.g., Vismara et al., 2026).

Second, the performance evaluation relies on a historical backtest design. Although backtesting is a necessary approach in this setting, it is conceivable that LLMs could base their portfolio allocation decisions on past return patterns. The performance metrics reported should therefore be interpreted with caution (Alonso, 2024; Levy, 2024; Lopez-Lira et al., 2025). Our analysis nevertheless places less emphasis on actual performance, but rather examines whether reasoning LLMs can incorporate an explicit VC-focused investment prompt into their portfolio recommendations. To this end, we benchmark performance only against other LLM-generated portfolios generated on the same day and based on the same set of knowledge.

Third, the study employs prompt engineering to correct response errors. Although these adjustments have improved data quality and ensured comparability, they may overstate the reliability of LLMs relative to a fully unattended setting. Furthermore, response errors may discourage or even omit user interaction (Germann and Merkle, 2023). Future research could investigate how investors actually interact with LLMs and whether they are able to make similar corrections.

Our research also raises important ethical and regulatory questions. LLM-generated recommendations should be transparent, consistent with investor suitability requirements, and accompanied by clear risk disclosures (Fieberg et al., 2024). Without appropriate guardrails, there is a risk that investors may over-rely on algorithmic advice or misinterpret the scope of LLM-generated outputs. Ensuring accountability, auditability, and fairness in AI-assisted advisory processes will thus be essential. Whether this is already the case in practice is an open research question.

Our results suggest that LLMs can integrate nuanced requirements, such as VC-focused investment prompts, while also accounting for other investor characteristics. However, this AI-generated investment advice will also likely require considerable transparency and regulatory conformity to become widely adopted.

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Appendix

Table A1: Investor profiles

No.	Home country	Investment horizon	Risk tolerance	VC-focused prompt	Investor status
1	United States	5	high	yes	accredited
2	United States	5	high	yes	retail
3	United States	5	high	no	accredited
4	United States	5	high	no	retail
5	United States	5	low	yes	accredited
6	United States	5	low	yes	retail
7	United States	5	low	no	accredited
8	United States	5	low	no	retail
9	United States	20	high	yes	accredited
10	United States	20	high	yes	retail
11	United States	20	high	no	accredited
12	United States	20	high	no	retail
13	United States	20	low	yes	accredited
14	United States	20	low	yes	retail
15	United States	20	low	no	accredited
16	United States	20	low	no	retail
17	China	5	high	yes	accredited
18	China	5	high	yes	retail
19	China	5	high	no	accredited
20	China	5	high	no	retail
21	China	5	low	yes	accredited
22	China	5	low	yes	retail
23	China	5	low	no	accredited
24	China	5	low	no	retail
25	China	20	high	yes	accredited
26	China	20	high	yes	retail
27	China	20	high	no	accredited
28	China	20	high	no	retail
29	China	20	low	yes	accredited
30	China	20	low	yes	retail
31	China	20	low	no	accredited
32	China	20	low	no	retail
33	United Kingdom	5	high	yes	accredited
34	United Kingdom	5	high	yes	retail
35	United Kingdom	5	high	no	accredited
36	United Kingdom	5	high	no	retail
37	United Kingdom	5	low	yes	accredited
38	United Kingdom	5	low	yes	retail
39	United Kingdom	5	low	no	accredited
40	United Kingdom	5	low	no	retail
41	United Kingdom	20	high	yes	accredited
42	United Kingdom	20	high	yes	retail
43	United Kingdom	20	high	no	accredited
44	United Kingdom	20	high	no	retail
45	United Kingdom	20	low	yes	accredited
46	United Kingdom	20	low	yes	retail
47	United Kingdom	20	low	no	accredited
48	United Kingdom	20	low	no	retail

Note: The table reports the 48 investor profiles used to elicit portfolio recommendations. Profiles differ along five dimensions: home country (US, China, UK), investment horizon (5 or 20 years), risk tolerance (high or low), VC focus (yes or no), and investor status (accredited or retail).

