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Essays on Volatility Timing and Centrality-Driven Liquidity in Equity and Cryptocurrency Markets

by

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Abstract

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This thesis includes three substantive chapters that collectively explore key aspects of risk and asset pricing across different markets. Two chapters empirically study the volatility timing effects in equity and cryptocurrency markets. Another chapter studies the relationship between stock liquidity and centrality based on mutual funds' common ownership of stocks. These chapters, while examining distinct markets and aspects, are unified by their emphasis on the connection among volatility, liquidity, and the compensation demanded by risk-averse investors for higher risks associated with volatility and illiquidity. Chapter 3 exploits the low-risk anomaly in the stock market and the empirically successful volatility timing strategy, improving portfolio returns and investor utility by constructing portfolios using option-based forward-looking volatility which better incorporates market expectations on risks. Chapter 4 develops a stock-level Connectedness-Weighted-Eigenvector-Centrality (CWEC) measure that proxies stocks' importance in the broad financial network by considering the strength of each link between pairwise stocks and the importance of each stock's neighbour in the network. Through panel regressions, vector autoregression analyses, and impulse response functions, this chapter demonstrates that stock centrality appears to have a preponderant effect on illiquidity and highlights the market's differentiated perception of stocks with varying centrality levels. Chapter 5 confirms the presence of the risk anomaly in the cryptocurrency market and examines the realised volatility timing strategy under specific market conditions. This chapter provides empirical insights into the nuanced effectiveness of volatility timing in a speculative and sentiment-driven market environment. Overall, this thesis provides rich empirical evidence on volatility and liquidity risk management and portfolio allocation, affording researchers and practitioners valuable insights into the asset pricing topics.

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I declare that this thesis and the work presented in it is my own and has been generated by me as the result of my own original research.

I confirm that:

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3. Where I have consulted the published work of others, this is always clearly attributed;
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To my beloved parents and the fabulous world.

Chapter 1

Introduction

1.1 Overview

There are three substantive chapters in this dissertation. Chapter 3 and 5 study the volatility timing effects in equity and cryptocurrency markets. Chapter 4 focuses on the liquidity of connected stocks based on mutual funds' common ownership. Each of these chapters studies the topics of asset pricing from complementary angles in different markets. Volatility can hardly be separated from liquidity. Risk-averse investors require higher returns as compensation for both volatility and illiquidity. Volatility captures the probability of large upside or downside price moves, translating directly into potential losses, while illiquidity imposes the risk of forced sales at a discount. Thus, both volatility and liquidity contribute to asset pricing.

Furthermore, the price changes due to liquidity can amplify volatility. As an example, if an open-end fund offers redemption on a frequent basis while holding illiquid assets, the volatility in asset markets tends to increase due to a higher probability of investor runs and asset fire sales (IMF, 2022). Those open-end funds will be subject to a liquidity mismatch between assets and liabilities if they hold assets which cannot be quickly liquidated without a material loss of value. This mismatch brings risks as investors can redeem shares from these funds at current net asset value, but the funds are not able to repay the redemption and have to sell their assets at a discount, putting downward pressure on the asset prices and causing potential investor runs and higher volatilities. The shock impact would then be amplified. Additionally, stock liquidity is crucial for volatility management. A higher transaction cost and liquidity or leverage constraint may impair the effectiveness of the volatility timing strategy (Moreira and Muir, 2017). On the other hand, heightened volatility often widens the bid–ask spread, thereby escalating trading costs and contributing to market illiquidity (Liu, 2006). The volatility timing strategy requires regular position adjustments, which also directly affect the trading volume and bid-ask spreads. Marshall et al. (2011) and Chung and Zhang (2014) claim that the bid-ask spread has been widely used as a popular benchmark for transaction costs and measurement of stock illiquidity. Integrating these considerations is therefore essential when evaluating the true net benefit of any volatility-driven trading approach.

Beyond the traditional stock market, the cryptocurrency market provides a modern laboratory for these dynamics. Determining whether the linear relationship between risk and reward holds within digital asset markets is crucial for understanding both the inherent characteristics of cryptocurrencies and the behaviour of their investors. By applying a volatility-timing strategy designed to exploit any divergence from the expected risk-reward trade-off, we can rigorously test for such anomalies. The effectiveness of this approach will not only shed light on the validity of conventional risk models in a new asset class but may also offer practical guidance for market participants seeking to optimise their returns under rapidly shifting volatility regimes.

Therefore, volatility and liquidity are both typical sources of risk, and their importance and relationship in different markets highlight the tight connection among the chapters in this dissertation.

1.2 Option-based volatility timing

Since Sharpe (1964)'s seminal paper, the capital asset pricing model (CAPM) has been widely applied in research and practical investments such as evaluating investment portfolio performance and estimating the cost of capital in decades (Fama and French, 2004). This model proposes a positive linear relationship between asset returns and risks, as presented by the security market line (SML). To make this simple model better evaluate market portfolios, some more complex linear models are proposed, generating better proxies in empirical tests.[1] However, in fact, asset risk and returns do not always move hand in hand as predicted by the theories. The imperfect relationship between stock risks (volatility or beta) and risk-adjusted returns has been documented in the literature.[2] It has been revealed that stocks with low return risks achieve higher risk-adjusted returns, which is known as the low-risk anomaly. Blitz and van Vliet (2007) and Baker et al. (2011) propose that the low-risk anomaly is slightly stronger when based on volatility instead of stock beta. Depending on the empirical evidence of low-risk anomaly and volatility persistence in the short run in the stock market, Moreira and Muir (2017) find that realised volatility-timing strategy exploiting the low-risk anomaly generate significant alphas, higher Sharpe ratios, and increased utility gains for mean-variance investors. Cederburg et al. (2020) apply Moreira and Muir (2017)'s approach on a larger sample and conclude that the realised volatility-managed strategy is overstated. The literature focuses on using backwards-looking risk measures such as realised volatility and lacks consideration of the assets' idiosyncratic characteristics.

Chapter 3 aims to comprehensively examine the effectiveness of stock-level risk-neutral volatility timing strategy in improving investment portfolio risk-adjusted returns. This sheds new light on stock option's important role in risk management and portfolio allocation. The objectives thus include studying the option-based volatility (Implied volatility (IV), Martin and Wagner (2019) MW, and Chabi-Yo et al. (2023) GLB) timing strategy's performance under portfolios constructed by different formation approaches and constructing portfolios on the firm-level risk factor basis, which improves the results from the conventional portfolios constructed at the macro-level in the literature with the assumption that the factors are well diversified.

[1] See Fama and French (1993, 2015) and Carhart (1997) for example.
[2] See Haugen and Heins (1975), Ang et al. (2006, 2009) for example.

We follow the spirit of Moreira and Muir (2017) and Cederburg et al. (2020) to construct volatility-managed portfolios by scaling excess returns with the reciprocal of corresponding variances, keeping the unconditional variances unchanged. However, we make several essential departures from the conventional approach. First, we scale the stock returns according to their volatilities rather than conventionally focusing on the factor level. Second, based on the stock-level analyses, instead of backwards-looking realised volatilities (RV), we use option-based volatilities including implied volatilities (IV), Martin and Wagner (2019)'s measure (MW), and Chabi-Yo et al. (2023)'s Generalised Lower Bound measure (GLB). These option-based volatilities contain the market-consensus forward-looking risk and return information derived from option market prices. Our approach thus enables investors to flexibly tailor their investment themes according to their risk-reward preference and avoid huge transaction costs to follow macro factors.

The empirical analyses start by confirming the low-risk anomaly in our sample stocks. The sample stocks are first sorted into equally weighted quartile portfolios according to their realised volatilities. The patterns indicate that the imperfect relationship does exist in our sample. On average, stocks with higher realised volatilities representing more risks fail to achieve higher returns. Based on the low-risk anomaly and empirical evidence of volatility persistency in the short term, we adjust the weights of stocks in portfolios according to their risk-neutral volatility measures. This is distinguished from the literature in terms of using forward-looking volatility measures in portfolio optimisation. The forward-looking measures are derived from equity option market prices, which contain information on investors' expectations of future stock returns and risks. IV is a popular risk-neutral return variation measure derived from market-observable option prices. MW and GLB are beneficial to the timing strategy regarding the investors' concern for fast-changing return volatility and return tails, respectively. IV, MW, and GLB are referred to as risk-neutral measures that comprehensively project stock return risk characteristics. Thus, this option-based volatility timing approach diverges from conventional two-moment analyses that entirely focus on returns and variances. Conventional realised volatility conveys past risks which do not correctly reflect investors' expectations and other potential issues such as leverage and liquidity constraints. Realised volatility is also delicate to extreme events such as significant portfolio rebalancing.

Besides using forward-looking risk measures, this study applies the weight adjustment to individual stocks instead of macro-level factors, so this study does not rely on the presumption of perfect portfolio diversification when an individual component's idiosyncratic return distribution is fat-tailed. This helps to take advantage of the crucial information implied by equity option prices. Also, the stock-level timing approach enables investors to flexibly tailor their portfolios according to their own risk preferences and risk-return requirements. Thus, the forward-looking stock-level method minimises realised volatility's limitations, contains richer expected movement information, provides more flexibility to investors, and requires lower rebalancing frequency.

After the return scaling and the formation of the portfolios in our sample of 1137 S&P500 historical constituents from January 1996 to December 2021, the scaled and unscaled returns, Sharpe ratios, Sortino measures, and Calmar measures are directly compared across different sub-samples and portfolios, which spanning regressions are also replicated in. Direct comparisons and spanning regressions generate consistent results that timing risk-neutral volatilities at the firm level reaches the best performance improvement. As a benchmark of beta risk management, we repeat the betting-against-beta strategy with realised betas introduced by Frazzini and Pedersen (2014). Instead of realised betas, we also apply the option-implied betas (Buss and Vilkov, 2012) to the betting-against-beta strategy with our sampled firms and reveal that option-implied betas improve the beta management strategy performance. The improved results generated by forward-looking volatility timing at the firm level are robust when the strategy is subject to realistic transaction costs, controlling for Fama-French-Carhart 4 factors (Carhart, 1997) and Schneider et al. (2020)'s ex-ante skewness, and across all subsamples and sorted portfolios.

This chapter contributes to the literature by providing empirical evidence that traditional systematic risk factors fail to explain low-risk anomalies. This study introduces an ex-ante risk management strategy for equity portfolios to determine portfolio weights with option-implied volatility. This strategy exploits the market's expectations of firm-level volatility and future stock returns, outperforming conventional ex-post volatility timing approach and popular factor pricing models. The forward-looking measures are particularly effective in adjusting portfolio weights during uncertain periods. Firm fundamentals such as capital structure matter for the risk timing effectiveness, especially when the market is distressed. The excess returns obtained from this strategy survive from transaction cost tests. This chapter thus sheds new light on informative options' contribution to the return moment insights and offers a new risk management and portfolio rebalancing approach.

1.3 Liquidity of central stocks

Although there has been a bunch of literature focusing on the financial interlinkages and commonality in liquidity, the studies fail to reach a consensus on both possible channels of influence[3]. Also, a comprehensive study of the relationship between the

[3]One strand of the literature such as Rubin (2007), Kamara et al. (2008), Koch et al. (2016), Agarwal et al. (2018), Deng et al. (2018), and Bradrania et al. (2021) finds the causality runs from financial interlinkages to liquidity, while the other strand such as Edelen (1999), Mitchell et al. (2002), and Teo (2011) shows that institutional investors have incentives to adjust their investment positions, which affects stocks' connectedness, to match their liquidity needs.

interlinkages and stock liquidity is still insufficient. The gap arises mainly from the difficulty of mapping complex and timely dynamic financial connections. Besides, equity has remained the dominant investment target of US mutual funds in the last decades when the mutual fund scale quickly rose[4], implying systematic risk challenges through mutual funds' equity ownership.

Chapter 4 aims to derive an informative stock centrality measure in the financial network and discover the centrality properties regarding the relationship with stock liquidity and contribution to returns. Indeed, the insights into stock centrality, liquidity, and returns help researchers and practitioners better understand stock's importance in the broad network and how its role will affect the liquidity and returns that are crucial in the asset pricing topic. The objectives thus include introducing a stock-level Connectedness-Weighted-Eigenvector-Centrality (CWEC) measure generated from the mutual fund common ownership to stocks, studying the relationship between stock centrality and illiquidity, and figuring market's different views on different stock centrality levels.

The empirical studies start by identifying the comprehensive quarterly pairwise combinations of stocks owned by mutual funds according to their common ownership. We introduce a two-step process to derive the stock-level CWEC. First, we follow Antón and Polk (2014) to compute the stock pairwise connectedness as the proportion of each pair of stocks' market capitalisation owned by a particular mutual fund in a cross-section and then rank-transform and standardise the connectedness. Second, we use the pairwise connectedness derived in the first step as the weight of each edge between pairs of stocks to compute the eigenvector centrality for each stock in the connected map. The CWEC thus departs from conventional pairwise studies by introducing a stock-level centrality measure weighted by stock connectedness, considering both the strength of the links related to the stock and the importance of the stock's neighbours and affording a fair measurement of stocks' importance in the financial network.

This chapter focuses on the large US stocks owned by the top US funds which cover the majority of the market from January 1999 to June 2022. This is informed by the theory that the largest firms are the most important participants in the market (Gabaix, 2011). Given the notion that market prices of large firms best disclose stock connections, this unique method provides a new and effective way to explain stock networks and liquidity. The largest stocks filtered in our sample guarantee that stocks are strongly connected in the network, addressing the concern that eigenvector centrality has limitations in effectively showing the peripheral node importance (Buraschi and Tebaldi, 2024).

The illiquidity measure proposed by Amihud (2002), which is adopted in this chapter, has been widely used in the literature and empirically proved effective. The Amihud

[4]The data is from the 2000 and 2023 Investment Company Institute Factbook.

measure is computed as the quotient of average absolute stock daily returns and stock daily trading volume, implying the return sensitivity to transactions. A larger Amihud measure refers to higher price fluctuation given the same amount of transactions and thus lower liquidity.

The stock-level centrality measure with a large universe of sample stocks enables us to study the relationship between stock centrality and liquidity, for which the literature has not reached a consensus as discussed in the context. The panel regressions with stock-level variables indicate stock centrality and illiquidity have statistically significant effects on each other. The bilateral effect provides motivations for further Vector Autoregression (VAR) analysis. Ang et al. (2006)'s stock idiosyncratic volatilities, VIX index, and money supply shock are controlled in the VAR model in this chapter. Since the idiosyncratic volatility is generated from the market-observable price regressions against Fama and French (1993) factors, the volatility adds market expectations to fundamental characteristics, basically containing comprehensive idiosyncratic information. VIX and money supply change stand for macro controls. The VIX index signals the market sentiment to the S&P500 price changes, which is important in the model as the sample covers highly uncertain periods with prominent risks. The money supply shock represents the overall market liquidity condition, which is a critical determinant of the financial intermediary's funding tightness and investment decisions. These micro- and macro-level control variables include abundant elements that could influence stock liquidity. The VAR results indicate that only the stock centrality effect on illiquidity is statistically significant. The IRF and replicated analyses for GFC-separated periods further confirm stock centrality's preponderant effect on stock's illiquidity. After that, according to the time-series centrality, illiquidity, and bank lending tightness plots, when the market funding liquidity tightens, stock centrality and illiquidity do not react consistently. The stock centrality shows "sticky" properties and is less correlated to the market funding liquidity. This sheds new light on the VAR and IRF results regarding that mutual funds are reluctant to alter their investment portfolio positions since the fund managers tend to stay at their familiarised and historical investment strategies, minimising the uncertainty caused by asymmetric information and transaction costs.

Tightly following the relationship analyses, this chapter then discovers whether the market views stocks' centrality differently. We sort stock centrality levels into quartile portfolios and compare the stock illiquidity, idiosyncratic volatilities, and Fama-French-Carhart 4 factor (Carhart, 1997) alphas to look for any centrality pricing evidence in the market. The sorting results indicate that stocks with higher centrality tend to be more liquid and yield lower excess returns which are attributed to investors' demand for liquidity risk compensation and fairer prices of more connected, liquid, and popular stocks. The premium of stock centrality is then supported by the statistically significant β^{CWEC} coefficients in the Fama and MacBeth (1973) regressions. We then run the predictive regressions of stock centrality on excess returns. The regressions generate significant coefficients, indicating that stock centrality is potentially a state variable. The potential evidence of centrality premium and centrality predictive power to excess returns motivate the betting-against-centrality (BAC) strategy to analyse the feasibility of making a profit by trading against centrality. The BAC factor is constructed by longing the lowest-connected stocks and shorting the highest-connected stocks with equal weights. The factor is regressed against Fama-French-Carhart 4 factors (Carhart, 1997). The insignificant alphas underscore the centrality's stickiness revealed and discussed in previous analyses. That is, investors can hardly exploit the pricing gap among stocks with different centrality levels, especially when the profits are subject to some conditions such as transaction costs.

This chapter contributes to the literature by first deriving the CWEC. CWEC exploits the connectedness and eigenvector centrality to capture the strength of each edge between pairwise nodes and the importance of each node's neighbours in the financial network which has not been studied in traditional pairwise correlation analyses. Relying on the fair stock-level centrality measure, this chapter reveals stock centrality's inverse relationship with and preponderant effect on stock illiquidity by sorting sample stocks into CWEC quartiles and applying statistical approaches such as VAR and IRF. Other results indicate that stock centrality is viewed differently in the market and appears to be a priced risk source. The empirical evidence affords researchers and practitioners deeper insights into characteristics of stock centrality and liquidity as well as their roles as priced risk factors, thus being indicative of risk management.

1.4 Volatility timing in Cryptocurrency markets

The cryptocurrency market inefficiency has been widely documented in the literature[5]. Some studies also reveal a speculative nature of the cryptocurrency market[6], which is relevant to the prevailing price mismatch and risk anomalies as studied by Leong and Kwok (2023). While the cryptocurrency market discrepancy between risk and return has been discovered, the strategies seeking excess returns based on the anomalies are still insufficiently studied.

Based on the empirically successful stock volatility timing strategy developed by Moreira and Muir (2017), this chapter aims to study the risk anomaly and realised volatility timing strategy in the cryptocurrency market.[7] Adopting a similar strategy for cryptocurrency markets, we not only provide empirical evidence of risk timing but also

[5]See Al-Yahyaee et al. (2018), Caporale et al. (2018), Charfeddine and Maouchi (2019), Hu et al. (2019), Jiang et al. (2018), Kristoufek (2018), and Zhang et al. (2018) for example

[6]See Cheah and Fry (2015), Baur et al. (2018), and Babiak and Bianchi (2023) for example.

[7]Chapter 5 also follows Moreira and Muir (2017) and Cederburg et al. (2020) volatility timing approach as in Chapter 3, but Chapter 5 is closer to the traditional approach in terms of using realised volatilities to scale the index excess returns.

introduce a new approach that can potentially generate excess returns. The separate analyses considering cryptocurrency sizes, lottery preference, penny stock comparisons, market turmoil, market funding liquidity, and market sentiments afford a deeper understanding of risk anomaly properties and volatility timing effectiveness with different systematic conditions in the cryptocurrency market.

The empirical studies are based on indices constructed by cryptocurrencies with different market capitalisations representing overall market performance. The realised volatility sorted portfolios indicate that the risk anomaly appears in the cryptocurrency market, implying that higher volatility exposures are inadequately compensated by returns. To assess risk management efficacy, we apply the realised volatility timing strategy, which is empirically successful in stock markets, to the cryptocurrency indices. Direct comparisons of scaled and unscaled returns, alongside risk-adjusted performance metrics (Sharpe and Sortino ratios), demonstrate the strategy's conditional effectiveness. Spanning regressions further investigate the drivers of volatility timing success. While portfolio sorting provides some evidence of volatility timing utility and hints at investor lottery preferences, the regression results fail to discover a systematic link between lottery-driven demand and volatility timing effectiveness.

Subsequent analyses replicate the timing method across the subsets of different cryptocurrency indices and market liquidity conditions, isolating the two-year COVID period. The realised volatility timing approach successfully generates significant alphas under elevated funding liquidity during market turmoil, with amplified effectiveness observed among smaller cryptocurrencies. The alphas are significant with specific conditions which lead to prominent risk anomalies. All the following conditions collectively contribute to the risk anomaly and significant alphas. First, cryptocurrencies' perceived hedging properties motivate risk-averse investors to enter the cryptocurrency market during highly uncertain periods. Second, lower federal fund rates imply a more prosperous market and active trading. Third, smaller cryptocurrencies are less exposed and thus have more potential to generate excess returns. Being different from cryptocurrencies, penny stocks lack safe-haven attributes and contain other risks such as default risks that make investors require extra compensation. Therefore, the volatility timing approach reaches different results in cryptocurrency and penny stock markets. This contrast underscores how volatility timing's success is contingent on market-specific risk-return dynamics and investor behavioural biases.

To further inspect the risk anomaly and realised volatility timing properties in the cryptocurrency market, we replicate the sorting and spanning regression analyses with consideration of sentiment indicators for the overall global financial market and cryptocurrency market respectively in this chapter. This new comparison between sentiment indicators in different markets which has never been conducted in the literature is motivated by some empirical evidence that the cryptocurrency market is driven by emotional and speculative transactions[8]. This analysis thus affords insights into cryptocurrency return and risk relationships as well as realised volatility timing effectiveness. Results reveal that significant alphas are generated by the realised volatility timing approach only for large cryptocurrencies during the growth stage of the overall global financial market sentiment. The new inflows to the cryptocurrency market tend to choose large cryptocurrencies and lead to more prominent risk anomalies. Otherwise, adjusting the investment positions according to past observed information in such a highly speculative market cannot effectively improve the excess returns compared to unmanaged portfolios.

This chapter contributes to the literature mainly in three ways. First, the risk anomaly evident in both the literature and the preliminary analysis and empirical evidence of volatility persistence in the short run in the cryptocurrency market (Zhang and Zhao, 2023) enable us to apply the empirically successful realised volatility timing strategy, which has not been tried in previous literature. Timing cryptocurrency volatility exploits the risk anomaly, being indicative of the strategy's effectiveness in yielding alphas and crucial to interested academic researchers and practitioners. The second main contribution of this chapter is the separate analyses of subsets according to cryptocurrency sizes, recent maximum returns, market funding conditions, market sentiment, and different macro environments. The separated analyses further test the anomaly and timing strategy's effectiveness and help to reveal the investor behaviour which leads to the phenomenon. Besides, the studies are also replicated on the penny stock index for comparisons to the cryptocurrency market, as both markets are notable for their speculative nature. This extended approach replication on the penny stock index discloses the difference between cryptocurrency and other speculative assets, providing a more comprehensive understanding of the cryptocurrency market properties. This chapter overall provides portfolio managers references to boost returns by adjusting their crypto allocations in specific periods, allows risk teams to tailor strategies to account for sudden volatility surges, and gives regulators clearer visibility into the factors that trigger dramatic price movements.

1.5 Schematic representation

Chapter 1 is an introduction of the thesis, separately highlighting the research context, research aims, methods, findings, and main contributions for each project.

Chapter 2 discusses the main background concepts and methods used in this thesis.

[8]See Cheah and Fry (2015), Baur et al. (2018), Babiak and Bianchi (2023), and Zhao et al. (2024) for example.

Chapter 3 analyses the effectiveness of realised and option-based volatility timing methods and different portfolio formation approaches.

Chapter 4 investigates the relationship between stock centrality and stock liquidity and market attitude to stocks with different centrality levels.

Chapter 5 explores the risk anomaly and volatility timing strategy effectiveness in the cryptocurrency market under different market conditions.

Chapter 6 concludes the chapters, critically examines the thesis, and makes some recommendations for future research.

Chapter 2

Methodology

2.1 Introduction

This chapter introduces the major background concepts and empirical methods applied in Chapter 3, 4, and 5. The background concepts in this chapter heavily draw on Anderson et al. (2009), Foucault et al. (2013), and Hull (2021), incorporating some minor adjustments. The major empirical methods follow the spirit of Moreira and Muir (2017), Cederburg et al. (2020), and Antón and Polk (2014)'s studies.

In Chapter 3, the forward-looking option-based implied volatility instead of conventional realised volatility in the literature is used for the timing strategy. Also in Chapter 5, the empirically effective realised volatility timing strategy in the stock market is transplanted in the cryptocurrency market. I thus first introduce the important concepts of realised volatility and implied volatility in Section 2.2 and 2.3, respectively, which are tightly followed by Section 2.4 where we illustrate the volatility timing strategy proposed by Moreira and Muir (2017). I also demonstrate the characteristics of the risk-adjusted ratios used in the direct comparisons of unscaled and volatility-managed portfolio performance in Section 2.5. After that, Chapter 4 proposes a two-step process to derive a stock-level Connectedness-Weighted-Eigenvector-Centrality measure originated from Antón and Polk (2014)'s common ownership and proxy the illiquidity by the empirically popular and effective Amihud (2002) measurement. So I briefly introduce the concepts of common ownership, eigenvector centrality, and Amihud ratio in Section 2.6, 2.7, and 2.8. To highlight the contribution of the stock-level centrality in Chapter 4 which affords the analyses with stock characteristics such as illiquidity, I refer to a basic liquidity premium model in Section 2.9. These concepts and methods help us better understand the contribution of the studies in this thesis to asset pricing topics.

2.2 Realised volatility

Since actual realisations of return volatility are not directly observable as raw returns, relying on strong parametric assumptions to infer the volatility has been a common solution to the return volatility latency. In contrast, without transaction costs, the volatility of realised returns may be measured without error by using continuously observed prices and realised returns. Realised variation is conceptually connected to the cumulative expected return variation with an arbitrage-free diffusive data-generating process over a particular period, avoiding strong auxiliary assumptions. This approach develops rapidly and is widely applied due to the better availability of high-quality transaction data for many financial assets, especially for liquid markets with high trading frequency and low transaction costs.

The notion of realised volatility is tightly connected to arbitrarily high-frequency data observations. Although we are only able to sample at discrete intervals, it is reasonable to study volatility in a continuous framework. In a continuous-time diffusive framework, we assume the absence of price jumps for the sake of simplicity, along with the presumption of a frictionless market, for the martingale asset logarithmic price s which rules out arbitrage opportunities,

$$ds_t = \mu_t dt + \sigma_t dW_t, \quad 0 \leq t \leq T, \tag{2.1}$$

where $\mu_t dt$ and $\sigma_t dW_t$ are the drift and diffusion functions respectively. W_t is a standard Brownian motion process. The μ_t and σ_t represent the instantaneous conditional mean and return volatility of the asset. μ_t and σ_t are both predictable processes with finite variation and strictly positive and square-integrable, respectively. For continuously compounded return from $t - h$ to t,

$$r(t,h) = s(t) - s(t-h) = \int_{t-h}^{t} \mu(\tau)d\tau + \int_{t-h}^{t} \sigma(\tau)dW(\tau), \quad 0 \leq h \leq t. \tag{2.2}$$

Since the mean term ($\mu_t dt$) is of lower order than the diffusion function ($\sigma_t dW_t$), the mean term can effectively be omitted when the high-frequency returns are integrated over a short period, h. Thus, the quadratic variation ($QV(t,h)$) coincides with the integrated variance ($IV(t,h)$)[1],

$$QV(t,h) = IV(t,h) = \int_{t-h}^{t} \sigma^2(\tau)d\tau. \tag{2.3}$$

The quadratic variation can be well estimated by the corresponding cumulative square return process without microstructure noise and measurement error. Consider a partition $t - h + \frac{j}{n}, j = 1, ..., n \cdot h$ of the $[t-h, t]$ interval. The asset return realised volatility (RV) is

$$RV(t,h;n) = \sum_{j=1}^{n \cdot h} r\left(t - h + \frac{j}{n}, \frac{1}{n}\right)^2. \tag{2.4}$$

Also,

$$RV(t,h;n) \longrightarrow QV(t,h), \quad as\ n \rightarrow \infty. \tag{2.5}$$

[1]The coincidence between QV and IV does not hold for more general return process such as the stochastic volatility jump-diffusion model.

Therefore, when the sampling frequency n increases to infinite, semimartingale theory ensures that the RV converges in probability to QV which is defined in Equation (2.3).

2.3 Implied volatility

As an alternative approach to the common ones making strong parametric assumptions, implied volatility relies on option pricing models and market observable prices.[2] Implied volatility is forward-looking and reflects the market consensus about the corresponding stock volatility, which cannot be figured out by backwards-looking measures such as historical volatilities[3]. This property provides us with the incentive to time implied volatility in Chapter 3.

The most prominent option pricing model is derived by Black and Scholes (1973). With the assumptions of permitted short selling, no transaction costs or taxes, non-dividend-paying securities, absent arbitrage opportunity, continuous security trading, and a persistent risk-free rate, the Black-Scholes-Merton pricing formulas for European call and put options are

$$c(s,t) = sN(d_1) - Ke^{-r(T-t)}N(d_2) \tag{2.6}$$
$$p(s,t) = Ke^{-r(T-t)}N(-d_2) - sN(-d_1), \tag{2.7}$$

where

$$d_1 = \frac{1}{\sigma\sqrt{T-t}}\left[\ln\left(\frac{s}{K}\right) + \left(r + \frac{\sigma^2}{2}\right)(T-t)\right]$$
$$d_2 = \frac{1}{\sigma\sqrt{T-t}}\left[\ln\left(\frac{s}{K}\right) + \left(r - \frac{\sigma^2}{2}\right)(T-t)\right] = d_1 - \sigma\sqrt{T-t}.$$

The function $N(\cdot)$ refers to the cumulative probability distribution for the variable which follows a standard normal distribution. The variables c and p are European call and put options; s is the stock price. K is the strike price; r is the risk-free rate with a continuous compound; $T-t$ is the time to the option maturity.

[2]This approach thus generally fails to provide unbiased forecasts of the underlying asset volatility as it still depends on pricing models and relates to a volatility risk premium which may change along with time.

[3]Historical volatility is computed as the standard deviation of a rolling sample return. It can provide volatility information as volatility is persistent, but volatility's mean-reverting property implies that the historical volatility measure is not optimal and unbiased.

As σ of the stock price is the parameter in the Black-Scholes-Merton pricing formulas that cannot be directly observed in the market, computing the volatility implied by the market-observable option prices becomes a common approach. Since it is complicated to invert Equation (2.6) to make a function $f(\sigma)$ expressed by the rest of the variables, an iterative trial method is normally applied to approach the implied volatility.

2.4 Volatility timing

Besides the empirical evidence that stocks with lower risks achieve abnormally higher returns (low-risk anomaly)[4], based on other evidence that volatility does not predict returns and is persistent in the short run, Moreira and Muir (2017) construct portfolios by timing realised volatilities to improve investors' utility:

$$R_{t+1}^{RV} = \frac{c}{\widehat{RV_t^2}} R_{t+1}, \tag{2.8}$$

where

$$\widehat{RV_t^2} = \frac{22}{D_t} \sum_{d=1}^{D_t} (r_t^d)^2.$$

R_{t+1}^{RV} and R_{t+1} are the realised volatility managed and buy-and-hold portfolio returns in month $t+1$, respectively. The constant c is used for making unscaled and scaled return variances the same for each company. Formally, c is defined as $c = \sqrt{\frac{var(R_{t+1})}{var \frac{R_{t+1}}{\widehat{RV_t^2}}}}$. D_t is number of daily observations in month t. Let $d = 1, ..., D_t$ in month t. In this setting, $\frac{c}{\widehat{RV_t^2}}$ implies the required leverage in month $t+1$. This volatility timing approach thus exploits the information of realised volatility in the last period.

The spanning regressions are applied to inspect the effectiveness of volatility timing:

$$R_t^{RV} = \alpha + \beta R_t + \epsilon_t. \tag{2.9}$$

Moreira and Muir (2017) claim that a statistically significant positive α indicates that the scaled portfolio has a higher Sharpe ratio than the unscaled one's, thus delivering utility gains to mean-variance investors. However, Cederburg et al. (2020) emphasise the importance of considering β, the estimated coefficient of the independent variable. They argue that the estimated coefficient is equivalent to the unconditional correlation coefficient between the scaled and unscaled returns ($\widehat{\beta} = \widehat{\rho}$). Consequently, the advantage of a positive constant is partially offset by a reduction in the Sharpe ratio.

[4]The empirical evidence appears in both stock and cryptocurrency markets. Chapter 3 and 5 have discussed this in detail.

Nevertheless, the inclusion of (positively weighted) scaled and unscaled factors could expand the mean-variance frontier (Gibbons et al., 1989).

2.5 Risk-adjusted performance measures

The first risk-adjusted ratio is the Sharpe ratio (SR), popularly used as a risk-adjusted return measurement. It is defined as the ratio of an asset or a portfolio's excess returns over its volatility measure:

$$Sharpe\,ratio = \frac{R_a - r_f}{\sigma_a}, \tag{2.10}$$

where R_a is the realised or expected return of the asset, σ_a is the asset return volatility, and r_f is the risk-free rate. The numerator generally represents the asset risk premium over a safe asset such as a treasury bill. The ratio thus implies how much excess returns an investor can gain when taking one unit of the volatility (risk). However, the standard deviation used in Equation (2.10) presumes that the market views price movements in either a positive or negative direction indifferently, which in fact does not hold for most investors.

As an alternative risk-adjusted return measurement, Sortino ratio is computed as the ratio of the asset excess return over the asset downside volatility:

$$Sortino\,ratio = \frac{R_a - r_f}{\sigma_d}, \tag{2.11}$$

where R_a is the asset's realized or expected return, σ_d is the downside volatility of the asset return, and r_f is the risk-free rate. Since the Sortino ratio only considers the negative price deviation, it sometimes better recognises risk-adjusted asset performance, as a positive price deviation is viewed as an award.

Another risk-adjusted performance measurement is the Calmar ratio, which uses the maximum price drop instead of volatilities as the risk measure:

$$Calmar\,ratio = \frac{R_a - r_f}{Maximum\,Drawdown}. \tag{2.12}$$

The Calmar ratio is simpler to calculate and understand. The maximum price drawdown explicitly shows the risk of the asset or portfolio.

Each of these risk-adjusted ratios highlights a different aspect of performance. The Sharpe ratio provides a straightforward benchmark for reward per unit of total variability, though it does not distinguish between upside and downside swings. The Sortino ratio builds on this by considering only downside deviations relative to a chosen minimum acceptable return, gently steering attention toward undesirable outcomes. The Calmar ratio brings in a drawdown-focused view that helps measure how well a strategy deals with its largest setbacks. Taken together, these three ratios balance comparability, downside emphasis, and drawdown resilience for a well-rounded assessment[5].

2.6 Common ownership

Inspired by the empirical evidence that stock returns comove beyond their fundamentals due to institutional features that significantly affect stock discount rates, Antón and Polk (2014) propose a new approach relying on mutual fund flow to gauge the institution-based comovement. The stock-level Connectedness-Weighted-Eigenvector-Centrality measure applied in Chapter 4 is derived from this approach. Formally, after comprehensive stock pairwise combinations have been discovered in the sample, Antón and Polk (2014)'s common ownership is measured by the total value of the pair of stocks owned by a common fund, scaled by the total market capitalisation of this pair of stocks. For a paired stock i and j,

$$FCAP_{ij,q} = \frac{\sum_{f=1}^{F} \left(S_{i,q}^{f} P_{i,q} + S_{j,q}^{f} P_{j,q} \right)}{S_{i,q} P_{i,q} + S_{j,q} P_{j,q}}, \tag{2.13}$$

where $S_{i,q}^{f}$ is stock i's number of shares held by fund f at quarter q traded at price $P_{i,q}$. $S_{i,q}$ is the total shares outstanding of stock i, and similar for stock j. This measurement enables researchers to study the comovements of characteristics for the pairs of stocks such as the pairwise stock liquidity commonality based on correlations. This method comprehensively considers all the nodes in the sample and weights their linkages by mutual funds' ownership, shedding new light on financial networks and linkages.

2.7 Eigenvector Centrality

The eigenvector centrality measure is based on the idea that a node is important in the network if it is linked to other important nodes (Bonacich, 2007). Assume a network constructed by a set of nodes $N = 1, 2, ..., n$. Let $A = a_{i,j}$[6], where $i, j \in N$ and $i \neq j$,

[5]More specialised metrics, such as the Homm and Pigorsch (2012) economic performance measures, can offer deeper insights, but they also tend to require richer data sets and more intricate calibration, which can complicate broad empirical application in the thesis setting.

[6]For undirected graphs as the connectedness-derived financial network studies in this thesis, where edges do not have a direction and the connection between pairwise nodes is bidirectional or mutual, it does not matter to use $a_{i,j}$ or $a_{j,i}$.

denote the network's adjacency matrix. The eigenvector centrality c_i of a node i is defined as

$$c_i = \frac{1}{\lambda} \sum_{k}^{N} a_{i,j} c_j, \tag{2.14}$$

where the scalar, λ, is the largest eigenvalue associated with the adjacency matrix, A.

$$\lambda c = cA$$

Therefore, each node i's eigenvector centrality is directly related to its neighbouring nodes' total centrality. A node is considered more important in the network if it is connected to more nodes and more important nodes.

2.8 Amihud illiquidity ratio

Liquidity can be measured in different dimensions such as trading costs, depth available for large orders, trading speed, protection against execution risk, and so on. Market participants are willing to apply trading strategies to minimize illiquidity's influence on their portfolios. For researchers and regulators, understanding liquidity measurements affords them insights into the relationship between market structure and performance. As discussed in Chapter 4, Amihud (2002)'s illiquidity ratio has been widely adopted in the literature and proven effective in measuring price impact which is one of the major sources of illiquidity. Formally, Amihud (2002) ratio, I_t, is defined as

$$I_t = \frac{|r_t|}{Vol_t}, \tag{2.15}$$

where $|r_t|$ is the stock return and Vol_t is the trading volume over the time period t. This measure quantifies the price changes given the amount of the trading volume, where a larger I_t indicates higher levels of illiquidity.

2.9 Illiquidity premium

In Chapter 4, transforming Antón and Polk (2014)'s concept of mutual fund common ownership from a pairwise level to a stock level offers significant advantages, particularly in studying stock connectedness and its effects on stock illiquidity which is a critical factor in asset pricing. Given its substantial impact on asset returns, illiquidity has been extensively examined by both researchers and practitioners. The first reason is that investors have to pay transaction costs which reduce their effective asset returns. Investors thus will pay less for illiquid assets, demanding an additional illiquidity premium alongside the standard risk premium. Illiquidity has been attributed to factors such as information asymmetry and search costs. Moreover, asset liquidity is not persistent and may vary over time. These variations in asset liquidity contribute to liquidity risk, adding to the risks inherent in financial assets. Risk-sensitive investors demand compensation for taking liquidity risks unless the risk can be effectively diversified. This section presents the basic framework originally derived by Amihud and Mendelson (1986), illustrating the liquidity effect on asset prices and required returns.

Consider a simple model in an illiquid market where an investor buys a non-dividend-paying security and plans to sell the security after k periods. The ask price at time t can be expressed as:

$$a_t = m_t(1 + \frac{s_t}{2}). \tag{2.16}$$

Also, for the bid price at time t:

$$b_t = m_t(1 - \frac{s_t}{2}). \tag{2.17}$$

The a_t, b_t, and s_t are the ask price, bid price, and the proportional bid-ask spread[7] at time t, respectively. m_t refers to the midquote which is assumed to be equal to the security fundamental value, so $m_t = \mu_t$. Let r be the investor's required rate of return per period, which depends on the security's risk characteristics. Thus, μ_t will compound at r if the market is perfectly liquid, $s_t = 0$, at any time. As the security is bought at time t and sold at time $t + k$,

$$a_t = \frac{b_{t+k}}{(1+r)^k}. \tag{2.18}$$

Substitute Equation (2.16) and (2.17) into Equation (2.18) and express the asset fundamental value at time t as an equation:

$$\mu_t = \frac{\mu_{t+k}}{(1+r)^k} \cdot \frac{1 - \frac{s_{t+k}}{2}}{1 + \frac{s_t}{2}}. \tag{2.19}$$

The left term of Equation (2.19) is the discounted future value, while the last term is a form of illiquidity measurement. When the spread at time t or $t + k$ increases which

[7]The bid-ask spread is a measure of trading costs including brokers' commissions and price impact due to transactions as examples.

refers to higher transaction costs and thus lower liquidity, the asset fundamental value at time t decreases. To investigate the return properties, move μ_{t+k} to the left-hand side and take the reciprocal of both sides:

$$(1+R)^k = (1+r)^k \cdot \frac{1+\frac{s_t}{2}}{1-\frac{s_{t+k}}{2}}, \tag{2.20}$$

where R is the average gross return per period required by investors holding this asset. R is surely greater than the basic return r as the right term of Equation (2.20) is larger than 1. This difference between R and r highlights the compensation for the transaction costs to investors.

Since the gross return R is also affected by the holding period k, the spread is assumed to be constant to make the effect clearer. That is, $s_t = s_{t+k} = s$. From Equation (2.20), take natural logarithm of both sides:

$$ln(1+R) = ln(1+r) + \frac{1}{k} \cdot ln(\frac{1+\frac{s}{2}}{1-\frac{s}{2}}).$$

As $\frac{d}{dx}ln(x+1) = \frac{1}{x+1}$ and $\frac{d}{dx}ln(\frac{1+\frac{x}{2}}{1-\frac{x}{2}}) = \frac{4}{4-x^2}$, $ln(x+1) \simeq x$ and $ln(\frac{1+\frac{x}{2}}{1-\frac{x}{2}}) \simeq x$ when x is small. Therefore, the gross return R can be approximated by:

$$R \simeq r + \frac{s}{k} \tag{2.21}$$

R has an inverse relationship with holding period k because the transaction costs only incur once every k periods. The positive relationship between the gross return R and the transaction cost s has been discussed above. Therefore, the gross required return R is the basic required return of the security r plus the liquidity risk premium $\frac{s}{k}$.

Chapter 3

Option-based Volatility Timing

3.1 Introduction

Literature documents that stocks featuring low return volatility or beta achieve higher risk-adjusted returns, leading to a notion of a low-risk anomaly (LRA).[1] Researchers have highlighted how systematic and idiosyncratic risks affect this anomaly.[2] The lack of consensus regarding the economic factors behind this anomaly stems from the inherent challenge of identifying the risks associated with non-normally distributed stock returns.

This paper empirically shows how portfolio weights based on *quantities* obtained under the *risk-neutral probability* measure (RNs) significantly enhance equity portfolio performance. Informed by option-implied market-observable risk expectations, we dynamically adjust stock weights according to their risk levels. Our approach is distinctive in the literature because we use forward-looking risk measures to implement the portfolio optimisation. By *ex-ante* risk timing at the single equity level, we leverage the forward-looking risk-reward expectations that equity option prices convey.[3] At the same time, we retain the diversification effects for the portfolio performance by exploiting the correlations in extensive equity portfolios. Moreover, our stock-level approach is informed by the literature showing the practical limitations of the perfect portfolio diversification assumption when the idiosyncratic return distributions are fat-tailed.[4]

The main point of divergence of our *ex-ante* risk timing strategy from previous literature is the use of forward-looking *stock-level* equity option prices to time risk rather than using the *ex-post portfolio* realised volatility.[5] Differently from the LRA literature using realised volatilities (RV), option prices inform on investors' expected stock return risk,

[1]The imperfect relationship between the risk and (risk-adjusted) returns, the LRA, was first documented by Haugen and Heins (1975), Ang et al. (2006, 2009). Blitz and van Vliet (2007) and Baker et al. (2011) find slightly stronger results when analysing volatility rather than stocks' beta. Recently, Asness et al. (2020) have reported a significant alpha for portfolios sorted on stocks' volatility.

[2]The literature relying on systematic risk stems from economic considerations of investors' leverage constraints originally theorised by Brennan (1971) and Black (1972) and empirically studied by Frazzini and Pedersen (2014, 2022). The stream focusing on the idiosyncratic risk comes from behavioural economic considerations of investors' preferences for skewed assets, proposed in the works of Brunnermeier et al. (2007) and Barberis and Huang (2008) and empirically studied by Ang et al. (2006, 2009) and Bali et al. (2011, 2017).

[3]See, for example, Black (1975) and Manaster and Rendleman Jr (1982).

[4]The impact of not diversified shocks on aggregated measures has been studied in several contexts. For example, Gabaix (2011) shows how, because of the fat-tailed distribution of large firms, their shocks are persistent and thus cannot be diversified, suggesting that the granular composition of the economy matters for the total factor productivity growth. Gordy (2003) analyses diversification risk issues in granular credit portfolios (see also Gagliardini and Gouriéroux, 2014). Ben-David et al. (2021) and Ghysels et al. (2021) study the impact of asset management industry concentration on the equity market.

[5]Several authors have illustrated the advantage of option-implied measures in forecasting returns over their counterparts under the physical probability measure, even when accounting for biases due to risk premia. See, for example, Chang et al. (2013), DeMiguel et al. (2013), and Cremers et al. (2015). Recently, Martin and Wagner (2019), Kadan and Tang (2020), and Chabi-Yo et al. (2023), among others, have used options information to predict stock returns. Schneider et al. (2020) proxy a coskewness risk factor using option prices.

which we use to implement a risk timing strategy.[6] Our ex-ante approach improves the RVs method by including projections of investors' preferences for assets with skewed return moments, driving expectations away from the standard two-moment assumptions invoked in the LRA literature that historical prices do not capture. RVs do not entirely reveal investors' expectations nor account for limits to diversification or mispricing likely to occur for illiquid portfolio components. Furthermore, the risk-timing performance derives from the accuracy in assessing the portfolio risk, and portfolio return RVs are not only affected by estimation risk but also cannot tell which portfolio constituents affect the estimation precision.[7] Portfolio return RVs are also susceptible to extreme changes in returns, inducing drastic portfolio rebalancing.[8] Our forward-looking stock-level approach is, therefore, less sensitive to these limitations of portfolio return RVs as volatility estimators. This approach anticipates movements in the underlying asset prices and thus requires less frequent and substantial rebalancing, affording investors' risk-reward preferences to be marked.

We examine two measures of returns variability: *ex-post* risk timing using realised volatility (RV) and *ex-ante* risk timing using implied volatility (IV). The distinction between the two measures is critical as relative successes in explaining LRA reported in the literature use backwards-looking risk estimates to benchmark their success. At the same time, we propose to leverage investors' tail expectations, whose practical relevance of portfolio allocation when assets have non-Gaussian return distributions has been documented since Samuelson (1970). The RV captures all the available pricing information observed in stock prices and is a commonly used proxy of risk in LRA literature. The forward-looking IV is the most primarily considered return variation measure under the risk-neutral probability measure. The unique attributes of these two risk measures provide a precise framework for comparing backwards-looking risk measures commonly used in the literature with the proposed forward-looking risk measure. We then add to the analysis two recently proposed measures designed to capture investors' preferences for higher return moments, the MW suggested by Martin and Wagner (2019) and the Generalised Lower Bounds (GLB) proposed by Chabi-Yo et al. (2023). These are also forward-looking option-based risk measures.[9] The MW benefits the strategy implementation when the return volatilities change fast. GLB, on the other hand, includes investors' consideration for return tails. Together with the IV, we conjecture that the MW and GLB provide a comprehensive risk characterisation of the stock returns. We use each stock's respective RV, IV, MW, and GLB information to time

[6] Moreira and Muir (2017) (MM) have documented that volatility-timing increases the alpha and Sharpe ratio of equity and option portfolios without altering their payoff structure. However, we do not use options as test assets as in MM; we use them for portfolio management. Also, strides have been made recently in explaining the anomaly through underreaction to lousy news and arbitrage costs (Atilgan et al., 2020) or by studying the high-income households' investments and preferences for lottery-like assets (Bali et al., 2023).

[7] DeMiguel et al. (2009), for example, show how significant estimation risk problems exist in portfolio management. Due to the estimation risk, equally weighted portfolios often outperform optimal portfolios.

[8] Barroso and Detzel (2021) show how transaction costs usually nullify the extra alpha in LRA.

[9] We refer to IV, MW, and GLB as risk-neutral (RN) measures.

the expected stock risk. We then group our risk-managed stocks into portfolios and refer to these results as firm-level.[10] It is important to note that our risk-timing strategy is flexible to accommodate any portfolio creation.

We sort stocks into equally weighted volatility quartile portfolios and provide evidence for the low-risk anomaly in our data, particularly for large and highly leveraged companies. For our sample of 1137 S&P 500 constituents from January 1996 to December 2021, we obtain the highest performance improvement when we scale returns at the firm level. Spanning regressions demonstrate that strategies obtained by stock-level risk timing based on IV, MW, and GLB outperform those of their unscaled, RV-scaled, and aggregate-level scaled counterparts. The ex-ante risk timing is also superior to the methods proposed by Moreira and Muir (2017) (MM). We also repeat our strategy for our sampled firms using option-implied betas (Buss and Vilkov, 2012) and the popular betting-against-beta (BAB) strategy with the realised betas proposed by Frazzini and Pedersen (2014). Comparing the results allows us to see how our stock-level ex-ante risk timing performs when benchmarked against beta risk approaches to LRA studies. Finally, we show how our method compares to the backwards-looking idiosyncratic volatility timing procedure proposed by Ang et al. (2006), which we repeat for our sampled firms.

Our results are robust when we subject our strategy to realistic transaction costs, controlling for traditional Fama-French-Carhart risk factors and recently proposed ex-ante coskewness of Schneider et al. (2020), and across different samples; we re-run parallel analyses for equally weighted quartile portfolios sorted on firms' leverage levels and repeat these analyses separately for financial and non-financial firms, equally weighted quartile portfolios formed on firms' size and across seven credit rating portfolios. We also repeat our analyses by isolating the Global Financial Crisis (GFC) and the COVID-19 pandemic that drastically changed expectations and asset price dynamics.[11] Additional robustness checks include double-sorted portfolios on firm leverage and volatility risk measures to achieve the highest Sharpe, Sortino and Calmar Ratios. Furthermore, we provide evidence of our strategy's out-of-sample benefits via Clark and West (2007)'s tests.

The remainder of the paper is organised as follows. Section 3.2 discusses the contribution to the literature. Section 3.3 describes the data and methods we use. Section 3.4 compares and discusses the results. Section 3.5 concludes.

[10] We also compute the cross-sectional averages of the daily RV, IV, MW, and GLB of all stocks in our sample and use that information to time risk for each stock in our sample, i.e., scale stocks' returns, and then form our portfolios. We define this scaling as aggregate-level. This approach does not yield significant alphas. We report these results in the appendix to save space.

[11] See, for example, Gormsen and Koijen (2020), Pagano et al. (2020), Giglio et al. (2021), and Hanspal et al. (2021).

3.2 Related Literature

The Capital Asset Pricing Model (CAPM) is a single market factor linear model based on investors' rational expectations. CAPM has been widely adopted in finance literature since it was proposed by Sharpe (1964). Based on CAPM, scholars in finance have extended the model by more common risk factors to better explain the excess returns of assets. Fama and French (1993) include market, size, and value as systematic factors and propose the Fama-French three-factor model. Carhart (1997) further introduces a momentum factor to the three-factor model. Later on, Fama and French (2015) release a five-factor model including market, size, value, profitability, and investment as systematic factors. However, many empirical studies reveal that the risk-return relationship is not linear as predicted by the asset pricing theories. Haugen and Heins (1975), Ang et al. (2006, 2009) document the imperfect relationship between the risk and risk-adjusted returns. That is, stocks with low return volatility or beta tend to achieve higher risk-adjusted returns, namely the low-risk anomaly. Frazzini and Pedersen (2014), Bali et al. (2017), and Novy-Marx and Velikov (2018) measure assets' risks by their betas and study beta anomalies, where stocks with high (low) beta have low (high) abnormal returns. Blitz and van Vliet (2007) and Baker et al. (2011) find that the low-risk anomaly is stronger when the risks are measured by volatility instead of beta. Asness et al. (2020) reveal that the portfolios sorted by stock volatility can generate significant excess returns.

Recent literature has proposed volatility-timing investment strategies where investors can increase their utility gains by exploiting the imperfect relationship between risks and expected returns. The volatility-timing strategy takes aggressive positions shortly after low volatility but conservative stances after high volatility periods. Moreira and Muir (2017), for example, find the strategy that exploits the discrepancies between changes in volatility and expected returns can generate significant alphas, Sharpe ratios, and increased utility gains for the mean-variance investor. Because the variance is persistent in the short run, it can be forecasted. However, forecasting uncertainty at longer time horizons is more challenging, and is barely related to future returns, which is fundamental for long-horizon mean-variance investors. Relying on this empirical evidence, MM propose volatility-managed portfolios to increase marginal utility for investors. They use the inverse of realised volatilities, implying that mean-variance investors ought to increase their exposures when the lagged volatility is low and reduce the risks if recent volatility is high. Assuming realised volatility to be closely related to the real conditional variance, MM's approach generates the optimal weights for mean-variance investors. MM's research focuses on systematic factors which contain general and aggregate information across different assets. They have discovered that the realised volatility-managed portfolios do produce significant alphas across various factors. This contributes to the conditional relationship between risk and return, indicating that applying data to the asset pricing model for those investors and researchers with rational expectations.

Cederburg et al. (2020) (COWY) use MM's approach over a significantly larger sample and apply different trading strategies with those previously applied in the literature (Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016; Eisdorfer and Misirli, 2020). They find that the volatility-managed returns do not significantly outperform original unscaled returns in direct comparisons, but the spanning regression results do support the precedent study even if the sample has been significantly extended. Moreover, they claim that the significant and positive alphas in the spanning regression results are more likely to be produced by realised volatility-managed portfolios, which supports MM's findings. However, they claim that the superior performance of the volatility-managed strategy is overstated because the volatility-managed strategies cannot be applied in real-time by investors. COWY argue that the positive alpha in the spanning regression indicates the mean-variance frontier can be expanded by the combination of scaled and unscaled portfolios instead of the scaled portfolio only. Since the optimal weights of scaled and original factors in the combination are unknown before the portfolio construction, investors cannot implement the volatility-managed strategies in real-time. Furthermore, due to the spanning regression's structural instability stemming from the unstable conditional risk-return trade-off and the estimation risk caused by unstable combination weights, the volatility-managed portfolios' in-sample alphas cannot be replicated in out-of-sample portfolios. In general, COWY research conservatively and comprehensively interprets the volatility-managed portfolios and demonstrates the practical value of these strategies.

To achieve the highest expected utility, a mean-variance investor needs to take views on the expected values of two quantities: the future variance and the expected returns. We, therefore, add to this literature two critical extensions. First, while we also use volatility proxies as in other volatility timing studies (Fleming et al., 2001, 2003; Moreira and Muir, 2017; Cederburg et al., 2020; Barroso and Detzel, 2021), we note that this literature uses only backwards-looking realised volatilities to construct portfolios, relying on the assumption that lagged volatilities are persistent in the short run. In contrast, we utilise option-implied forward-looking volatilities information content to construct our volatility-managed portfolio weights, since these market-observed prices incorporate the market's projections of risks and expectations. Chang et al. (2013), DeMiguel et al. (2013), and Cremers et al. (2015) find that option-implied measures are advantageous over counterparts in forecasting returns.

Second, we use better proxies to forecast the expected return. MM's and COWY's realised volatility-timing strategy relies solely on predicting volatilities and omits the expected return projections, which are critical for a rational mean-variance investor. Martin and Wagner (2019), MW henceforth, introduce the volatility index MW which is the risk-neutral volatility derived from option prices. MW has the properties of both risk-neutral volatilities and lower bounds of returns. This allows for a reasonable extension to Chabi-Yo et al. (2023)'s Generalised Lower Bounds (GLB). Chabi-Yo et al. (2023) claim that GLB performs significantly better in terms of predicting returns, being relatively unbiased in terms of predicting both conditional and unconditional expected returns. Consequently, we use the IV (Implied Volatility), MW, and GLB to include the expected return information and provide mean-variance investors with more comprehensive views to achieve the highest expected utility.

In addition to these two extensions, we take similar approaches as MM with some improvements to explain firm-level risks, which could provide broad investors with some references to volatility timing applications in real life. Both MM and COWY analyse volatility timing strategies by using systematic factors which contain macro information through a variety of assets. However, the idiosyncratic risk-return relationship is insufficiently analysed. From the perspective of investors, this kind of strategy is hard to actually implement because they cannot afford the high costs of constructing portfolios by macro factors. Ang et al. (2006) find that, compared to Fama and French (1993) model, higher idiosyncratic volatilities lead to significantly lower average returns, highlighting the importance of the relationship between idiosyncratic volatilities and future stock returns. Therefore, our contribution to explaining idiosyncratic risks with firm-level risk-neutral volatilities is meaningful.

3.3 Data

We collect daily stock prices for 1,137 companies that were constituents of the S&P 500 between January 1996 and December 2021. From these prices, we compute daily log returns as the natural logarithm of the ratio of consecutive closing prices and aggregate them into monthly average returns. We calculate monthly realised volatility as the square root of the sum of squared daily returns. This approach captures the magnitude of return fluctuations without adjusting for the mean, making it suitable for modelling observed price variability. These return and risk measures serve as partial core inputs to the volatility-timing strategies examined in our analysis. The 1-month T-bill is the reference asset for excess return computation. Other data, such as the S&P, Fitch, and Moody's credit ratings, come from Bloomberg. Daily IV, MW, and GLB are from short-maturity equity call and put options and serve as risk-neutral volatilities.[12] We control our regressions for the equity factors described in Fama and French (1993), Carhart (1997), and Schneider et al. (2020).

[12] We thank Vilkov for providing this data. $https://osf.io/7xcqw/$ (accessed 23 March 2022)

3.3.1 Test portfolios

We scale each test portfolio weight by a risk measure, either RV, IV, MW, or GLB, and multiply it by a normalisation constant, making the estimates of unscaled and scaled portfolio return variances match. We analyse performance measures for risk-timing strategies in light of the firms' capital structures. We also form test portfolios based on the firm's size, seven credit ratings, and financial and non-financial entities.

The leverage ratio is computed as the current- and long-term debt divided by total equity and current- and long-term debt. The leverage thus represents the moneyness of the put option implicit in the firm's debt that gains in value during times of distress and increased uncertainty for the firm. Also, as Frazzini and Pedersen (2014) noted, high-beta stocks have embedded leverage which has economic value for investors with leverage constraints or averse to borrowing. Since one of the basic principles of economics is that expectations influence decisions, it is of practical importance to see whether investors' expectations expressed in the options markets, which contain leverage options, can provide mean-variance investors with improved utility than the traditional volatility-managed using statistical measures of volatility or even the non-managed portfolios. To analyse the role of leverage, we divide the sample into leverage quartile portfolios and implement the risk timing strategy separately for each portfolio.

We also analyse how our strategy performs for equities issued by firms of different sizes. The size of a company is directly represented by the market capitalisation and often goes hand-in-hand with leverage. Rajan and Zingales (1995), Dinlersoz et al. (2019), and Chatterjee and Eyigungor (2022) have documented the positive relationship between the company size and the leverage in different regions and markets. Large firms are often heavily leveraged because of their ability to diversify the risk away. We can see how the volatility-managed strategies perform in portfolios with different-sized companies by separating and sorting the sampled firms into quartile portfolios based on the market capitalisation. Combining the observations in the firm size and the leverage quartiles, we can study how the volatility-management strategy performs by different firms' capital structures. This provides more comprehensive insights into the volatility-management method. We scale the market capitalisation by one million to reach more easily comparable numbers. We take the logarithm of the average market capitalisation for each company and sort these into size quartile portfolios.

Next, extensive literature shows a strong relationship between credit rating and leverage.[13] Higher ratings signal higher creditworthiness of the companies and lower bond yields, which impacts capital structure decisions. By separating the credit ratings and

[13] Kisgen (2006) argues that firms' capital structure decisions are significantly influenced by credit ratings due to the trade-off between the rating upgrade benefits and the downgrade costs. Faulkender and Petersen (2005) and Sufi (2007) also find that the leverage of rated companies is higher than those not rated due to higher accessibility to capital. For the rated companies, Maung and Chowdhury (2014) claim

analysing the volatility-management effects in each tranche, we can see how the relationship between credit ratings and leverages engages in volatility-management processes. This provides us with a more comprehensive understanding of the strategy application. We perform the risk-timing strategies for portfolios of equities issued by firms with different credit ratings and costs of debt. We sort equities into seven credit-rating portfolios based on the S&P, Fitch, and Moody's ratings. We adopt the S&P terminology to denote the credit-worthiness.

Finally, due to financial entities' usual very high leverage, for robustness, we run separate analyses for financial and non-financial entities to ensure that their inclusion does not drive our results. There are 190 financial companies and 947 non-financial companies in our sample. In the appendix, we report the results for portfolios formed based on firms' size and credit rating, as well as financial and non-financial entities

3.3.2 Portfolio constructions

We make an essential departure from the traditional volatility-managed portfolio construction by scaling returns based on firm-level risk factors instead of market factors. This is for two reasons. First, the long-run relationship between variables often arises from no-arbitrage or market efficiency conditions that might not necessarily hold on firm-level and short-run. Second, because MW and GLB are computed from individual firms' option prices, this affords investors a market-consensus forward-looking expected risk and stock return information allowing them to tailor their investment themes by their risk-reward considerations. Our approach enables investors to target stocks and corresponding weights directly rather than constructing large portfolios that typically incur substantial transaction costs, thus affording them increased utility.

We follow Moreira and Muir (2017) and Cederburg et al. (2020) to compute the realised volatility scaled return for each company:

$$R^{f-s}_{i,t+1} = \frac{c_i}{\widehat{RV}^2_{i,t}} R_{i,t+1}, \tag{3.1}$$

where

$$\widehat{RV}^2_{i,t} = \frac{22}{d_t} \sum_{i=1}^{d_t} (r_{i,t})^2.$$

$\widehat{RV}^2_{i,t}$ is the month t realised volatility of each firm i in our sample. d_t is the number of trading days in month t. $r_{i,t}$ is each day log return in month t. We then replace the rv with the risk-neutral forward-looking volatilities, namely IV, MW, and GLB. $R_{i,t+1}$ and

that both rating upgrades and downgrades affect firms' leverage, and the rating downgrade effect is long-lasting. Aktan et al. (2019) further reveal that firms tend to be less leveraged after being upgraded to the investment grade.

$R^{f-s}_{i,t+1}$ are the unscaled and firm-level volatility-scaled excess return of each company at month *t+1*, respectively. The constant c is used for making unscaled and scaled return variances the same for each company. Formally, c is defined as $c_i = \sqrt{\frac{var(R_{t+1})}{var(\frac{R_{t+1}}{\widehat{av}^2_t})}}$, where $\widehat{av}_t$ represents any firm-level RV, IV, MW, and GLB. The quotients of the constants and different kinds of squared volatilities represent the weight of the investment position in the related company in month t.

We apply and compare two different approaches to combine firm-level information: firm-level scaling and aggregate-level scaling. The first approach is that all returns are scaled by RV, IV, MW, and GLB at the individual firm level only. Then the scaled firm excess returns are summed into portfolios based on firm characteristics. These characteristics are firm leverage ratios, financial and non-financial industries, firm size, and firms' credit ratings.[14] We denote these volatility-managed portfolios as firm-level scaling portfolios.

Alternatively, we first compute the average variances (squared RV, IV, MW, or GLB) for each portfolio formed on the firm characteristics described above. We then use these average portfolio variances to scale the excess returns in each portfolio. We call them aggregate-scaling returns:

$$\overline{av^2_{t,j}} = \frac{\sum_{i=1}^{n_j} av^2_{t,i}}{n_j}, \tag{3.2}$$

$$R^{a-s}_{t+1,j} = \frac{c_j}{\overline{av^2_{t,j}}} R_{t+1,j}, \tag{3.3}$$

where $\overline{av^2_{t,j}}$ is the average of any one of the squared volatilities (RV, IV, MW, or GLB) for the portfolio j at month t. $av^2_{t,i}$ is any squared volatility (RV, IV, MW, or GLB) of the company i in month t. $R_{t+1,j}$ is the unscaled return of the portfolio j in month *t+1*. $R^{a-s}_{t+1,j}$ is aggregate-level scaled excess return by any volatility (RV, IV, MW, or GLB) of the portfolio j in month *t+1*. For each portfolio and each kind of squared volatility, $c_j = \sqrt{\frac{var(R_{t+1,j})}{var(\frac{R_{t+1,j}}{\overline{av^2_{t,j}}})}}$, which is used for making the unconditional variance of portfolio returns consistent. By dividing our sample into different portfolios constructed based on these firm characteristics, we not only gain deeper insights into the performance of volatility-managed strategies for different firm characteristics and at the aggregate macro level as traditionally considered in the literature, but we can also see whether our

[14]The four leverage and size portfolios are constructed as follows: Portfolio1 (QL) contains entities that have up to 25% leverage or market capitalisation. The second portfolio (Q2) contains entities with leverage or market capitalisation between 25% and 50%. The third portfolio (Q3) contains 50% to 75% and the last is over 75% leverage or market capitalisation. The industries are divided into financial and non-financial. The credit rating portfolios are constructed by S&P's rating nomenclature, from AAA to CCC.

results remain robust across different samples. We report the aggregate-level scaling results in the appendix to save space.

We apply the volatility timing strategy based on monthly return data because higher-frequency trading incurs high costs for investors. For robustness, we also isolate the GFC period and split the sample into before and after January 2020, coinciding with the start of the COVID-19 pandemic and the US elections. This approach allows us to see how our trading strategy changes during essential structural shocks.

3.3.3 Spanning regressions

We first compute the full sample average excess returns to analyse the entire sample's systematic risk. This approach is similar to the typical factor scaling method used in the literature, such as MM and COWY. We run univariate regressions for firm- and aggregate-level managed separately and test the intercept and coefficient, similar to the spanning regression methods used by both MM and COWY[15].

$$R_t^{f/a-s} = \alpha + \beta R_t + \epsilon_t, \tag{3.4}$$

where $R_t^{f/a-s}$ is the portfolio excess return in month t scaled by the squared firm- or aggregate-level RV, IV, MW, and GLB. R_t is the corresponding unscaled excess return in month t.

MM claim that a statistically significant positive α indicates that the scaled portfolio exhibits a higher Sharpe ratio than the unscaled portfolio, thereby affording mean-variance investors additional utility gains. In contrast, COWY argue that the estimated coefficient, β, associated with the independent variable must also be considered. They suggest that this coefficient is equivalent to the unconditional correlation coefficient between the scaled and unscaled returns ($\widehat{\beta} = \widehat{\rho}$). Under this interpretation, the benefit from a positive constant is partially offset by a decline in the Sharpe ratio. Nonetheless, as demonstrated by Gibbons et al. (1989), a positively weighted combination of scaled and unscaled factors can expand the mean-variance frontier.

Following the spanning regression, we also compute the appraisal ratio (AR), which is the proportion of the estimated intercept and the estimated standard error of the spanning regression. AR measures the scale of changes on the slope of the mean-variance efficient frontier (Gibbons et al., 1989; Moreira and Muir, 2017).

[15]The variables used in the spanning regression are return series, which are generally considered to be stationary in the finance literature.

3.4 Empirical Results

We assess the performance of our stock-level ex-ante risk timing method using option-implied volatility and the ex-post risk timing using realised volatility. We also add two ex-ante tail risk measures, the MW and GLB, to characterise the stock risk better. We use the daily stock price, RV, IV, MW, and GLB of 1137 companies in the S&P 500 from January 1996 to December 2021.[16] We run parallel analyses for the total sample and isolate the Global Financial Crisis and COVID-19. We also repeat these analyses for quartile portfolios formed based on firms' leverage levels. Further, we re-run these analyses for quartile portfolios formed on firms' size, seven credit rating portfolios and by separating financial from non-financial firms, results of which we report in the appendix to save space.

Low-risk anomaly for leverage, size and volatility levels

The beta anomaly implies that beta risk is overvalued in equity securities and undervalued in debt. Baker et al. (2020) show that firms with high-risk assets reduce their cost of capital by keeping low debt levels. On the other hand, low leverage levels for low-risk firms imply substantial costs as they use undervalued equity. Thus, they minimise their capital cost at much higher leverage levels. The anomaly generates a trade-off that predicts an inverse relationship between systematic risk and leverage. Furthermore, the standard trade-off theory also implies an inverse relationship between debt and systematic risk (Long and Malitz, 1985). We then analyse how the LRA varies across the issuer's capital structure and equity return volatility. To illustrate this, we form RV, IV, MW, or GLB quartile portfolios and compute their average excess returns, firm leverage, and size. Table 3.1 aggregates the findings.

The first column of Table 3.1 shows that the highly volatile equities have lower or negative excess returns across historical and forward-looking volatility-sorted portfolios. The inverse relationship between risk and return provides evidence of the LRA, which also appears to be a data feature for the forward-looking risk measures.

The second column of Table 3.1 highlights another crucial finding. Leverage appears inversely related to risk, assessed by the RV or an RN. As discussed earlier, in structural models, leverage represents the "moneyness" of the put option implicit in a firm's debt. This option gains in value during distress and financial uncertainty for the firm. Highly leveraged entities, therefore, represent at-the-money options. In contrast, low-leverage entities would need to suffer catastrophic deterioration of their assets before reaching default, so they are out-the-money options. Our results thus support the beta anomaly trade-off predictions (Baker et al., 2020). The inverse relationship between

[16] We also use the cross-sectional averages of RV and RNs to time-risk of our sampled firms. We refer to these results as the aggregate level, as discussed in Section 3.3.

TABLE 3.1: Risk-sorted portfolios

This table reports the monthly average excess returns, leverages, and size proxies of equally weighted quartile portfolios sorted for RV, IV, MW and GLB. The portfolios include equities of 1,137 stocks from January 1996 to December 2021. The lowest risk quartile is denoted as "Low", and the highest as "High". The leverage is computed as debt-asset ratios. The size proxy is the market capitalisation, calculated as the logarithm of the product of stock prices and outstanding shares divided by one million.

	Excess return	Leverage	Size
RV			
Low	0.0120	0.6720	10.1270
Q2	0.0128	0.6529	10.0090
Q3	0.0118	0.6168	9.9181
High	-0.0022	0.6030	9.6178
IV			
Low	0.0124	0.6782	10.2018
Q2	0.0136	0.6492	10.0180
Q3	0.0093	0.6286	9.8566
High	-0.0009	0.5886	9.5909
MW			
Low	0.0118	0.6858	10.2087
Q2	0.0133	0.6495	10.0444
Q3	0.0095	0.6286	9.8183
High	-0.0001	0.5807	9.5961
GLB			
Low	0.0098	0.6732	9.9377
Q2	0.0095	0.6325	10.0049
Q3	0.0072	0.6262	9.9708
High	0.0080	0.6134	9.7576

capital structure and risk assessed by the RV or an RN is a robust feature also for the forward-looking risk data.[17]

Furthermore, the last column of Table 3.1 shows that firm size moves hand-in-hand with leverage. Larger firms tend to have more debt, as they are usually better diversified with lower default probabilities and associated bankruptcy costs, allowing them to take on more leverage (Rajan and Zingales, 1995). This finding is also consistent with the recent results of Kita and Tortorice (2021), who prove that the premium for bearing variance risk is highest for firms with the lowest leverage. This effect is because small firms of this type do not increase their leverage, as doing so incurs a market risk premium.

[17] Choi and Richardson (2016) and Schwert and Strebulaev (2014) also find that high-leverage firms have lower average asset volatility and beta, respectively.

3.4.1 Risk timing strategy

As discussed, we pay particular attention to analysing the distinctive performances between our stock-level *ex-ante* risk timing using IV and *ex-post* timing using RV. We then add two new ex-ante measures that capture investors' preferences for higher return moments. In addition to the statistical significance of our alphas and the appraisal ratios, we also use three additional Performance Ratios (PR) to assess the success of our strategy. The first is the standard Sharpe Ratio that scales the excess returns with their total volatility. However, we conjecture that options-market information is particularly informative in capturing investors' projections for non-Gaussian returns and risks; thus, our results could be driven by excessive tail risk. In response, we also control for our strategies Sortino Ratio, a risk-adjusted performance measure that evaluates the return of an investment relative to its downside risk (the standard deviation of negative returns). Finally, we report the Calmar Ratio, a risk-adjusted performance measure popular among practitioners designed to capture the downside risk. Calmar divides the excess returns with the maximum drawdown measure, which is the largest peak-to-trough decline in value over a specified period, in our case, a month.

Equally weighted portfolios

Table 3.2 reports the estimated PRs for equally weighted portfolios with and without (unscaled) risk timing. Panel A refers to the entire period, and the other panels refer to the periods before and from January 2020. The table also includes the PRs for the risk-timing implemented based on RV and RNs. The stock-level MW-managed portfolios achieved the best performance, followed by the IV- and GLB-managed ones. The results for the period up to December 2019 are qualitatively similar. In the subsequent period, the highest PRs are achieved by managing the portfolio using the GLBs (Panel C). Similar results for the aggregate-level scaling are reported in the appendix to save space.

Overall, the results reported in Table 3.2 suggest superior information for risk timing embedded in the forward-looking option prices rather than historical portfolio values. This information on volatility and expected return affords investors a leverage option, providing an effective risk measure in constructing ex-ante risk-managed portfolios. In particular, GLB's performance is striking from January 2020 to December 2021, a period of exceptionally high market uncertainty. GLB aims to delineate bounds on the conditional expected excess returns, which differs from MW, which is directly tight to variance (Martin, 2017). Models delineating practical limitations of perfect portfolio diversification when firm shocks are fat-tailed find support in our data. Another intriguing result is that risk timing performed by scaling returns at the firm level performs better than those obtained by scaling at the aggregate level.

TABLE 3.2: Performance measures for equally-weighted portfolios

This table reports the average monthly Sharpe, Sortino, and Calmar ratios of the original portfolios ("Unscaled") and the corresponding RV, IV, MW, and GLB risk-managed portfolios. Panel A includes the results of the whole sample from January 1996 to December 2021, and Panels B and C do so for the sample period before or after January 2020, respectively.

	Unscaled	RV	IV	MW	GLB
Panel A: January 1996 to December 2021					
Sharpe Ratio	0.1049	0.0844	0.1577	0.2035	0.1573
Sortino	0.1457	0.1222	0.2324	0.2747	0.1994
Calmar	0.4961	0.2771	0.6669	0.9203	0.7018
Panel B: January 1996 to December 2019					
Sharpe Ratio	0.1049	0.0779	0.1576	0.2057	0.1518
Sortino	0.1138	0.0978	0.2114	0.2690	0.1947
Calmar	0.5073	0.2697	0.6832	0.9455	0.6936
Panel C: January 2020 to December 2021					
Sharpe Ratio	0.1211	0.1382	0.1567	0.1777	0.2557
Sortino	0.1869	0.2079	0.1709	0.1813	0.1836
Calmar	0.3620	0.3655	0.4718	0.6182	0.7998

Leverage-sorted portfolios

As discussed earlier and from the results in Table 3.1, the beta anomaly generates a trade-off between debt and equity, leading to an inverse relationship between leverage and risk. We take leverage-sorted quartile portfolios as test assets to study this phenomenon and how it impacts the performance of the ex-ante risk timing strategy. Even controlling for leverage levels, risk timing appears more effective when based on firm-level risk measures, especially when accounting for information from option prices.

Table 3.3 reports the monthly performance ratios of these leverage-sorted firm-level scaled portfolios with and without risk timing. The Low, Q2, Q3, and High portfolios contain entities that have up to 25%, between 25% and 50%, from 50% to 75%, and over 75% leverage. Over the whole sample and pre-pandemic period, the PR has a decreasing tendency in the leverage level (Panels A and B). Similar to the findings in Table 3.2, timing volatility using RVs does not augment excess returns and alphas. Differently, risk timing based on the RNs augments the PR. In particular, the drop in pointwise PR estimate as a function of leverage is much more severe in the RV-managed portfolios. These portfolios experience a loss of about 50 per cent in PR compared to only a 10 to 35 per cent loss in RN-managed portfolios. The hypothesis that RNs account more for the firm's capital structure when flagging risk than RV appears consistent with this finding.

The relationship between PR and leverage level inverts during COVID-19. The results reported in Panel C indicate an overall PR increase in the leverage level. Overall, the RN-managed portfolios, particularly the GLB-managed ones, have the highest PR. This finding again emphasises the advantages of measures from option prices to implement risk-timing strategies.

TABLE 3.3: Performance measures for leverage-sorted portfolios

This table reports the average monthly Sharpe, Sortino, and Calmar ratios of the original portfolios ("Unscaled") and the corresponding RV, IV, MW, and GLB risk-managed portfolios. The sample consists of 1,137 stocks, cross-sectionally aggregated in equally weighted leverage portfolio quartiles. The equities are divided into quartiles based on the average level of leverage of firms: "Low" includes firms with leverage less than 25%, "Q2" includes firms with leverage from 25% to 50%, "Q3" includes firms with leverage from 50% to 75%, and "High" includes firms with leverage above 75%. Panel A refers to the entire sample covering January 1996 to December 2021. Panel B reports the results for the pre-COVID-19 period. Panel C repeats the analyses from January 2020 to December 2021.

	Sharpe ratio				Sortino ratio				Calmar measure			
	Low	Q2	Q3	High	Low	Q2	Q3	High	Low	Q2	Q3	High
Panel A: January 1996 to December 2021												
Unscaled	0.1348	0.1210	0.1022	0.0450	0.1976	0.1644	0.1432	0.0611	0.6084	0.5997	0.5024	0.1979
RV	0.1001	0.0940	0.0818	0.0525	0.1407	0.1333	0.1183	0.0798	0.4232	0.3730	0.2771	0.0537
IV	0.1742	0.1645	0.1456	0.1373	0.2491	0.2405	0.2131	0.2121	0.8047	0.7223	0.6135	0.5030
MW	0.1986	0.2135	0.1697	0.1699	0.2589	0.2808	0.2307	0.2243	0.9820	1.0043	0.7176	0.7981
GLB	0.1878	0.1528	0.1399	0.1352	0.2576	0.1921	0.1543	0.1710	0.9443	0.6532	0.6803	0.6305
Panel B: January 1996 to December 2019												
Unscaled	0.1386	0.1229	0.1046	0.0353	0.1568	0.1303	0.1143	0.0393	0.6287	0.6184	0.5180	0.1867
RV	0.0936	0.0900	0.0771	0.0423	0.1081	0.1105	0.0991	0.0573	0.4201	0.3739	0.2759	0.0324
IV	0.1754	0.1652	0.1461	0.1346	0.2260	0.2193	0.1988	0.1938	0.8270	0.7433	0.6313	0.5058
MW	0.2030	0.2169	0.1687	0.1718	0.2509	0.2767	0.2215	0.2303	1.0195	1.0282	0.7059	0.8158
GLB	0.1864	0.1468	0.1339	0.1267	0.2593	0.1859	0.1503	0.1611	0.9599	0.6442	0.6689	0.6090
Panel C: January 2020 to December 2021												
Unscaled	0.1336	0.1273	0.1046	0.1176	0.2085	0.1868	0.1663	0.1659	0.3653	0.3756	0.3141	0.3325
RV	0.1573	0.1312	0.1233	0.1368	0.2760	0.1971	0.1801	0.1859	0.4611	0.3613	0.2927	0.3099
IV	0.1647	0.1542	0.1389	0.1667	0.1973	0.1692	0.1458	0.1687	0.5378	0.4706	0.3993	0.4697
MW	0.1729	0.1698	0.1783	0.1481	0.2427	0.1536	0.1696	0.0980	0.5325	0.7177	0.8581	0.5849
GLB	0.2273	0.2474	0.2633	0.2805	0.1472	0.1868	0.1637	0.2160	0.7582	0.7611	0.8172	0.8885

3.4.2 Spanning regressions

To assess the success of our ex-ante risk timing strategy, we closely follow the standard approach adopted in the literature (Moreira and Muir, 2017; Cederburg et al., 2020). The spanning regressions are as in Equation (3.4). We consider multiple test portfolios and all the risk timing implementations discussed so far, controlling for widely recognised equity risk factors.

Equally weighted and leverage-sorted portfolios

Table 3.4 reports the estimation results of risk-managed equally-weighted portfolio returns regressed on original returns as per Equation (3.4).

TABLE 3.4: Spanning regressions for full sample

This table reports the spanning regressions of monthly portfolio excess returns, as in Equation (3.4). Panel A reports the regression results for the entire sample, accounting for firm and month-fixed effects. The sample includes 1,137 stocks. Panel A.1 reports the results when regressions control for the three Fama and French (1993) and Carhart (1997) risk factors (FFC). We also control for the ex-ante coskewness risk factor proposed by Schneider et al. (2020), available only until December 2014. Panels B and C are similar to Panel A but refer to pre- and post-pandemic periods. Including the coskewness risk factor in Panel B yields similar results as those reported in Panel A. We do not control for the ex-ante coskewness risk factor in Panel C due to data limitation. The alpha and appraisal ratios are annualised. Robust standard errors are in parentheses. The R-squared is adjusted for the number of predictors. The superscripts * * *, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	RV	IV	MW	GLB
Panel A: January 1996 - December 2021				
α	-0.0033*	0.0478***	0.0335***	0.0420***
	(0.0020)	(0.0017)	(0.0023)	(0.0021)
β	0.5926***	0.6569***	0.1829***	0.3358***
	(0.0013)	(0.0011)	(0.0015)	(0.0015)
Adjusted R^2	0.3522	0.4892	0.0351	0.1283
Appraisal Ratio	-0.0101	0.1760	0.0900	0.1200
Panel A.1: Controlling for FFC4 and ex-ante skewness factors				
α	0.0034*	0.0438***	0.0345***	0.0373***
	(0.0021)	(0.0017)	(0.0024)	(0.0022)
Adjusted R^2	0.3568	0.4934	0.0357	0.1298
Appraisal Ratio	0.0104	0.1621	0.0926	0.1066
Panel B: January 1996 - December 2019				
α	-0.0015	0.0510***	0.0351***	0.0449***
	(0.0020)	(0.0017)	(0.0024)	(0.0023)
β	0.5956***	0.6803***	0.1927***	0.3652***
	(0.0014)	(0.0012)	(0.0017)	(0.0016)
Adjusted R^2	0.3459	0.4880	0.0365	0.1366
Appraisal Ratio	-0.0089	0.1865	0.0927	0.1231
Panel B.1: Controlling for FFC4 factors				
α	0.0035*	0.0537***	0.0380***	0.0439***
	(0.0021)	(0.0018)	(0.0025)	(0.0024)
Adjusted R^2	0.3501	0.4941	0.0375	0.1388
Appraisal Ratio	0.0078	0.1975	0.1009	0.1212
Panel C: January 2020 - December 2021				
α	-0.0080	0.0090**	0.0209***	0.0194***
	(0.0080)	(0.0049)	(0.0080)	(0.0049)
β	0.5716***	0.4986***	0.1156***	0.1329***
	(0.0042)	(0.0026)	(0.0042)	(0.0026)
Adjusted R^2	0.3951	0.5652	-0.0145	0.0686
Appraisal Ratio	-0.0228	0.0406	0.0594	0.0895
Panel C.1: Controlling for FFC4 factors				
α	-0.0018	-0.0242***	0.0104	0.0071*
	(0.0083)	(0.0052)	(0.0086)	(0.0052)
Adjusted R^2	0.4331	0.5774	-0.0138	0.0833
Appraisal Ratio	-0.0052	-0.1114	0.0292	0.0327

In line with the literature, a positive intercept in the linear regression of Equation (3.4) indicates the minimum lower bar for a successful risk-managed strategy relative to a positive Sharpe Ratio difference in the direct comparison analyses of Section 3.4.1. As Cederburg et al. (2020) indicate, this volatility timing can lead to a drop from about 20% in Sharpe Ratio while producing positive alpha in the spanning regressions. To address this concern, we also include the beta estimates. A positive intercept of scaled and original factors (with positive weight on the scaled factor) can expand the mean-variance frontier (Gibbons et al., 1989). For the entire sample, we confirm the benefits of ex-ante risk timing when risk is assessed by stocks' RNs (Panel A). Only in this case does the alpha become statistically significant at the 1% level and economically relevant.

To gain more insights into the performance of the distinct risk timing implementations, we compute the appraisal ratios (ARs) as

$$AR = \frac{\widehat{\alpha}}{\widehat{\sigma_{\epsilon}}}, \tag{3.5}$$

where $\widehat{\alpha}$ is the estimated intercept and $\widehat{\sigma_{\epsilon}}$ is the estimated standard error of the regression residuals in Equation (3.4). The large ARs of the RN-managed portfolios favour the ex-ante risk timing in expanding the dynamic mean-variance frontier relative to the original portfolios. More to the point, the ARs for RN-managed portfolios are solidly larger than their counterparts managed using RVs. Our results are robust to controls for the Fama and French (1993) and Carhart (1997) factors and when we control for the ex-ante coskweness measure proposed by Schneider et al. (2020) (data available from Jan 1996 to Dec 2014). Results do not qualitatively change when we disregard the pandemic period. Interestingly, during the COVID-19 period, the portfolio performance improvement due to our ex-ante risk timing is less clear, as Panel C illustrates. Managing the portfolio based on RVs appears detrimental when we control for standard equity risk factors. Only the alpha for our strategy implemented by GLBs is statistically significantly positive at 10%.

These results indicate that the RN-managed portfolios appear to expand the dynamic mean-variance frontier when the portfolio weight scaling is at the firm level. On the other hand, this effect is not shared by the volatility-timing strategies based on RVs. Strikingly, these findings also extend when we restrict our analyses for the Global Financial Crisis (GFC) from July 2007 to June 2009 (Table 3.5).