Table A2: Portfolio composition robustness

	Asset class exposure					VC-like investments		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Public equity	Fixed income	Cash	Alternative assets	VC investments	VC	BDCs	PE
VC prompt	0.010	-0.221***	0.003	0.004	0.203***	0.064***	0.121***	0.019***
	(0.032)	(0.026)	(0.010)	(0.009)	(0.020)	(0.012)	(0.018)	(0.006)
Accredited investor	-0.056*	0.003	-0.009	0.016*	0.047**	0.005	0.025	0.017**
	(0.032)	(0.026)	(0.010)	(0.009)	(0.020)	(0.012)	(0.018)	(0.006)
20-year horizon	0.044	-0.033	-0.013	-0.005	0.008	0.008	-0.009	0.009
	(0.032)	(0.026)	(0.010)	(0.009)	(0.020)	(0.012)	(0.018)	(0.006)
High risk tolerance	0.365***	-0.416***	-0.048***	0.024***	0.075***	0.032***	0.025	0.018***
	(0.032)	(0.026)	(0.010)	(0.009)	(0.020)	(0.012)	(0.018)	(0.006)
UK investor	0.031	-0.021	0.032***	0.020**	-0.062**	0.081***	-0.131***	-0.012*
	(0.039)	(0.031)	(0.012)	(0.009)	(0.026)	(0.017)	(0.024)	(0.007)
Chinese investor	0.003	0.006	0.046***	0.030***	-0.085***	-0.001	-0.086***	0.002
	(0.038)	(0.033)	(0.011)	(0.011)	(0.025)	(0.008)	(0.025)	(0.009)
Constant	0.444***	0.536***	0.050***	-0.007	-0.023	-0.058***	0.058*	-0.023**
	(0.047)	(0.046)	(0.015)	(0.012)	(0.030)	(0.019)	(0.030)	(0.011)
LLM FE	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	192	192	192	192	192	192	192	192
Adj. R^2	0.416	0.645	0.141	0.071	0.429	0.293	0.322	0.111

Note: The table reports OLS regression coefficients of portfolio shares allocated to public equity, fixed income, cash, alternative assets, and VC-like investments as broad asset classes, as well as on the individual components of VC-like investments on investor characteristics. We calculate VC-like investments as the sum of the portfolio weights invested in VC, BDCs, crowdfunding, and PE. Alternative assets include all financial products outside the preceding categories, such as commodities, cryptocurrencies, hedge funds, and real estate. Developed markets follow the MSCI classification with the addition of Luxembourg and Liechtenstein. Emerging markets follow the MSCI definition. We omit frontier and standalone markets due to negligible portfolio weights. Omitted reference categories are: "5 years" (investment horizon), "low" (risk tolerance), "US" (home country), "no" (VC prompt), and "retail investor" (investor status). All regressions include LLM fixed effects. Heteroskedasticity-robust standard errors are reported in parentheses ($^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$).

Table A3: Interaction of VC-focused prompt with risk tolerance and accreditation

	(1) VC	(2) BDCs	(3) PE
Panel A: Interaction of VC focus and high risk tolerance			
VC prompt	0.032***	0.099***	0.007
	(0.012)	(0.024)	(0.005)
High risk tolerance	0.001	0.003	0.006
	(0.009)	(0.013)	(0.005)
VC prompt ×	0.063***	0.044	0.023*
High risk tolerance	(0.024)	(0.035)	(0.013)
Constant	-0.042***	0.069**	-0.017*
	(0.016)	(0.028)	(0.009)
LLM FE	✓	✓	✓
Profile controls	✓	✓	✓
Obs.	192	192	192
Adj. R^2	0.315	0.324	0.121
Panel B: Interaction of VC focus and accredited investor status			
VC prompt	0.059***	0.099***	0.008*
	(0.017)	(0.024)	(0.004)
Accredited investor	0.001	0.003	0.006
	(0.010)	(0.013)	(0.005)
VC prompt ×	0.008	0.043	0.021
Accredited investor	(0.024)	(0.035)	(0.013)
Constant	-0.056***	0.069**	-0.018*
	(0.019)	(0.029)	(0.009)
LLM FE	✓	✓	✓
Profile controls	✓	✓	✓
Obs.	192	192	192
Adj. R^2	0.290	0.324	0.119

Notes: This table reports OLS regression coefficients of portfolio shares allocated to alternative investment categories on investor characteristics. Panel A reports the interaction between the VC-focused prompt and high risk tolerance. Panel B reports the interaction between the VC-focused prompt and accredited investor status. Profile controls include investment horizon, home country, investor status (in Panel A), and risk tolerance (in Panel B) or accreditation status (in Panel A). All regressions include LLM fixed effects. Standard errors are heteroskedasticity-robust. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.