TABLE 3.5: Spanning regressions for equally weighted portfolios: The Global Financial Crisis

This table reports the results of the same spanning regressions as those in Table 3.4 focusing on just the Global Financial Crisis from July 2007 to June 2009. The sample includes 1,137 stocks. The alpha and appraisal ratios are annualised. Robust standard errors are in parentheses. The R-squared is adjusted for the number of predictors. The superscripts * * *, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	RV	IV	MW	GLB
	July 2007 - June 2009			
α	-0.0066	0.0461***	0.0275***	0.0242***
	(0.0053)	(0.0043)	(0.0040)	(0.0026)
β	0.2186***	0.3059***	0.0384***	0.0484***
	(0.0026)	(0.0021)	(0.0020)	(0.0013)
Adjusted R^2	0.1803	0.4212	-0.0285	0.0099
Appraisal Ratio, AR	-0.0281	0.2384	0.1528	0.2064
Additional controls for FFC4 and ex-ante skewness factors				
α	0.0570***	0.0806***	0.0405***	0.0495***
	(0.0069)	(0.0057)	(0.0053)	(0.0034)
Adjusted R^2	0.1932	0.4301	-0.0272	0.0248
Appraisal Ratio, AR	0.2443	0.4200	0.2254	0.4248

Table 3.6 repeats these tests by studying the performance of our strategy for firms with different capital structures. We sort firms into four equally weighted portfolios based on their leverage ratios. As in the previous section, our spanning regressions control for Fama-French-Carhart and the coskewness risk factors. While the standard trade-off theory predicts an inverse relationship between the systematic risk and leverage, also presented in our results reported in Table 3.3, we do not find materially different results between different leverage levels. The RN-managed portfolios expand the dynamic mean-variance frontier, while the RVs, once controlled for risk factors, do not. However, once we isolate our analyses for the GFC period, we note that highly leveraged entities expand the mean-variance frontier only at a 10% significance level (Table 3.7).

TABLE 3.6: Spanning regressions for leverage-sorted portfolios

This table reports the regression results similar to Table 3.4 but for portfolios sorted on the firm's average leverage level. The equally weighted leverage portfolio quartiles are: less than 25% is the quartile of firms with the lowest average level of leverage (Low), from 25% to 50% is the quartile with the second lowest (Q2), from 50% to 75% is the quartile with the second highest (Q3), and above 75% is the quartile of firms with the highest average level of leverage (High). The sample includes 1,137 stocks. The alpha and appraisal ratios are annualised. Robust standard errors are in parentheses. The R-squared is adjusted for the number of predictors. The superscripts * * *, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Low	RV	IV	MW	GLB	Q3	RV	IV	MW	GLB
α	-0.0066	0.0459***	0.0410***	0.0463***		-0.0076**	0.0355***	0.0252***	0.0369***
	(0.0042)	(0.0034)	(0.0048)	(0.0045)		(0.0035)	(0.0029)	(0.0043)	(0.0041)
β	0.5809***	0.6826***	0.2342***	0.3687***		0.6404***	0.7185***	0.1801***	0.3407***
	(0.0027)	(0.0022)	(0.0031)	(0.0029)		(0.0026)	(0.0022)	(0.0032)	(0.0030)
Adjusted R^2	0.3391	0.5144	0.0579	0.1516		0.4116	0.5593	0.0323	0.1265
Appraisal Ratio	-0.0192	0.1642	0.1056	0.1271		-0.0266	0.1486	0.0714	0.1113
Controlling for the Fama and French (1993), Carhart (1997) and Schneider et al. (2020) factors									
α	0.0093***	0.0473***	0.0453***	0.0437***		0.0012	0.0351***	0.0272***	0.0351***
	(0.0044)	(0.0036)	(0.0050)	(0.0047)		(0.0037)	(0.0031)	(0.0045)	(0.0043)
Adjusted R^2	0.3459	0.5189	0.0596	0.1537		0.4171	0.5630	0.0326	0.1271
Appraisal Ratio	0.0274	0.1701	0.1167	0.1201		0.0044	0.1477	0.0771	0.1058

Q2					High				
α	-0.0082**	0.0405***	0.0326***	0.0322***		0.0065	0.0638***	0.0313***	0.0517***
	(0.0038)	(0.0031)	(0.0045)	(0.0042)		(0.0043)	(0.0037)	(0.0047)	(0.0044)
β	0.6226***	0.6803***	0.1851***	0.3460***		0.5394***	0.5715***	0.1305***	0.2965***
	(0.0026)	(0.0022)	(0.0031)	(0.0029)		(0.0028)	(0.0024)	(0.0031)	(0.0029)
Adjusted R^2	0.3883	0.5315	0.0364	0.1376		0.2915	0.3848	0.0171	0.1035
Appraisal Ratio	-0.0261	0.1584	0.0892	0.0937		0.0184	0.2106	0.0821	0.1430
Controlling for the Fama and French (1993), Carhart (1997) and Schneider et al. (2020) factors									
α	0.0025	0.0403***	0.0341***	0.0300***		-0.0014	0.0475***	0.0272***	0.0392***
	(0.0040)	(0.0033)	(0.0047)	(0.0044)		(0.0045)	(0.0039)	(0.0049)	(0.0047)
Adjusted R^2	0.3938	0.5359	0.0368	0.1392		0.2949	0.3904	0.0179	0.1061
Appraisal Ratio	0.0079	0.1585	0.0933	0.0874		-0.0040	0.1576	0.0714	0.1088

TABLE 3.7: Spanning regressions for leverage-sorted portfolios: The Global Financial Crisis

This table runs the same spanning regressions as those in Table 3.6 but focuses only on the Global Financial Crisis period from July 2007 to June 2009. The sample includes 1,137 stocks. The alpha and appraisal ratios are annualised. Robust standard errors are in parentheses. The R-squared is adjusted for the number of predictors. The superscripts * * *, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	July 2007 - June 2009							
Low	RV	IV	MW	GLB	Q3 RV	IV	MW	GLB
α	0.0065	0.0606***	0.0387***	0.0434***	-0.0091	0.0445***	0.0229***	0.0221***
	(0.0118)	(0.0087)	(0.0098)	(0.0066)	(0.0102)	(0.0079)	(0.0065)	(0.0039)
β	0.2746***	0.4319***	0.0783***	0.0789***	0.2247***	0.3318***	0.0386***	0.0435***
	(0.0066)	(0.0048)	(0.0054)	(0.0037)	(0.0054)	(0.0042)	(0.0034)	(0.0021)
Adjusted R^2	0.1791	0.5432	-0.0108	0.0259	0.1755	0.4753	-0.0234	0.0244
Appraisal Ratio	0.0248	0.3159	0.1784	0.2947	-0.0399	0.2543	0.1598	0.2583
	Controlling for the Fama and French (1993), Carhart (1997) and Schneider et al. (2020) factors							
α	0.0980***	0.1118***	0.0619***	0.0860***	0.0609***	0.0897***	0.0389***	0.0452***
	(0.0153)	(0.0112)	(0.0128)	(0.0086)	(0.0133)	(0.0102)	(0.0085)	(0.0050)
Adjusted R^2	0.2002	0.5570	-0.0078	0.0479	0.1940	0.4935	-0.0210	0.0447
Appraisal Ratio	0.3785	0.5922	0.2859	0.5913	0.2714	0.5215	0.2716	0.5332
Q2					High			
α	-0.0019	0.0449***	0.0264***	0.0237***	-0.0366***	0.0089	0.0148**	0.0030
	(0.0098)	(0.0097)	(0.0090)	(0.0054)	(0.0101)	(0.0077)	(0.0068)	(0.0048)
β	0.2149***	0.2992***	0.0409***	0.0404***	0.1817***	0.2164***	0.0119***	0.0395***
	(0.0046)	(0.0046)	(0.0042)	(0.0026)	(0.0044)	(0.0033)	(0.0030)	(0.0021)
Adjusted R^2	0.2205	0.3788	-0.0286	-0.0046	0.1773	0.3726	-0.0410	0.0125
Appraisal Ratio	-0.0087	0.2081	0.1319	0.1957	-0.1634	0.0523	0.0977	0.0286
	Controlling for the Fama and French (1993), Carhart (1997) and Schneider et al. (2020) factors							
α	0.0724***	0.0811***	0.0384***	0.0496***	-0.0164	0.0231**	0.0184*	0.0129*
	(0.0128)	(0.0127)	(0.0118)	(0.0071)	(0.0133)	(0.0100)	(0.0090)	(0.0063)
Adjusted R^2	0.2383	0.3868	-0.0268	0.0094	0.1787	0.3782	-0.0415	0.0213
Appraisal Ratio	0.3364	0.3781	0.1921	0.4134	-0.0732	0.1368	0.1220	0.1223

Leverage and performance ratio double-sorted portfolios

We estimate the spanning regression of Equation (3.4) with multiple test portfolios, reaching qualitatively similar conclusions as those reported in the previous section. In the appendix, additional robustness checks are performed for financial and non-financial firms, with portfolios sorted by firms' size and seven credit ratings. Here, we limit the discussion to double-sorted quartile portfolios based on leverage and performance ratios, including Sharpe, Sortino, and Calmar measures.

TABLE 3.8: Risk timing for leverage and performance ratios double-sorted portfolios

This table reports the average monthly return for portfolios double-sorted based on leverage and Sharpe, Sortino, and Calmar ratio in Panel A, B and C, respectively. The sample includes 1,137 firms and spans January 1996 to December 2021. We first sort all individual stock excess returns into leverage quartiles. Within each, we sort in quartiles for the indicated performance measure. Low, Q2, Q3, and High refer to the portfolios in the lowest, second lowest, second highest, and highest performance measure quartiles. High-Low is the difference in average return from the lowest to the highest performance measure quartile, and t-statistic indicates its statistical significance.

	Unscaled	RV	IV	MW	GLB
Panel A: Sharpe ratio sorted					
Low	-0.0428	-0.0865	0.0469	-0.2088	-0.0713
Q2	0.1017	0.0668	0.1396	0.1220	0.1184
Q3	0.1450	0.1297	0.1867	0.2995	0.2105
High	0.2048	0.2013	0.2605	0.3715	0.3144
High-Low	0.2476	0.2878	0.2136	0.5803	0.3856
t-stat.	6.7265	9.8588	8.4597	12.0310	8.9402
Panel B: Sortino sorted					
Low	-0.0585	-0.1078	0.0678	-0.2101	-0.0730
Q2	0.1468	0.0987	0.2029	0.2064	0.1566
Q3	0.2041	0.1991	0.2878	0.6368	0.3420
High	0.3088	0.3268	0.4258	0.7134	0.5577
High-Low	0.3673	0.4346	0.3580	0.9235	0.6308
t-stat.	8.4992	9.7563	8.8143	10.7720	9.0824
Panel C: Calmar sorted					
Low	-0.4504	-0.3142	0.0173	0.2771	0.2951
Q2	0.4618	0.2593	0.6415	0.8285	0.5522
Q3	0.5757	0.4216	0.6714	1.0173	0.7062
High	0.7706	0.6177	0.9083	1.1536	0.9084
High-Low	1.2210	0.9319	0.8911	0.8765	0.6132
t-stat.	9.0654	7.2908	5.8094	3.2512	6.2618

Table 3.8 reports the double-sorted portfolios for our ex-ante risk timing based on RNs. We first group the stocks based on the leverage levels described in Section 3.4.1. Then, focusing on each group singularly, we form the PR-sorted quartile portfolios: Low, Q2,

Q3, and High portfolios are ranked from the lowest to highest ratios. Strategies with ex-ante risk timing using idiosyncratic RNs outperform the counterpart portfolios without risk timing with high statistical significance. The high-minus-low ratio difference is positive for all risk timing implementations with high statistical significance. The implementation based on MW leads to the highest ratios for the Q3 and High portfolios and the highest high-minus-low Sharpe Ratio difference. These results substantiate the fact that, when controlling for firm leverage levels, MW-managed portfolios perform the best.

Alternative LRA explanations

In three horse race exercises, we check if we can explain the LRA using our data through alternative explanations in the literature. Specifically, with our sampled firms and period, we analyse the volatility-timing strategy of Moreira and Muir (2017) and Cederburg et al. (2020), and those of Frazzini and Pedersen (2014) and Ang et al. (2006). We control for the common Fama-French-Carhart risk factors and add the ex-ante skewness factors proposed by Schneider et al. (2020). Results reported in Table 3.9 show that the MM's strategy yields statistically significant and positive alphas only for momentum and Betting-Against-Beta (BAB) factors. However, these results do not extend during the COVID-19 period. Table 3.10 reports the results when we implement a betting against beta strategy similar to the one proposed by Frazzini and Pedersen (2014). However, given the limitations of their method discussed in Novy-Marx and Velikov (2018), we make two changes to their strategy to mitigate these biases. First, we utilise the option-implied betas from the Buss and Vilkov (2012) method. Next, we apply the high-beta-minus-low-beta trading strategy, which is consistent with the strategy proposed here and similar in spirit to their original method. We find that option-implied betas also deliver high and statistically significant alphas even when we control for typical risk factors and co-skewness and during distressed market periods. We also compute the BAB strategy from the original Frazzini and Pedersen (2014)'s method. We re-run these estimates using backwards-looking realised betas and the option-implied betas. We find that when we implement the BAB strategy with realised beta estimates as originally implemented by Frazzini and Pedersen (2014), the BAB strategy does not lead to significant alphas. On the other hand, option-implied betas deliver marginally significant alphas once we control for traditional risk factors and the coskewness. To save space, we report these results in the appendix. Finally, when we implement Ang et al. (2006) strategy, we note that when we control for Carhart's momentum and Schneider et al. (2020) ex-ante skewness factors, their strategy does not yield statistically significant alphas in any of the quintile portfolios. Overall, these results indicate that the options market is particularly informative on investors' attention to return tails.[18]

TABLE 3.9: The Moreira and Muir (2017)'s volatility timing strategy based on realised variance

This table repeats Moreira and Muir (2017) strategy for the period January 1996 to December 2021. Regressions have the same specification as those in Table 3.4. Panel A reports the regression results for the excess market return (MKTRF), size (SMB), value (HML), profitability (RMW), investment (CMA), momentum (MOM), and betting-against-beta (BAB) factors, respectively. Panel A.1 reports the results when regressions controlled for the remaining Fama and French (2015), Carhart (1997) and Schneider et al. (2020) risk factors. Panels B and C are similar to Panel A but refer to pre- and post-pandemic periods, not accounting for the ex-ante coskewness risk factor due to data limitation. The alpha and appraisal ratios are annualised. Robust standard errors are in parentheses. The R-squared is adjusted for the number of predictors. The superscripts * * *, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	MktRF	SMB	HML	RMW	CMA	MOM	BAB
Panel A: January 1996 - December 2021							
α	2.3467	-1.4242	0.9205	2.2253	-0.9740	9.3536***	0.1247***
	(2.4221)	(1.3419)	(1.8987)	(1.5795)	(1.0591)	(2.8524)	(0.0180)
β	0.6331***	0.7881***	0.5341***	0.5891***	0.6791***	0.5660***	0.5292***
	(0.0440)	(0.0350)	(0.0480)	(0.0459)	(0.0417)	(0.0468)	(0.0482)
Adjusted R^2	0.3989	0.6198	0.2829	0.3449	0.4594	0.3181	0.2777
Appraisal Ratio	0.1927	-0.2084	0.0951	0.2787	-0.1812	0.6446	1.4210
Panel A.1: Controlling for the Fama and French (1993), Carhart (1997) and Schneider et al. (2020) factors							
α	0.8076	-1.5270	0.6344	3.6283	-0.7799	10.0688***	0.1332***
	(2.0726)	(1.5588)	(2.7266)	(2.2144)	(1.3313)	(3.7955)	(0.0241)
Adjusted R^2	0.5251	0.6191	0.2455	0.3171	0.4425	0.3116	0.2766
Appraisal Ratio	0.0955	-0.2399	0.0570	0.4088	-0.1451	0.6498	1.4283
Panel B: January 1996 - December 2019							
α	3.3263	-0.7803	1.0359	2.6870	-0.7666	9.5538***	0.1322***
	(2.5347)	(1.3940)	(2.0205)	(1.6949)	(1.1112)	(3.0625)	(0.0192)
β	0.6622***	0.8063***	0.5941***	0.5976***	0.6844***	0.5783***	0.5491***
	(0.0475)	(0.0368)	(0.0540)	(0.0496)	(0.0440)	(0.0500)	(0.0519)
Adjusted R^2	0.4022	0.6252	0.2949	0.3344	0.4564	0.3167	0.2787
Appraisal Ratio	0.2709	-0.1144	0.1047	0.3259	-0.1415	0.6385	1.4706
Panel B.1: Controlling for the Fama and French (1993) and Carhart (1997) factors							
α	2.3127	-0.9250	0.8490	2.8562	-1.2911	8.0081***	0.1250***
	(2.5443)	(1.4183)	(2.0710)	(1.7464)	(1.1044)	(3.0478)	(0.0198)
Adjusted R^2	0.4121	0.6288	0.2918	0.3482	0.4933	0.3506	0.2884
Appraisal Ratio	0.1899	-0.1363	0.0857	0.3501	-0.2469	0.5490	1.3996
Panel C: January 2020 - December 2021							
α	-8.5457	-9.1481*	-3.4995	-3.0816	-3.5826	6.2438	0.0278
	(7.3284)	(4.5765)	(2.7493)	(2.3829)	(3.5334)	(4.7813)	(0.0279)
β	0.4777***	0.6295***	0.2394***	0.5275***	0.6177***	0.3856***	0.3323***
	(0.1003)	(0.1039)	(0.0463)	(0.0640)	(0.1303)	(0.0853)	(0.0682)
Adjusted R^2	0.4852	0.6084	0.5281	0.7439	0.4826	0.4578	0.4972
Appraisal Ratio	-0.8701	-1.4160	-0.9056	-0.9527	-0.7171	0.9234	0.7268
Panel C.1: Controlling for the Fama and French (1993) and Carhart (1997) factors							
α	-8.8481	-9.4063*	-6.1760**	-5.0545*	-5.7807	6.2150	0.0309
	(7.6824)	(4.8403)	(2.6992)	(2.6847)	(3.8931)	(5.2679)	(0.0299)
Adjusted R^2	0.4626	0.6250	0.6072	0.7534	0.4761	0.4384	0.4907
Appraisal Ratio	-0.8817	-1.4877	-1.7517	-1.5925	-1.1499	0.9032	0.8022

[18] We further check whether including past maximum stock returns and the safe-minus-risky factors of Bali et al. (2017) and Kapadia et al. (2019) along with the already mentioned factors affect our alpha. We report these results in the appendix.

TABLE 3.10: The Frazzini and Pedersen (2014)'s betting-against-beta strategy

This table reports the monthly results from option-implied beta estimates, as from Buss and Vilkov (2012), of the equally weighted quartile portfolios for our 1,137 S&P 500 sampled firms from January 1996 to December 2021. BAB is the betting-against-beta factor constructed by taking a long position on the low-beta portfolio and a short position on the high-beta portfolio. This approach is similar to the original BAB strategy proposed by Frazzini and Pedersen (2014). In the appendix, we also implement the original Frazzini and Pedersen (2014)'s approach and sort our sample firms into deciles according to their option-implied beta estimates and the realised betas, finding some evidence of the benefits when option-implied betas are used only. Consistent with our previous test, we add to Fama and French (1993) 3-factors the Carhart (1997)'s momentum and the ex-ante coskewness of Schneider et al. (2020) risk factors as additional control factors. Panels B and C are similar to Panel A but refer to pre- and post-pandemic periods, not accounting for the ex-ante coskewness risk factor due to data limitations. The alpha and appraisal ratios are annualised. Robust standard errors are in parentheses. The R-squared is adjusted for the number of predictors. The superscripts * * *, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Low	Q2	Q3	High	BAB
Panel A: January 1996 - December 2021					
α	0.2076***	0.1414**	0.0688	-0.1580***	0.3656***
	(0.0632)	(0.0600)	(0.0582)	(0.0590)	(0.0296)
Adjusted R^2	0.0984	0.0795	0.1065	0.3080	0.6819
Appraisal Ratio	0.6548	0.4694	0.2355	-0.5337	2.4625
Panel A.1: Controlling for the Carhart (1997) and Schneider et al. (2020) factors					
α	0.1277*	0.0697	0.0035	-0.1851***	0.3128***
	(0.0659)	(0.0637)	(0.0611)	(0.0658)	(0.0304)
Adjusted R^2	0.0663	0.0815	0.1670	0.4303	0.8034
Appraisal Ratio	0.4759	0.2687	0.0142	-0.6914	2.5262
Panel B: January 1996 - December 2019					
α	0.1859***	0.1193**	0.0515	-0.1693***	0.3552***
	(0.0599)	(0.0569)	(0.0548)	(0.0572)	(0.0291)
Adjusted R^2	0.0394	0.0456	0.1048	0.3456	0.7027
Appraisal Ratio	0.6427	0.4341	0.1945	-0.6135	2.5324
Panel B.1: Controlling for the Carhart (1997) factor					
α	0.1687***	0.1074*	0.0461	-0.1543***	0.3230***
	(0.0602)	(0.0574)	(0.0554)	(0.0575)	(0.0260)
Adjusted R^2	0.0499	0.0496	0.1032	0.3512	0.7659
Appraisal Ratio	0.5865	0.3916	0.1740	-0.5615	2.5949
Panel C: January 2020 - December 2021					
α	0.2096	0.1839	0.0665	-0.1325	0.3422**
	(0.3481)	(0.3375)	(0.3408)	(0.3359)	(0.1346)
Adjusted R^2	0.5027	0.4295	0.3631	0.2481	0.7193
Appraisal Ratio	0.4598	0.4158	0.1489	-0.3011	1.9399
Panel C.1: Controlling for the Carhart (1997) factor					
α	0.2338	0.2106	0.0961	-0.1199	0.3537**
	(0.3558)	(0.3440)	(0.3465)	(0.3458)	(0.1369)
Adjusted R^2	0.4866	0.4146	0.3499	0.2130	0.7131
Appraisal Ratio	0.5046	0.4701	0.2131	-0.2662	1.9834

TABLE 3.11: The Ang et al. (2006)'s idiosyncratic volatility strategy

This table reports the estimation results for the Ang et al. (2006)'s strategy for our sample of 1,137 from January 1996 to December 2021. We follow Ang et al. (2006) in sorting our entire sample into quintiles according to their idiosyncratic volatilities, denoted as "Low," "Q2," "Q3," "Q4," and "High." The idiosyncratic volatility is defined as each stock's standard deviation of Fama and French (1993) 3-factor regression errors. Column 'High-Low' represents the difference between Portfolio High and Portfolio Low. The quintile portfolios are rebalanced each month. Panel A reports the Fama and French (1993) 3-factor regression results for each quintile portfolio and the difference portfolio, respectively. Panel A.1 reports the results when regressions are controlled for the Carhart (1997) momentum factor and the ex-ante coskewness risk factor of Schneider et al. (2020). Panels B and C are similar to Panel A but refer to pre- and post-pandemic periods and omit the ex-ante coskewness risk factor due to data limitation. The alpha and appraisal ratios are annualised. Robust standard errors are in parentheses. The R-squared is adjusted for the number of predictors. The superscripts * * *, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Low	Q2	Q3	Q4	High	High-Low
Panel A: January 1996 - December 2021						
α	0.1467**	0.1406**	0.1233**	0.0961	-0.1508**	-0.2974***
	(0.0608)	(0.0603)	(0.0605)	(0.0587)	(0.0603)	(0.0341)
Adjusted R^2	0.0701	0.0760	0.0768	0.1117	0.3151	0.6140
Appraisal Ratio	0.4801	0.4639	0.4053	0.3257	-0.4976	-1.7345
Panel A.1: Controlling for the Carhart (1997) and Schneider et al. (2020) factors						
α	0.0477	0.0530	0.0596	0.0722	-0.1105	-0.1581***
	(0.0643)	(0.0632)	(0.0632)	(0.0629)	(0.0677)	(0.0343)
Adjusted R^2	0.0617	0.0923	0.1162	0.1749	0.4386	0.7590
Appraisal Ratio	0.1815	0.2056	0.2311	0.2814	-0.3997	-1.1301
Panel B: January 1996 - December 2019						
α	0.1270**	0.1198**	0.1064*	0.0857	-0.1565***	-0.2836***
	(0.0575)	(0.0570)	(0.0570)	(0.0563)	(0.0587)	(0.0336)
Adjusted R^2	0.0237	0.0413	0.0611	0.1154	0.3572	0.6222
Appraisal Ratio	0.4566	0.4348	0.3858	0.3150	-0.5514	-1.7474
Panel B.1: Controlling for the Carhart (1997) factor						
α	0.1117*	0.1062*	0.0947	0.0807	-0.1416**	-0.2533***
	(0.0579)	(0.0574)	(0.0575)	(0.0569)	(0.0591)	(0.0315)
Adjusted R^2	0.0323	0.0475	0.0646	0.1135	0.3621	0.6741
Appraisal Ratio	0.4033	0.3865	0.3442	0.2962	-0.5009	-1.6808
Panel C: January 2020 - December 2021						
α	0.1164	0.1418	0.0854	0.0199	-0.1872	-0.3036**
	(0.3384)	(0.3373)	(0.3484)	(0.3325)	(0.3607)	(0.1437)
Adjusted R^2	0.4607	0.4450	0.3912	0.3232	0.0872	0.7776
Appraisal Ratio	0.2620	0.3201	0.1867	0.0455	-0.3951	-1.6082
Panel C.1: Controlling for the Carhart (1997) factor						
α	0.1415	0.1704	0.1180	0.0425	-0.1776	-0.3191**
	(0.3447)	(0.3423)	(0.3523)	(0.3395)	(0.3715)	(0.1444)
Adjusted R^2	0.4463	0.4348	0.3844	0.3024	0.0422	0.7781
Appraisal Ratio	0.3142	0.3812	0.2564	0.0958	-0.3660	-1.6922

3.4.3 Out-of-sample strategy performance

Investors' preferences regarding risk and expected return may vary over time. We argue that, in particular, such swings manifest more clearly during highly stressed market periods, such as those during COVID-19. Because the time-varying weights affect the performance of optimal portfolios out of the sample, the estimation risk in Equation (3.4) is a genuine concern. Thus, the model estimation and over-fitting risks are crucial in our analysis of forward-looking risk timing and realised risk measures. To address these concerns, we check if the in-sample results of the previous sections carry on in an out-of-sample performance analysis. For this, we use two sample periods. The first sample covers January 1996 through December 2019, deliberately omitting the heightened volatility of the pandemic period. Using an expanding-window framework, we reserve the subsequent six-, twelve-, and twenty-four-month horizons as out-of-sample validation periods. The second sample extends from January 1996 through December 2021. In this case, we likewise employ an expanding window, but designate the final six-, twelve-, and twenty-four-month spans for validation.

TABLE 3.12: Out-of-sample performance

This table reports the out-of-sample forecast errors for our RV-, IV-, MW-, and GLB-based ex-ante risk timing strategy in our sample of 1,137 from January 1996 to December 2021. The in-sample regression specification is shown in Equation (3.4) and its estimated parameters are in Table 3.4. The left side panel spans January 1996 to December 2019, thus excluding the extreme market uncertainty of the pandemic period. We take six, twelve, and twenty-four months *ahead* as the validation period. The right side panel spans January 1996 to December 2021. Here, we leave the *last* six, twelve, and twenty-four months of COVID-19 as the validation period. The root mean squared error (RMSE) is computed as the square root of the average value of the squared difference between forecasted and actual values. The mean absolute error (MAE) is calculated as the average absolute value of the difference between forecasted and actual values. The Mean Absolute Percent Error (MAPE) is computed as the average of the ratios of the absolute value of the difference between forecasted and actual values and the absolute value of the actual values.

	January 1996 to December 2019				January 1996 to December 2021			
	RV	IV	MW	GLB	RV	IV	MW	GLB
RMSE6	0.0526	0.0356	0.0106	0.0151	0.0479	0.0083	0.0195	0.0156
RMSE12	0.0486	0.0340	0.0245	0.0139	0.0411	0.0239	0.0311	0.0269
RMSE24	0.0486	0.0335	0.0371	0.0553	0.0755	0.0663	0.0310	0.0547
MAE6	0.0312	0.0229	0.0081	0.0107	0.0314	0.0072	0.0153	0.0131
MAE12	0.0319	0.0238	0.0129	0.0102	0.0298	0.0152	0.0229	0.0191
MAE24	0.0316	0.0247	0.0207	0.0269	0.0521	0.0436	0.0239	0.0391
MAPE6	0.5202	0.2276	0.6334	0.4484	1.7887	0.2552	0.7145	2.6255
MAPE12	0.4143	0.4645	0.6653	0.4155	1.3830	0.2525	0.7801	2.6480
MAPE24	0.8330	0.5630	0.9670	0.6273	1.6260	1.1467	3.0046	9.3000

Table 3.12 reports the results for equally weighted portfolios as test assets and ex-ante risk timing implemented by scaling returns before portfolio aggregation. The left panel refers to the period from January 1996 to December 2019, while the other is from January 1996 to December 2021. We note some evidence of the out-of-sample performance of the RN-managed portfolios. RN-managed portfolios have the lowest Root Mean

Squared Error (RMSE) and Mean Absolute Error (MAE) in 6-, 12-, and 24-month forecast periods than the RV-managed ones in the pre-pandemic period. Interestingly, excluding the COVID-19 period, the Mean Absolute Percentage Error (MAPE) is below 1 for all the risk timing implementations, indicating they are all superior to a random walk. However, once the pandemic period is included, we find a positive out-of-sample performance for the RN-managed portfolios. The MAPE results for the 24 months suggest that no risk-timing strategy outperforms a random walk process. However, IV-managed and MW-managed portfolios outperform backwards-looking RVs for the pandemic's last 6- and 12 months statistically significantly. This finding indicates that option prices incorporate expectations of the underlying asset prices up to one year ahead more promptly than the historical risk measures traditionally used in volatility timing studies. Overall, the risk timing implementations based on options prices offer the most accurate predictions.

We obtain qualitatively similar results for leverage-sorted portfolios as test assets. Also, we further compare the out-of-sample results from our model with those from the AR(1) model, both before and including the pandemic period, and report the 12-month ahead forecast RMSEs for both models.

3.4.4 Transaction costs

The higher the portfolio weights' volatility, the more intense the portfolio rebalancing, and, in turn, the higher the transaction costs. A critique of the LRA based on this idea has been put forward recently by Barroso and Detzel (2021), who find that reasonable transaction costs usually nullify the extra alpha of volatility-timing strategies implemented through portfolio return RV. Therefore, a caveat for our findings concerns the transaction costs eroding the discussed alphas. Consequently, we check whether plausible transaction costs for realistic portfolio rebalancing frequencies nullify the alpha of our ex-ante risk timing strategy. In doing so, we move from the idea that portfolio rebalancing depends on the investors' characteristics, which include risk preferences, tax considerations, and leverage constraints. In practice, several asset managers purposely avoid frequent portfolio rebalancing.[19] As RNs anticipate stock price movements, we argue they afford look-ahead risk management with fewer total transactions. However, the relationship is complex. On the one hand, we expect RNs to contain limited portfolio adjustments. On the other hand, we expect it will be massive if they suggest portfolio rebalancing. From the analyses of the time-series properties of the RVs and RNs and repeating the spanning regression estimations adding plausible transaction

[19] See, for example, the Wall Street Journal article of January 6, 2023, reporting that the most common frequency of portfolio rebalancing is yearly, at the beginning of January *https://www.wsj.com/articles/case-against-rebalancing-your-portolio-11673014712*. Vanguard's research also supports the idea that annual rebalancing is optimal for most investors *https://corporate.vanguard.com/content/corporatesite/us/en/corp/articles/tuning-frequency-for-rebalancing.html*.

costs, we find that risk-timing strategies based on RNs afford look-ahead risk management with less transaction costs than RVs.

Transaction costs and leverage constraints

Risk management that cannot cope with intermediate paper losses and, therefore, subjects trading to monthly rebalancing can substantially erode the extra alpha. We assess our risk timing strategy accounting for transaction costs of either 1bps, 5bps, 10bps, 15bps, or 20bps. The 1bp and 10bps costs are informed by Fleming et al. (2003) and Frazzini et al. (2015), respectively. We adopt a conservative standpoint and report the results incorporating potential higher transaction costs during distressed markets. Informed by our strategies' half-life test, which measures how long it takes for the risk-managed returns to depreciate to half of their value, we consider rebalancing monthly or every two, three and six months. Table 3.13 tabulates the results. At the 5% confidence level, the alpha of an ex-ante risk timing strategy based on an RN statistically survives up to 5bps transaction costs with monthly rebalancing.[20] For the rebalancing with two to three months, our strategy survives up to 15bps transaction costs; for semiannual rebalancing, up to 20bps transaction costs.[21]

All the risk timing strategy implementations are heavily penalised by leverage constraints. Table 3.13 includes the results when leveraging is either not allowed or permitted for only up to 50%. In particular, leverage bounds strongly constrain our risk timing strategy which is designed to exploit firm-specific information. It limits the possibility of weighting heavier stocks with low RN, thus wasting valuable option-based details and missing timing opportunities.

[20] We run similar regressions as Equation (3.4), replacing the dependent variables with the net-of-cost scaled returns. This is close to the generalised alpha approach applied by Barroso and Detzel (2021).

[21] With yearly rebalancing, as suggested by many practitioners, our option-based volatility timing strategy survives up to 30bps transaction costs (see Footnote 19).

TABLE 3.13: Transaction costs

This table reports the pointwise estimates of the alphas for the ex-ante risk timing strategies with and without Transaction Costs (TC), which are statistically significant at the 5%-confidence level. We consider transaction costs of 1-, 5-, 10-, 15- and 20bps. The cost estimations of 1bp and 10bps are grounded in the studies of Fleming et al. (2003) and Frazzini et al. (2015), respectively. To ensure a conservative approach, we also report the outcomes incorporating higher transaction costs, reflecting the potential elevated costs during distressed market conditions. We also restrict the strategies to no and up to 50% investment leverage. Panel A reports the results for the stock-level risk timing strategies implemented by RV, IV, MW, and GLB one month ahead. Panels B, C, and D repeat these analyses with rebalancing every two, three, and six months. The rebalancing is informed by half-life analyses showing that the costs of trading effects are absorbed by the overall portfolio performance in just over two months. The sample includes 1,137 firms and spans January 1996 to December 2021.

Scaling factor	Leverage	α	1 bps	5 bps	10 bps	15 bps	20 bps
			Panel A: Monthly TC				
$\frac{c}{RV_i^2}$		-0.0033	-0.0191	-0.0817	-0.1582	-0.2321	-0.3016
$min(\frac{c}{RV_i^2}, 1)$	0	-0.0011	-0.0118	-0.0543	-0.1065	-0.1575	-0.2068
$min(\frac{c}{RV_i^2}, 1.5)$	50%	-0.0002	-0.0144	-0.0650	-0.1271	-0.1874	-0.2453
$\frac{c}{IV_i^2}$		0.0478	0.0290	-0.0458	-0.1388	-0.2301	-0.3190
$min(\frac{c}{IV_i^2}, 1)$	0	0.0116	-0.0026	-0.0594	-0.1296	-0.1989	-0.2671
$min(\frac{c}{IV_i^2}, 1.5)$	50%	0.0048	-0.0031	-0.0742	-0.1624	-0.2493	-0.3345
$\frac{c}{MW_i^2}$		0.0335	0.0275	0.0032	-0.0276	-0.0576	-0.0854
$min(\frac{c}{MW_i^2}, 1)$	0	-0.0066	-0.0107	-0.0274	-0.0482	-0.0684	-0.0881
$min(\frac{c}{MW_i^2}, 1.5)$	50%	-0.0026	-0.0168	-0.0383	-0.0649	-0.0909	-0.1161
$\frac{c}{GLB_i^2}$		0.0420	0.0309	-0.0141	-0.0693	-0.1222	-0.1715
$min(\frac{c}{GLB_i^2}, 1)$	0	0.0013	-0.0067	-0.0384	-0.0776	-0.1158	-0.1526
$min(\frac{c}{GLB_i^2}, 1.5)$	50%	0.0018	-0.0105	-0.0505	-0.0998	-0.1479	-0.1940
			Panel B: Bi-monthly TC				
$\frac{c}{RV_i^2}$		-0.0033	-0.0120	-0.0469	-0.0902	-0.1328	-0.1742
$min(\frac{c}{RV_i^2}, 1)$	0	-0.0011	-0.0070	-0.0306	-0.0598	-0.0886	-0.1168
$min(\frac{c}{RV_i^2}, 1.5)$	50%	-0.0002	-0.0088	-0.0369	-0.0718	-0.1061	-0.1397
$\frac{c}{IV_i^2}$		0.0478	0.0376	-0.0032	-0.0539	-0.1038	-0.1528
$min(\frac{c}{IV_i^2}, 1)$	0	0.0116	0.0038	-0.0272	-0.0656	-0.1035	-0.1409
$min(\frac{c}{IV_i^2}, 1.5)$	50%	0.0048	0.0050	-0.0339	-0.0821	-0.1296	-0.1765
$\frac{c}{MW_i^2}$		0.0335	0.0301	0.0169	0.0002	-0.0162	-0.0320
$min(\frac{c}{MW_i^2}, 1)$	0	-0.0066	-0.0088	-0.0179	-0.0291	-0.0402	-0.0511
$min(\frac{c}{MW_i^2}, 1.5)$	50%	-0.0026	-0.0144	-0.0260	-0.0404	-0.0547	-0.0687
$\frac{c}{GLB_i^2}$		0.0420	0.0360	0.0116	-0.0188	-0.0489	-0.0782
$min(\frac{c}{GLB_i^2}, 1)$	0	0.0013	-0.0030	-0.0203	-0.0417	-0.0629	-0.0836
$min(\frac{c}{GLB_i^2}, 1.5)$	50%	0.0018	-0.0059	-0.0276	-0.0546	-0.0812	-0.1074
			Panel C: Quarterly TC				
$\frac{c}{RV_i^2}$		-0.0033	-0.0093	-0.0330	-0.0618	-0.0897	-0.1164
$min(\frac{c}{RV_i^2}, 1)$	0	-0.0011	-0.0051	-0.0208	-0.0401	-0.0590	-0.0775
$min(\frac{c}{RV_i^2}, 1.5)$	50%	-0.0002	-0.0065	-0.0253	-0.0483	-0.0708	-0.0927
$\frac{c}{IV_i^2}$		0.0478	0.0411	0.0145	-0.0181	-0.0500	-0.0810
$min(\frac{c}{IV_i^2}, 1)$	0	0.0116	0.0064	-0.0140	-0.0393	-0.0642	-0.0886
$min(\frac{c}{IV_i^2}, 1.5)$	50%	0.0048	0.0083	-0.0173	-0.0488	-0.0797	-0.1100
$\frac{c}{MW_i^2}$		0.0335	0.0311	0.0216	0.0104	-0.0006	-0.0107
$min(\frac{c}{MW_i^2}, 1)$	0	-0.0066	-0.0081	-0.0143	-0.0219	-0.0294	-0.0366
$min(\frac{c}{MW_i^2}, 1.5)$	50%	-0.0026	-0.0135	-0.0214	-0.0312	-0.0407	-0.0501
$\frac{c}{GLB_i^2}$		0.0420	0.0380	0.0223	0.0029	-0.0160	-0.0343
$min(\frac{c}{GLB_i^2}, 1)$	0	0.0013	-0.0016	-0.0129	-0.0268	-0.0405	-0.0539
$min(\frac{c}{GLB_i^2}, 1.5)$	50%	0.0018	-0.0040	-0.0182	-0.0357	-0.0528	-0.0696
			Panel D: Semi-annual TC				
$\frac{c}{RV_i^2}$		-0.0033	-0.0063	-0.0182	-0.0328	-0.0471	-0.0611
$min(\frac{c}{RV_i^2}, 1)$	0	-0.0011	-0.0031	-0.0111	-0.0209	-0.0306	-0.0401
$min(\frac{c}{RV_i^2}, 1.5)$	50%	-0.0002	-0.0041	-0.0137	-0.0254	-0.0370	-0.0484
$\frac{c}{IV_i^2}$		0.0478	0.0444	0.0307	0.0140	-0.0025	-0.0187
$min(\frac{c}{IV_i^2}, 1)$	0	0.0116	0.0090	-0.0015	-0.0143	-0.0270	-0.0396
$min(\frac{c}{IV_i^2}, 1.5)$	50%	0.0048	0.0115	-0.0015	-0.0176	-0.0335	-0.0491
$\frac{c}{MW_i^2}$		0.0335	0.0322	0.0271	0.0213	0.0156	0.0100
$min(\frac{c}{MW_i^2}, 1)$	0	-0.0066	-0.0074	-0.0105	-0.0144	-0.0181	-0.0219
$min(\frac{c}{MW_i^2}, 1.5)$	50%	-0.0026	-0.0125	-0.0165	-0.0215	-0.0263	-0.0311
$\frac{c}{GLB_i^2}$		0.0420	0.0400	0.0317	0.0214	0.0113	0.0013
$min(\frac{c}{GLB_i^2}, 1)$	0	0.0013	-0.0002	-0.0059	-0.0130	-0.0200	-0.0269
$min(\frac{c}{GLB_i^2}, 1.5)$	50%	0.0018	-0.0022	-0.0095	-0.0184	-0.0272	-0.0359

3.5 Conclusion

We contribute to the literature by providing empirical evidence that in the cross-section of the returns, low-risk anomalies are a market feature that is not explained by traditional systematic risk factors. Analyses based on firms' fundamentals indicate that the capital structure matters for the risk timing, especially during market distressed periods when high-levered firms only marginally span the mean-variance frontier. Our results underscore the role of the return higher moments as they appear in option prices not captured by conventional historical risk measures. While we report results based on the implied variance and the risk measures introduced by Martin and Wagner (2019) and Chabi-Yo et al. (2023), our approach offers promising opportunities for advancing our understanding of risk management and portfolio allocation that future research can exploit.

We have demonstrated how stock-level ex-ante risk timing augments the risk-adjusted returns of large portfolios of US equity stocks. We show how leveraging the information on investors' expectations of extreme returns outperforms the backwards-looking volatility timing methods. Our strategy allows investors to take advantage of skewed stock returns while adjusting to a more conservative approach in the face of a higher likelihood of extreme negative returns. We show that our results are robust when we include realistic transaction costs and across samples formed on firms' leverage levels, size, credit ratings and separating financial and non-financial entities. We obtain qualitatively similar results when we isolate the analyses for different market conditions, the Global Financial Crisis and the COVID-19 pandemic.

Chapter 4

Liquidity of Central Stocks

4.1 Introduction

While the significance of financial interlinkages for liquidity is widely acknowledged, a comprehensive understanding of how these interlinkages influence stock liquidity is lacking. This knowledge gap is primarily due to the challenge of mapping the intricate and dynamic financial interconnections. The nonlinearities in financial linkages and feedback loops further complicate the creation of simple and easily interpretable models linking financial networks and asset liquidity. Yet, the scale of the US mutual funds holdings is increasingly top-heavy and has increased significantly over the last two decades from 6.8 trillion dollars in 1999 to $22.1 trillion by 2022, posing significant liquidity and systematic risk challenges.[1]

This chapter contributes to the asset pricing literature by first introducing a new stock-level centrality measure based on mutual fund common ownership, departing from conventional studies which stay at the pairwise level. CWEC captures both the strength of stock connections and the importance of neighbouring stocks in the financial network, offering a more informative view than traditional pairwise measures. Using this centrality metric, the chapter shows that higher stock centrality is associated with lower illiquidity and has a persistent effect on liquidity, as demonstrated through centrality-based portfolio sorts and statistical methods like VAR and IRF. Additionally, the findings suggest that the market views and prices stocks differently based on their centrality, indicating that centrality may act as a priced risk factor. These results provide deeper insights into the roles of centrality and liquidity in financial markets and offer practical implications for risk management and asset pricing.

This chapter considers how market-observable prices of the connected stocks via the common funds' ownership relate to stock liquidity. Based on the notion that financial networks are best revealed in market-observable stock prices, we propose a two-step process by first identifying the connected pairs of stocks in comprehensive pairwise combinations of stocks owned by the largest US mutual funds[2], and for each stock-connected pair, computing the Antón and Polk (2014)'s connectedness measure, namely the ratios of the total value of the two stocks held by the mutual fund and the total market capitalisation of the two stocks from a large universe of our sampled stocks.[3] Second, we compute our stock-level Connectedness-value-Weighted-Eigenvector-Centrality (CWEC) measure by augmenting the Eigenvector Centrality

[1]See for example the Financial Times report of June 16, 2024 $https://www.ft.com/content/db08d94e-1c7c-438d-8c9f-20158652452a$. The data comes from the 2023 Investment Company Institute Factbook $https://www.ici.org/system/files/2023-05/2023-factbook.pdf$.

[2]In each cross-section, two stocks are paired if they are commonly owned by at least one mutual fund.

[3]As in Antón and Polk (2014) we compute the standardised rank-transformed connectedness measure in each cross-section for each stock. This ensures that our connectedness measure is not affected by the changes in the number of mutual funds holding the stock and ensures comparability across different cross-sections.

measure[4] with weights derived by the proportion of the holdings of US mutual funds of the connected stocks in step one.[5] In this way, each stock's eigenvector centrality measure is value-weighted by connectedness levels and transactions derived in step one. Our CWEC, therefore, recognises the number of connections in a node and the importance of those connections since a node connected to influential nodes is considered more central. Moreover, because our CWEC is value-weighted and considers the entire network structure, it helps identify essential nodes across the complex financial interlinked networks. In this way, we depart from Antón and Polk (2014)'s simple pair-level correlation approach by introducing a standardised connectedness-weighted measure of stock centrality. We argue that this approach allows for fair identification of the relationships and patterns among different stocks, their connectedness level, and their importance in the financial networks. We apply this method to our sample of 200 US mutual funds and 608 stocks, forming 113,523 pairs from the first quarter of 1999 to the end of the second quarter of 2022. We focus on the largest funds and stocks as these have been shown to drive the stock markets (Jiang et al., 2024). Because their shocks do not average out, when the firm size distribution is fat-tailed, these shocks are thus persistent and drive the economy (Gabaix, 2011). We then proceed to study how our CWEC relates to the changes in the liquidity of the stocks in our sample.

This framework permits us to identify the number of connections, the importance of those connections, and the weights associated with them, allowing us to contribute to the literature on financial networks and the commonality of liquidity. Existing literature on financial networks primarily focuses on systemic risk, market freezes, investment decisions, and corporate governance. Notable works have demonstrated the influence of network patterns of trades on market behaviour and returns (Cohen-Cole et al., 2014), the asymmetries in the degree of connectedness and outcomes among types of firms (Billio et al., 2012), and the complex and mutually reinforcing nature of market and funding liquidity (Brunnermeier and Pedersen, 2008). Recent studies have shifted attention to firms' idiosyncratic risk and the role of adverse asymmetric shocks in causing firm interactions (Chen et al., 2023). Recently, Buraschi and Tebaldi (2024) show that financial interlinkages can trigger priced contagion endogenously. These accounts

[4]Eigenvector centrality is widely used to model networks in different disciplines. In network science, Gutiérrez et al. (2021) experiment on resistor circuits, neural networks, and paradigmatic networks to show the feasibility of using eigenvalue spectra to estimate resistance distance and eigenvector centrality of a network. In neuroscience, Lohmann et al. (2010), Binnewijzend et al. (2014), and Van Duinkerken et al. (2017) apply eigenvector centrality to map human brain networks. In biochemistry, Negre et al. (2018) use eigenvector centrality to characterise protein allosteric pathways. In psychology, Sadria et al. (2019) apply the eigenvector centrality on eye-gaze data to study autism spectrum disorder. In sociology, Carrizosa et al. (2020) design a mathematical programming formulation based on eigenvector centrality to detect key members in a social network. In Finance literature, eigenvector centrality has been used by Evgeniou et al. (2022) to study market-timing ability and firm performance. To the best of our knowledge, this method has not been used in modelling liquidity commonality of connected stocks in comprehensive financial networks.

[5]Throughout the paper, we use interchangeably CWEC or value-weighted centrality measure. The value refers to the dollar value held by mutual funds of stock pairs that affects the edge strength in the financial network.

reinforce the findings that Herskovic et al. (2020) report, showing that network effects are essential to explaining the joint evolution of the empirical firm size and firm volatility distributions. The literature focused on the commonality of liquidity has gained prominent attention since the seminal paper of Chordia et al. (2000), which focused on the correlated movements in liquidity.[6] A common approach in this literature is to match the liquidity commonality via the institutional ownership or pairwise connectedness measure.[7] However, this approach of identifying stocks' pairwise correlation via proportion owned by institutions to study liquidity commonality is useful only in identifying a stock's direct connections due to its direct relationships. Yet, it cannot determine the connections' influence or centrality in a network, which would allow for a better understanding of their effects within the broader network.

Figure 4.1 highlights the differences between the simple pairwise correlation of connected stocks used in the literature and our CWEC measure of stocks. When the commonality of liquidity is identified via pairwise correlation of connected stocks, this approach correlates strongly with the degree of centrality measure computed by counting the number of edges connected to each stock throughout the sample. Panel A of Figure 4.1 visually presents the unweighted degree centrality and stock average pairwise connectedness, yielding a widely dispersed pattern of a network. The pattern indicates incorporating mutual funds' ownership of stocks into the assessment of a stock's role within the financial network offers a qualitatively different approach compared to merely enumerating the connections between stocks, underscoring our first step in deriving the CWEC measure. Therefore, the conventional approach does not allow for clearly identifying relationships and patterns in a network. Moreover, as the more concentrated pattern in Panel B, our CWEC measure improves from stock average connectedness by further considering each stock's importance in the broad financial network, allowing for better identification of relationships and patterns in the data and identification of stock connections' influence. This matches our second step in deriving the CWEC measure. Therefore, the CWEC two-step process visualised by Figure 4.1 sheds new light on the relationship between the stock's centrality and liquidity and their systematic risk importance.

The literature has no consensus on the directional relationship between the stocks' connectedness and liquidity commonality. A large body of literature shows that changes in connectedness levels affect liquidity.[8] Yet, another strand in the literature shows that

[6]See Hasbrouck and Seppi (2001); Coughenour and Saad (2004); Brunnermeier and Pedersen (2008); Kamara et al. (2008); Karolyi et al. (2012); Moshirian et al. (2017); Koch et al. (2016); Deng et al. (2018), among others.

[7]See Kamara et al. (2008), Antón and Polk (2014), Koch et al. (2016), Agarwal et al. (2018), Deng et al. (2018), Bradrania et al. (2021), for example.

[8]Kamara et al. (2008) measure stock connectedness by the proportion of each stock's market capitalisation owned by funds, showing that their stock connectedness measure affects the stock's liquidity beta. Deng et al. (2018) show that there's a convex relationship between stocks' foreign institutional ownership and liquidity commonality. Bradrania et al. (2021) find that foreign institutional ownership affects the liquidity risk exposure of the stocks with larger market capitalisation. Agarwal et al. (2018) adopt both

institutional investors such as mutual and hedge funds often trade stocks in anticipation of their liquidity needs. This practice can be driven by several factors, including investor redemptions, rebalancing portfolios, managing cash flow, or preparing for anticipated market conditions.[9] Therefore, the literature has not reached a consensus on these effects, and thus, it is an empirical imperative to distinguish the nature of these two sources of influence. When we regress our stock centrality measure on illiquidity or illiquidity on stocks' centrality levels, we observe that both have positive and statistically significant effects on each other, presenting an apparent dichotomy. However, when we run VAR with GMM-style regressions and control for stock idiosyncratic volatility (Ang et al., 2006), the volatility index VIX, and Money supply shock, M1, we find clear and statistically strong evidence of the importance of the stocks' centrality for liquidity, but not the other way around. We also corroborate this finding in our Impulse Response Function (IRF) analyses across the entire period of our sample and during significant market distress periods such as the Global Financial Crisis (GFC).

When we plot the time series of our CWEC measure and illiquidity against the bank lending tightness standards SLOOS, a proxy indicating changes in funding constraints of institutions, we find that the CWEC and illiquidity behave differently.[10] Stock illiquidity reacts promptly to changes in credit availability in the market, and their correlation is strong at 0.62. Conversely, stock connectedness appears much more "sticky". The correlation between connectedness and bank lending tightness is statistically insignificant, shedding new light on the causality between the stocks' connectedness and liquidity commonality, which we explore in VAR regressions, showing that fund managers potentially avoid taking additional risk, rebalancing and transaction costs, thus affecting the liquidity of stocks.

After identifying the significant impact of stock centrality on illiquidity, an essential risk factor, we aim to investigate whether the market perceives stocks with varying centrality levels differently. For this, first, we sort our firms on equally weighted quartile portfolios based on the stocks' CWEC levels to see if there is any pricing evidence of stock centrality in the markets. We find that stocks in the highest CWEC quartile portfolios tend to be larger and more liquid. Their realised returns and Fama-French-Carhart

Koch et al. (2016)'s and Antón and Polk (2014)'s stock connectedness proxies and find that the measures positively affect stock liquidity commonality. These studies are based on individual stock proportions owned by institutions or pairwise correlation of stocks. At the same time, our connectedness measure comes from the cross-section of all ownership of a large universe of the sampled stock.

[9] Edelen (1999) find that mutual funds tend to sell stocks during periods of high investor redemptions, which can exacerbate market downturns and increase volatility. Teo (2011) find that hedge funds adjust their holdings in response to anticipated liquidity needs and market conditions, often selling stocks to increase their cash positions during periods of expected market stress. Mitchell et al. (2002) reveal that institutional investors engage in rebalancing activities that involve selling stocks to meet liquidity needs and maintain their strategic asset allocations. Financial Stability Board (2017) has highlighted the importance of liquidity management in investment funds, noting that funds may sell stocks to sustain adequate liquidity buffers in response to anticipated or actual liquidity needs.

[10] SLOOS is the Federal Reserve's quarterly Senior Loan Officer Opinion Survey on Bank Lending Practices indicating the anticipated tightening or loosening of lending criteria.

four-factor alphas are significantly lower than those in the lowest quartile, indicating that these large and liquid stocks are fairly priced and thus cannot offer significant returns. We also run Fama and MacBeth (1973) regressions to find significant β^{CWEC} coefficients, providing some evidence of the *centrality premium* in the markets. Then, we run predictive regressions of centrality on stocks' returns, finding centrality to be a statistically significant predictor for stock returns and, thus, potentially a state variable.

Finally, if centrality is a state variable which commands a market premium, we test whether an investor can profitably exploit the pricing gap among different stock centrality levels. Thus, we construct a betting-against-centrality (BAC) factor by taking a long position on the stocks in the lowest CWEC quartile portfolio and a short position on the highest quartile portfolio with equal weights. Then, we regress the BAC returns against the Fama-French-Carhart factors. However, we fail to find statistically robust evidence that investors can exploit the pricing gap among different stock centrality levels. Furthermore, other real trading conditions such as transaction costs can further erode its potential profitability.[11] Overall, our results indicate that centrality is one of the crucial determinants of stock liquidity within a broader network of stocks. This is consistent with Buraschi and Tebaldi (2024)'s finding of network risk premium.

The remainder of the paper is organised as follows. Section 4.2 discusses the contribution to the literature. Section 4.3 describes the data and methods we use. Section 4.4 compares and discusses the results. Section 4.5 concludes.

4.2 Related Literature

Liquidity attracts much attention from researchers because of its sophisticated association with risk and asset pricing. Brennan and Subrahmanyam (1996) claim that a higher rate of returns should be expected for illiquid stocks. A less liquid asset is expected to yield higher returns because investors require higher returns as compensation for taking additional risks of investing assets with less liquidity. Market illiquidity expectation positively affects stock excess return, which partially represents an illiquidity premium (Amihud, 2002). Amihud et al. (2005) confirm that the liquidity effect on asset pricing is economically important and statistically significant. Liu (2006) also documents that liquidity is a critical risk component in asset pricing as there is a significant liquidity premium which is robust to the Capital Asset Pricing Model and Fama-French three-factor model (Fama and French, 1993). Acharya and Pedersen (2005) propose a liquidity-adjusted capital asset pricing model and conclude that both stock-level expected liquidity and the covariance between stock and market return and liquidity affect stock required rate of return, supporting Pástor and Stambaugh (2003) findings.

[11] We have also replicated the strategy by constructing BAC portfolios with stock centrality levels and different percentile portfolios. The results do not qualitatively change.

Hameed et al. (2010) propose an asymmetric positive influence from market return to liquidity and find that the negative returns have a much larger influence than positive returns. The liquidity importance in asset pricing inspires our research to base on the stock level which will be discussed in the following paragraphs.

Liquidity measurements are extensively and comprehensively studied. Liu (2006) describes liquidity from four dimensions which are trade volume with fixed cost (trading quantity), time required for a security to be traded with fixed cost and quantity (trading speed), trade-relative expenses for a trade volume (trading costs), and influence on price for a given trade volume (price impact). On the other hand, illiquidity is known as the difficulty of trading securities. Amihud et al. (2005) have listed several sources of illiquidity: exogenous unavoidable transaction costs, demand pressure or inventory risk due to frictional scarcity of trading counterparties, information asymmetry, and difficulty in finding a counterparty for a tailored deal. Market participants face the trade-off between keeping exploring and trading at a discount. There are many liquidity measurements developed in the literature due to their importance. We focus on low-frequency measurements first because of their advantages, including better data availability across different regions and time horizons. High-frequency data with the same region and time span would require extensive computation resources and power. Second, the low-frequency liquidity proxies match the time frame of other components in our study. Goyenko et al. (2009) and Corwin and Schultz (2012) have proven that low-frequency measures perform well with relatively high-frequency liquidity benchmarks at lower costs. Our choice of frequency is a trade-off between data availability and market microstructure capture. As there are many liquidity measurements developed, We pick and discuss some popular ones that can be allocated to the dimensions.

Amihud (2002) proposes one of the most popular liquidity measurements, the illiquidity ratio, from the price impact aspect (Lou and Shu, 2017). It is defined as the average absolute value of daily returns divided by daily trading volume. This essentially gauges the price change sensitivity to the dollar trading volume. The higher Amihud illiquidity ratio means lower stock liquidity, as a small volume change could lead to a huge stock price movement. Similar to the data required for spread computation, the daily price and trading volume data used to compute the illiquidity ratio are also highly available, allowing analyses through long time horizons across different markets. Lou and Shu (2017) criticise that the Amihud illiquidity ratio captures the liquidity premium on stock returns through the trading volume component instead of the price impact, although they confirm that the return-to-volume ratio does perform well in measuring stock illiquidity. Goyenko et al. (2009) compare many low-frequency liquidity measures with high-frequency ones. They find that low-frequency measures can capture the key information from high-frequency transaction costs, making the expensive high-frequency data less necessary. They also showe that among the low-frequency measures, the Amihud illiquidity ratio works very well for measuring price impact. Similarly, Fong et al. (2017) compare low-frequency measures with high-frequency benchmarks and confirm that the Amihud daily illiquidity ratio is the best tool for tracking price impact. Their results indicate that the daily Amihud illiquidity ratio is the best illiquidity measurement from a price impact perspective.

The literature on financial networks mainly concentrates on systemic risks, market behaviours, and investment decisions. Cohen-Cole et al. (2014) discover the fact that market behaviour and returns are captured by trade network patterns. Billio et al. (2012) find hedge funds, banks, brokers/dealers, and insurance companies are becoming more interrelated, highlighting the prevailing systemic risks in finance through complicated and timely dynamic financial networks. The attention of recent literature has shifted to firm idiosyncratic risks. Chen et al. (2023) study the contagion and feedback effects of firms' adverse impact on industry peers through intense competition during financial distress. Buraschi and Tebaldi (2024) reveal that financial networks endogenously lead to price contagion and introduce the network risk premium. These studies support that network effects play a crucial role in understanding the combined development of empirical distributions of firm size and volatility (Herskovic et al., 2020). Since Chordia et al. (2000) first discovered the evidence of commonality in liquidity in the stock market, abundant studies have focused on this important component in finance literature.[12] Kamara et al. (2008) build the bridge between institutional ownership and stock sensitivity to systematic liquidity shocks. They recognise that different proportions of institutional ownership can explain different liquidity betas of firms with different sizes. Koch et al. (2016) figure out that stocks with a larger proportion owned by mutual funds are more likely to co-move with those similar stocks that also have high mutual fund ownership. Deng et al. (2018) find foreign institutional ownership has a convex relationship with stock commonality in liquidity. Bradrania et al. (2021) suggest that foreign institutional ownership leads to larger exposure of stocks with higher market value to unanticipated liquidity shocks in the local market. Especially for stocks with market value above the average level, there is a positive relationship between foreign institutional ownership and stock liquidity commonality. These studies discover the relationship between liquidity commonality and institutional ownership. However, the proportion of each security owned by an institution or a fund still stays on the individual level. Therefore, it still has limited explanatory power for stock connectedness.

Antón and Polk (2014) develop a common ownership measurement called FCAP, computed as the ratio of the common fund's total value of pairwise stocks and their total market capitalisations. They regress the cross-sectional realised correlations of pairwise stock abnormal returns against their FCAPs. It is summarised that stock connectedness is generated from their common fund owners. Pairwise connected stocks have higher

[12] See Hasbrouck and Seppi (2001); Coughenour and Saad (2004); Brunnermeier and Pedersen (2008); Kamara et al. (2008); Karolyi et al. (2012); Moshirian et al. (2017); Koch et al. (2016); Deng et al. (2018) for example.

cross-sectional return variation correlation. When common owner funds are experiencing large net inflows or outflows, the effect of common ownership will become stronger to subsequent stock abnormal return correlations. Agarwal et al. (2018) adopt both Koch et al. (2016) stock-level and Antón and Polk (2014) pair-level methods to examine the relationship between ETF ownership and liquidity commonality. Unlike Antón and Polk (2014), instead of the correlation of abnormal stock returns, Agarwal et al. (2018) regress the cross-sectional pairwise correlations of changes in Amihud illiquidity ratios against ETFFCAP (the common ownership as defined by Antón and Polk (2014) but for ETF).[13] Agarwal et al. (2018) view Antón and Polk (2014) approach as a complement to Koch et al. (2016) approach, and conclude that both stock-level and pair-level methods imply that ETF ownership has a significant positive effect on liquidity commonality Agarwal et al. (2018) have linked direct stock connectedness, FCAP, to liquidity commonality. Although this is an improvement from staying on the stock-level proportion owned by funds, the influence of stock connectedness on stock-level liquidity still has not been sufficiently studied. Current literature either stays on the stock level, focusing on stock proportion owned by funds and ignoring connectedness, or sticks on the pair level anyway, studying the commonality of liquidity.

On the other hand, a popular method to measure a node's connection strength and importance in a network is the eigenvector centrality which has been adopted in different disciplines such as biology and medicine (Lohmann et al., 2010; Binnewijzend et al., 2014; Martínez et al., 2015; Van Duinkerken et al., 2017; Negre et al., 2018; Sadria et al., 2019), social network (Carrizosa et al., 2020), and physics (Newman, 2006; Gutiérrez et al., 2021). Regarding finance studies, Evgeniou et al. (2022) and Nezami et al. (2024) utilise eigenvector centrality to study and model market-timing ability and firm performance. Eigenvector centrality considers neighbours' importance for each node when deciding the centrality of that node. We thus propose a new stock-level Connectedness-Weighted-Eigenvector-Centrality (CWEC) measure. CWEC considers both the strength of each connection edge and the importance of other close nodes around. This variable also solves the stock-level and pair-level compatibility issues and enables us to study the relationship between stock-level liquidity and connectedness or centrality in which the literature fails to reach a consensus. While a strand of literature supports that the causality goes from connectedness to liquidity[14], another stream of literature proposes that the causality runs oppositely as institutional investors tend to adjust their investment allocations according to their expectations to liquidity needs. Edelen (1999) discover that during times of significant investor redemptions, mutual funds are inclined to sell stocks, which can worsen the market situation and heighten volatility. Teo (2011) find that hedge funds modify their portfolios based on predicted liquidity requirements

[13] All Kamara et al. (2008); Koch et al. (2016); Agarwal et al. (2018); Deng et al. (2018); Bradrania et al. (2021) use Amihud illiquidity ratios as their liquidity proxies. This supports the Amihud illiquidity ratio popularity discussed above.

[14] See Kamara et al. (2008), Deng et al. (2018), Agarwal et al. (2018), and Bradrania et al. (2021) as discussed above for example.

and prevailing market conditions, often selling stocks to boost their cash reserves during times of anticipated market turbulence. Mitchell et al. (2002) disclose that institutional investors participate in rebalancing activities, selling stocks to fulfil liquidity requirements and keep their strategic asset allocations. This stock-level CWEC measure also enables us to apply further approaches to discover the relationship between stock liquidity and centrality such as Vector Autoregression (VAR), Impulse Response Function (IRF), and Granger Causality tests. Since stock-level liquidity has a direct effect on asset pricing which highlights its importance, this research thus can be useful for researchers and practitioners interested in asset pricing.

4.3 Data and Method

4.3.1 Data and sample

Our sample includes 200 US mutual funds and 608 stocks, forming 113,523 pairs from January 1999 to June 2022. The mutual fund ownership data comes from the Thomson Reuters quarterly Mutual Fund Holdings database and is used to generate our value-weighted centrality measure. We filter the mutual fund holdings data and focus on US funds with positions on stocks from the US. Our data selection is based on two criteria. First, we focus on US mutual funds with the top 1% total net asset at the end of each quarter. This covers over 50% of total assets held by mutual funds in the US. Next, we focus on US stocks whose end-of-quarter market capitalisations are larger than the top 10% stocks' sizes traded on the NYSE. These stocks cover over 80% of the total market capitalisations of the stocks owned by the top 1% largest funds.[15] This screening criteria affords a comprehensive modelling of the financial network and asset liquidity based on the theory that the largest firms are the systemically most important as their shocks are persistent and not easily diversifiable (Gabaix, 2011).

Daily stock prices, trading volumes, and market capitalisation are provided by the CRSP database. We use these stock characteristic data to compute our stock liquidity measures and idiosyncratic volatilities. The trading volume and market capitalisation data also compute our value-weighted centrality measure. The Bloomberg database provides the option-implied CBOE volatility index VIX, a common fear-gauge proxy, and the changes in money supply in the US, the M1, our proxy for institutions' funding constraints.

[15] While this is different from Antón and Polk (2014), which uses top 50%, we balance the market cover and computation power as the number of stocks expands the number of pairwise combinations quickly. We have tried the top 50% largest stocks and the top 10% largest mutual funds. The funds cover over 80% of the total net assets and the stocks capture over 95% of the entire market capitalisation owned by these mutual funds. This larger sample generates over 1.18 billion pairs, which is too computationally extensive.

4.3.2 Stock-level measures

We propose a two-step process to derive our stock-level Connectedness-value-Weighted-Eigenvector-Centrality (CWEC) measure. First, we follow closely Antón and Polk (2014) connectedness method to generate comprehensive pairwise combinations for stocks owned by each mutual fund in each quarter to compute the connectedness measure. For each pair of stocks owned by a mutual fund, f, we compute the sum of the market capitalisation of the pair of stocks owned by that fund,

$$Connectedness_{ij,q} = \frac{\sum_{f=1}^{F} \left(S_{i,q}^{f} P_{i,q} + S_{j,q}^{f} P_{j,q} \right)}{S_{i,q} P_{i,q} + S_{j,q} P_{j,q}}. \tag{4.1}$$

Each pair includes stock i and stock j. $S_{i,q}^{f}$ and $S_{j,q}^{f}$ are the number of shares of stock i and j held by mutual fund f at quarter q. $P_{i,q}$ and $P_{j,q}$ are the trading prices of stocks i and j. $S_{i,q}$ and $S_{j,q}$ are outstanding shares of stock i and j. We derive the normalised rank-transformed connectedness in each quarter for each pair of stocks to prevent this measure from being dominated by changes in the number of mutual funds and make the variable comparable across different cross-sections.

Then in the second step, this normalised rank-transformed connectedness measure is used to derive the value-weighted eigenvector centrality measure for our sample as follows:

$$CWEC_i = \frac{1}{\lambda} \sum_{j \neq i} A_{ij} CWEC_j. \tag{4.2}$$

The scalar λ is the eigenvalue associated with our centrality measure, CWEC. A_{ij} is the connectedness-value-weighted adjacency matrix corresponding to the connection between stock i and j derived from mutual fund holdings, as from Equation (4.1). As discussed in the introduction, eigenvector centrality has been widely adopted in the literature in different disciplines. Our CWEC distinguishes from the literature as it contains additional information on the edge's strength, assigning influence scores to nodes based on their connections, factoring in the number of connections, their importance, and the associated weights. A stock's CWEC is proportional to the total CWEC of its connected neighbouring stocks. In the financial network in our sample stocks, a stock is more central if it is connected to more central ones (Bonacich, 2007). CWEC thus captures the influence of the stock within the broader network of connected stocks. Also, based on mutual funds' ownership, our stock network is undirected and does not involve negative connections.[16]

[16] In an undirected network, edges do not have directions and can be traversed in either direction.

Our two-step process thus involves connectedness, which informs the eigenvector centrality. The CWEC assigns a centrality score to each stock in the network based on the strength of the edges between pairwise stocks and the neighbour's centrality associated with the edge's strength. In addition, our sampling approach is well-informed by the theory of the persistency of the shocks of the largest firms and thus their systematic importance (Gabaix, 2011). We conjecture that our method is less susceptible to the criticism that eigenvector centrality can hardly capture the roles of peripheral nodes (Buraschi and Tebaldi, 2024).

Our CWEC measure contributes to the literature by introducing a stock-level centrality measure not adopted in conventional studies, primarily focused on stocks' pairwise correlation to study liquidity commonality.[17] Pairwise correlation and liquidity commonality studies only recognise the unweighted connections between pairwise stocks. Our stock-level CWEC, on the other hand, is presented by the eigenvector centrality value for each stock. Second, we diverge from the stream of literature measuring stock's role in a connected network implied from the proportion of the stock invested by institutions as that measure is limited only to the information on the stock's ownership structure.[18] The stock proportion owned by institutions is subject to some biases, such as a lack of filtering of fund characteristics and insufficient reflections on the fund's positions in other stocks, affecting the clear identification of the stocks' systematic importance in a complex interlinked financial network. Third, we take advantage of the weighted eigenvector centrality, which considers the neighbours' importance for each node in the broad map of financial interlinkages. The weights we apply are informed by the changes in the proportion of the total value of the two stocks held by the mutual fund and their total market capitalisation (Antón and Polk, 2014). We conjecture that our stock's centrality measure is linked dynamically to the changes in stock prices and market capitalisation. Thus, we consider it an effective direct measure of the stock's importance in the financial network. The centrality measure fluctuates when the conditions of the other linked stocks change, providing a more accurate value-weighted centrality measure. Therefore, our CWEC affords a fairly comparable centrality measure that takes advantage of mutual funds' connected stock information and allows us to study the influence of the stock's network centrality on liquidity, which is helpful for investors and policymakers alike.

We also compute each stock's average connectedness and unweighted pairwise connection to make explicit comparisons with conventional pairwise correlated stock studies. The pairwise connection of each stock is computed as the number of stock pairs that the stock engages in, also known as degree centrality, regardless of how strong each pair's

[17]See Antón and Polk (2014) and Agarwal et al. (2018) for example of pairwise correlation.

[18]See Kamara et al. (2008), Koch et al. (2016), Deng et al. (2018) and Bradrania et al. (2021) for example of stock proportion owned by institutions.

connection is.[19] We plot the degree centrality, time-series average of our 608 stocks' pairwise connection (the cross-sectional average of connectedness measure), and our CWEC measure in Figure 4.1.

Figure 4.1 Panel A presents the unweighted pairwise connection and average connectedness measure. Conventional studies such as Antón and Polk (2014) and Agarwal et al. (2018) identify the interlinkages between pairwise stocks and focus on their relationship with pairwise stock return correlation or liquidity commonality at the stock pairwise level. This is essentially similar to the degree centrality measure that recognises and equally counts the edges between each pair of nodes. The dispersed pattern in Panel A thus indicates that considering mutual funds' ownership of stocks when measuring a stock's role in the financial network is qualitatively distinct from simply counting the number of edges between stocks, highlighting the contribution of our first step in the CWEC two-step process. On the other hand, Panel B shows the relationship between our value-weighted centrality measure, CWEC, and average connectedness. As discussed above, since both the CWEC and the average connectedness originate from Antón and Polk (2014) method, containing sensitivity to situations of other directly linked stocks in the financial network[20], the CWEC is more informative in terms of identifying each stock's importance according to its neighbours' importance in the financial network. The more concentrated pattern in Panel B thus implies the improvement made by the second step in our CWEC two-step process. Therefore, the dispersion in Panel A in Figure 4.1 and the concentrated pattern in Panel B highlight the qualitative improvements that can be obtained by implying a weighted eigenvector centrality measure with weights derived from mutual funds ownership of stocks.

Next, we measure stock illiquidity by using Amihud (2002), which is defined as the average absolute value of daily returns divided by daily trading volume:

$$Amihud_{i,q} = \frac{1}{D_{i,q}} \sum_{d=1}^{D_{i,q}} \frac{|R_{i,q,d}|}{Dollarvolume_{i,q,d}}, \tag{4.3}$$

where $D_{i,q}$ is stock i number of trading days in quarter period q, $R_{i,q,d}$ is stock i return on day d within the quarter q, $Dollarvolume_{i,q,d}$ is stock i dollar value on day d in the quarter q.

This ratio essentially gauges the price change sensitivity to the dollar trading volume. The higher Amihud illiquidity ratio means lower stock liquidity, as a small volume change could lead to a huge stock price movement.[21]

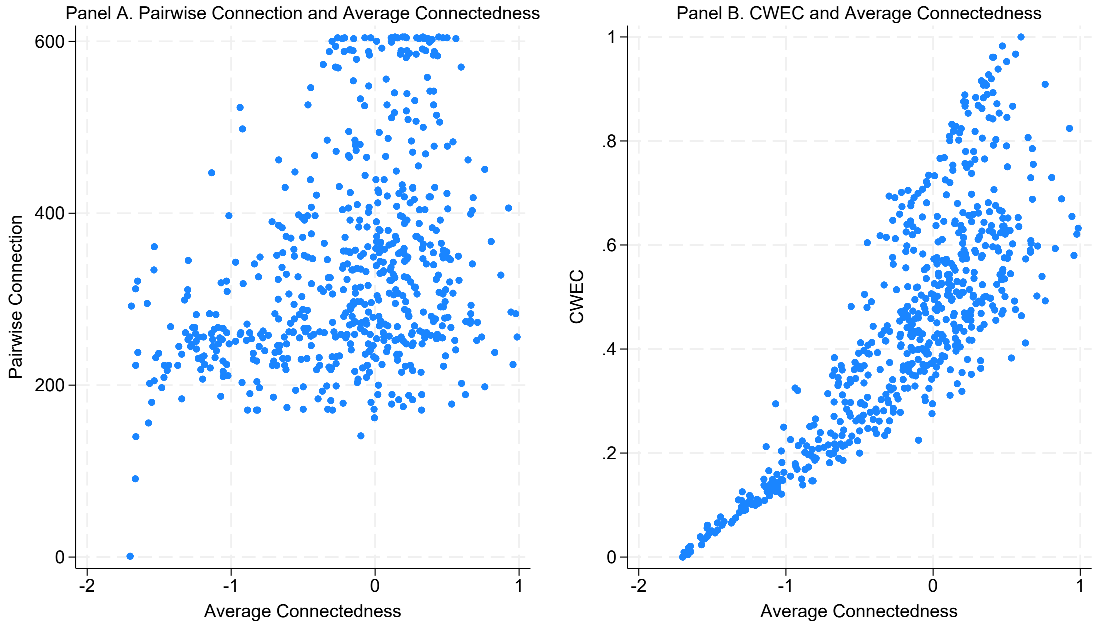
[19]Degree centrality of a node is defined as the number of its direct edges to other nodes. It reflects the node's immediate impact or risk because of its direct connections.

[20]Our main results also hold when we imply stock connections from the average connectedness.

[21]Goyenko et al. (2009) compare a wide range of low-frequency liquidity measures with high-frequency measures and conclude that, first, high-frequency measures of transaction costs can be well captured by low-frequency measures and thus are not worth their high costs. Second, regarding low-frequency

FIGURE 4.1: Centrality measures and connectedness

This figure displays the scatter plots of stocks' pairwise connection, average connectedness, and our stock CWEC. Within our sample of 608 stocks, Panel A shows each stock's pairwise connection and average connectedness. Pairwise connection is measured by degree centrality which is the number of edges connected to each stock throughout the entire sample period from 1999 Q1 to 2022 Q2. It is an unweighted centrality measure counting stocks' edges. Connectedness is defined as in Equation (4.1). Panel B presents our CWEC and stock average connectedness. Each stock's CWEC is derived from the two-step procedure of computing stock average connectedness and the weighted eigenvector centrality as in Equation (4.1) and (4.2).



4.3.3 Modelling the relationship between centrality and illiquidity

The stocks' value-weighted centrality measure that we derive allows us to shed new light on its relationship with stock illiquidity, which is important for systemic risk. As discussed earlier, the literature has not reached a consensus on the relationship between stocks' connectedness in the financial network and liquidity. Therefore, it is empirically important to see how our value-weighted centrality measure relates to the stocks' liquidity. For this, we initially run predictive panel regressions of lagged CWEC on our illiquidity measure estimated in Equation (4.3). However, we make no claims to causality in our tests, and thus, in response, we also run predictive regressions employing the lagged illiquidity measure of Amihud (2002) as an explanatory variable on CWEC. Our regressions also control for socks' idiosyncratic volatility, the VIX index, and changes

measures, the Amihud illiquidity ratio performs well in measuring price impact. Fong et al. (2017) also run comprehensive horseraces of low-frequency liquidity measurements with high-frequency benchmarks. Their results support the strong performance of Amihud's daily illiquidity ratio as the best illiquidity price impact measurement. The popularity of the Amihud ratio and its empirical success make it suitable for our study.

in money supply, M1 (Money Shock).[22] The VIX index considers historical information and forward-looking expectations, representing overall expectations of changes in the US stock market. Changes in M1, the most liquid market money supply indicator, proxy the money shock and, thus, intermediaries' funding constraints. The money shock is thus an explicit indicator of overall market liquidity, which can affect all financial intermediaries' funding conditions. Therefore, our control variables account for both realised and expected idiosyncratic and systematic risks. Formally, our predictive regressions are as follows:

$$y_{i,q} = \beta_{i,q-1}x_{i,q-1} + \beta_{i,q-2}x_{i,q-2} + \beta_{i,q-3}x_{i,q-3} + \sum_{k=1}^{3} \beta_k Control_{i,q-1,k} + FE_i + \epsilon_{i,q}, \quad (4.4)$$

where y is the stock illiquidity (or CWEC), x is the corresponding CWEC (or illiquidity), $Control_{i,q-1,k}$ are our k_{th} control variables, namely the stock idiosyncratic volatility , the VIX index, and the money supply shocks. FE_i is the fixed effect that captures time-invariant characteristics specific to each stock i. We run these quarterly, q, panel regressions for each stock i.

We also refer to the bank lending tightness data from the Federal Reserve's quarterly Senior Loan Officer Opinion Survey (SLOOS) on Bank Lending Practices. This indicator is useful in exploring the relationship between the expected tightening (or loosening) of funding constraints and changes in our value-weighted centrality measure and illiquidity. We thus plot SLOOS against our stock illiquidity and CWEC to investigate their time-series relationship. Lastly, because this work's empirical focus is to examine the relationship between stocks' network centrality and liquidity without making explicit predictions on causality, it is essential to study the time-series properties of CWEC and liquidity in a multivariate Vector Autoregressive Model (VAR). Since the panel regressions confirm statistically significant mutual effects and substantial serial correlation, we estimate a predictive VAR using the Generalised Method of Moments (as in Equation (4.4)) to ensure consistent, testable, and efficient inference on their interplay. The Impulse Response Functions (IRF) are also applied to further explore the relationship between stock illiquidity and CWEC. The IRF reveals the reaction of illiquidity or connectedness in response to a sudden impact of a one-unit change in connectedness or illiquidity. We separate the IRF analyses with exclusion and isolation of GFC to better understand the relationship between illiquidity and connectedness during highly uncertain periods.

[22] We follow following Ang et al. (2006) to estimate the idiosyncratic volatility, computed by using the square root of the regression error variance, which is derived from the regressions of stock returns against Fama-French 3 factors (Fama and French, 1993). This is our proxy for stock-specific fundamental characteristics. The VIX and money shock data come from Bloomberg.

4.4 Empirical Results

4.4.1 Preliminary results

We report the summary statistics on the number and value of stocks and mutual funds in our sample and the combined stock pairs in Table 4.1, spanning the full period from 1999 Q1 to 2022 Q2. Separate statistics are reported for the full sample, the period excluding the Global Financial Crisis (GFC), and the GFC period (2007 Q3 to 2009 Q2).

Panel A provides an overview of the number of stocks, stock pairs, and funds in the full sample and each separated period. In total, 608 stocks and 200 funds form 113,523 stock pairs across the sample. During the GFC, 225 stocks and 61 funds made 23,667 stock pairs. Panel B summarises the average number of stocks held by each fund, the number of funds holding the same stock, and the corresponding investment values. On average, each mutual fund invests in 62 US companies with stock positions valued at over $21 billion, while each stock is typically owned by 14 funds. Interestingly, despite the relatively stable average number of stocks held by each mutual fund and the number of mutual funds investing in each stock during the GFC, there is a substantial decline in the value of investment positions. Specifically, the average investment per mutual fund in these stocks has decreased from approximately $22 billion to $12.5 billion. Concurrently, the aggregate value of each stock held by mutual funds has fallen from about $5 billion to over $3 billion. Panel C presents stock pair and pairwise connectedness dynamics. In Panel C, a decrease in the number of pairs of stocks owned by mutual funds is evident, corresponding to the reduction in the number of stocks and funds during the GFC as depicted in Panel A. Furthermore, the latter part of Panel C indicates a decline in the pairwise connectedness, suggesting weakened linkages among stocks during this uncertain period. The reduction in mutual funds' investment positions and the diminished stock connectedness underscore the financial pressures experienced by institutions during market disruptions.

TABLE 4.1: Summary statistics

This table reports summary statistics for 113,523 pairs of stocks created by the 608 firms owned by 200 funds in our sample. The full sample period is from 1999 Q1 to 2022 Q2. We separately report the statistics for the full sample, excluding the GFC, and the GFC period (from 2007 Q3 to 2009 Q2). Panel A lists the number of stocks, pairs, and funds included in the full sample period, excluding the GFC, and the GFC period. The number of pairs is computed as the comprehensive pairwise combination of all stocks owned by a fund in each cross-section. Panel B summarises the number of stocks held by each fund and the number of funds which hold the same stock in our full sample and separated periods. Panel B also reports the summary statistics of the value of stocks held by each fund and the value owned by funds per stock in our full and separated periods. Panel C summarises the number of pairs held by each fund and the number of pairs that a stock engages in based on our full sample and separated periods. Panel C also includes the summary statistics of pairwise connectedness in our sample.

Panel A: Number of stocks, pairs, and funds

Period	Stocks	Pairs	Funds
Full Sample	608	113523	200
Excluding GFC	602	110719	187
GFC	225	23667	61

Panel B: Funds and stocks

Period	Mean	Median	SD	Min	Max
Number of stocks per fund					
Full Sample	61.5134	45	54.6666	1	222
Excluding GFC	62.2193	46	55.6623	1	222
GFC	55.2425	43	44.4361	1	170
Number of funds per stock					
Full Sample	14.0461	14	6.5989	1	41
Excluding GFC	14.0429	14	6.6927	1	41
GFC	14.0792	13	5.5739	1	34
Value of stocks held by each fund ($ in billion)					
Full Sample	21.8782	10.8260	40.6653	0.0000	557.7647
Excluding GFC	22.9332	11.3874	42.5649	0.0000	557.7647
GFC	12.5073	8.5468	12.3479	0.0009	60.0423
Value owned by funds per stock ($ in billion)					
Full Sample	4.9957	2.5420	8.7961	0.0003	160.5025
Excluding GFC	5.1760	2.6409	9.1271	0.0003	160.5025
GFC	3.1876	1.9760	3.7808	0.0027	27.7401

Panel C: Pairs and pairwise connectedness

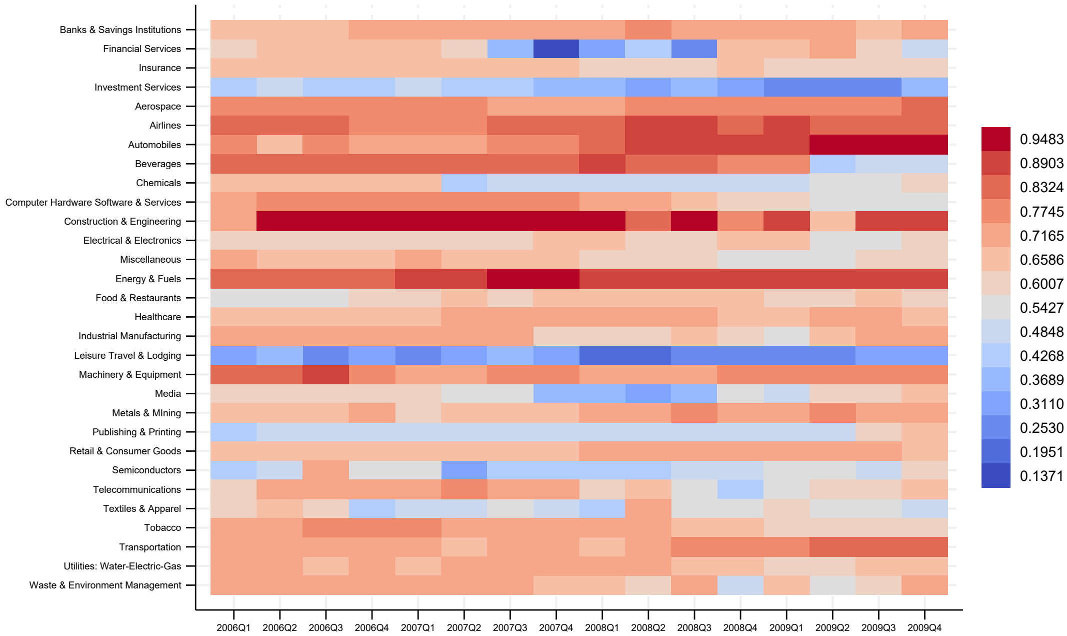
Period	Mean	Median	SD	Min	Max
Number of pairs per fund					
Full Sample	3487.5643	1081	5271.2594	1	25651
Excluding GFC	3588.6254	1081	5407.4363	1	25651
GFC	2587.4350	990	3738.5019	1	14535
Number of pairs per stock					
Full Sample	1534.7121	1481	757.4766	1	3614
Excluding GFC	1561.4346	1536	781.2873	1	3614
GFC	1266.8769	1274.5	357.4416	35	2220
Pairwise connectedness					
Full Sample	0.0592	0.0537	0.0392	0.0000	0.4263
Excluding GFC	0.0601	0.0563	0.0401	0.0000	0.4263
GFC	0.0483	0.0424	0.0252	0.0000	0.2306

Figure 4.2 presents a heatmap of average CWEC values for our sample stocks, categorised by the industry sectors according to the Thomson Reuters database. The heatmap period spans from 2006Q1 to 2009Q4, covering both the pre-crisis phase and

the full duration of the GFC. Notably, the financial services sector experienced a significant decline in CWEC from 2007Q2, coinciding with the early stages of the GFC when the then Federal Reserve Chairman Ben Bernanke claimed that the US economy would not be seriously harmed by increasing cases of mortgage defaults (CNBC, 2007). Our CWEC measure thus tends to be an early warning identifier potentially anticipates systematic risk concerns, signalling that the market has already priced the systematic risk and mutual funds have invested less within this sector. The CWEC returned to the pre-crisis level after the worst period of the economic situation in 2008Q3, in which the Lehman Brothers collapsed and the government had to provide bailouts to others. The centrality and systematic importance of the firms in the financial services sector dropped significantly during the GFC because of their heavy involvement in complicated financial products such as mortgage-backed securities and collateralised obligations. Such high exposure makes risk-averse market participants quickly withdraw their positions in these firms to prevent their liquidity from drying out when the crisis contagion starts, leading to a significant decline in these firms' centrality. In contrast, banks and savings institutions were supported by regulatory provisions such as deposit insurance and emergency liquidity facilities. These regulations helped banks preserve their core functions in the financial network during the market turmoil. Consequently, the centrality of the banks and savings institutions was much more stable than that of the financial services.

FIGURE 4.2: Industry CWEC heatmap

This figure depicts a heatmap of the average CWEC values for our sample stocks, aggregated by industry over the period 2006Q1 to 2009Q4. Industry classifications are sourced from the Thomson Reuters database, with the first four rows representing the finance industry. Each stock's CWEC is derived from the two-step procedure of computing stock average connectedness and the weighted eigenvector centrality as in Equation (4.1) and (4.2).



Additionally, the varying connectedness and centrality dynamics presented in Table 4.1 and Figure 4.2 during the GFC motivate us to isolate this specific period in subsequent analyses of the relationship between CWEC and illiquidity.

4.4.2 Relationship between CWEC and illiquidity

Given the lack of consensus in existing literature regarding the causal relationship between stock connectedness or centrality and liquidity, we aim to employ the more sophisticated centrality measure to examine this relationship, in hopes of uncovering new insights.

TABLE 4.2: Panel Regressions

We run univariate and multivariate quarterly predictive regressions of illiquidity (left side) and stock Connectedness-Weighted-Eigenvector-Centrality (CWEC, right side) in Panel A of the following specification:

$$y_{i,q} = \beta_{i,q-1}x_{i,q-1} + \beta_{i,q-2}x_{i,q-2} + \beta_{i,q-3}x_{i,q-3} + \sum_{k=1}^{3} \beta_k Control_{i,q-1,k} + FE_i + \epsilon_{i,q}.$$

y is the stock illiquidity (or CWEC), x is the corresponding CWEC (or illiquidity) and $Control_{i,q-1,k}$ are our k_{th} control variables, namely the volatilities (the square root of the variance of Fama-French three factors regression error term of each stock, known as idiosyncratic volatility in Ang et al. (2009)), the volatility index VIX, and the changes in the money supply, M1 (Money Shock). FE_i is the fixed effect that captures time-invariant characteristics specific to each stock i. We run these quarterly panel regressions in q for each stock i. Panel B of this table reports the results of the predictive panel VAR with GMM-style regressions with three lags of similar specifications. The Akaike information criterion determines the lag. The time subscripts $q-1$, $q-2$, and $q-3$ denote lag-one, -two, and -three in the independent variables. Each stock's CWEC is derived from the two-step procedure of computing stock average connectedness and the weighted eigenvector centrality as in Equation (4.1) and (4.2). Illiquidity is estimated as in Equation (4.3). The sample includes 608 stocks from 1999 Q1 to 2022 Q2. Robust standard errors are in parentheses. The superscripts ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Illiquidity			CWEC	
Panel A: Predictive regressions					
	(1)	(2)		(1)	(2)
$CWEC_{q-1}$	-0.1094***	-0.1339***	$Illiquidity_{q-1}$	-0.0178**	-0.0391***
	(0.0329)	(0.0295)		(0.0083)	(0.0093)
$CWEC_{q-2}$	-0.0785**	-0.0673**	$Illiquidity_{q-2}$	-0.0213**	-0.0197*
	(0.0364)	(0.0327)		(0.0099)	(0.0101)
$CWEC_{q-3}$	-0.1279***	-0.1072***	$Illiquidity_{q-3}$	-0.0203***	-0.0085
	(0.0255)	(0.0229)		(0.0071)	(0.0073)
Volatility		16.3518***	Volatility		1.0711***
		(0.6214)			(0.3374)
VIX		0.0228***	VIX		0.0008**
		(0.0007)			(0.0003)
Money Shock		0.0000***	Money Shock		0.0000***
		(0.0000)			(0.0000)
Adjusted R^2	-0.0231	0.1757		-0.0248	-0.0200
Panel B: VAR regressions					
CWEC		3.2830***	CWEC		1.0105***
		(1.1668)			(0.1339)
Illiquidity		0.6122***	Illiquidity		-0.0163
		(0.1628)			(0.0173)
Volatility		19.3541*	Volatility		1.2600
		(11.2254)			(1.1257)
VIX		-0.0028	VIX		-0.0021**
		(0.0095)			(0.0010)
Money shock		0.0000	Money shock		0.0000*
		(0.0000)			(0.0000)

We first run the panel regression as in Equation (4.4) to identify the relationship between CWEC and illiquidity. Table 4.2 Panel A reports the results, showing that both lagged CWEC (the left side) and illiquidity (the right side) have negative and statistically significant correlations with each other. An increase in CWEC (or illiquidity) in the last quarter is associated with lower illiquidity (or CWEC) in the current quarter.

This statistically significant relationship between stock CWEC and illiquidity matches the inconclusive evidence reported in the literature. The coefficient of lagged stock centrality supports the hypothesis of the literature stream such as Kamara et al. (2008), Koch et al. (2016), Deng et al. (2018), and Bradrania et al. (2021) revealing that stocks' interlinkages affect liquidity or liquidity commonality. On the other hand, we disclose the significant inverse effect of stock illiquidity on stocks' centrality in the financial network. Stock illiquidity's statistically significant effect on centrality is attributed to institutional investor behaviour. Edelen (1999), Mitchell et al. (2002), Teo (2011), and Financial Stability Board (2017) show that institutions may adjust their investment portfolios due to investor redemptions, portfolio rebalancing, cash flow management, and preparation for expected market conditions according to their anticipated liquidity requirements. The changes in investment portfolios could affect stock liquidity and their centrality in the network. Our results in Table 4.2 Panel A thus highlight this clear dichotomy reported in the literature.

The bidirectional relationship reported in Panel A in Table 4.2 also holds when we control for both micro and macro control variables of idiosyncratic volatility, VIX, and money shock. As discussed in Section 4.3, our control variables consider historical and forward-looking idiosyncratic and systematic stock information. The consistently significant coefficients thus highlight the strong relation between CWEC and illiquidity. Since CWEC is based on mutual funds' investment positions, the strong correlation between CWEC and illiquidity requires further decomposition of the funds' characteristics as an intermediary.

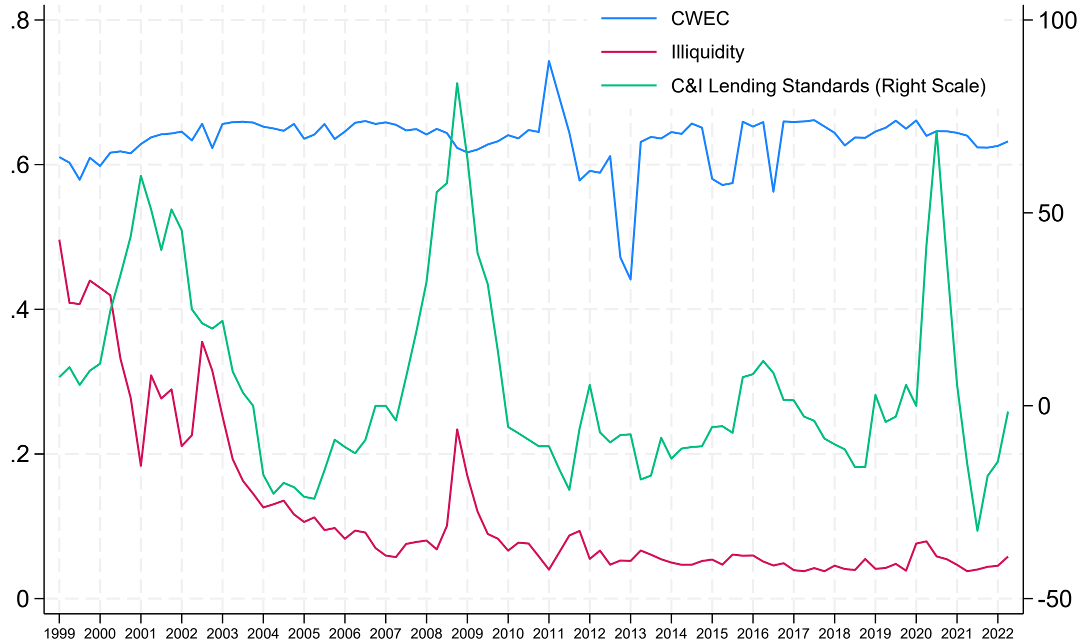
Results in Panel A in Table 4.2 thus mirror the inclusive results reported in the literature on the stock ownership and liquidity commonality and their relationship. Because our CWEC is dynamically linked to changes in stock prices and institutions' changes in investment portfolios, we can thus further explore how our CWEC relates to changes in the funding constraints of institutions. In Figure 4.3, we plot the stock CWEC and illiquidity against the SLOOS, the net percentage of banks whose credit standards on commercial and industrial loans to large and middle-market firms are reportedly tightening.[23] The percentage of banks tightening credit standards indicates the changes in the overall market funding liquidity. For stock illiquidity and the market funding liquidity, there are two typical peaks around 2002 and 2008, highlighting the market liquidity drought due to the .com crisis and the GFC. Stock illiquidity also increases after 2020. For January 1999 to June 2022, the correlation between stock illiquidity and bank lending tightness is 0.40 with a t-statistic of 4.24, showing a statistically significant co-movement. The tightness of the bank lending standard directly influences financial intermediary funding liquidity; when more banks raise credit standards, the entire market contracts and liquidity dries (Brunnermeier and Pedersen, 2008). Bank

[23] The data is obtained from the Federal Reserve's quarterly Senior Loan Officer Opinion Survey (SLOOS) on Bank Lending Practices, available at *https://fred.stlouisfed.org/searchresults/?st=SLOOS*.

lending is among the most important funding sources for many financial market participants, as evinced by the statistically significant positive correlation between market overall illiquidity and stock illiquidity.

FIGURE 4.3: Illiquidity, CWEC, and bank lending tightness

This figure displays the time series of stock CWEC, illiquidity, and bank lending tightness as presented by the blue, red, and green lines. The lending tightness is proxied by the percentage of banks reporting their credit standards on commercial and industrial (C&I) loans to large and middle-market firms. The data are obtained from the Federal Reserve's quarterly Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS). The sample includes 608 stocks spanning from 1999 Q1 to 2022 Q2.



Now, we focus on the dynamic relationship between the CWEC and the tightening lending standards. For the entire period, the correlation between CWEC and SLOOS is -0.02 with a t-statistic of -0.18, showing insufficient evidence of the co-movement between centrality and bank lending tightness. Thus, the fluctuations of market financing constraints significantly correlate with stock illiquidity but not stock centrality. Since our CWEC considers the strength of the linkage between each pair of stocks, distinguishing our measure from conventional approaches, stock CWEC appears to be "sticky" when facing both systematic and idiosyncratic liquidity changes. This implies that mutual funds, in fact, do not significantly alter their positions when the market liquidity condition changes. Gnabo and Soudant (2022) claim that mutual funds are reluctant to deviate from their familiar and preferred investment strategy. Fund managers tend to stay with their historical positions to minimise the information asymmetry risk when there is an unconventional monetary policy change. Besides this, fund managers are also concerned about portfolio rebalancing and transaction costs. Therefore, stock centrality is significantly correlated with stock illiquidity as in the panel regressions reported in Panel A in Table 4.2, but behaves differently from changes in institutions' funding constraints, possibly due to funds' preference to maintain the investment positions during changes in the systematic liquidity conditions.

The nuanced interactions between CWEC and illiquidity reported in Panel A in Table 4.2 and Figure 4.3 inform us to explore further their time-series relationship in an unrestricted multivariate Vector Autoregressive (VAR) model with the Generalised Method of Moments. The model includes the CWEC, illiquidity, and control variables simultaneously as in Equation (4.4). The lags are informed by Akaike information criteria. Table 4.2 Panel B reports the VAR results. We note that the lagged CWEC still has a statistically significant coefficient, showing a significant predictive ability on illiquidity. However, as presented on the right side of the panel, the illiquidity coefficient is no longer significant. This is indicative of the notion that its influence on centrality does not extend in the VAR context.[24] Our results therefore support the strand of literature showing changes in connectedness affect liquidity.[25] The insignificant illiquidity coefficients support our findings in Figure 4.3 and our conjecture that stock centrality is "sticky" due to funds' reluctance to change their investment themes and, with that, affecting the liquidity.

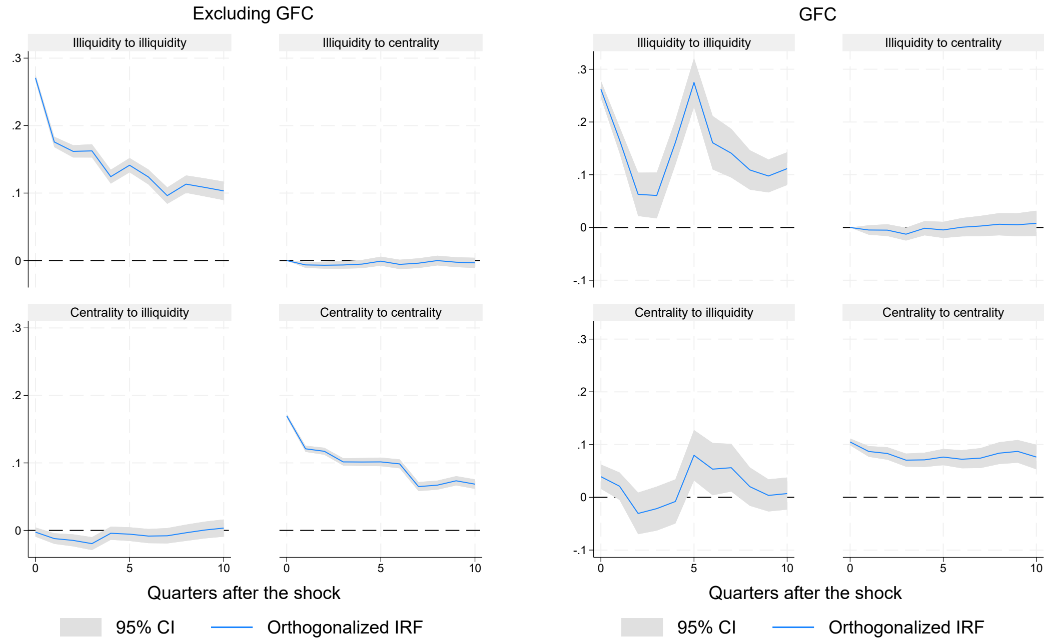
Next, we compute the Impulse Response Function (IRF) to our VAR to further investigate the response of CWEC (illiquidity) to a sudden shock in the other variable. Figure 4.4 presents the IRF of the endogenous variables to an orthogonalized shock to the stock illiquidity and our value-weighted centrality measure. The graphs in the left panel show the results of IRF applied to our entire period, excluding the GFC. The right panels present the IRF results during the GFC period. As shown in the left panel, an unexpected increase of one standard deviation in CWEC immediately leads to a significant decrease in stock illiquidity. The reaction broadly depreciates and becomes insignificant after 4 quarters. Conversely, the response of our value-weighted centrality measure to a sudden shock in illiquidity is much weaker and does not show any clear trend. In the right panel focusing on the GFC period, the CWECs response to the shock in illiquidity remains flat and statistically insignificant at a 95% confidence interval. Both VAR and IRF results are consistent and hold when we add the same idiosyncratic and systematic control variables as in the panel regressions discussed above. The IRF further strengthens the findings in the VAR and credit constraint plots, as discussed above.

[24] We also see that CWEC Granger causes illiquidity and the inverse causality does not hold. These results are robust to alternative identification schemes in which the variables are ordered differently in the VAR.

[25] See Kamara et al. (2008), Koch et al. (2016), Agarwal et al. (2018), Deng et al. (2018), and Bradrania et al. (2021) for example.

FIGURE 4.4: Impulse Response Function: The GFC

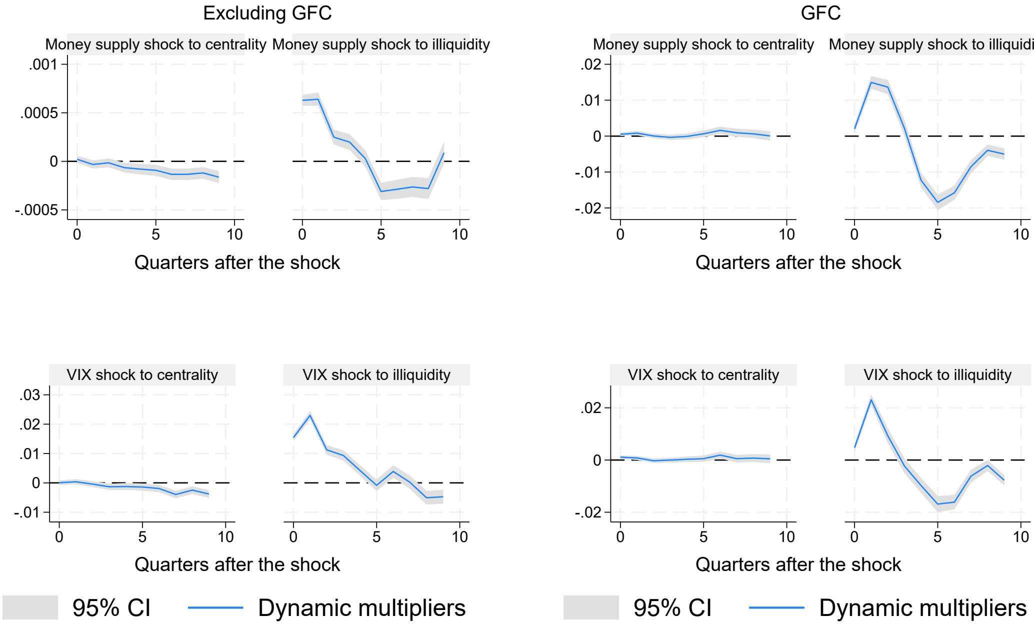
This figure displays the stock illiquidity or CWEC impulse responses to a one-standard-deviation orthogonalised shock to the connectedness or illiquidity with isolation of the GFC. The left panel is based on our full sample from 1999 Q1 to 2022 Q2 but excludes the GFC period from 2007 Q3 to 2009 Q2, while the right panel is for the GFC period from 2007 Q3 to 2009 Q2. The solid line indicates the estimated impulse response, while the shades indicate the 95% confidence interval.



The impulse responses of stock illiquidity to centrality are attributed to mutual funds' behaviours. Since our CWEC is based on the mutual funds' ownership, its characteristics imply the funds' holding positions. Mutual funds cannot alter their positions frequently to tightly follow stock illiquidity changes, which fail to lead to significant centrality fluctuations. Due to transaction and other costs, they tend to keep their positions and portfolio compositions. The "stickiness" of stock centrality is also supported by the local projection IRF with exogenous variables as displayed in Figure 4.5. When there is a one-unit shock in the VIX and the money supply shock, illiquidity has a statistically significant response, while the centrality response curve stays flat, showing insignificant responses to the changes in exogenous variables. This also holds when we isolate the highly uncertain period, the GFC.

FIGURE 4.5: Local Projection Impulse Response Function

This figure displays the response of stock illiquidity and CWEC to a one-unit shock in the VIX index and money supply shock over a horizon of 10 quarters. The left panel is based on our full sample from 1999 Q1 to 2022 Q2 but excludes the GFC period from 2007 Q3 to 2009 Q2, while the right panel is for the GFC period from 2007 Q3 to 2009 Q2. The solid line indicates the estimated impulse response, while the shades indicate the 95% confidence interval.



To conclude, the credit constraint plots reveal that changes in the market credit tightness do not correlate with stock centrality. This is presumably caused by the funds' reluctance to largely change their positions during funding liquidity changes. The VAR and IRF analyses further support the centrality "stickiness" conjecture by establishing the influence of stock centrality on illiquidity but not the other way around. Depending on the value-weighted centrality which departs from the literature, we firmly stand on the stock level and reveal the relationship between stock centrality and illiquidity. The stock-level analyses explicitly provide investors with more flexibility to tailor their portfolios according to their liquidity preferences given the portfolio components' centrality information.

4.4.3 Valuation of Centrality

Given our discovery of centrality's significant impact on illiquidity, which is a key risk factor in the market, we proceed to examine whether the market treats stocks differently based on their CWEC levels. We first construct equally weighted CWEC-sorted quartile portfolios and analyse the median illiquidity, firm size, stock realised return, and their alpha. Table 4.3 aggregates these findings. We note that the Amihud illiquidity ratio decreases monotonically from 0.0864 to 0.0524 when stocks are in the higher CWEC quartile (the second column). The illiquidity difference between the lowest and the highest centrality portfolios is statistically significant. The inverse relationship between contemporaneous stock centrality and illiquidity shows that more central stocks have, on average, higher liquidity. An interesting finding in the third column of Table 4.3 shows that firm sizes move hand in hand with their stocks' centrality. Because our CWEC is computed by large mutual fund ownership, a higher CWEC implies a more central position of the stock in a network and higher investor concentration, which are inherent properties of larger firms. These properties naturally lead to higher trading volume, faster transactions, lower trading costs, and lower price impact (Liu, 2006). Our results suggest that larger stocks have higher centrality measures and tend to be more liquid.

TABLE 4.3: CWEC Sorts

This table reports the results of equally weighted CWEC-sorted quartile portfolios. We summarise the quarterly median illiquidity measures, sizes, realised returns, and annualised Fama-French-Carhart four-factor alphas of each quartile portfolio. Stock CWEC level is derived from the two-step procedure of computing stock average connectedness and the weighted eigenvector centrality as in Equation (4.1) and (4.2). Illiquidity is computed as in Equation (4.3). Size is proxied by the natural logarithm of stock market capitalisation. The realised returns are stocks' quarterly realised returns. The four-factor alphas are generated by regressions based on daily data in each quarter. 608 stocks from 1999 Q1 to 2022 Q2 are included in the portfolios. QL-QH represents the difference between the lowest to the highest CWEC quartiles. The t-statistic denotes the significance of the QL-QH returns.

CWEC	Illiquidity	Size	Realised Return	α
QL	0.0864	16.8354	0.0309	0.0047
Q2	0.0725	16.9728	0.0264	0.0047
Q3	0.0626	17.1460	0.0236	-0.0011
QH	0.0524	17.4866	0.0259	-0.0026
QL-QH	0.0340	-0.6512	0.0050	0.0073
t-stat.	1.9253	-39.5000	2.9335	1.9754

Another interesting finding in Table 4.3 is the highest realised return and Fama-French-Carhart four-factor alpha in the lowest centrality quartile portfolio.[26] The gradually decreasing alphas in the last column highlight the negative centrality and liquidity contributions to stock-level excess returns. The median Fama-French-Carhart four-factor alphas of the highest CWEC quartile subsample are also statistically significantly lower than those in the lowest CWEC quartile. The median excess returns of the stocks in the highest two CWEC quartile subsamples become negative. Those least popular stocks with low centrality and liquidity tend to yield higher excess returns, as the market demands compensation for bearing the risk of holding less central stocks that can be liquidated at a slower pace than others. Such compensation for liquidity risks built into asset returns has been widely recognized as a liquidity premium in the literature.

[26] Although both realised returns and alphas serve to measure investment performance, they provide distinct insights. Realised returns explicitly indicate actual gain or loss achieved by investment, while alphas reflect the investment performance relative to a benchmark (in this case, the Fama-French-Carhart four-factor model) known as excess return.

Pástor and Stambaugh (2003) reveal that expected stock returns cross-sectionally correlate with return sensitivity to overall liquidity changes. Acharya and Pedersen (2005) propose that stock expected liquidity is one of the determinants of its required return. Amihud (2002); Amihud et al. (2005) find liquidity premium contributes to stock realised returns. Liu (2006) also discovers that liquidity risk is significantly priced and robust to both the CAPM and the Fama-French 3-factor model. Therefore, the large firms' highly central stocks with lower illiquidity tend to be more popular, frequently traded, and thus fairly priced. The abundant investor interests and transactions represented by higher centrality largely restrict the potential opportunities for generating excess returns. This finding also agrees with the significance of the small-minus-big (SMB) factor in the Fama and French (1993) three-factor model. The statistically significant high-minus-low differences of returns in Table 4.3 indicate that stock centrality could be a state variable and further motivate us to study whether the centrality is priced.

TABLE 4.4: Fama-Macbeth regression

This table presents the results of univariate and multivariate Fama and MacBeth (1973) regressions for stock CWEC levels. The sample is consistent with the one in Table 4.2. We add the β of idiosyncratic volatility (Volatility) as described in Table 4.2 and Fama-French-Carhart four factors as controls. Robust standard errors are in parentheses. The sample includes 608 stocks spanning from 1999 Q1 to 2022 Q2. The superscripts ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
β^{CWEC}	-0.0113**	-0.0250***
	(0.0044)	(0.0051)
$\beta^{Volatility}$		-4.5770***
		(0.6697)
β^{MKT}		0.0116***
		(0.0031)
β^{SMB}		0.0002
		(0.0014)
β^{HML}		0.0022
		(0.0016)
β^{UMD}		0.0015
		(0.0017)
Constant	0.0017	0.0061**
	(0.0094)	(0.0029)
$Adjusted R^2$	0.0006	0.1893

We now analyse the economic importance of our stock centrality by applying Fama and MacBeth (1973) two-step multifactor regression. Table 4.4 presents the results. We control for stocks' idiosyncratic volatility and also include Fama-French-Carhart's four factors as common pricing control factors. In the first stage of the regressions, we estimate the return exposures to each variable, β, by running the time-series regressions of 608 stocks' quarterly returns against the CWEC and corresponding control variables. Then, we regress the stock returns against the βs obtained in the first step for each variable's risk premium. The consistently significantly negative β^{CWEC} coefficients indicate the presence of a centrality risk premium. The premium remains robust after controlling for each stock's idiosyncratic volatility and Fama-French-Carhart's four factors. This finding supports the evidence on the potential role of centrality in determining stock prices shown in Tables 4.3, 4.6, and 4.7 and reports a significant network premium also recently reported by Buraschi and Tebaldi (2024). We also separate the sample according to CWEC quartiles and replicate the approach applied in Table 4.4 for each quartile subsample. Table 4.5 aggregates these results. The statistically significant negative β^{CWEC} coefficients in the lowest CWEC quartile are highly consistent with the results in previous tables, implying that less central stocks tend to generate higher returns as they incur a network premium. Peripheral stocks have less investor attention and institutional holdings and, thus, are not as fairly priced as those core and popular stocks in the financial network.

TABLE 4.5: Fama-Macbeth regression with CWEC sorts

This table presents similar results of univariate and multivariate Fama and MacBeth (1973) regressions for stock CWEC levels as in Table 4.4 but for each CWEC-sorted quartile from the lowest (QL) to the highest (QH). Robust standard errors are in parentheses. The sample includes 608 stocks spanning from 1999 Q1 to 2022 Q2. The superscripts ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	QL		Q2		Q3		QH	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
β^{CWEC}	-0.0140**	-0.0181***	0.0305	0.0060	-0.0392	0.0117	0.0397	0.0763**
	(0.0055)	(0.0061)	(0.0332)	(0.0302)	(0.0678)	(0.0508)	(0.0384)	(0.0337)
$\beta^{Volatility}$		-2.0661**		-3.8343***		-3.8199***		-3.8808***
		(0.8158)		(0.8476)		(0.8076)		(0.8598)
β^{MKT}		0.0090***		0.0211***		0.0149**		0.0070*
		(0.0027)		(0.0051)		(0.0061)		(0.0039)
β^{SMB}		0.0012		-0.0007		-0.0021		0.0009
		(0.0017)		(0.0013)		(0.0023)		(0.0019)
β^{HML}		0.0044**		-0.0011		-0.0006		0.0013
		(0.0020)		(0.0022)		(0.0039)		(0.0024)
β^{UMD}		-0.0004		0.0028		0.0001		0.0005
		(0.0029)		(0.0035)		(0.0024)		(0.0018)
Constant	-0.0006	0.0046*	0.0246	0.0031	-0.0097	0.0093*	0.0108	0.0058**
	(0.0135)	(0.0025)	(0.0223)	(0.0038)	(0.0243)	(0.0050)	(0.0103)	(0.0028)
$Adjusted R^2$	0.0014	0.0970	0.0063	0.1316	0.0036	0.1259	-0.0039	0.0919

Additionally, we run the predictive regressions of stock returns against lagged CWEC to further study CWEC's predictive power on future returns. Table 4.6 summarises the results. Our stock centrality measure has statistically weakly significant negative coefficients in univariate and controlled regressions. We keep the same controls as in Table 4.4. The negative CWEC coefficients support the generally decreasing trend of realised returns with more central stocks as reported in Table 4.3. We also replicate the analyses of Table 4.6 for each CWEC quartile subsample and report the results in Table 4.7. The univariate and controlled predictive regressions only generate statistically significant negative CWEC coefficients in the lowest CWEC quartile. This strengthens the explanation for the inverse relationship between realised return and CWEC in Table 4.3 and the negative coefficients in Table 4.6. Less central stocks are more likely to generate higher returns in the next quarter.

TABLE 4.6: CWEC and stock returns

In this table we regress quarterly stock returns on the lagged stock's CWEC level. As in Model (4):

$$r_{i,q+1} = \beta_{i,q} CWEC_{i,q} + \beta_{i,q} Volatility_{i,q} + \sum_{k=1}^{4} \beta_k Control_{i,q,k} + FE_i + \epsilon_{i,q+1}.$$

$r_{i,q+1}$ is the return of stock i in quarter $q+1$, $CWEC_{i,q}$ is the CWEC of stock i in quarter q, $Control_{i,q,k}$ are Fama-French-Carhart four-factor controls at quarter q, and FE_i is the fixed effect that captures time-invariant characteristics specific to each stock i. Stock CWEC level is derived from the two-step procedure of computing stock average connectedness and the weighted eigenvector centrality as in Equation (4.1) and (4.2). Illiquidity is proxied as in Equation (4.3). Model (1) reports the univariate regression results, while Model (2) shows controls Fama and French (1993) three factors, market (MKT), size (SMB), and value (HML) and Carhart (1997)'s momentum factor (UMD). Model (3) controls both idiosyncratic volatility and Fama-French-Carhart's four factors. Robust standard errors are in parentheses. The R-squared values are adjusted. The sample includes 608 stocks spanning from 1999 Q1 to 2022 Q2. The superscripts * * *, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively

	(1)	(3)	(4)
CWEC	-0.0178*	-0.0195*	-0.0180*
	(0.0106)	(0.0106)	(0.0106)
Volatility			-0.8261*
			(0.4283)
MKT		0.0006	-0.0001
		(0.0017)	(0.0017)
SMB		-0.0096***	-0.0090***
		(0.0028)	(0.0028)
HML		-0.0194***	-0.0195***
		(0.0018)	(0.0018)
UMD		-0.0095***	-0.0096***
		(0.0015)	(0.0016)
Adjusted R^2	0.0723	0.0803	0.0811

TABLE 4.7: CWEC and stock returns regressions with CWEC sorts

This table presents similar results of univariate and multivariate Fama and MacBeth (1973) regressions for stock CWEC levels as in Table 4.6 but for each CWEC-sorted quartile from the lowest (QL) to the highest (QH). Robust standard errors are in parentheses. The sample includes 608 stocks spanning from 1999 Q1 to 2022 Q2. The superscripts ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	QL		Q2		Q3		QH	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
CWEC	-0.0286**	-0.0276**	-0.0509	-0.0433	-0.0036	-0.0288	0.1415	0.0987
	(0.0123)	(0.0121)	(0.0870)	(0.0868)	(0.0698)	(0.0695)	(0.0882)	(0.0881)
Volatility		0.4490		-1.8204		0.5188		-1.9282***
		(0.6225)		(1.1494)		(0.5952)		(0.6491)
MKT		-0.0004		-0.0039		-0.0028		0.0002
		(0.0027)		(0.0045)		(0.0021)		(0.0024)
SMB		-0.0118***		0.0026		-0.0098***		-0.0090**
		(0.0044)		(0.0073)		(0.0034)		(0.0040)
HML		-0.0311***		-0.0210***		-0.0119***		-0.0112***
		(0.0028)		(0.0048)		(0.0022)		(0.0025)
UMD		-0.0054**		0.0147***		-0.0083***		-0.0092***
		(0.0025)		(0.0041)		(0.0019)		(0.0022)
$Adjusted R^2$	0.1220	0.1560	0.4263	0.4302	0.0663	0.0767	0.0195	0.0292

After disclosing the potential pricing pattern, we want to explore whether investors can make a profit by exploiting it. We construct quartile portfolios based on the centrality of our sample stocks. Then, we construct our BAC factor by putting a long position on the lowest centrality quartile portfolio and a short position on the highest one. The stocks are equally weighted, and the portfolios are rebalanced quarterly. The BAC factor returns are then regressed against the Fama-French-Carhart factors. Table 4.8 aggregates these results.[27] The BAC factor generates an insignificant 1.07% quarterly alpha, implying that the investors pursuing BAC strategy cannot significantly improve the portfolio performance, especially when transaction costs are included. Overall, our results suggest that despite the evidence of the centrality premium discussed above, investors seeking excess returns by trading the stocks at different centrality levels are ineffective. This finding, to a large extent, lays support to our previous results showing that stock centrality is "sticky". This is due to the institutions' preferences for maintaining their investment positions, which in turn does not alter stocks' centrality position in the financial network and, therefore, cannot yield excess returns.

[27] We have also replicated the analyses on quintile centrality portfolios and centrality-weighted portfolios. The results do not qualitatively change.

TABLE 4.8: Betting against CWEC

This table reports the results of the betting-against-CWEC strategy which uses our sample of 608 stocks over the period from 1999 Q1 to 2022 Q2. We sort our sample stocks into quartiles according to their CWEC, represented from QL (Low) to QH (High). Stock CWEC level is derived from the two-step procedure of computing stock average connectedness and the weighted eigenvector centrality as in Equation (4.1) and (4.2). The BAC denotes the betting-against-CWEC factor. BAC is constructed by putting a long position on the lowest CWEC quartile portfolio and a short position on the rest of the portfolios. Stocks are equally weighted. The portfolios are rebalanced each quarter. This table reports alphas, robust standard errors, adjusted R-squared, and appraisal rations of Carhart (1997) four-factor regressions. Robust standard errors are in parentheses. The superscripts ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	QL	Q2	Q3	QH	BAC
α	-0.0411***	-0.0320***	-0.0320***	-0.0304***	0.0107
	(0.0075)	(0.0051)	(0.0060)	(0.0049)	(0.0077)
Adjusted R^2	0.6786	0.8043	0.7444	0.7955	0.1313
Appraisal Ratio	-2.0772	-2.3847	-2.0015	-2.3511	0.5278

4.5 Conclusion

We contribute to the literature by first deriving the Connectedness-value-Weighted-Eigenvector-Centrality (CWEC) measure. This is computed by the two-step process of computing Antón and Polk (2014)'s pairwise connectedness and using the connectedness as the weight for eigenvector centrality. Our centrality measure includes information on the stocks' connections with other stocks owned by the same mutual funds and the importance of those stocks directly connected to each stock. This stock-level informative centrality measure enables us to study the relationship between stock centrality and illiquidity on individual stock levels. We use quarterly data of large US stocks owned by top US mutual funds from January 1999 to June 2022.

Second, relying on the informative CWEC measure, we find that centrality affects stock illiquidity. This contributes to the debate in the literature about the relationship between financial interlinkages and asset liquidity. Panel regression results show that stock centrality and illiquidity have a significantly positive influence on each other, while further VAR and IRF analyses reveal that only centrality affects liquidity. In our sample, the stock centrality is not affected significantly when facing liquidity and other exogenous shocks. This is also supported when we plot the time series of our centrality level with changes in the funding liquidity. We conjecture that funds tend not to frequently adjust their strategies to closely follow the liquidity fluctuations as they are associated with asymmetric information risk and incur rebalancing and transaction costs. The centrality sorted results indicate an inverse relationship between stock illiquidity and centrality. The higher-connected stocks tend to yield lower realised returns and alphas against Fama-French-Carhart's four factors. This is because more connected stocks tend to be more liquid and thus priced more fairly.

Lastly, we find some evidence of the centrality premium by applying the centrality portfolio sorts, Fama and MacBeth (1973) regressions, and predictive regressions. A trading strategy that exploits the pricing gap among different stock centrality levels fails to yield statistically significant alphas. Other realistic trading conditions such as transaction costs further make it harder to make a profit.

Chapter 5

Volatility Timing in Cryptocurrency Markets

5.1 Introduction

While the cryptocurrency pricing models are developing quickly[1], abundant studies have disclosed the persistent inefficiencies within the cryptocurrency market.[2] Makarov and Schoar (2020) find that the price mismatch in the cryptocurrency market cannot be fixed by arbitrageurs due to the strong information barriers and transaction hurdles. Cheah and Fry (2015), Baur et al. (2018), and Babiak and Bianchi (2023) reach the consensus that speculation is one of the main purposes of cryptocurrency investors. The cryptocurrency market's inefficiency and speculative nature introduce risk anomalies and the potential to seek excess returns. Leong and Kwok (2023) reveal the inverse relationship between idiosyncratic volatility and future returns in the cryptocurrency market and explain the anomaly by statistical noises and limits-to-arbitrage theory. They thus develop a trading strategy betting against idiosyncratic diffusive volatility[3]. They claim this strategy generates statistically significant excess returns, demonstrating the potential to exploit the mispricing. However, despite these findings, research on leveraging risk anomalies and addressing mispricing in the cryptocurrency market remains insufficient, leaving significant gaps in understanding and application. Further incorporating a volatility-timing framework into cryptocurrency trading could therefore be pivotal. Adapting exposure dynamically to shifting volatility regimes may not only enhance risk-adjusted returns but also deepen our insight into the market characteristics and investor behaviour and preferences in this emerging asset class.

This chapter makes three key contributions to our understanding of cryptocurrency markets. First, building on the documented risk anomaly and the well-known short-term persistence of volatility in cryptocurrencies (Zhang and Zhao, 2023), we introduce a realised-volatility timing strategy that hasn't been tested before in this market. By adjusting exposure when volatility is forecasted to rise or fall, this approach exploits directly the market's risk anomaly and delivers attractive risk-adjusted returns, which could be a valuable insight for both academic researchers and market practitioners. Second, we break down the analysis across different market conditions to see when and where the strategy works best. We look separately at large versus small coins, cryptocurrencies' recent maximum returns, periods of high and low funding costs, shifts in overall sentiment, and contrasting macroeconomic backdrops. These subgroup tests not only reinforce the basic timing idea but also shed light on the underlying investor behaviours that drive these results. Finally, we run the same tests on a penny-stock index, since both penny stocks and cryptocurrencies are known for speculative trading. Comparing the two markets shows that timing volatility in the cryptocurrency market

[1] See Cong et al. (2020) and Biais et al. (2023) for example.

[2] See Al-Yahyaee et al. (2018), Caporale et al. (2018), Jiang et al. (2018), Kristoufek (2018), Zhang et al. (2018), Charfeddine and Maouchi (2019), and Hu et al. (2019) for example.

[3] The idiosyncratic diffusive volatility is computed by the return observations lower than a threshold which is a multiple of the return standard error. This approach filters away huge fluctuations.

behaves differently. This broader comparison gives us a fuller picture of cryptocurrencies' unique characteristics. In practical terms, these findings could provide valuable references to help portfolio managers improve returns by dynamically scaling their cryptocurrency exposure, risk teams adjust their strategies around volatility spikes, and regulators better understand the conditions that lead to extreme price swings.

This study analyses the daily index data of cryptocurrencies and penny stocks, using the S&P Cryptocurrency Broad Digital Market Index (BDMI), S&P Cryptocurrency LargeCap Index (BDMLCI), and S&P Cryptocurrency BDM Ex-LargeCap Index (BDMXLCI) data to proxy the overall performance of the entire cryptocurrency market, large cryptocurrencies, and small cryptocurrencies, respectively. The analysis is further extended to the penny stock index (PSI) for comparative purposes. We first follow the volatility timing method applied by Moreira and Muir (2017) and Cederburg et al. (2020) to scale the cryptocurrencies' excess returns by the reciprocal of their rolling monthly realised volatilities (RV), which has not been covered in previous studies. Based on extensive evidence of volatility persistence, market inefficiencies, and risk anomalies documented in prior researches[4], this approach exploits the risk-reward mismatches by adjusting investment position weights dynamically. Applying the empirically successful volatility timing strategy in the stock market[5] to the cryptocurrency market helps to shed new light on the characteristics of the cryptocurrency risk anomaly and provides empirical evidence of the strategy's effectiveness in seeking cryptocurrency excess returns. The findings offer valuable insights for researchers and practitioners, particularly in risk management and portfolio construction. Second, the study conducts detailed analyses across subsets defined by cryptocurrency market capitalisations, recent extreme returns, market liquidity, sentiment conditions, and periods of heightened uncertainty. These segmented analyses reveal nuanced characteristics of cryptocurrency risk anomalies and the conditions under which volatility timing strategies are most effective. Third, we adopt the same approach for the penny stock index, leveraging the speculative and lottery-like characteristics of penny stocks often associated with the low-price effect. This comparative perspective provides an additional understanding of the unique features of the cryptocurrency market, offering a novel contribution to the existing literature.

The RV-sorted results indicate that higher returns consistently fail to compensate for higher RVs adequately and this phenomenon prevails across all cryptocurrency indices and time period subsets. This effect agrees with the literature that the risk anomaly exists in the cryptocurrency market. We then time the RV and scale the excess returns

[4] See Bariviera (2017), Phillip et al. (2018), Chaim and Laurini (2019), Al-Yahyaee et al. (2020), and Zhang and Zhao (2023) for example of the cryptocurrency volatility memory and persistence. See Al-Yahyaee et al. (2018), Caporale et al. (2018), Jiang et al. (2018), Kristoufek (2018), Charfeddine and Maouchi (2019), and Hu et al. (2019) for example of cryptocurrency market inefficiency. The preliminary analyses in this chapter also provide evidence of risk anomaly in the cryptocurrency market.

[5] See Moreira and Muir (2017), Cederburg et al. (2020), and the empirical results in Chapter 3 for example.

of our sample indices, making comparisons among their scaled and unscaled excess returns, Sharpe ratios, and Sortino measures. The direct comparison result indicates that the RV-timing strategy is effective for the BDMI in all subsample periods and all indices, including PSI during the market turmoil. We further sort the indices' returns according to their recent extreme returns and show the positive relationship pattern between the short-run returns and recent extreme returns. This hints at the influence of lottery preference. However, the spanning regression within each subsample does not provide conclusive evidence of how the lottery preference affects the volatility timing effectiveness.

Building on the findings of Dong et al. (2022) regarding the influence of market liquidity on cryptocurrency anomalies, we sort the federal funds rate (FFR) into two halves and observe that cryptocurrencies mostly achieve higher excess returns during periods of high liquidity. To deeply analyse the RV-scaling approach's effectiveness on cryptocurrency indices, we also run the spanning regressions of all indices' scaled returns against the unscaled ones for each subset separated by a two-year COVID period and low and high FFR rates. Overall, the RV-scaling strategy proves effective for BDMI and BDMLCI across the entire sample period. However, in subsample analyses, the strategy generates statistically significant alphas only during periods of higher market liquidity coinciding with heightened uncertainty, such as the COVID period. The significant alphas imply the empirical success of the volatility timing strategy applied in the cryptocurrency market under specific market conditions. Also, the statistically significant higher BDMXLCI alphas generated by the RV timing approach when the market liquidity is high during market distortion highlight the hedging properties of the cryptocurrencies[6]. The panic formed in the extremely uncertain period stimulates the demand for hedging which motivates investors to enter the cryptocurrency market, leading to an unprecedented money injection (Kumar et al., 2022). Moreover, the low FFR signals prosperous market conditions with high liquidity and more active transactions. In contrast to widely traded large-cap cryptocurrencies, smaller-cap cryptocurrencies exhibit greater potential to generate excess returns, attracting speculative investors. Consequently, the heightened hedging demand, expansionary market conditions, and the speculative appeal of smaller cryptocurrencies collectively explain the empirical results observed in this study.

As for penny stocks, although some effects observed in the cryptocurrency market are applicable, there are other risk factors considered by the market participants such as the company default risk, which is less likely to exist in the cryptocurrency market. During periods of market distress, the market exhibits a divergent attitude toward penny stocks. Unlike cryptocurrencies, penny stocks lack hedging properties and are more vulnerable to heightened default risks in such scenarios. As a result, the RV-scaling

[6]See Dyhrberg (2016), Bouri et al. (2017), Urquhart and Zhang (2019), Jiang et al. (2021), and Melki and Nefzi (2022) for example.

method fails to generate any significant alphas for penny stocks, even during highly volatile periods. This underscores the fundamental differences between penny stocks and cryptocurrencies, particularly in their risk profiles and market dynamics during periods of uncertainty.

In addition to the lottery preference and liquidity analyses, we extend the investigation by replicating the sorting and spanning regressions using both a global financial market sentiment indicator and a cryptocurrency-specific sentiment indicator. This novel comparison between sentiment indicators across different markets, which has not previously been explored in the literature, is inspired by empirical evidence suggesting that the cryptocurrency market is significantly influenced by emotional and speculative behaviour[7]. This investigation, therefore, offers valuable insights into the relationships between cryptocurrency returns, risks, and the effectiveness of realised volatility timing. Results indicate that the volatility timing strategy is effective only for cryptocurrencies with large market capitalisation when the overall financial market is at the growth stage. The money newly entering the cryptocurrency market tends to pick larger and more notable cryptocurrencies. As an overview of the realised volatility timing strategy's effectiveness in the cryptocurrency market, this approach is only effective with some specific situations that largely strengthen the risk-return anomaly. The failure of many cases of realised volatility timing can be attributed to the backwards-looking property which is critical in highly speculative markets influenced by market consensus such as the cryptocurrency market. Using past information to adjust the investment positions cannot catch the market's live changes. This is highlighted by all the insignificant alphas in the spanning regressions with the Crypto Fear & Greed Index subsamples.

The remainder of this chapter is organised as follows. Section 5.2 reviews the relevant literature in the cryptocurrency market. Section 5.3 describes and summarises the data and method used and applied in this study. Section 5.4 reports and analyses our empirical results. Finally, Section 5.5 concludes this study.

5.2 Related Literature

There is a large body of literature studying cryptocurrency pricing. Ciaian et al. (2015) apply time-series analytical approaches on daily data for five years and disclose that both market demand and supply forces and cryptocurrency-specific factors largely determine Bitcoin prices. The impact on Bitcoin prices varies over time. Shen et al. (2020) propose a three-factor pricing model for cryptocurrencies including market excess return, size (small-minus-big), and reversal (down-minus-up) factors. Their three-factor

[7] See Cheah and Fry (2015), Baur et al. (2018), Babiak and Bianchi (2023), and Zhao et al. (2024) for further reference.

model outperforms the traditional CAPM used in the cryptocurrency market. Liu et al. (2022) also find that standard asset pricing models are also effective on cryptocurrencies. They build a three-factor model with market, size, and momentum factors and successfully use it to capture the cryptocurrency price dynamics. Based on Shen et al. (2020)'s study, Shahzad et al. (2021) follow Londono (2019)'s approach to measure contagion factor by the large left-tail events in the cryptocurrency return disturbances and consider the contagion measure as the fourth factor in the model. They claim that the four-factor model has stronger explanatory power than both CAPM and Shen et al. (2020)'s three-factor model. Chi et al. (2023) focus on cryptocurrency futures and concur with the above studies in terms of the conventional asset pricing approach's effectiveness in the cross-sectional cryptocurrency analysis. Besides the factor pricing models, Cong et al. (2020) introduce a dynamic cryptocurrency pricing model and discover that, instead of traditional valuation methods, the demand of total heterogeneous traders using digital platforms forms the equilibrium cryptocurrency prices. Biais et al. (2023) propose another general equilibrium pricing model and separately attribute the Bitcoin price to its fundamental and other extrinsic volatility. They use transaction costs and benefits based on future prices to proxy the fundamentals which are critical in determining Bitcoin returns over time. The extra price fluctuations are caused by extrinsic volatilities.

Regarding the risk pricing in the cryptocurrency market, Zhang and Li (2020) disclose a consistent positive relationship between idiosyncratic volatility and cryptocurrency expected returns by conducting both portfolio and Fama and MacBeth (1973) regression analysis. Bouri et al. (2022) also find that additional risks measured by idiosyncratic volatility have a positive relationship with expected cryptocurrency returns and CAPM/Shen et al. (2020)'s three-factor model alphas, confirming that idiosyncratic volatilities are priced in the cryptocurrency market and investors are compensated by the risk premium. However, Bouri et al. (2022) further reveal that this positive relationship only exists on the cryptocurrencies subject to microstructure noises. Besides idiosyncratic volatility, Zhang et al. (2021) find that the downside risks in the cryptocurrency market are also priced, which can be explained by the risk-return tradeoff and limits-to-arbitrage theories. The upside risks' relation to expected returns depends on the downside risk, whose premium is mostly from volatility.

Besides the exploration of the cryptocurrency pricing method, another strand of literature reveals the cryptocurrency market's inefficiency and related properties. Urquhart (2016) discovers strong inefficiency in the Bitcoin market over the entire sample period from 2011 to 2017, but efficiency in the latter period. This study thus concludes that the currently inefficient market is becoming more efficient, as Bitcoin has attracted more attention regarding transactions and studies. Bariviera (2017) finds that the Bitcoin daily returns behave more efficiently after 2014, which supports Urquhart (2016)'s findings.

Nadarajah and Chu (2017) and Tiwari et al. (2018) follow Urquhart (2016) and find similar results supporting the Bitcoin market efficiency. Sensoy (2019) use high-frequency data to study the weak-firm efficiency in the Bitcoin market and also reveal that the market efficiency improves along with time and when the data frequency is higher. Oppositely, there is much evidence pointing to the cryptocurrency market's inefficiency. Al-Yahyaee et al. (2018), Jiang et al. (2018), Kristoufek (2018), and Al-Yahyaee et al. (2020) focus on the Bitcoin market and investigate the long-term memory of Bitcoin. They reach the consensus that the Bitcoin market is inefficient. Caporale et al. (2018), Zhang et al. (2018), Charfeddine and Maouchi (2019), and Hu et al. (2019) also provide evidence of market inefficiency in other cryptocurrencies such as Litecoin and Ripple.

The abundant criticism and evidence against the pricing theory development and efficient market hypothesis in the cryptocurrency market introduce the potential opportunities for seeking excess returns and anomalies. Cheah and Fry (2015) provide empirical evidence of Bitcoin's substantial speculative bubble and zero fundamental price. Baur et al. (2018) find that Bitcoin is uncorrelated with conventional assets like fixed-income securities, equity, and commodities. This property is consistent in normal and highly uncertain periods. Baur et al. (2018) conclude that Bitcoin investors' purpose is mainly for speculation. Makarov and Schoar (2020) investigate the cryptocurrency arbitrage and price information. They disclose that the cryptocurrency market's dispersed characteristics result in extensive information barriers and trading obstacles, which could cause price discrepancies that can hardly be corrected by arbitrageurs. Babiak and Bianchi (2023) exploit the instrumental principal component analysis (IPCA) and show that cryptocurrency returns largely depend on systematic mispricing and risk compensation, which are dominated by cryptocurrencies' speculative demands and liquidity properties. Babiak and Bianchi (2023) also find that the speculative demand significance is associated with the market consensus, implying that cryptocurrencies may be linked to lottery-like stocks by investors. Zhao et al. (2024) provide an outline of the strategies employed by speculative and lottery-like investors in the cryptocurrency market and examine the influence of their behaviour on cryptocurrency pricing. They find that cryptocurrency investors are attracted by low-priced assets for cheap bets, which is known as the lottery preference low-price effect.

As a contradiction to the risk pricing studies discussed above, Dong et al. (2022) disclose that cryptocurrency liquidity and overall efficiency are affected by systematic liquidity. Many recognised anomalies in the stock market appear in the cryptocurrency market, where the anomalies are more prominent when the cryptocurrency liquidity condition is worse. Leong and Kwok (2023)'s study also discovers the idiosyncratic risk anomaly in the cryptocurrency market. They reveal that idiosyncratic risks move inversely with future returns in the cryptocurrency market. They also follow Kapadia et al. (2019)'s spirit and decompose cryptocurrency idiosyncratic returns into jumps and diffusive variations. The jumps are defined as the return observations over the threshold which is a multiple of the cryptocurrency return standard error. The rest of the observations lower than the threshold are thus regarded as diffusion. Leong and Kwok (2023) develop a trading strategy putting a long position on cryptocurrencies with high idiosyncratic diffusive volatility and a short position on those with low idiosyncratic diffusive volatility. This strategy yields statistically significant huge negative annualised returns. The idiosyncratic jumps also present negative predictive power to future returns but with weaker statistical significance. Leong and Kwok (2023) attribute the low idiosyncratic risk anomaly to potential statistical confounders and limits-to-arbitrage theory. Their investigation shows that volatility explains the anomaly, but higher statistical moments do not and arbitrageurs may fail to correct cryptocurrency prices due to their constraints in leverage availability and liquidity requirements.

Another stream of literature reveals the volatility persistence in the cryptocurrency market. Bariviera (2017) finds that Bitcoin volatility exhibits long memory during a sample period from 2011 to 2017, reflecting a different dynamic process of Bitcoin prices and volatility. Phillip et al. (2018) show that predictable patterns appear in the cryptocurrency market and many stylised factors hold in the Bitcoin market such as long memory. Chaim and Laurini (2019) also document the apparent long memory of major cryptocurrencies. Zhang and Zhao (2023) confirm the existence of cryptocurrency volatility persistence and further discover that cryptocurrency volatility is more correlated to past positive returns.

Given the abundant evidence of risk anomaly and the volatility persistence in the cryptocurrency market, we contribute to the literature by following Moreira and Muir (2017)'s and Cederburg et al. (2020)'s spirits to time the cryptocurrency index volatility to exploit the risk anomaly in the cryptocurrency market. This approach avoids the presumption of factor models' efficiency which has to be established in regression-based models and has been criticised by some literature. We are also inspired by the cryptocurrency speculation and lottery preference behaviours discussed in the literature to include penny stocks in our analyses. Neither volatility timing nor penny stock study has been sufficiently studied in the cryptocurrency literature. This enables us to study the volatility timing strategy effectiveness in highly speculative assets with evidence of risk anomalies and whether investors can be better off with excess returns.

5.3 Data and Method

5.3.1 Data overview

This study utilises daily data from the S&P Cryptocurrency Broad Digital Market Index (BDMI)[8], S&P Cryptocurrency LargeCap Index (BDMLCI), and S&P Cryptocurrency BDM Ex-LargeCap Index (BDMXLCI), all obtained from S&P Global. The sample period spans from March 2017 to December 2023. The BDMLCI and BDMXLCI represent subsets of the BDMI. The BDMLCI includes cryptocurrencies with large market capitalisations, defined as the product of price and effective coin supply, and sufficient liquidity[9]. Conversely, the BDMXLCI comprises the remaining digital assets, excluding those included in the BDMLCI. These indices effectively capture the performance of the cryptocurrency market while segmenting digital assets based on their market size. To provide a contrasting perspective, we compare the results of the cryptocurrency indices with those of the Penny Stock Index (PSI). The PSI data, sourced from Bloomberg, covers the same sample period and frequency as the cryptocurrency indices. Given the speculative nature of the cryptocurrency market[10], penny stocks, often targeted by lottery-seeking investors, serve as a useful benchmark to highlight similarities and differences between these asset classes. Recognising the well-documented persistence of cryptocurrency volatility[11] and the prevalence of monthly frequencies in volatility timing literature, largely due to transaction cost considerations[12], we compute the monthly realised volatilities (RV) of BDMI, BDMLCI, BDMXLCI, and PSI. These volatilities are calculated on a rolling basis using daily observations to smooth fluctuations and provide more stable measures,

$$\widehat{RV^2_{i,d}} = \sum_{t=0}^{21} (r_{i,d-t})^2. \tag{5.1}$$

$\widehat{RV^2_{i,d}}$ is the monthly realised variance of the index i, BDMI, BDMLCI, BDMXLCI, or PSI on day d. $r_{i,d-t}$ is the daily logarithm excess return of the index i on day $d-t$. We then sort the daily realised volatilities (RV) of BDMI, BDMLCI, BDMXLCI, and PSI into quartiles to study the patterns of their excess returns.

[8]BDMI is constructed by the digital assets traded on Lukka Prime-covered exchanges, excluding any stablecoin or other pegged assets. For the details of the selection criteria, see https://www.spglobal.com/spdji/en/indices/digital-assets/sp-cryptocurrency-broad-digital-market-index. (Accessed in January 2024)

[9]To be included in the BDMLCI, constituents must have a market capitalisation of at least USD 1 billion and a three-month median daily trading value of over USD 1 million.

[10]See Cheah and Fry (2015) and Baur et al. (2018) for example.

[11]See Bariviera (2017), Phillip et al. (2018), Chaim and Laurini (2019), and Zhang and Zhao (2023) for example.

[12]See Moreira and Muir (2017), and Cederburg et al. (2020) for example.

To further analyse the risk anomaly and the effectiveness of volatility timing, we compute the maximum daily return (Max) and incorporate the federal funds rate (FFR) as proxies for lottery preferences and market liquidity, respectively. Following the approach of Bali et al. (2011), Max is calculated as the highest daily return in the previous month, using a rolling window. This measure captures the influence of extreme positive returns, which have been shown to affect expected returns significantly (Bali et al., 2011). In highly speculative markets such as cryptocurrency and penny stocks, past extreme returns can be critical in shaping investment decisions. We then include the FFR, with data sourced from the Federal Reserve Bank of New York, to account for market funding liquidity. A higher FFR signifies tighter funding conditions and reduced liquidity in the broader economy. Given the relatively small market capitalisation of the cryptocurrency market compared to traditional financial markets such as stocks and bonds, we adopt the assumption from Dong et al. (2022) that the FFR is unaffected by cryptocurrency market activities. The FFR is utilised to evaluate index return performance under varying systemic funding conditions. Since FFR does not change frequently as indices, we sort and divide the FFR time series into two halves to facilitate comparative analyses. Additionally, Huang et al. (2022) find that cryptocurrency assets provide diversification benefits consistently, regardless of the economic uncertainty, while Hikouatcha et al. (2024)'s study reveals that the risk factors and premiums of digital assets with a larger size are more likely to be affected by the COVID pandemic. Thus, we follow the spirit in the literature to separately analyse the index returns in the COVID period which spans from January 2020 to December 2021.

Given the abundant literature indicating that the cryptocurrency market is heavily influenced by emotional transactions and investor sentiment as discussed in Section 5.2, we further incorporate two market sentiment indicators to better understand the cryptocurrency market's risk anomalies and the effectiveness of volatility timing. The first is the SG Sentiment Indicator[13], which is used to construct the SG Global Sentiment Index. This indicator is derived from various cross-asset capital market metrics, representing overall global financial market sentiment. It segments the market into three phases: shrinking, intermediate, and growth. The shrinking and growth phases correspond to low and high investor risk appetites, respectively. The market participants tend to be more aggressive when there is a growth phase. The second sentiment indicator is the Crypto Fear & Greed Index provided by alternative.me[14]. This index focuses on the cryptocurrency market, particularly Bitcoin, and considers factors such as volatility and market momentum. It classifies market sentiment into five categories: extreme fear, fear, neutral, greed, and extreme greed. As Bitcoin is the largest and most popular cryptocurrency, we use the Crypto Fear & Greed Index to proxy the overall cryptocurrency market sentiment. By incorporating both the SG Sentiment Indicator and the Crypto Fear & Greed Index, we aim to analyse risk anomalies and volatility

[13]The SG Sentiment Indicator data is available at *https://sg-global-sentiment.com/*.
[14]The data is available from *https://alternative.me/crypto/fear-and-greed-index/*.

timing effects under different market conditions of general and crypto-specific market consensus.[15]

5.3.2 Return scaling

As discussed in Section 5.3.1, the documented presence of risk anomalies in the cryptocurrency market (Leong and Kwok, 2023) and volatility persistence (Zhang and Zhao, 2023) provide a foundation for adopting the approach of Moreira and Muir (2017). Specifically, we scale the monthly index returns[16] by the reciprocals of their realised volatilities while maintaining the unconditional variance of the scaled returns equivalent to that of the unscaled returns. This approach basically exploits the risk anomalies in the cryptocurrency market and bets against the RV. The coefficients of the unscaled returns are essentially the weights in the strategy.

$$r_{i,d+1}^{scaled} = \frac{c_i}{\widehat{RV_{i,d}^2}} r_{i,d+1}, \tag{5.2}$$

where $\widehat{RV_{i,d}^2}$ is computed as in Equation (5.1). $r_{i,d+1}^{scaled}$ and $r_{i,d+1}$ are scaled and unscaled returns of index i, which can be BDMI, BDMLCI, BDMXLCI, or PSI. The constant c keeps the scaled and unscaled return unconditional variances the same. The coefficient of unscaled return represents the required leverage to invest in index i on the day d. The effectiveness of the scaling method in different assets helps researchers and practitioners better understand their characteristics.

5.3.3 Spanning regressions

We run the spanning regression for the scaled returns generated by each of the cryptocurrency indices. This originates from the typical scaling methods for systematic factor returns in the literature such as Moreira and Muir (2017) and Cederburg et al. (2020):

$$r_{i,d}^{scaled} = \alpha + \beta r_{i,d} + \epsilon_d, \tag{5.3}$$

[15] The correlation table detailing the relationship between the premium generated by the RV-timing approach and various factors, including Max, FFR, FGI, and SGI, is reported in the appendix for reference. Additionally, sorting and spanning regression analyses are conducted using the VIX, which serves as an alternative indicator of financial market sentiment. The results of these analyses are also provided in the appendix.

[16] Consistent with the definition of RV in Equation (5.1), monthly index returns are calculated on a rolling basis using daily data to ensure more stable measurements. Accordingly, all returns associated with scaling are computed as monthly returns derived from daily observations on a rolling basis.

where $r_{i,d}^{scaled}$ and $r_{i,d}$ are the scaled and unscaled cryptocurrency returns of index i, which can be BDMI, BDMLCI, BDMXLCI, or PSI, as defined in Equation (5.2).

The estimated alpha for each index in our sample tells us how well the realised volatility timing strategy works in the cryptocurrency market. When alpha is statistically positive, it means that adjusting portfolio weights based on recent volatility spans the mean-variance efficient frontier to the north-west, improving overall investor satisfaction. To deepen our analysis, we also calculate the appraisal ratio (AR), which helps us see whether the strategy brings more reward per unit of risk (Gibbons et al., 1989; Moreira and Muir, 2017).

5.4 Empirical results

5.4.1 RV sorts and direct comparisons

We start the analyses by sorting the realised volatilities of the index returns into quartiles. Examining the return patterns across these RV quartiles provides insight into whether higher returns in the cryptocurrency and penny stock markets compensate for risks during periods of elevated volatility. Table 5.1 summarises the results of RV sorts. All the cryptocurrency indices generate higher returns when their RV stays at the lowest level. This high-low difference is more prominent for BDMXLCI and during the COVID period. The pattern implies that the cryptocurrency market's systematic risks are not adequately compensated by higher returns, especially during highly uncertain periods and for those crypto coins with smaller market capitalisation. Similarly, PSI does not exhibit a clear monotonic relationship between RV and excess returns. It only performs slightly better on average when RV is high, also indicating insufficient risk compensation in penny stocks. The daily return gap between the highest and lowest RV quartiles widens significantly during uncertain periods, highlighting a stronger risk anomaly during such times for both cryptocurrency indices and penny stocks.

The abnormally low returns observed in the highest cryptocurrency RV quartile can be attributed to several reasons. First, in a volatile market such as cryptocurrency, price fluctuations generate more opportunities for higher returns, attracting lottery-preferred investors who are seeking higher returns and ignoring potential elevated risks. This observation is consistent with Babiak and Bianchi (2023)'s conclusion that the cryptocurrency market is inherently speculative. Additionally, both cryptocurrency and penny stock investors often have a gambling mindset, aiming to invest small amounts in pursuit of huge possible returns. They focus on the uncapped benefits although their capitals are exposed to high potential losses. This confirms Zhao et al. (2024)'s findings on the presence of the low-price effect in the cryptocurrency market. The combination of lottery preferences and the low-price effect increases demand for assets during volatile

TABLE 5.1: RV sorts

This table reports the time-series average daily excess returns of BDMI, BDMLCI, BDMXLCI, and PSI of quartiles sorted for corresponding return realised volatilities (RV). The sample period is from March 2017 to December 2023. Panel A reports the sorted results for the entire sample period, while Panel B and Panel C report similar results but for the period excluding COVID and only for COVID, respectively. The lowest RV quartile is labelled ”Low” and the highest RV quartile is labelled ”High”. The RV is computed as in Equation (5.1).

	BDMI	BDMLCI	BDMXLCI	PSI
Panel A: March 2017 to December 2023				
Low	0.0046	0.0049	0.0022	-0.0004
Q2	0.0009	0.0007	0.0039	-0.0006
Q3	0.0016	0.0008	0.0015	-0.0002
High	0.0004	0.0004	-0.0005	-0.0001
H-L	-0.0041	-0.0045	-0.0027	0.0003
Panel B: Excluding January 2020 to December 2021				
Low	0.0028	0.0034	0.0015	-0.0004
Q2	0.0011	0.0003	-0.0005	-0.0007
Q3	-0.0015	-0.0010	0.0003	-0.0013
High	0.0013	-0.0002	0.0006	-0.0002
H-L	-0.0015	-0.0036	-0.0009	0.0001
Panel C: January 2020 to December 2021				
Low	0.0089	0.0086	0.0083	-0.0007
Q2	0.0010	0.0000	0.0101	0.0015
Q3	0.0058	0.0057	0.0026	0.0005
High	0.0010	0.0022	-0.0017	0.0004
H-L	-0.0079	-0.0064	-0.0100	0.0011

periods, temporarily inflating prices and leaving less room for subsequent excess returns. Besides the investors' lottery preference, the leverage and liquidity constraints can also contribute to the risk anomaly in the cryptocurrency market (Leong and Kwok, 2023). Investors are forced to long riskier assets to achieve the target portfolio returns when there is limited availability to leverage and liquidity. Similar to the lottery preference, this effect increases the demand for cryptocurrencies in more volatile periods, pushing up the prices in the short run and causing lower excess returns and thus risk anomaly. The leverage and liquidity constraints also limit arbitrageurs' efficiency in correcting the price and fixing anomalies (Leong and Kwok, 2023). In contrast, penny stock index returns exhibit a distinct pattern. Although penny stocks are also known for their highly speculative nature, they also carry additional risks, such as the potential for company defaults or shutdowns, which makes investors require higher returns for the risk compensation. This distinction underscores the different mechanisms driving risk anomalies in cryptocurrencies and penny stocks.

After recognising the return anomaly in the cryptocurrency market, we scale the returns according to the indices' RV and make direct comparisons between unscaled and RV-scaled returns. We report the results of the direct comparison between unscaled and RV-managed returns in Table 5.2. The Sharpe ratio evaluates excess returns relative to the standard deviation, while the Sortino ratio considers only the standard deviation of negative excess returns, providing a measure of downside risk-adjusted performance. Regarding the BDMI which represents the overall cryptocurrency market, the Sharpe ratios indicate that the RV-managed returns have better performance than the unscaled returns, regardless of sample periods. However, the Sortino ratios present a contrasting perspective, as shown by slightly lower RV-managed returns than those unscaled.

TABLE 5.2: Direct comparison

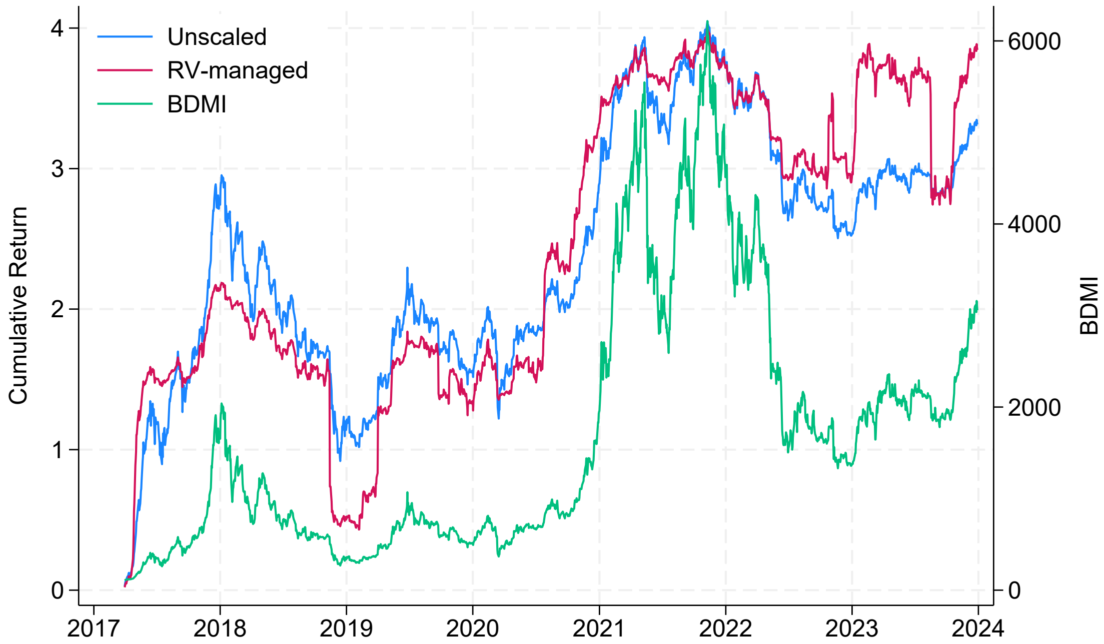
This table reports the daily excess returns, Sharpe ratios, and Sortino measures of the unscaled excess returns and RV-managed returns for BDMI, BDMLCI, BDMXLCI, and PSI, respectively. The scaled returns are computed in Equation (5.2). Panel A reports the results for the entire sample period, while Panel B and Panel C report similar results but for the period excluding COVID and only for COVID, respectively.

	BDMI		BDMLCI		BDMXLCI		PSI	
	Unscaled	RV-managed	Unscaled	RV-managed	Unscaled	RV-managed	Unscaled	RV-managed
Panel A: March 2017 to December 2023								
Excess Return	0.0019	0.0022	0.0017	0.0018	0.0018	0.0013	-0.0003	-0.0007
Sharpe Ratio	0.0408	0.0473	0.0367	0.0400	0.0327	0.0232	-0.0127	-0.0253
Sortino	0.0514	0.0510	0.0470	0.0432	0.0406	0.0250	-0.0147	-0.0280
Panel B: Excluding January 2020 to December 2021								
Excess Return	0.0009	0.0012	0.0006	0.0007	0.0005	-0.0006	-0.0007	-0.0012
Sharpe Ratio	0.0197	0.0239	0.0141	0.0140	0.0092	-0.0109	-0.0275	-0.0429
Sortino	0.0250	0.0245	0.0182	0.0144	0.0116	-0.0113	-0.0299	-0.0473
Panel C: January 2020 to December 2021								
Excess Return	0.0042	0.0046	0.0041	0.0046	0.0048	0.0057	0.0004	0.0006
Sharpe Ratio	0.0916	0.1209	0.0910	0.1180	0.0872	0.1250	0.0148	0.0307
Sortino	0.1134	0.1821	0.1138	0.1840	0.1047	0.1769	0.0196	0.0371

Besides, when we segment the index by the component cryptocurrencies' market capitalisation, the RV scaling approach tends to effectively improve the Sharpe ratio and Sortino measure during the COVID period for both BDMLCI and BDMXLCI. This matches the findings in Table 5.1 that the abnormally high returns in the lowest RV quartile are more prominent during uncertain periods. As depicted in Figure 5.1, the cumulative RV-managed index returns started to outperform the unscaled returns from the middle of 2020, highlighting the volatility timing strategy's effectiveness in exploiting risk anomaly and improving investment performance during uncertain periods. Additionally, the marginal contribution of the volatility timing approach on BDMXLCI is slightly greater than that on BDMLCI. This also signals a more prominent risk anomaly in small-cap cryptocurrencies as shown in Table 5.1. Large-cap cryptocurrencies, being more widely traded and exposed to the public, exhibit higher liquidity and market efficiency, lower price impacts from trades, and less potential for generating large excess returns. In contrast, small-cap cryptocurrencies, which are more attractive to investors seeking lottery-like assets or constrained by leverage and liquidity, present more pronounced risk anomalies. For PSI, the RV-scaling method improves the Sharpe and Sortino ratios only when the average excess returns are positive during volatile periods. These findings reveal varying strengths of risk anomalies and different performances of the volatility timing approach across indices and periods. This variation provides incentives for further investigation into the underlying drivers of the risk anomaly and the efficiency of risk timing strategies.

FIGURE 5.1: Cumulative returns

This figure illustrates the time series of cumulative daily returns for unscaled and RV-scaled portfolios, as well as the Broad Digital Market Index (BDMI). The blue, red, and green lines represent the unscaled portfolios, RV-scaled portfolios, and BDMI, respectively. The BDMI is constructed from unpegged digital assets traded on Lukka Prime-covered exchanges. Data are sourced from S&P Global. The sample period extends from March 2017 to December 2023.



5.4.2 Max sorts and spanning regressions

The further investigation into risk anomalies and volatility timing begins with analysing lottery preferences. As lottery preference has been well-documented in the literature[17], we follow Bali et al. (2011)'s Max approach to compute the recent extreme positive returns. Using this measure, we sort the time-series unscaled and RV-managed returns of the indices into quartiles based on their Max values. We also isolate the COVID period as in Table 5.1 and 5.2. As the results reported in Table 5.3, the Max sorting shows the pattern of both unscaled and scaled returns, implying the realised volatility

[17] See Babiak and Bianchi (2023); Zhao et al. (2024) for example.

timing effectiveness within each Max-sorted quartile subsample. The first pattern to be noticed in this table is the positive relationship between Max and the excess return of the cryptocurrency indices. Higher recent extreme returns are more likely to attract lottery-preferred investors and push up short-run returns, supporting the lottery preference explanation to the risk anomaly shown in Table 5.1 as discussed above[18]. Second, the realised volatility management strategy fails to effectively improve unscaled returns within the Max quartiles. In many cases, keeping the original investments without changing positions yields better returns. This evidence implies the limitation of the Max and realised volatility timing strategy which are both backwards-looking. They do not contain the market expectation information which is crucial in the highly speculative markets. Regarding penny stocks, the PSI returns act as cryptocurrency returns when excluding the uncertain period, reaching high levels when recent extreme returns are high. The realised volatility timing strategy improves the PSI unscaled daily returns from 0.10% to 0.28% when the COVID time is excluded. This indicates that the appearance of a high speculation opportunity makes the volatility timing strategy work properly at normal times.

After the direct comparisons in Max-sorted subsamples, we follow the Moreira and Muir (2017); Cederburg et al. (2020)'s approach to run the spanning regression of the RV-managed returns against the unscaled returns. A statistically significant alpha in a spanning regression indicates that the mean-variance frontier can be expanded by the combination of scaled and unscaled returns (Cederburg et al., 2020). Additionally, we compute the appraisal ratio (AR), defined as the ratio of the estimated intercept to the standard error of the spanning regression. This analysis with the separation of cryptocurrency sizes, a highly uncertain COVID period, and Max sorts demonstrates the risk anomaly strength and RV-timing strategy effectiveness under different market conditions. Table 5.4 reports the results. Significant alphas are not consistently observed, indicating that volatility timing strategies are generally ineffective during normal periods (excluding COVID) or within the lowest Max quartile. These insignificant alphas suggest that Max is not a robust explanation for the risk anomaly in the cryptocurrency market. While past extreme returns may attract some investors, they do not appear to be the primary driver of the anomaly. For the PSI during the COVID period, realised volatility timing contributes to the excess returns when Max is relatively high. This finding aligns with the corresponding results of PSI returns in the highest Max quartile subsample during COVID in Table 5.3.

[18] In Table 5.1, the overall relationship between RV and index returns depends on other factors besides lottery preference as discussed in Section 5.4.1. Thus, Table 5.3 and 5.1 present different index return dynamics.

TABLE 5.3: Max sorts

This table reports the time-series average daily excess returns and RV-managed returns of BDMI, BDMLCI, BDMXLCI, and PSI subsets with the Max sorts. Max is the maximum daily return in the last month, being computed on a rolling basis. The sample period is from March 2017 to December 2023. Panel A reports the sorted results for the entire sample period, while Panel B and Panel C report similar results but for the period excluding COVID and only for COVID, respectively.

	BDMI		BDMLCI		BDMXLCI		PSI	
	Unsclaed	RV-managed	Unsclaed	RV-managed	Unsclaed	RV-managed	Unsclaed	RV-managed
	Panel A: March 2017 to December 2023							
Low	-0.0036	-0.0038	-0.0037	-0.0048	-0.0055	-0.0084	-0.0029	-0.0066
Q2	-0.0030	0.0014	-0.0021	0.0025	0.0017	0.0050	-0.0001	0.0005
Q3	0.0058	0.0060	0.0053	0.0035	0.0004	0.0035	0.0006	0.0003
High	0.0086	0.0053	0.0078	0.0063	0.0107	0.0051	0.0011	0.0034
H-L	0.0123	0.0092	0.0115	0.0111	0.0162	0.0135	0.0040	0.0100
	Panel B: Excluding January 2020 to December 2021							
Low	-0.0047	-0.0058	-0.0048	-0.0073	-0.0072	-0.0139	-0.0030	-0.0075
Q2	-0.0021	0.0019	-0.0008	0.0035	-0.0003	0.0051	-0.0001	0.0000
Q3	0.0039	0.0039	0.0040	0.0024	-0.0006	0.0023	-0.0005	0.0001
High	0.0070	0.0052	0.0046	0.0044	0.0106	0.0045	0.0010	0.0028
H-L	0.0117	0.0110	0.0094	0.0117	0.0178	0.0184	0.0040	0.0103
	Panel C: January 2020 to December 2021							
Low	-0.0017	0.0004	-0.0061	-0.0015	-0.0055	0.0013	-0.0020	-0.0026
Q2	-0.0042	0.0013	0.0023	0.0052	0.0091	0.0074	0.0010	0.0003
Q3	0.0088	0.0095	0.0084	0.0091	0.0029	0.0064	0.0028	0.0032
High	0.0151	0.0067	0.0150	0.0066	0.0144	0.0082	0.0003	0.0020
H-L	0.0168	0.0062	0.0211	0.0082	0.0199	0.0069	0.0023	0.0046

TABLE 5.4: Max-sorted spanning regression

This table reports the results of the spanning regressions of RV-managed monthly returns on unscaled monthly returns for BDMI, BDMLCI, BDMXLCI, and PSI, respectively, as in Equation (5.3). Panel A reports the regression results for the RV-managed returns for Max-sorted quartile subsets, labelled from ”Low” to ”High”, and the full sample. Max is computed as in Table 5.3. Panel B and Panel C report similar results but for the period excluding COVID and only for COVID, respectively. The appraisal ratio (AR) is computed by the ratio of alphas and regression errors. Both alphas and appraisal ratios are annualised. The coefficient standard errors are reported in parentheses. The superscript ***, **, and * indicate statistical significance at 1%, 5%, and 10% respectively.

	BDMI					BDMLCI					BDMXLCI					PSI				
	Low	Q2	Q3	High	Full sample	Low	Q2	Q3	High	Full sample	Low	Q2	Q3	High	Full sample	Low	Q2	Q3	High	Full sample
Panel A: March 2017 to December 2023																				
α	0.3180	0.9697***	0.5515*	0.4399*	0.2251	0.1003	1.0795***	0.2081	0.6606*	0.1717	0.3189	0.9291***	0.8056**	0.3200	0.0101	0.0255	0.1531	0.0270	0.7774**	-0.1262
	(0.5085)	(0.3301)	(0.3111)	(0.2666)	(0.2018)	(0.5052)	(0.3303)	(0.1782)	(0.3813)	(0.2009)	(0.6037)	(0.2866)	(0.3509)	(0.2122)	(0.2374)	(0.2414)	(0.1017)	(0.0602)	(0.3781)	(0.1373)
β	1.4084***	0.7999***	0.6520***	0.4158***	0.6855***	1.3995***	0.8255***	0.5130***	0.4726***	0.6853***	1.7640***	0.7632***	0.6943***	0.3551***	0.6867***	2.3358***	1.6873***	0.2750***	0.3318***	0.4596***
	(0.0633)	(0.0283)	(0.0286)	(0.0178)	(0.0174)	(0.0639)	(0.0283)	(0.0157)	(0.0263)	(0.0174)	(0.0669)	(0.0227)	(0.0250)	(0.0120)	(0.0173)	(0.0794)	(0.0655)	(0.0154)	(0.0316)	(0.0212)
R^2	0.5261	0.6433	0.5432	0.5569	0.4696	0.5200	0.6498	0.7125	0.4311	0.4693	0.6123	0.7174	0.6379	0.6699	0.4713	0.6571	0.6061	0.4187	0.2006	0.2107
AR	0.4737	2.2201	1.3584	1.2738	0.4223	0.1510	2.4295	0.8967	1.3466	0.3235	0.4046	2.4411	1.7396	1.1642	0.0161	0.0814	1.1513	0.3391	1.5671	-0.3478
Panel B: Excluding January 2020 to December 2021																				
α	0.2847	0.3492	0.1876	0.1709	0.1337	0.1208	0.4156	0.0696	0.2448	0.0575	0.0376	0.1450	0.2937	-0.3527	-0.2463	0.0350	-0.0115	-0.2055**	0.0824	-0.2110
	(0.4023)	(0.3311)	(0.3094)	(0.3199)	(0.2640)	(0.3946)	(0.3302)	(0.3026)	(0.3304)	(0.2604)	(0.4644)	(0.4022)	(0.4239)	(0.4085)	(0.3077)	(0.1516)	(0.0764)	(0.0912)	(0.2127)	(0.1764)
β	1.1790***	0.9830***	0.9269***	0.6621***	0.7031***	1.1757***	0.9840***	0.8389***	0.6953***	0.7003***	1.3656***	1.1360***	1.0813***	0.6437***	0.7080***	2.3333***	1.6773***	0.5838***	0.4118***	0.5389***
	(0.0427)	(0.0351)	(0.0313)	(0.0265)	(0.0226)	(0.0424)	(0.0345)	(0.0297)	(0.0280)	(0.0224)	(0.0453)	(0.0379)	(0.0383)	(0.0290)	(0.0226)	(0.0655)	(0.0520)	(0.0347)	(0.0299)	(0.0295)
R^2	0.5395	0.5553	0.5488	0.4385	0.4383	0.5393	0.5618	0.5204	0.4443	0.4402	0.5875	0.5652	0.5436	0.3806	0.4414	0.6342	0.6286	0.2849	0.2027	0.2116
AR	0.4417	0.6678	0.3592	0.3003	0.2286	0.1901	0.7931	0.1349	0.4243	0.0998	0.0511	0.2179	0.4268	-0.4854	-0.3613	0.1372	-0.0972	-1.3448	0.2260	-0.5401
Panel C: January 2020 to December 2021																				
α	0.5739	0.9244**	0.9836	-0.0959	0.4786*	0.6457	0.9749**	0.6084**	0.2477	0.4760*	0.5398	1.0636**	0.8984	0.5962**	0.6733**	0.0248	0.5197	0.1415**	0.6469*	0.1184
	(0.4221)	(0.4201)	(0.7059)	(0.2715)	(0.2664)	(0.4322)	(0.4302)	(0.2792)	(0.8688)	(0.2786)	(0.9933)	(0.4726)	(0.7039)	(0.2747)	(0.3269)	(0.4087)	(0.5132)	(0.0692)	(0.3662)	(0.1927)
β	1.0315***	0.6705***	0.6411***	0.4668***	0.6409***	1.0353***	0.6809***	0.4613***	0.6413***	0.6469***	1.1056***	0.7215***	0.6655***	0.4051***	0.6350***	1.6868***	0.9680***	0.2648***	0.2785***	0.3412***
	(0.0585)	(0.0306)	(0.0634)	(0.0213)	(0.0231)	(0.0601)	(0.0312)	(0.0245)	(0.0705)	(0.0242)	(0.1103)	(0.0371)	(0.0458)	(0.0184)	(0.0235)	(0.1045)	(0.1827)	(0.0187)	(0.0333)	(0.0255)
R^2	0.7195	0.7735	0.4049	0.8150	0.5951	0.7032	0.7801	0.7326	0.3844	0.5769	0.7081	0.6677	0.5374	0.8160	0.5838	0.7805	0.3513	0.5212	0.2444	0.2547
AR	1.9632	2.9642	1.8489	-0.5626	1.2534	2.1228	3.1220	3.1069	0.4126	1.1920	1.3597	2.6077	1.5093	3.4022	1.4365	0.1181	2.2790	2.4218	1.9223	0.4271

5.4.3 FFR sorts and spanning regressions

Another common explanation for the risk anomaly is liquidity constraints. Dong et al. (2022)'s study discovers that lower overall market funding liquidity reduces cryptocurrency liquidity, which makes the cryptocurrency market inefficient. These inefficiencies amplify anomalies in the cryptocurrency market. To explore this further, we isolate the two-year COVID period and sort the FFR into halves within each period subset to compare unscaled and RV-managed returns, as reported in Table 5.5.

TABLE 5.5: FFR sorts

This table reports the time-series average daily excess returns of BDMI, BDMLCI, BDMXLCI, and PSI of quartiles sorted for the federal fund rates (FFR). The sample period is from March 2017 to December 2023. Panel A reports the sorted results for the entire sample period, while Panel B and Panel C report similar results but for the period excluding COVID and only for COVID, respectively. The lower FFR half is labelled "Low" and the higher FFR half is labelled "High".

	BDMI		BDMLCI		BDMXLCI		PSI	
	Unsclaed	RV-managed	Unsclaed	RV-managed	Unsclaed	RV-managed	Unsclaed	RV-managed
Panel A: March 2017 to December 2023								
Low	0.0030	0.0034	0.0026	0.0027	0.0040	0.0034	-0.0004	-0.0005
High	0.0006	0.0008	0.0007	0.0009	-0.0007	-0.0011	-0.0003	-0.0008
H-L	-0.0024	-0.0026	-0.0019	-0.0018	-0.0047	-0.0045	0.0001	-0.0002
Panel B: Excluding January 2020 to December 2021								
Low	0.0011	0.0010	0.0005	-0.0001	0.0017	0.0003	-0.0009	-0.0014
High	0.0008	0.0013	0.0008	0.0015	-0.0008	-0.0016	-0.0004	-0.0009
H-L	-0.0003	0.0003	0.0004	0.0016	-0.0025	-0.0020	0.0006	0.0005
Panel C: January 2020 to December 2021								
Low	0.0050	0.0051	0.0050	0.0052	0.0052	0.0046	0.0009	0.0004
High	0.0010	0.0024	0.0008	0.0021	0.0033	0.0099	-0.0012	0.0013
H-L	-0.0040	-0.0027	-0.0042	-0.0031	-0.0019	0.0052	-0.0020	0.0009

Since the FFR does not fluctuate frequently, this approach allows for an analysis of strategy performance under varying market liquidity conditions. The most explicit pattern in Table 5.5 is the inverse relationship between FFR and cryptocurrency returns. Lower FFR implies an expansionary monetary policy which aims at making the market prosperous. Lower FFR makes savings less attractive and leverages less costly, leading to more money pouring into the cryptocurrency market to look for higher returns and pushing up the prices in the short run. The large gap between the returns in low and high FFR periods highlights the sensitivity of cryptocurrencies to funding liquidity, supporting the cryptocurrency's speculative nature. One exception is the BDMLCI returns in Panel B Table 5.5. BDMLCI exhibits higher returns during periods of tight systematic liquidity. The different pattern of BDMLCI returns when excluding the highly uncertain period signals that large-cap cryptocurrencies are developed and more stable than those with small market capitalisation. Large-cap cryptocurrencies are often perceived as more stable investments and, in some cases, as hedging assets, contrasting with small-cap cryptocurrencies, which are primarily speculative instruments. Penny stocks, on the other hand, generate negative returns in most scenarios, except during relatively liquid periods within highly volatile conditions. This indicates that while penny stocks share some speculative characteristics with cryptocurrencies, their performance is more constrained by prevailing market conditions.

We then regress the RV-managed returns against the unscaled returns within each FFR-sorted subsample, with a distinction for the two-year COVID period as a highly uncertain market environment. This approach evaluates the performance of the RV-scaling strategy under varying systematic liquidity conditions. Table 5.6 summarises these results. Over the entire sample period, the RV-scaling strategy proves effective only for BDMI and BDMLCI when market funding liquidity is relatively high. When the highly volatile COVID period is excluded, the RV-scaling strategy fails to generate any significant alpha with all indices. Conversely, the approach demonstrates greater effectiveness during the COVID period, particularly when the FFR is low, as evidenced by the statistically significant alphas reported in Table 5.6, Panel C.

These findings align with the results in Table 5.4, which similarly indicate significant alphas for cryptocurrency indices in Panels B and C but do not reveal a clear trend within Max sorts. Thus, the analysis of FFR-sorted regressions in Table 5.6 provides a more comprehensive understanding of the RV-scaling strategy's effectiveness in different liquidity and market environments.

The effectiveness of the RV timing strategy highlights the pronounced risk anomaly observed during periods of market turmoil and heightened liquidity. This phenomenon is attributed to investors' preference for the hedging properties of cryptocurrencies. Bouri et al. (2017) and Dyhrberg (2016) establish Bitcoin as a viable hedge against stock market uncertainty. Besides, Jiang et al. (2021), Melki and Nefzi (2022), and Urquhart and Zhang (2019) demonstrate that cryptocurrencies can serve as safe havens against economic policy uncertainty, commodity market fluctuations, and currency instabilities during periods of extreme market disruption. When the market suffers from panic due to uncertainty, more investors, especially those who are risk-averse and have to hedge their positions, such as commodity futures traders and proprietary asset management investors, will bring cryptocurrencies into their portfolios to hedge their risks[19]. This heightened demand suppresses potential excess returns, reinforcing the risk anomaly and enhancing the effectiveness of the RV timing strategy. The risk anomaly caused by the strong hedging demand during market turmoil is amplified by higher market liquidity. As previously discussed, lower FFRs signal higher liquidity and more active market conditions, reducing opportunities for excess returns, even for high-risk assets.

[19]The heightened demand is reflected in Figure 5.1, where the BDMI curve sharply elevated from mid-2020.

TABLE 5.6: FFR-sorted spanning regression

This table reports the results of the spanning regressions of RV-managed monthly returns on unscaled monthly returns for BDMI, BDMLCI, BDMXLCI, and PSI, respectively, as in Equation (5.3). Panel A reports the regression results for the RV-managed returns for FFR-sorted subsets, labelled as "Low" and "High", and the full sample. Panel B and Panel C report similar results, but for the period excluding COVID and only for COVID, respectively. The appraisal ratio (AR) is computed by the ratio of alphas and regression errors. Both alphas and appraisal ratios are annualised. The coefficient standard errors are reported in parentheses. The superscript ***, **, and * indicate statistical significance at 1%, 5%, and 10% respectively.

	BDMI			BDMLCI			BDMXLCI			PSI		
	Low	High	Full sample	Low	High	Full sample	Low	High	Full sample	Low	High	Full sample
Panel A: March 2017 to December 2023												
α	0.4467**	0.0577	0.2251	0.3259*	0.0606	0.1717	0.3286	-0.0911	0.0101	-0.1092	-0.1090	-0.1262
	(0.1944)	(0.3533)	(0.2018)	(0.1846)	(0.3566)	(0.2009)	(0.2292)	(0.4004)	(0.2374)	(0.1650)	(0.1996)	(0.1373)
β	0.5422***	0.9293***	0.6855***	0.5366***	0.9382***	0.6853***	0.5176***	1.0422***	0.6867***	0.3154***	1.1689***	0.4596***
	(0.0153)	(0.0343)	(0.0174)	(0.0146)	(0.0347)	(0.0174)	(0.0148)	(0.0353)	(0.0173)	(0.0203)	(0.0512)	(0.0212)
R^2	0.5716	0.4714	0.4696	0.5892	0.4697	0.4693	0.5665	0.5132	0.4713	0.2037	0.3866	0.2107
AR	1.1949	0.0903	0.4223	0.9176	0.0940	0.3235	0.7458	-0.1259	0.0161	-0.3436	-0.3021	-0.3478
Panel B: Excluding January 2020 to December 2021												
α	0.2496	0.1001	0.1337	0.1374	0.1058	0.0575	-0.3038	-0.0009	-0.2463	-0.3289**	-0.0961	-0.2110
	(0.3054)	(0.3156)	(0.2640)	(0.2930)	(0.3186)	(0.2604)	(0.4002)	(0.3609)	(0.3077)	(0.1605)	(0.1775)	(0.1764)
β	0.6922***	0.8855***	0.7031***	0.6797***	0.8928***	0.7003***	0.6877***	0.9901***	0.7080***	0.3335***	1.1487***	0.5389***
	(0.0267)	(0.0298)	(0.0226)	(0.0258)	(0.0302)	(0.0224)	(0.0292)	(0.0310)	(0.0226)	(0.0256)	(0.0476)	(0.0295)
R^2	0.4488	0.4861	0.4383	0.4576	0.4839	0.4402	0.4016	0.5219	0.4414	0.1697	0.3843	0.2116
AR	0.4525	0.1648	0.2286	0.2596	0.1726	0.0998	-0.4202	-0.0013	-0.3613	-1.1348	-0.2816	-0.5401
Panel C: January 2020 to December 2021												
α	0.5089*	0.2487	0.4786*	0.5068*	0.2234	0.4760*	0.7201**	0.1100	0.6733**	0.1813	-0.0513	0.1184
	(0.2743)	(0.5810)	(0.2664)	(0.2873)	(0.5536)	(0.2786)	(0.3355)	(1.0086)	(0.3269)	(0.1981)	(0.1695)	(0.1927)
β	0.6298***	0.9918***	0.6409***	0.6361***	1.0007***	0.6469***	0.6221***	0.9427***	0.6350***	0.3373***	2.2265***	0.3412***
	(0.0237)	(0.0569)	(0.0231)	(0.0249)	(0.0554)	(0.0242)	(0.0241)	(0.0715)	(0.0235)	(0.0257)	(0.0996)	(0.0255)
R^2	0.5838	0.9410	0.5951	0.5655	0.9449	0.5769	0.5703	0.9010	0.5838	0.2541	0.9633	0.2547
AR	1.3204	1.5639	1.2534	1.2557	1.4747	1.1920	1.5270	0.3982	1.4365	0.6487	-1.2249	0.4271

In contrast, PSI does not show any significant alpha in the spanning regressions in any subset, even if both cryptocurrencies and penny stocks are known for their highly speculative nature attracting lottery-preferred investors gambling for potentially uncapped returns by paying low prices. This underlines the critical difference between cryptocurrencies and other speculative assets. During highly volatile periods such as COVID, while penny stocks, which are more connected to firm fundamentals, are exposed to higher default risks, cryptocurrencies are more popular due to their hedging property. The market participants' preference for speculative assets tilts during uncertain periods. This market opinion divergence is consistent with Zhao et al. (2024)'s findings of time-varying investor preference.

Table 5.6 further shows that BDMXLCI consistently achieves higher alphas than other indices. These findings align with Table 5.2, which highlights the effectiveness of RV timing for small-cap cryptocurrencies during uncertain periods. The significant risk-return anomaly is also evidenced by the largest return gap between the highest and lowest RV quartiles for BDMXLCI in Table 5.1, Panel C. Unlike the head cryptocurrencies such as Bitcoin and Ethereum, cryptocurrencies with small market capitalisation are less focused by the public, less liquid, and fewer transactions. This creates a higher potential for excess returns, drawing a large number of speculators during uncertain periods. However, the influx of speculators erodes the opportunity for excess returns despite the elevated risks. The huge risk-return mismatch creates better opportunities for the scaling strategy, which places a higher (lower) position on small-cap cryptocurrencies when the recent RV is low (high). Therefore, the risk anomaly of small-cap cryptocurrencies may be dampened by weaker hedging functions but compensated by much more speculative demands during market turmoil. This dynamic reflects the nuanced interplay between hedging properties and speculative behaviour in shaping the cryptocurrency market's risk anomalies.

5.4.4 Market sentiment and risk anomaly

In addition to recent extreme returns and market liquidity conditions, we incorporate two sentiment indicators to further investigate the risk anomaly and realised volatility timing in the cryptocurrency market. As discussed in Section 5.3, the SG Sentiment Indicator (SGI) captures global market sentiment, while the Crypto Fear & Greed Index (CFGI) reflects sentiment specific to the cryptocurrency market. To explore these relationships, we sort unscaled and RV-managed returns based on their respective sentiment classifications and include Max to examine the connection between market sentiment and extreme returns. The sorted results are reported in Table 5.7. In Panel A which sorts the SGI, both unscaled return and Max of the cryptocurrency indices increase when the SGI becomes more aggressive from Shrinking to Growth. RV-managed returns also tend to outperform unscaled returns when the global market is in a growth phase. Since SGI reflects the global overall financial market sentiment, the growth stage implies a higher risk appetite that investors actively seek investment targets with higher possible returns. The capital inflow into the cryptocurrency market boosts short-run cryptocurrency index returns. Similarly, PSI achieves high returns during growth periods. The increased demand for cryptocurrencies during these times also elevates extreme returns, as evidenced by the higher Max values. In Table 5.7 Panel B which reports the CFGI sorts, cryptocurrency unscaled returns also rise when the cryptocurrency market sentiment moves from extreme fear to extreme greed. PSI likewise experiences elevated returns during periods classified as extreme greed. However, Max displays a distinct pattern, increasing whenever the sentiment becomes extreme. These findings underscore the interlinkages between market sentiment, extreme returns, and RV timing strategies in speculative markets. The results highlight the importance of sentiment-driven investment demand in shaping short-term returns and amplifying risk anomalies in the cryptocurrency market.

To further study the realised volatility timing effectiveness across different sentiment subsamples, we run spanning regressions similar to those discussed in Sections 5.4.2 and 5.4.3, now applied to sentiment-based classifications. The results are reported in Table 5.8[20]. In Panel A which reports the SGI classified results, the realised volatility timing strategy yields significant positive alphas of BDMI and BDMLCI when the overall financial market is at the growth stage. This evidence is consistent with the pattern that RV-managed returns outperform unscaled returns as reported in Table 5.7 Panel A. A plausible explanation is that the risk anomaly in the cryptocurrency market becomes more prominent when more money enters the market due to a higher risk appetite. The newly invested money tends to be placed on those cryptocurrencies with larger market capitalisation. Consequently, popular cryptocurrencies face reduced potential for excess returns, leading to insufficient compensation for higher risks. Conversely, when sentiment is classified using CFGI, the RV timing strategy fails to yield significant alphas in any subsample. This implies that a backwards-looking approach is less effective in managing highly volatile and speculative assets like cryptocurrencies. These findings emphasise the limitations of RV-timing strategies under certain market conditions and highlight the distinct dynamics of sentiment-driven behaviours in the cryptocurrency market.

[20]The COVID period is not isolated in this table due to the presumption that market sentiment has already incorporated relevant information and expectations.

TABLE 5.7: Sentiment sorts

This table reports the time-series average daily excess returns, RV-managed returns, and past month max daily excess returns of BDMI, BDMLCI, BDMXLCI, and PSI subsets with both the SG Sentiment Indicator and Crypto Fear & Greed Index sentiment classifications. SG Sentiment Indicator is used to construct the SG Global Index, considering the global market sentiment across a variety of asset classes, including equities, government bonds, and commodities. SG Sentiment Indicator represents the overall financial market sentiment. In contrast, the Crypto Fear & Greed Index sentiment index focuses on the Bitcoin market sentiment, broadly representing the cryptocurrency market sentiment. The sample period is from March 2017 to December 2023. Panel A reports the sorted results for the entire sample period, while Panel B and Panel C report similar results but for the period excluding COVID and only for COVID, respectively.

	BDMI			BDMLCI			BDMXLCI			PSI		
	Unsclaed	RV-managed	Max	Unsclaed	RV-managed	Max	Unsclaed	RV-managed	Max	Unsclaed	RV-managed	Max
Panel A: SG Sentiment Indicator												
Shrinking	-0.0053	-0.0057	0.0833	-0.0052	-0.0058	0.0839	-0.0081	-0.0075	0.0870	-0.0034	-0.0034	0.0453
Intermediate	0.0027	0.0016	0.0864	0.0027	0.0016	0.0873	0.0019	0.0000	0.0955	0.0002	-0.0008	0.0487
Growth	0.0060	0.0086	0.0895	0.0053	0.0075	0.0893	0.0087	0.0088	0.0978	0.0012	0.0015	0.0430
G-S	0.0112	0.0142	0.0062	0.0105	0.0133	0.0054	0.0168	0.0163	0.0109	0.0045	0.0050	-0.0023
Panel B: Crypto Fear & Greed Index sorts												
Extreme Fear	-0.0050	-0.0013	0.0791	-0.0049	-0.0013	0.0790	-0.0069	-0.0026	0.0881	-0.0012	-0.0017	0.0340
Fear	-0.0022	-0.0011	0.0783	-0.0023	-0.0011	0.0785	-0.0016	-0.0021	0.0816	-0.0004	-0.0014	0.0408
Neutral	-0.0008	-0.0053	0.0759	-0.0007	-0.0053	0.0764	-0.0013	-0.0069	0.0734	-0.0012	-0.0027	0.0274
Greed	0.0067	0.0088	0.0911	0.0069	0.0091	0.0921	0.0045	0.0067	0.0908	-0.0002	0.0021	0.0501
Extreme Greed	0.0130	0.0082	0.1063	0.0128	0.0079	0.1087	0.0154	0.0140	0.1019	0.0036	0.0015	0.0691
EG - EF	0.0180	0.0094	0.0273	0.0178	0.0092	0.0296	0.0223	0.0166	0.0138	0.0047	0.0032	0.0351

TABLE 5.8: Sentiment-classified spanning regression

This table reports the results of the spanning regressions of RV-managed monthly returns on unscaled monthly returns for BDMI, BDMLCI, BDMXLCI, and PSI, respectively, as in Equation 5.3. Panel A reports the regression results for the RV-managed returns for the sentiment-classified subsets as defined in Table 5.7. Panel B and Panel C report similar results but for the period excluding COVID and only for COVID, respectively. The appraisal ratio (AR) is computed by the ratio of alphas and regression errors. Both alphas and appraisal ratios are annualised. The coefficient standard errors are reported in parentheses. The superscript ***, **, and * indicate statistical significance at 1%, 5%, and 10% respectively.

Panel A: SG Sentiment Indicator

	BDMI				BDMLCI			
	Shrinking	Intermediate	Growth	Full sample	Shrinking	Intermediate	Growth	Full sample
α	-0.5003	-0.0150	1.0159***	0.2251	-0.5311	-0.0006	0.8672**	0.1717
	(0.6102)	(0.2058)	(0.3763)	(0.2018)	(0.6142)	(0.2099)	(0.3621)	(0.2009)
β	0.6919***	0.6118***	0.7666***	0.6855***	0.7043***	0.6095***	0.7613***	0.6853***
	(0.0450)	(0.0183)	(0.0353)	(0.0174)	(0.0456)	(0.0186)	(0.0344)	(0.0174)
R^2	0.3738	0.5914	0.4706	0.4696	0.3758	0.5812	0.4797	0.4693
AR	-0.6580	-0.0417	1.8802	0.4223	-0.6940	-0.0017	1.6651	0.3235

Panel A: SG Sentiment Indicator

	BDMXLCI				PSI			
	Shrinking	Intermediate	Growth	Full sample	Shrinking	Intermediate	Growth	Full sample
α	-0.5644	-0.3053	0.4960	0.0101	-0.7949***	-0.2195	0.2104	-0.1262
	(0.6491)	(0.2778)	(0.4632)	(0.2374)	(0.1347)	(0.2635)	(0.1975)	(0.1373)
β	0.6470***	0.6325***	0.7918***	0.6867***	0.0836***	0.5730***	0.5968***	0.4596***
	(0.0417)	(0.0208)	(0.0366)	(0.0173)	(0.0197)	(0.0378)	(0.0339)	(0.0212)
R^2	0.3773	0.5445	0.4688	0.4713	0.0414	0.2288	0.3686	0.2107
AR	-0.7006	-0.6291	0.7497	0.0161	-4.7487	-0.4766	0.7354	-0.3478

Panel B: Crypto Fear & Greed Index

	BDMI						BDMLCI					
	Extreme Fear	Fear	Neutral	Greed	Extreme Greed	Full sample	Extreme Fear	Fear	Neutral	Greed	Extreme Greed	Full sample
α	0.3433	0.1776	-1.0504	0.5888	0.0265	0.2251	0.3341	0.1955	-1.0495	0.5927	0.0087	0.1717
	(0.3095)	(0.3195)	(0.8966)	(0.4396)	(0.4032)	(0.2018)	(0.3074)	(0.3171)	(0.9097)	(0.4683)	(0.4071)	(0.2009)
β	0.5230***	0.8125***	1.4815***	0.9607***	0.6213***	0.6855***	0.5327***	0.8182***	1.4873***	0.9734***	0.6110***	0.6853***
	(0.0232)	(0.0316)	(0.1039)	(0.0473)	(0.0288)	(0.0174)	(0.0233)	(0.0316)	(0.1058)	(0.0499)	(0.0289)	(0.0174)
R^2	0.5739	0.5739	0.4858	0.5559	0.7834	0.4696	0.5813	0.5780	0.4788	0.5353	0.7766	0.4693
AR	0.9124	0.3997	-1.2717	1.1922	0.0949	0.4223	0.8939	0.4433	-1.2522	1.1275	0.0309	0.3235

Panel B: Crypto Fear & Greed Index

	BDMXLCI						PSI					
	Extreme Fear	Fear	Neutral	Greed	Extreme Greed	Full sample	Extreme Fear	Fear	Neutral	Greed	Extreme Greed	Full sample
α	0.2558	-0.1502	-1.2272	0.5865	0.3283	0.0101	-0.3790***	-0.2710	-0.5521**	0.5833	0.2320	-0.1262
	(0.4086)	(0.4105)	(0.9440)	(0.3719)	(0.9948)	(0.2374)	(0.1212)	(0.2879)	(0.2576)	(0.4225)	(0.2227)	(0.1373)
β	0.5179***	0.9168***	1.4930***	0.9656***	0.8255***	0.6867***	0.1512***	0.6757***	0.4476***	1.1570***	0.1758***	0.4596***
	(0.0260)	(0.0367)	(0.0935)	(0.0354)	(0.0645)	(0.0173)	(0.0251)	(0.0491)	(0.0704)	(0.0731)	(0.0322)	(0.0212)
R^2	0.5137	0.5599	0.5426	0.6928	0.5599	0.4713	0.0859	0.2781	0.1555	0.4311	0.1835	0.2107
AR	0.5157	-0.2629	-1.4115	1.3884	0.4784	0.0161	-2.5654	-0.6757	-2.3332	1.2083	1.4745	-0.3478

5.5 Conclusion

This study uses daily cryptocurrency market index and penny stock index data to analyse and exploit the risk anomaly in the cryptocurrency market. We separately study the index of cryptocurrencies with different sizes and penny stocks for comprehensiveness. We also isolate the two-year COVID period for the extreme market uncertainty, separate the sample according to recent extreme returns, halve the sample for the market liquidity, and separate the sample with market sentiment classifications. Based on empirical evidence of risk anomaly and volatility persistence in the cryptocurrency market, this study applies the volatility timing approach to the cryptocurrency and penny stock indices as a contrast to exploit the risk anomaly and examine this approach's effectiveness in generating cryptocurrency excess returns as in the conventional equity market. This could be indicative to both researchers and practitioners in the field of cryptocurrency investment and risk management.

By conducting RV and FFR sorting, direct comparisons, and spanning regressions, we disclose that the risk anomaly exists in the cryptocurrency market. The recent extreme return may attract some lottery-preferred investors but does not tend to be a dominant reason for risk anomaly. During the market distortion, the increased hedging demand strengthens the cryptocurrencies' prices and thus leads to less potential for excess returns and a more prominent risk anomaly. Cryptocurrencies with different market capitalisations are viewed differently. The higher risk appetite at the growth stage of overall market sentiment pushes up the large cryptocurrency demand and also causes lower potential excess returns. Penny stocks have different properties from cryptocurrencies, although they are all speculative assets attracting lottery-preferred investors. Investors' preference for speculative assets changes due to a lack of hedging properties and higher default risks on penny stocks.

Overall, the RV timing strategy only successfully yields statistically significant alphas when the risk anomaly is magnified due to some specific conditions, including high market liquidity during market turmoil and higher risk appetite in the overall global financial market. Otherwise, using realised volatilities, based on past information, to adjust the investment positions in such a highly speculative market sensitive to the consensus fails to improve the unscaled original index returns.

Chapter 6

Concluding Remarks

6.1 Conclusion

This thesis empirically studies asset pricing topics from different aspects in different markets. The tight connection between volatility and liquidity highlights the coherent body of the work in this thesis. First, both volatility and liquidity risks are priced as risk-averse investors require compensation for the possibility of suffering losses due to price fluctuations and discounts to sell assets. Second, liquidity can affect price changes and then transfer to volatility. Conversely, volatility can lead to a higher bid-ask spread which incurs higher transaction cost and thus lower liquidity.

Chapter 3 highlights the contribution of stock options in delivering timely insights into firm capital structure and return moments. It proves to be highly beneficial for risk management and portfolio allocation. This chapter departs from the literature in terms of applying a volatility timing strategy which exploits the low-risk anomaly on a single equity level and using option-based volatilities to scale stock returns. This approach affords investors the flexibility to tailor their investment portfolios according to their risk-return preferences and higher utility by exploiting the market consensus and expectation on firm-level volatility and future returns, as the option-based volatilities are derived from observable option market prices. These forward-looking volatilities outperform traditional backwards-looking measures such as realised volatility in scaling stock excess returns and improving portfolio performance, especially during uncertain periods. The results also hold across different subset portfolios sorted by firms' characteristics such as leverage. The excess returns enhanced by our volatility timing strategy survive from transaction costs. Therefore, the information on stock-level return risks embedded in forward-looking option market observable prices helps implement volatility timing strategies.

Chapter 4 introduces a two-step process which derives a new informative stock-level Connectedness-value-Weighted-Eigenvector-Centrality (CWEC) measure and studies the relationship between financial interlinkages and illiquidity at a single equity level. This chapter also discovers some evidence of the market's different views on stock centrality levels. These findings imply valuable insights into systematic and liquidity risk management, helping practitioners to better understand each stock's importance in the broad financial network and its potential effects on illiquidity and asset prices. In this chapter, we use US mutual fund common ownership to US stocks to derive a stock-level centrality measure representing each stock's importance in the broad financial network. The stock-level measure allows us to depart from the literature that stays on the pairwise correlation and commonality and fails to reflect the node importance at the single equity level. Although panel regressions show that stock centrality and illiquidity have significant effects on each other, the following vector autoregressions and impulse response function analyses indicate that stock centrality tends to have a preponderant influence on stock illiquidity. The property that stock centrality does not change frequently and is not significantly affected by other variables such as liquidity is attributed to mutual funds' reluctance to adjust investment positions and tendency to stick to their familiar investment targets. This helps avoid unknown information asymmetry. The centrality sorts, Fama and MacBeth (1973) regressions, and betting-against-centrality strategy provide some evidence that the market cares about stock centrality levels, although it tends to be hard to make extra profits by exploiting centrality.

Chapter 5 focuses on the risk anomaly and stock-market empirically successful volatility timing approaches in the cryptocurrency market. The separated analyses of subsets of cryptocurrency indices according to sizes, recent maximum returns, market liquidity conditions, and market sentiments further disclose investor behaviour and preferences that lead to the results. The Penny stock index is also compared as another type of highly speculative asset, highlighting the specific characteristics of the cryptocurrency market. The transplanted approach which has never been applied in the cryptocurrency literature and following subset and penny stock analyses thus affords researchers a more comprehensive understanding of volatility timing strategy effectiveness in exploiting discovered risk-return anomalies. This chapter follows the spirit of Moreira and Muir (2017) and Cederburg et al. (2020) to time realised volatilities and scale the cryptocurrency indices returns, providing empirical evidence of realised volatility management effectiveness in generating excess returns in the cryptocurrency market. The analyses in subsets considering cryptocurrency sizes, lottery preference, market uncertainty, penny stock comparisons, market liquidity, and market sentiments reveal that risk anomaly exists in the cryptocurrency market, but realised volatility timing strategy only generates statistically significant excess returns when the risk-return anomaly is magnified by some specific systematic conditions including higher market liquidity during uncertain periods and aggressive risk appetite in the overall global financial market. In other cases, the volatility timing strategy fails to beat the buy-and-hold strategy in such a highly volatile and speculative market, since realised volatility is backwards-looking and lacks information on market sentiment and expectations.

In sum, Chapter 3 and 5 depart from the conventional volatility timing literature in terms of using stock-level forward-looking risk measures and transplanting to the cryptocurrency market, respectively. Both provide abundant empirical evidence on exploiting risk-return anomalies and contribute to a more comprehensive understanding of volatility timing strategy and thus better risk management and investment portfolio allocation. Chapter 4 explores the asset pricing topic from another aspect which is stock-level financial interlinkages and illiquidity, also contributing to the systematic and liquidity risk management.

6.2 Future research direction

This thesis has empirically studied risk-return anomaly and stock-option-based volatility timing strategies, stock connectedness and illiquidity, and realised volatility timing strategy in the cryptocurrency market, contributing to different aspects of the asset pricing topic. The latter research and investigations could be extended further to provide more insights by proxying liquidity in alternative ways, taking advantage of stock-level centrality measures, and timing more informative volatilities in the cryptocurrency market.

Instead of using Amihud (2002) to proxy the stock illiquidity, future research could investigate the centrality effects on other aspects of illiquidity such as trading quantity, trading speed, and trading costs as introduced in Liu (2006). Other techniques such as principal component analysis could be applied. This affords researchers and practitioners a more comprehensive view of how a stock's liquidity is affected by its importance in the broad financial network. Furthermore, the stock-level CWEC introduced in Chapter 4 which contains information on each stock's importance in the financial networks can be exploited and analysed with other stock characteristics.

Finally, it could be interesting to time forward-looking volatilities which contain richer information including market consensus and expectations instead of only referring to backwards-looking realised volatilities in the cryptocurrency market. Using forward-looking measures could be especially effective in such a highly speculative market that has been proven sensitive to market sentiment[1]. Also, following the approach in Chapter 3 to exploit the risk anomaly at a single cryptocurrency level also has the potential to further improve portfolio performance.

[1] See Cheah and Fry (2015) and Baur et al. (2018) for example.

Appendix A

Additional Results in Option-based Volatility Riming

Appendix 1. Portfolio sorts

We extend the performance analysis of an ex-ante risk-timing strategy to different portfolio constructions, all based on a total sample of 1,137 stocks. We compare the original portfolios and the corresponding RV, IV, MW, and GLB risk-managed portfolios. These portfolios are either cross-sectionally averaged with equal weighting or aggregated into leverage-sorted, financial and non-financial, size-sorted, or credit-rating portfolios.

Table A.1 reports the results for portfolios with "aggregate-level risk timing" for the entire, pre-, and post-pandemic periods. Part of the table replicates the results of Table 3.2 for convenience. The results in Tables A.2 to A.7 follow a similar structure. In particular, Tables A.2, A.3, and A.4 present results for leverage-sorted portfolios, while Table A.5 covers financial and non-financial portfolios. Table A.6 reports results for size-sorted portfolios, where firm sizes are approximated by market capitalizations, calculated as stock price multiplied by outstanding shares, divided by one million. The logarithm of each company's average market capitalization is used to sort firms into quartile portfolios. Data for industry, share prices, and outstanding shares are sourced from Bloomberg. Table A.7 reports results for credit-rating portfolios, where credit ratings for 722 firms come from S&P, Fitch, and Moody's via Bloomberg. The remaining 415 firms are unrated or lack available data. The sample includes 4 AAA-rated firms, 27 AA-rated, 175 A-rated, 344 BBB-rated, 116 BB-rated, 51 B-rated, and 5 CCC-rated companies.

Tables A.8 through A.19 include additional results on spanning regression estimations, to directly compare with those in Tables 3.4-3.7 in the main paper. We consider equal-weighted, leverage-sorted portfolios, financial and non-financial portfolios, size-sorted portfolios, and credit-rating portfolios. Table A.8 refers to spanning regressions incorporating the Fama and French (1993)'s three factors, the Carhart (1997)'s momentum factor, the Schneider et al. (2020) ex-ante coskewness risk factor, and Bali et al. (2017) MAX factor. This analysis helps assess the impact of factor inclusion on alpha.

Lastly, we consider the out-of-sample performance of the ex-ante risk-timing strategy implemented based on "aggregate-level risk timing," and report out-of-sample forecast errors based on the AR(1) model, similar to Table 3.12 in the main paper.

TABLE A.1: Performance measures for equally-weighted portfolios with aggregate-level risk timing

This table reports the average monthly Sharpe, Sortino, and Calmar ratios for both the original ('Unscaled') portfolios and the corresponding RV, IV, MW, and GLB risk-managed portfolios, constructed using distinct methods. The sample consists of 1,137 stocks. For "Firm-level risk timing", each stock is first scaled by its corresponding RV, IV, MW, or GLB (one at a time) and then grouped into an equal-weighted portfolio. Alternatively, for "Aggregate-level risk timing", a cross-sectional average of either squared RV, IV, MW, or GLB is first obtained (one at a time), and this average is used to scale the equal-weighted portfolio return. The former results are already presented in Table 3.2 in the main paper and are reproduced here for convenience. Panel A reports the results of the whole sample from January 1996 to December 2021, and Panels B and C do so for the sample period before or after January 2020, respectively.

	Firm-level					Aggregate-level			
	Unscaled	RV	IV	MW	GLB	RV	IV	MW	GLB
Panel A: January 1996 to December 2021									
Excess Return	0.0094	0.0069	0.0143	0.0063	0.0090	0.0079	0.0101	0.0072	0.0064
Sharpe Ratio	0.1049	0.0844	0.1577	0.2035	0.1573	0.0886	0.1128	0.0804	0.0712
Sortino	0.1457	0.1222	0.2324	0.2747	0.1994	0.1211	0.1584	0.0966	0.0863
Calmar	0.4961	0.2771	0.6669	0.9203	0.7018	0.3491	0.4536	0.3535	0.2996
Panel B: January 1996 to December 2019									
Excess Return	0.0086	0.0060	0.0142	0.0063	0.0089	0.0074	0.0100	0.0073	0.0061
Sharpe Ratio	0.1049	0.0779	0.1576	0.2057	0.1518	0.0863	0.1122	0.0797	0.0659
Sortino	0.1138	0.0978	0.2114	0.2690	0.1947	0.1100	0.1489	0.0974	0.0817
Sharpe Ratio	0.5073	0.2697	0.6832	0.9455	0.6936	0.3481	0.4631	0.3501	0.2702
Panel C: January 2020 to December 2021									
Excess Return	0.0190	0.0183	0.0165	0.0063	0.0106	0.0139	0.0109	0.0054	0.0100
Sharpe Ratio	0.1211	0.1382	0.1567	0.1777	0.2557	0.1104	0.1171	0.1133	0.2041
Sortino	0.1869	0.2079	0.1709	0.1813	0.1836	0.1378	0.1217	0.0612	0.1100
Calmar	0.3620	0.3655	0.4718	0.6182	0.7998	0.3606	0.3406	0.3944	0.6526

TABLE A.2: Sharpe ratios for leverage-sorted portfolios with aggregate-level risk timing

This table is similar to the Sharpe ratio panel in Table 3.3 in the main paper but it refers to the results for the aggregate-level risk timing. It includes the monthly Sharpe ratios of the original portfolios and those managed by RV, IV, MW, and GLB for each leverage quartile portfolio. The left side and right side of the table report the Sharpe ratios when we use the firm-level and aggregate-level risk-timing approach, respectively. Panel A refers to the entire sample covering January 1996 to December 2021. Panel B focuses on the period from January 1996 to December 2019 to eliminate the unusually high uncertainty period of the pandemic and its impact on our strategy. Panel C repeats the analyses from January 2020 to December 2021 to assess our trading strategy's performance during heightened market risk periods. The equally weighted leverage portfolio quartiles are: less than 25% is the quartile of firms with the lowest averaged leverage (Low), from 25% to 50% is the quartile with the second lowest(Q2), from 50% to 75% is the quartile with the second highest(Q3), and above 75% is the quartile of firms with the highest averaged leverage (High). The sample includes 1,137 stocks.

	Firm-level				Aggregate-level			
	Low	Q2	Q3	High	Low	Q2	Q3	High
	Panel A: January 1996 to December 2021							
Unscaled	0.1348	0.1210	0.1022	0.0450	0.1348	0.1210	0.1022	0.0450
RV	0.1001	0.0940	0.0818	0.0525	0.1155	0.0964	0.0863	0.0377
IV	0.1742	0.1645	0.1456	0.1373	0.1336	0.1279	0.1105	0.0738
MW	0.1986	0.2135	0.1697	0.1699	0.0918	0.0952	0.0848	0.0602
GLB	0.1878	0.1528	0.1399	0.1352	0.0922	0.0901	0.0608	0.0394
	Panel B: January 1996 to December 2019							
Unscaled	0.1386	0.1229	0.1046	0.0353	0.1386	0.1229	0.1046	0.0353
RV	0.0936	0.0900	0.0771	0.0423	0.1105	0.0854	0.0911	0.0406
IV	0.1754	0.1652	0.1461	0.1346	0.1355	0.1276	0.1115	0.0684
MW	0.2030	0.2169	0.1687	0.1718	0.0920	0.0950	0.0854	0.0568
GLB	0.1864	0.1468	0.1339	0.1267	0.0885	0.0855	0.0564	0.0308
	Panel C: January 2020 to December 2021							
Unscaled	0.1336	0.1273	0.1046	0.1176	0.1336	0.1273	0.1046	0.1176
RV	0.1573	0.1312	0.1233	0.1368	0.1621	0.1934	0.0317	0.0182
IV	0.1647	0.1542	0.1389	0.1667	0.1129	0.1291	0.0962	0.1374
MW	0.1729	0.1698	0.1783	0.1481	0.0952	0.1245	0.0980	0.1434
GLB	0.2273	0.2474	0.2633	0.2805	0.1971	0.2112	0.1906	0.2181

TABLE A.3: Sortino ratios for leverage-sorted portfolios with aggregate-level risk timing

This table is similar to the Sortino ratio panel in Table 3.3 in the main paper, but it refers to the results obtained by the aggregate-level risk timing. The table includes the monthly Sortino ratios of the original portfolios and those managed by RV, IV, MW, and GLB for each leverage quartile portfolio. The left side and right side of the table report the Sharpe ratios when we use the firm-level and the aggregate-level risk-timing approach, respectively. Panel A refers to the entire sample covering January 1996 to December 2021. Panel B focuses on the period from January 1996 to December 2019 to eliminate the unusually high uncertainty period of the pandemic and its impact on our strategy. Panel C repeats the analyses from January 2020 to December 2021 to assess our trading strategy's performance during heightened market risk periods. The equally weighted leverage portfolio quartiles are: less than 25% is the quartile of firms with the lowest averaged leverage (Low), from 25% to 50% is the quartile with the second lowest(Q2), from 50% to 75% is the quartile with the second highest(Q3), and above 75% is the quartile of firms with the highest averaged leverage (High). The sample includes 1,137 stocks.

	Firm-level				Aggregate-level			
	Low	Q2	Q3	High	Low	Q2	Q3	High
Panel A: January 1996 to December 2021								
Unscaled	0.1976	0.1644	0.1432	0.0611	0.1976	0.1644	0.1432	0.0611
RV	0.1407	0.1333	0.1183	0.0798	0.1626	0.1267	0.1188	0.0500
IV	0.2491	0.2405	0.2131	0.2121	0.1854	0.1776	0.1561	0.1097
MW	0.2589	0.2808	0.2307	0.2243	0.1064	0.1142	0.1051	0.0780
GLB	0.2576	0.1921	0.1543	0.1710	0.1167	0.1115	0.0704	0.0469
Panel B: January 1996 to December 2019								
Unscaled	0.1568	0.1303	0.1143	0.0393	0.1568	0.1303	0.1143	0.0393
RV	0.1081	0.1105	0.0991	0.0573	0.1358	0.0997	0.1219	0.0521
IV	0.2260	0.2193	0.1988	0.1938	0.1760	0.1670	0.1501	0.0956
MW	0.2509	0.2767	0.2215	0.2303	0.1079	0.1163	0.1080	0.0742
GLB	0.2593	0.1859	0.1503	0.1611	0.1147	0.1083	0.0669	0.0372
Panel C: January 2020 to December 2021								
Unscaled	0.2085	0.1868	0.1663	0.1659	0.2085	0.1868	0.1663	0.1659
RV	0.2760	0.1971	0.1801	0.1859	0.2357	0.2345	0.0313	0.0248
IV	0.1973	0.1692	0.1458	0.1687	0.1282	0.1247	0.0939	0.1388
MW	0.2427	0.1536	0.1696	0.0980	0.0629	0.0602	0.0438	0.0809
GLB	0.1472	0.1868	0.1637	0.2160	0.1017	0.1121	0.0894	0.1351

TABLE A.4: Calmar ratios for leverage-sorted portfolios with aggregate-level risk timing

This table is similar to the Calmar ratio panel in Table 3.3 in the main paper but includes results for the aggregate-level risk-timing approach. The table reports the monthly Calmar ratio of the original portfolios and those managed by RV, IV, MW, and GLB for each leverage quartile portfolio. The left side and right side of the table report the Sharpe ratios when we use the firm-level and aggregate-level risk-timing approach, respectively. Panel A refers to the entire sample covering January 1996 to December 2021. Panel B focuses on the period from January 1996 to December 2019 to eliminate the unusually high uncertainty period of the pandemic and its impact on our strategy. Panel C repeats the analyses from January 2020 to December 2021 to assess our trading strategy's performance during heightened market risk periods. The equally weighted leverage portfolio quartiles are: less than 25% is the quartile of firms with the lowest average level of leverage (Low), from 25% to 50% is the quartile with the second lowest(Q2), from 50% to 75% is the quartile with the second highest(Q3), and above 75% is the quartile of firms with the highest average level of leverage (High). The sample includes 1,137 stocks.

	Firm-level				Aggregate-level			
	Low	Q2	Q3	High	Low	Q2	Q3	High
Panel A: January 1996 to December 2021								
Unscaled	0.6084	0.5997	0.5024	0.1979	0.6084	0.5997	0.5024	0.1979
RV	0.4232	0.3730	0.2771	0.0537	0.4064	0.4721	0.3185	0.1131
IV	0.8047	0.7223	0.6135	0.5030	0.5843	0.5690	0.4557	0.1649
MW	0.9820	1.0043	0.7176	0.7981	0.4929	0.4285	0.3443	0.0881
GLB	0.9443	0.6532	0.6803	0.6305	0.4166	0.3974	0.2824	0.0892
Panel B: January 1996 to December 2019								
Unscaled	0.6287	0.6184	0.5180	0.1867	0.6287	0.6184	0.5180	0.1867
RV	0.4201	0.3739	0.2759	0.0324	0.4029	0.4571	0.3355	0.1169
IV	0.8270	0.7433	0.6313	0.5058	0.6044	0.5834	0.4695	0.1503
MW	1.0195	1.0282	0.7059	0.8158	0.5049	0.4282	0.3404	0.0612
GLB	0.9599	0.6442	0.6689	0.6090	0.3960	0.3734	0.2556	0.0414
Panel C: January 2020 to December 2021								
Unscaled	0.3653	0.3756	0.3141	0.3325	0.3653	0.3756	0.3141	0.3325
RV	0.4611	0.3613	0.2927	0.3099	0.4480	0.6521	0.1140	0.0678
IV	0.5378	0.4706	0.3993	0.4697	0.3423	0.3967	0.2896	0.3396
MW	0.5325	0.7177	0.8581	0.5849	0.3494	0.4321	0.3907	0.4110
GLB	0.7582	0.7611	0.8172	0.8885	0.6631	0.6861	0.6040	0.6627

TABLE A.5: Sharpe ratios for portfolios of financial and non-financial entities

This table reports the Sharpe ratios of reference financial and non-financial portfolios and their counterparts managed by RV, IV, MW, and GLB to time risk. The left side and right side of the table report the Sharpe ratios when we use the firm-level and aggregate-level risk-timing approach, respectively. We report our estimates for the entire sample covering January 1996 to December 2021. The period from January 1996 to December 2019 isolates the unusually high uncertainty period of the pandemic and its impact on our strategy. From January 2020 to December 2021, we test our trading strategy's performance during heightened market risk periods. The sample includes 190 financial companies and 947 non-financial companies.

	Firm-level		Aggregate-level	
	Financial	Non-financial	Financial	Non-financial
Full Sample January 1996 to December 2021				
Unscaled	0.0974	0.0980	0.0974	0.1054
RV	0.0991	0.0803	0.0919	0.0871
IV	0.1595	0.1559	0.1295	0.1109
MW	0.1526	0.2030	0.1179	0.0794
GLB	0.1331	0.1605	0.0895	0.0693
Number of firms	190	947	190	947
January 1996 to December 2019				
Unscaled	0.0952	0.0981	0.0952	0.1057
RV	0.0916	0.0740	0.0836	0.0851
IV	0.1567	0.1564	0.1266	0.1110
MW	0.1525	0.2050	0.1179	0.0792
GLB	0.1235	0.1563	0.0824	0.0646
January 2020 to December 2021				
Unscaled	0.1226	0.1120	0.1226	0.1205
RV	0.1649	0.1322	0.1607	0.1069
IV	0.1884	0.1493	0.1626	0.1082
MW	0.1508	0.1781	0.1599	0.1028
GLB	0.3008	0.2398	0.2278	0.1979

TABLE A.6: Sharpe ratios for size-sorted portfolios

This table reports the Sharpe ratios of the size quartile portfolios and their counterparts managed by RV, IV, MW, and GLB to time risk. The left and right sides of the table report the Sharpe ratios when we use the firm-level and aggregate-level risk-timing approach, respectively, as defined in Table 3.3 in the main paper. We report our estimates for the entire sample covering January 1996 to December 2021. The period from January 1996 to December 2019 isolates the unusually high uncertainty period of the pandemic and its impact on our strategy. From January 2020 to December 2021, we test our trading strategy's performance during heightened market risk periods. The equally-weighted size portfolio quartiles are: less than 25% is the quartile of firms with the lowest averaged size (Low), from 25% to 50% is the quartile with the second lowest(Q2), from 50% to 75% is the quartile with the second highest(Q3), and above 75% is the quartile of firms with the highest averaged size (High). The sample includes 1,137 stocks.

	Firm-level				Aggregate-level			
	Low	Q2	Q3	High	Low	Q2	Q3	High
	Full Sample January 1996 to December 2021							
Unscaled	0.0241	0.1144	0.1271	0.1308	0.0241	0.1144	0.1271	0.1308
RV	0.0069	0.0954	0.1025	0.1062	0.0032	0.0890	0.1057	0.1088
IV	0.1041	0.1679	0.1683	0.1677	0.0315	0.1231	0.1320	0.1424
MW	0.1915	0.2054	0.1534	0.1985	0.0169	0.1001	0.0933	0.1231
GLB	0.1082	0.1762	0.1626	0.1561	0.0025	0.0784	0.0890	0.1107
	January 1996 to December 2019							
Unscaled	0.0130	0.1164	0.1309	0.1359	0.0130	0.1164	0.1309	0.1359
RV	-0.0052	0.0898	0.0979	0.1043	-0.0039	0.0816	0.1047	0.1093
IV	0.1006	0.1683	0.1705	0.1679	0.0284	0.1241	0.1328	0.1412
MW	0.1925	0.2086	0.1544	0.1970	0.0159	0.0997	0.0930	0.1198
GLB	0.0990	0.1703	0.1589	0.1508	-0.0010	0.0738	0.0845	0.1049
	January 2020 to December 2021							
Unscaled	0.1049	0.1195	0.1228	0.1247	0.1049	0.1195	0.1228	0.1247
RV	0.1175	0.1444	0.1465	0.1329	0.1024	0.1571	0.1232	0.1281
IV	0.1466	0.1630	0.1455	0.1647	0.0804	0.1101	0.1195	0.1524
MW	0.1748	0.1655	0.1511	0.2114	0.0634	0.1203	0.1262	0.1970
GLB	0.2608	0.2734	0.2371	0.2555	0.1177	0.1905	0.2144	0.2503

TABLE A.7: Sharpe ratios for credit rating portfolios

This table reports the Sharpe ratios of credit-rating portfolios and their counterparts managed by RV, IV, MW, and GLB to time risk. The left and right sides of the table report the Sharpe ratios when we use the firm-level and aggregate-level risk-timing approach, respectively, as defined in Table 3.3 in the main paper. We report our estimates for the entire sample covering January 1996 to December 2021. The period from January 1996 to December 2019 isolates the unusually high uncertainty period of the pandemic and its impact on our strategy. From January 2020 to December 2021, we test our trading strategy's performance during heightened market risk periods. As reported, the credit ratings from S&P, Fitch and Moody's are obtained from Bloomberg. The sample includes 722 firms. The remaining 415 firms are either not rated or do not have credit rating data available.

	Full Sample January 1996 to December 2021						
	Firm-level						
	AAA	AA	A	BBB	BB	B	CCC
Unscaled	0.0263	0.1667	0.1317	0.1288	0.1015	0.0353	-0.0666
RV	0.0494	0.1253	0.0996	0.0986	0.0775	0.0091	0.0027
IV	0.1273	0.1832	0.1675	0.1612	0.1508	0.1084	0.0484
MW	0.0890	0.1648	0.1888	0.1478	0.2002	0.1616	0.0320
GLB	0.1496	0.1750	0.1543	0.1436	0.1419	0.1103	0.0922
Number of firms	4	27	175	344	116	51	5
	Aggregate-level						
Unscaled	0.0263	0.1667	0.1317	0.1288	0.1015	0.0353	-0.0666
RV	0.0425	0.1138	0.1045	0.1043	0.0801	0.0020	0.0215
IV	0.0966	0.1596	0.1379	0.1325	0.1197	0.0734	-0.0006
MW	0.0038	0.1147	0.1097	0.0979	0.1041	0.0984	0.1095
GLB	0.1100	0.1724	0.0988	0.0778	0.0809	0.0546	0.0399
Number of firms	4	27	175	344	116	51	5
	January 1996 to December 2019						
	Firm-level						
Unscaled	0.0342	0.1786	0.1366	0.1329	0.0968	0.0275	-0.0725
RV	0.0439	0.1344	0.0975	0.0933	0.0692	-0.0002	0.0054
IV	0.1200	0.1820	0.1678	0.1623	0.1496	0.1049	0.0537
MW	0.0924	0.1464	0.1855	0.1477	0.1997	0.1611	0.0336
GLB	0.1474	0.1666	0.1457	0.1387	0.1370	0.1115	0.0955
	Aggregate-level						
Unscaled	0.0342	0.1786	0.1366	0.1329	0.0968	0.0275	-0.0725
RV	0.0479	0.1214	0.1027	0.0998	0.0751	-0.0005	0.0284
IV	0.1041	0.1579	0.1372	0.1326	0.1180	0.0729	0.0022
MW	0.0075	0.0760	0.1042	0.0974	0.1048	0.1012	0.1144
GLB	0.1125	0.1642	0.0908	0.0724	0.0779	0.0546	0.0424
	January 2020 to December 2021						
	Firm-level						
Unscaled	-0.0407	0.1358	0.1288	0.1240	0.1457	0.0981	-0.0536
RV	0.1052	0.1009	0.1263	0.1465	0.1470	0.1454	-0.0534
IV	0.2154	0.1956	0.1635	0.1483	0.1621	0.1881	-0.0675
MW	0.1521	0.3195	0.2273	0.1515	0.2064	0.3172	-0.0529
GLB	0.4050	0.3423	0.3151	0.2229	0.2468	0.0925	0.0414
	Aggregate-level						
Unscaled	-0.0407	0.1358	0.1288	0.1240	0.1457	0.0981	-0.0536
RV	-0.0245	0.1052	0.1348	0.1540	0.1290	0.0564	-0.0963
IV	0.0028	0.1788	0.1450	0.1290	0.1438	0.0970	-0.0630
MW	-0.0510	0.3352	0.1643	0.1234	0.1423	0.1014	-0.0646
GLB	0.0923	0.3306	0.2424	0.2123	0.2165	0.0922	-0.0276

Appendix 2. Spanning regression results

This appendix reports the regression coefficients with the inclusion of Fama–French–Carhart four factors, Schneider et al. (2020) ex-ante skewness factors, and Bali et al. (2017) MAX factor in Table A.8. This analysis is used to compare the factor inclusion effect on our alpha. This appendix also reports the spanning regression results similar to Table 3.4 in the main paper but for the full sample, leverage-sorted quartile portfolios, financial and non-financial portfolios, size-sorted quartile portfolios, and credit rating portfolios , respectively.

TABLE A.8: Spanning regression controlling for skewness and MAX

This table reports the estimated spanning regression coefficients for different beta-pricing models. *Unscaled* denotes the average excess return without risk timing. MKT (market), SMB (size), and HML (value) are Fama and French (1993)'s three factors. UMD is Carhart (1997)'s momentum factor. SK is Schneider et al. (2020)'s ex-ante coskewness factor. MAX is the maximum stock returns of Bali et al. (2017). Alphas are annualised. The R-squared is adjusted for the number of predictors. The sample includes 1,137 stocks. The superscripts * * *, **, and * indicate statistical significance at the 1%, 5%, and 10%-confidence levels, respectively.

	1				2				3				4			
	RV	IV	MW	GLB	RV	IV	MW	GLB	RV	IV	MW	GLB	RV	IV	MW	GLB
α	-0.0193***	0.0476***	0.0338***	0.0224***	-0.0177***	0.0480***	0.0344***	0.0223***	-0.0174***	0.0318***	0.0265***	0.0265***	-0.0328***	0.0334***	0.0269***	0.0044
	(0.0036)	(0.0032)	(0.0045)	(0.0044)	(0.0037)	(0.0032)	(0.0046)	(0.0045)	(0.0021)	(0.0018)	(0.0024)	(0.0023)	(0.0038)	(0.0033)	(0.0047)	(0.0046)
Unscaled Excess return	0.5722***	0.7770***	0.2070***	0.4185***	0.5722***	0.7770***	0.2070***	0.4185***	0.5891***	0.6519***	0.1814***	0.3330***	0.5710***	0.7758***	0.2064***	0.4170***
	(0.0021)	(0.0018)	(0.0026)	(0.0025)	(0.0021)	(0.0018)	(0.0026)	(0.0025)	(0.0014)	(0.0011)	(0.0016)	(0.0015)	(0.0021)	(0.0018)	(0.0026)	(0.0025)
xr	-0.0006***	-0.0007***	-0.0003***	0.0003***	-0.0006***	-0.0007***	-0.0003***	0.0003***	0.0005***	0.0008***	0.0003***	0.0008***	0.0004***	0.0002***	0.0002*	0.0014***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
SMB	-0.0012***	-0.0017***	-0.0006***	-0.0017***	-0.0012***	-0.0017***	-0.0006***	-0.0017***	0.0001**	-0.0003***	-0.0002***	-0.0002***	-0.0001	-0.0007***	-0.0001	-0.0005***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
HML	-0.0011***	-0.0017***	0.0002	-0.0003***	-0.0012***	-0.0017***	0.0002	-0.0003***	-0.0028***	-0.0022***	-0.0007***	-0.0008***	-0.0022***	-0.0027***	-0.0004***	-0.0015***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
UMD	0.0006***	0.0009***	0.0004***	0.0013***	0.0006***	0.0009***	0.0004***	0.0013***	0.0004***	0.0006***	0.0003***	0.0005***	0.0005***	0.0007***	0.0003***	0.0012***
	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0001)
LUSK	-0.0507***	-0.0752***	-0.0127***	-0.0533***												
	(0.0037)	(0.0033)	(0.0046)	(0.0045)												
USK					0.0696***	0.0800***	0.0198*	0.0523***					0.0693***	0.0797***	0.0197*	0.0520***
					(0.0088)	(0.0077)	(0.0109)	(0.0106)					(0.0088)	(0.0077)	(0.0109)	(0.0106)
LSK					-0.0245**	-0.0685***	-0.0029	-0.0547***					-0.0255**	-0.0694***	-0.0034	-0.0558***
					(0.0116)	(0.0101)	(0.0144)	(0.0140)					(0.0116)	(0.0101)	(0.0144)	(0.0140)
MAX									-0.0017***	-0.0013***	-0.0005***	-0.0010***	-0.0014***	-0.0014***	-0.0007***	-0.0017***
									(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Adjusted R^2	0.3592	0.5778	0.0398	0.1719	0.3593	0.5778	0.0398	0.1719	0.3591	0.4948	0.0360	0.1306	0.3609	0.5791	0.0402	0.1740

TABLE A.9: Spanning regressions for equally weighted portfolios with aggregate-level risk timing

This table is similar to Table 3.4 in the main paper but includes aggregate-level results, reporting the estimation results of univariate and multivariate spanning regressions of monthly excess returns for portfolios managed to time risk onto those of the original portfolios. The sample includes 1,137 stocks. Panel A reports the regression results for the RV-, IV-, MW-, and GLB-managed portfolios constructed by the firm-level or aggregate-level risk-timing approach, respectively. Firm-level regressions include firm and month-fixed effects. Panel A.1 reports the results when regressions control for the Fama and French (1993), Carhart (1997) and Schneider et al. (2020) risk factors. Panels B and C are similar to Panel A but refer to pre- and post-pandemic periods, not accounting for the ex-ante coskewness risk factor due to data limitation. Including the coskwness risk factor in Panel B yields similar results as those reported in Panel A. We do not control for the ex-ante coskewness risk factor in Panel C due to data limitation. The alpha and appraisal ratios are annualised. Robust standard errors are in parentheses. The R-squared is adjusted for the number of predictors. The superscripts * * *, **, and * indicate statistical significance at the 1%, 5%, and 10%-confidence levels, respectively.

	Firm-level				Aggregate-level			
	RV	IV	MW	GLB	RV	IV	MW	GLB
	Panel A: January 1996 - December 2021							
α	-0.0033*	0.0478***	0.0335***	0.0420***	0.0034	0.0231	0.0085	0.0124
	(0.0020)	(0.0017)	(0.0023)	(0.0021)	(0.0356)	(0.0302)	(0.0442)	(0.0503)
β	0.5926***	0.6569***	0.1829***	0.3358***	0.8130***	0.8696***	0.6912***	0.5687***
	(0.0013)	(0.0011)	(0.0015)	(0.0015)	(0.0331)	(0.0280)	(0.0410)	(0.0467)
Adjusted R^2	0.3522	0.4892	0.0351	0.1283	0.6598	0.7555	0.4761	0.3212
Appraisal Ratio	-0.0101	0.1760	0.0900	0.1200	0.0188	0.1513	0.0380	0.0486
	Panel A.1: Controlling for the Fama and French (1993), Carhart (1997) and Schneider et al. (2020) factors							
α	0.0034*	0.0438***	0.0345***	0.0373***	0.0136	0.0231	0.0112	-0.0047
	(0.0021)	(0.0017)	(0.0024)	(0.0022)	(0.0366)	(0.0314)	(0.0461)	(0.0524)
Adjusted R^2	0.3568	0.4934	0.0357	0.1298	0.6684	0.7562	0.4737	0.3209
Appraisal Ratio	0.0104	0.1621	0.0926	0.1066	0.0762	0.1509	0.0498	-0.0184
	Panel B: January 1996 - December 2019							
α	-0.0015	0.0510***	0.0351***	0.0449***	0.0015	0.0209	0.0031	0.0026
	(0.0020)	(0.0017)	(0.0024)	(0.0023)	(0.0360)	(0.0297)	(0.0446)	(0.0521)
β	0.5956***	0.6803***	0.1927***	0.3652***	0.8488***	0.9644***	0.8259***	0.6817***
	(0.0014)	(0.0012)	(0.0017)	(0.0016)	(0.0366)	(0.0302)	(0.0453)	(0.0530)
Adjusted R^2	0.3459	0.4880	0.0365	0.1366	0.6517	0.7801	0.5361	0.3646
Appraisal Ratio	-0.0089	0.1865	0.0927	0.1231	0.0083	0.1442	0.0142	0.0103
	Panel B.1: Controlling for the Fama and French (1993) and Carhart (1997) factors							
α	0.0035*	0.0537***	0.0380***	0.0439***	0.0150	0.0368	0.0245	-0.0019
	(0.0021)	(0.0018)	(0.0025)	(0.0024)	(0.0366)	(0.0298)	(0.0455)	(0.0540)
Adjusted R^2	0.3501	0.4941	0.0375	0.1388	0.6682	0.7959	0.5540	0.3715
Appraisal Ratio	0.0078	0.1975	0.1009	0.1212	0.0877	0.2636	0.1152	-0.0074
	Panel C: January 2020 - December 2021							
α	-0.0080	0.0090**	0.0209***	0.0194***	0.0099	0.0057	0.0106	0.0775
	(0.0080)	(0.0049)	(0.0080)	(0.0049)	(0.1641)	(0.0896)	(0.0746)	(0.0992)
β	0.5716***	0.4986***	0.1156***	0.1329***	0.6921***	0.5509***	0.2374***	0.1857***
	(0.0042)	(0.0026)	(0.0042)	(0.0026)	(0.0885)	(0.0483)	(0.0402)	(0.0535)
Adjusted R^2	0.3951	0.5652	-0.0145	0.0686	0.7232	0.8486	0.5950	0.3241
Appraisal Ratio	-0.0228	0.0406	0.0594	0.0895	0.0428	0.0455	0.1009	0.5564
	Panel C.1: Controlling for the Fama and French (1993) and Carhart (1997) factors							
α	-0.0018	-0.0242***	0.0104	0.0071*	0.0540	-0.0316	-0.0156	0.0621
	(0.0083)	(0.0052)	(0.0086)	(0.0052)	(0.1756)	(0.1013)	(0.0871)	(0.1159)
Adjusted R^2	0.4331	0.5774	-0.0138	0.0833	0.7278	0.8339	0.5261	0.2092
Appraisal Ratio	-0.0052	-0.1114	0.0292	0.0327	0.2364	-0.2401	-0.1379	0.4121

TABLE A.10: Spanning regressions for equally weighted portfolios with aggregate-level risk timing: the Global Financial Crisis

This table reports the estimation results of similar spanning regressions as those in Table A.9 but focused on the Global Financial Crisis period from July 2007 to June 2009. The alpha and appraisal ratios are annualised. Robust standard errors are in parentheses. The R-squared is adjusted for the number of predictors. The superscripts * * *, **, and * indicate statistical significance at the 1%, 5%, and 10%-confidence levels, respectively.

	Firm-level				Aggregate-level			
	RV	IV	MW	GLB	RV	IV	MW	GLB
	July 2007 - June 2009							
α	-0.0066	0.0461***	0.0275***	0.0242***	0.0212	0.0297	0.0261	0.0351
	(0.0053)	(0.0043)	(0.0040)	(0.0026)	(0.0784)	(0.0617)	(0.0594)	(0.0340)
β	0.2186***	0.3059***	0.0384***	0.0484***	0.2045***	0.3069***	0.0893***	0.0405***
	(0.0026)	(0.0021)	(0.0020)	(0.0013)	(0.0465)	(0.0366)	(0.0352)	(0.0202)
Adjusted R^2	0.1803	0.4212	-0.0285	0.0099	0.4433	0.7509	0.1910	0.1162
Appraisal Ratio, AR	-0.0281	0.2384	0.1528	0.2064	0.1919	0.3417	0.3125	0.7338
	Additional controls for Fama–French–Carhart four factors and Schneider et al. (2020) skewness							
α	0.0570***	0.0806***	0.0405***	0.0495***	0.0061	-0.0033	-0.0027	0.0211
	(0.0069)	(0.0057)	(0.0053)	(0.0034)	(0.0869)	(0.0709)	(0.0680)	(0.0396)
Adjusted R^2	0.1932	0.4301	-0.0272	0.0248	0.4610	0.7401	0.1621	0.0534
Appraisal Ratio, AR	0.2443	0.4200	0.2254	0.4248	0.0565	-0.0377	-0.0314	0.4259

TABLE A.11: Spanning regressions for leverage-sorted portfolios with aggregate-level risk timing

This table is similar to Table 3.6 in the main paper but includes the results for the aggregate-level risk-timing approach. The table reports the regression results similar to Table A.9 but for average leverage quartile portfolios. The equally weighted leverage portfolio quartiles are: less than 25% is the quartile of firms with the lowest averaged leverage (Low), from 25% to 50% is the quartile with the second lowest (Q2), from 50% to 75% is the quartile with the second highest (Q3), and above 75% is the quartile of firms with the highest averaged leverage (High). The alpha and appraisal ratios are annualised. Robust standard errors are in parentheses. The sample includes 1,137 stocks from January 1996 to December 2021. The superscripts * * *, **, and * indicate statistical significance at the 1%, 5%, and 10%-confidence levels, respectively.

	Firm-level				Aggregate-level					Firm-level				Aggregate-level			
Low	RV	IV	MW	GLB	RV	IV	MW	GLB	Q3	RV	IV	MW	GLB	RV	IV	MW	GLB
α	-0.0066	0.0459***	0.0410***	0.0463***	0.0049	0.0168	-0.0020	0.0153		-0.0076**	0.0355***	0.0252***	0.0369***	0.0036	0.0233	0.0156	0.0053
	(0.0042)	(0.0034)	(0.0048)	(0.0045)	(0.0361)	(0.0303)	(0.0457)	(0.0517)		(0.0035)	(0.0029)	(0.0043)	(0.0041)	(0.0357)	(0.0303)	(0.0447)	(0.0517)
β	0.5809***	0.6826***	0.2342***	0.3687***	0.8240***	0.8485***	0.6937***	0.5810***		0.6404***	0.7185***	0.1801***	0.3407***	0.8170***	0.8710***	0.6891***	0.5469***
	(0.0027)	(0.0022)	(0.0031)	(0.0029)	(0.0322)	(0.0271)	(0.0409)	(0.0462)		(0.0026)	(0.0022)	(0.0032)	(0.0030)	(0.0328)	(0.0279)	(0.0412)	(0.0475)
Adjusted R^2	0.3391	0.5144	0.0579	0.1516	0.6779	0.7710	0.4796	0.3354		0.4116	0.5593	0.0323	0.1265	0.6664	0.7579	0.4731	0.2969
Appraisal Ratio	-0.0192	0.1642	0.1056	0.1271	0.0267	0.1097	-0.0086	0.0587		-0.0266	0.1486	0.0714	0.1113	0.0201	0.1511	0.0685	0.0201
Controlling for the Fama and French (1993), Carhart (1997) and Schneider et al. (2020) factors																	
α	0.0093***	0.0473***	0.0453***	0.0437***	0.0296	0.0198	0.0041	0.0001		0.0012	0.0351***	0.0272***	0.0351***	0.0079	0.0187	0.0088	-0.0127
	(0.0044)	(0.0036)	(0.0050)	(0.0047)	(0.0367)	(0.0314)	(0.0475)	(0.0538)		(0.0037)	(0.0031)	(0.0045)	(0.0043)	(0.0372)	(0.0316)	(0.0469)	(0.0539)
Adjusted R^2	0.3459	0.5189	0.0596	0.1537	0.6932	0.7737	0.4808	0.3338		0.4171	0.5630	0.0326	0.1271	0.6668	0.7573	0.4679	0.2950
Appraisal Ratio	0.0274	0.1701	0.1167	0.1201	0.1668	0.1301	0.0177	0.0003		0.0044	0.1477	0.0771	0.1058	0.0439	0.1213	0.0385	-0.0482
Q2									High								
α	-0.0082**	0.0405***	0.0326***	0.0322***	0.0007	0.0246	0.0131	0.0246		0.0065	0.0638***	0.0313***	0.0517***	0.0042	0.0390	0.0322	0.0147
	(0.0038)	(0.0031)	(0.0045)	(0.0042)	(0.0371)	(0.0305)	(0.0446)	(0.0510)		(0.0043)	(0.0037)	(0.0047)	(0.0044)	(0.0402)	(0.0332)	(0.0453)	(0.0504)
β	0.6226***	0.6803***	0.1851***	0.3460***	0.7976***	0.8676***	0.6855***	0.5552***		0.5394***	0.5715***	0.1305***	0.2965***	0.7600***	0.8423***	0.6773***	0.5744***
	(0.0026)	(0.0022)	(0.0031)	(0.0029)	(0.0343)	(0.0282)	(0.0413)	(0.0472)		(0.0028)	(0.0024)	(0.0031)	(0.0029)	(0.0370)	(0.0306)	(0.0418)	(0.0465)
Adjusted R^2	0.3883	0.5315	0.0364	0.1376	0.6349	0.7520	0.4682	0.3060		0.2915	0.3848	0.0171	0.1035	0.5762	0.7085	0.4569	0.3277
Appraisal Ratio	-0.0261	0.1584	0.0892	0.0937	0.0038	0.1596	0.0581	0.0952		0.0184	0.2106	0.0821	0.1430	0.0207	0.2303	0.1395	0.0572
Controlling for the Fama and French (1993), Carhart (1997) and Schneider et al. (2020) factors																	
α	0.0025	0.0403***	0.0341***	0.0300***	0.0161	0.0246	0.0161	0.0091		-0.0014	0.0475***	0.0272***	0.0392***	0.0075	0.0346	0.0287	-0.0049
	(0.0040)	(0.0033)	(0.0047)	(0.0044)	(0.0380)	(0.0317)	(0.0466)	(0.0530)		(0.0045)	(0.0039)	(0.0049)	(0.0047)	(0.0411)	(0.0343)	(0.0472)	(0.0525)
Adjusted R^2	0.3938	0.5359	0.0368	0.1392	0.6464	0.7520	0.4646	0.3057		0.2949	0.3904	0.0179	0.1061	0.5939	0.7148	0.4596	0.3320
Appraisal Ratio	0.0079	0.1585	0.0933	0.0874	0.0874	0.1597	0.0709	0.0353		-0.0040	0.1576	0.0714	0.1088	0.0373	0.2069	0.1245	-0.0191

TABLE A.12: Spanning regressions for leverage-sorted portfolios with aggregate-level risk timing: COVID-19

This table reports the estimation results of similar spanning regressions as those in Table A.9 but focused on the COVID-19 period from January 2020 to December 2021. The alpha and appraisal ratios are annualised. Robust standard errors are in parentheses. The R-squared is adjusted for the number of predictors. The superscripts * * *, **, and * indicate statistical significance at the 1%, 5%, and 10%-confidence levels, respectively.

	January 2020 - December 2021																
	Firm-level				Aggregate-level					Firm-level				Aggregate-level			
Low	RV	IV	MW	GLB	RV	IV	MW	GLB	Q3	RV	IV	MW	GLB	RV	IV	MW	GLB
α	0.0114	0.0206*	0.0338	0.0131	0.0900	-0.0141	-0.0066	0.0686		-0.0153	0.0007	0.0273*	0.0202**	-0.0701	-0.0009	0.0077	0.0674
	(0.0187)	(0.0118)	(0.0212)	(0.0116)	(0.2063)	(0.1015)	(0.0934)	(0.0988)		(0.0142)	(0.0093)	(0.0151)	(0.0089)	(0.1140)	(0.0829)	(0.0625)	(0.0886)
β	0.6440***	0.5553***	0.1895***	0.1317***	0.7103***	0.6066***	0.2837***	0.1785***		0.5150***	0.4769***	0.0811***	0.1140***	0.5281***	0.5090***	0.1939***	0.1616***
	(0.0093)	(0.0059)	(0.0105)	(0.0057)	(0.1064)	(0.0523)	(0.0482)	(0.0510)		(0.0073)	(0.0048)	(0.0078)	(0.0046)	(0.0600)	(0.0436)	(0.0329)	(0.0466)
Adjusted R^2	0.4125	0.5691	0.0069	0.0478	0.6543	0.8529	0.5941	0.3287		0.4253	0.5978	-0.0261	0.0669	0.7689	0.8547	0.5945	0.3236
Appraisal ratio	0.0276	0.0792	0.0721	0.0510	0.3112	-0.0991	-0.0503	0.4956		-0.0488	0.0032	0.0819	0.1023	-0.4371	-0.0081	0.0879	0.5410
	Controlling for the Fama and French (1993), Carhart (1997) factors																
α	0.5307***	0.3824***	0.2169***	0.1747***	0.2123	-0.0661	-0.0471	0.0505		0.4055***	0.3021***	0.0979***	0.1640***	-0.0348	-0.0359	-0.0149	0.0526
	(0.0280)	(0.0201)	(0.0269)	(0.0149)	(0.2234)	(0.1129)	(0.1083)	(0.1151)		(0.0216)	(0.0166)	(0.0190)	(0.0116)	(0.1281)	(0.0941)	(0.0727)	(0.1037)
Adjusted R^2	0.4538	0.5809	0.0073	0.0567	0.6517	0.8436	0.5312	0.2178		0.4742	0.6118	-0.0223	0.0811	0.7499	0.8395	0.5305	0.2064
Appraisal ratio	1.3337	1.4886	0.4629	0.6861	0.7314	-0.4506	-0.3345	0.3376		1.3483	1.4983	0.2941	0.8386	-0.2090	-0.2931	-0.1576	0.3894
Q2									High								
α	-0.0233	-0.0002	0.0160	0.0146	0.1250	0.0123	0.0137	0.0794		-0.0067	0.0116	0.0082	0.0302***	-0.1393	0.0335	0.0327	0.0980
	(0.0158)	(0.0097)	(0.0153)	(0.0108)	(0.1642)	(0.0861)	(0.0696)	(0.0991)		(0.0151)	(0.0086)	(0.0102)	(0.0080)	(0.1675)	(0.0959)	(0.0829)	(0.1117)
β	0.5696***	0.4937***	0.0900***	0.1391***	0.6561***	0.5328***	0.2138***	0.1821***		0.5519***	0.4534***	0.0764***	0.1533***	0.8237***	0.5675***	0.2719***	0.2259***
	(0.0082)	(0.0051)	(0.0080)	(0.0056)	(0.0890)	(0.0467)	(0.0377)	(0.0538)		(0.0095)	(0.0054)	(0.0064)	(0.0050)	(0.0972)	(0.0557)	(0.0481)	(0.0648)
Adjusted R^2	0.4146	0.5863	-0.0231	0.0742	0.6985	0.8488	0.5749	0.3128		0.3272	0.5115	-0.0210	0.1093	0.7549	0.8173	0.5736	0.3262
Appraisal ratio	-0.0669	-0.0011	0.0472	0.0612	0.5430	0.1016	0.1406	0.5714		-0.0200	0.0612	0.0365	0.1706	-0.5925	0.2484	0.2808	0.6246
	Controlling for the Fama and French (1993), Carhart (1997) factors																
α	0.4490***	0.3320***	0.1223***	0.2056***	0.2077	-0.0217	-0.0083	0.0627		0.3180***	0.2528***	0.0589***	0.1786***	-0.1316	0.0015	0.0087	0.0876
	(0.0237)	(0.0170)	(0.0194)	(0.0140)	(0.1676)	(0.0978)	(0.0815)	(0.1152)		(0.0222)	(0.0145)	(0.0129)	(0.0105)	(0.1789)	(0.1092)	(0.0972)	(0.1310)
Adjusted R^2	0.4549	0.5984	-0.0231	0.0924	0.7298	0.8323	0.4983	0.2017		0.3559	0.5266	-0.0209	0.1293	0.7601	0.7968	0.4969	0.2053
Appraisal ratio	1.3350	1.5724	0.3606	0.8712	0.9527	-0.1710	-0.0783	0.4187		0.9693	1.3488	0.2605	1.0198	-0.5658	0.0103	0.0690	0.5144

TABLE A.13: Spanning regressions for leverage-sorted portfolios with aggregate-level risk timing: The Global Financial Crisis

This table reports the estimation results of similar spanning regressions as those in Table A.11 but focused on the Global Financial Crisis period from July 2007 to June 2009. The alpha and appraisal ratios are annualised. Robust standard errors are in parentheses. The R-squared is adjusted for the number of predictors. The superscripts * * *, **, and * indicate statistical significance at the 1%, 5%, and 10%-confidence levels, respectively.

	July 2007 - June 2009																
	Firm-level				Aggregate-level					Firm-level				Aggregate-level			
Low	RV	IV	MW	GLB	RV	IV	MW	GLB	Q3	RV	IV	MW	GLB	RV	IV	MW	GLB
α	0.0065	0.0606***	0.0387***	0.0434***	0.0480	0.0630	0.0701	0.0915		-0.0091	0.0445***	0.0229***	0.0221***	-0.0024	0.0516	0.0517	0.0469
	(0.0118)	(0.0087)	(0.0098)	(0.0066)	(0.0767)	(0.0647)	(0.0743)	(0.0535)		(0.0102)	(0.0079)	(0.0065)	(0.0039)	(0.0705)	(0.0694)	(0.0685)	(0.0345)
β	0.2746***	0.4319***	0.0783***	0.0789***	0.2795***	0.4141***	0.1534***	0.0621*		0.2247***	0.3318***	0.0386***	0.0435***	0.2064***	0.3088***	0.0955**	0.0403*
	(0.0066)	(0.0048)	(0.0054)	(0.0037)	(0.0491)	(0.0414)	(0.0475)	(0.0342)		(0.0054)	(0.0042)	(0.0034)	(0.0021)	(0.0428)	(0.0420)	(0.0415)	(0.0209)
Adjusted R^2	0.1791	0.5432	-0.0108	0.0259	0.5772	0.8117	0.2907	0.0908		0.1755	0.4753	-0.0234	0.0244	0.4924	0.6971	0.1572	0.1055
Appraisal Ratio	0.0248	0.3159	0.1784	0.2947	0.4426	0.6887	0.6679	1.2102		-0.0399	0.2543	0.1598	0.2583	-0.0244	0.5270	0.5354	0.9640
	Controlling for the Fama and French (1993), Carhart (1997) and Schneider et al. (2020) factors																
α	0.0980***	0.1118***	0.0619***	0.0860***	0.1705*	0.1203	0.1290	0.1597**		0.0609***	0.0897***	0.0389***	0.0452***	0.0812	0.1113	0.1087	0.0863*
	(0.0153)	(0.0112)	(0.0128)	(0.0086)	(0.0901)	(0.0890)	(0.1012)	(0.0674)		(0.0133)	(0.0102)	(0.0085)	(0.0050)	(0.0851)	(0.0885)	(0.0879)	(0.0427)
Adjusted R^2	0.2002	0.5570	-0.0078	0.0479	0.6718	0.7990	0.2568	0.1870		0.1940	0.4935	-0.0210	0.0447	0.5822	0.7211	0.2151	0.2257
Appraisal Ratio	0.3785	0.5922	0.2859	0.5913	1.7832	1.2725	1.2007	2.2325		0.2714	0.5215	0.2716	0.5332	0.8992	1.1844	1.1660	1.9038
Q2									High								
α	-0.0019	0.0449***	0.0264***	0.0237***	0.0389	0.0387	0.0305	0.0444		-0.0366***	0.0089	0.0148**	0.0030	-0.0821	-0.0574	-0.0498	-0.0296
	(0.0098)	(0.0097)	(0.0090)	(0.0054)	(0.0726)	(0.0604)	(0.0554)	(0.0331)		(0.0101)	(0.0077)	(0.0068)	(0.0048)	(0.0874)	(0.0652)	(0.0483)	(0.0303)
β	0.2149***	0.2992***	0.0409***	0.0404***	0.1897***	0.3182***	0.0902***	0.0385*		0.1817***	0.2164***	0.0119***	0.0395***	0.1544***	0.2190***	0.0515*	0.0305*
	(0.0046)	(0.0046)	(0.0042)	(0.0026)	(0.0422)	(0.0351)	(0.0321)	(0.0192)		(0.0044)	(0.0033)	(0.0030)	(0.0021)	(0.0455)	(0.0339)	(0.0251)	(0.0158)
Adjusted R^2	0.2205	0.3788	-0.0286	-0.0046	0.4557	0.7797	0.2304	0.1163		0.1773	0.3726	-0.0410	0.0125	0.3133	0.6384	0.1219	0.1067
Appraisal Ratio	-0.0087	0.2081	0.1319	0.1957	0.3796	0.4547	0.3903	0.9516		-0.1634	0.0523	0.0977	0.0286	-0.6809	-0.6381	-0.7475	-0.7075
	Controlling for the Fama and French (1993), Carhart (1997) and Schneider et al. (2020) factors																
α	0.0724***	0.0811***	0.0384***	0.0496***	0.1435*	0.0784	0.0648	0.0804*		-0.0164	0.0231**	0.0184*	0.0129*	-0.1105	-0.0730	-0.0582	-0.0352
	(0.0128)	(0.0127)	(0.0118)	(0.0071)	(0.0802)	(0.0800)	(0.0734)	(0.0421)		(0.0133)	(0.0100)	(0.0090)	(0.0063)	(0.1202)	(0.0750)	(0.0592)	(0.0373)
Adjusted R^2	0.2383	0.3868	-0.0268	0.0094	0.6237	0.7811	0.2334	0.1882		0.1787	0.3782	-0.0415	0.0213	0.2556	0.7257	0.2426	0.2235
Appraisal Ratio	0.3364	0.3781	0.1921	0.4134	1.6856	0.9238	0.8315	1.7967		-0.0732	0.1368	0.1220	0.1223	-0.8802	-0.9321	-0.9417	-0.9038

TABLE A.14: Spanning regressions for industry portfolios

This table reports the univariate and multivariate predictive regressions of monthly excess returns for portfolios with risk timing onto the original portfolio counterparts, similarly to Table 3.6 in the main paper but for industry portfolios. The sample includes 1,137 stocks. It reports the regression results for the original portfolios and those managed by RV, IV, MW, and GLB, constructed by the firm-level or aggregate-level risk-timing approach, respectively. The results when regressions control for the Fama and French (1993) and Carhart (1997) four factors are also reported. The alpha and appraisal ratios are annualised. The R-squared is adjusted for the number of regressors. The superscripts * * *, **, and * indicate statistical significance at the 1%, 5%, and 10%-confidence levels, respectively.

	Firm-level				Aggregate-level			
Fin	RV	IV	MW	GLB	RV	IV	MW	GLB
α	0.0143***	0.0532***	0.0214***	0.0470***	0.0229	0.0562	0.0678	0.0402
	(0.0044)	(0.0039)	(0.0051)	(0.0048)	(0.0432)	(0.0369)	(0.0518)	(0.0536)
β	0.5906***	0.6225***	0.0883***	0.3335***	0.7415***	0.8181***	0.5923***	0.5520***
	(0.0033)	(0.0029)	(0.0039)	(0.0036)	(0.0382)	(0.0327)	(0.0458)	(0.0474)
Adjusted R^2	0.3488	0.4348	0.0056	0.1244	0.5484	0.6682	0.3488	0.3025
Appraisal Ratio, AR	0.0483	0.2046	0.0623	0.1463	0.1046	0.2997	0.2582	0.1480
Additional controls for Fama-French-Carhart four factors and Schneider et al. (2020) skewness								
α	0.0143***	0.0460***	0.0202***	0.0412***	0.0278	0.0490	0.0560	0.0252
	(0.0046)	(0.0040)	(0.0054)	(0.0050)	(0.0436)	(0.0380)	(0.0542)	(0.0558)
Adjusted R^2	0.3569	0.4421	0.0060	0.1272	0.5778	0.6760	0.3432	0.3027
Appraisal Ratio, AR	0.0488	0.1779	0.0588	0.1286	0.1312	0.2643	0.2121	0.0926
Nfin	RV	IV	MW	GLB	RV	IV	MW	GLB
α	-0.0068***	0.0468***	0.0363***	0.0411***	0.0007	0.0198	0.0065	0.0099
	(0.0022)	(0.0018)	(0.0025)	(0.0024)	(0.0346)	(0.0293)	(0.0439)	(0.0502)
β	0.5929***	0.6624***	0.1980***	0.3362***	0.8249***	0.8775***	0.6959***	0.5707***
	(0.0015)	(0.0012)	(0.0017)	(0.0016)	(0.0322)	(0.0272)	(0.0408)	(0.0466)
Adjusted R^2	0.3527	0.4982	0.0418	0.1290	0.6795	0.7692	0.4827	0.3236
Appraisal Ratio, AR	-0.0205	0.1711	0.0962	0.1154	0.0039	0.1332	0.0292	0.0388
Additional controls for Fama-French-Carhart four factors and Schneider et al. (2020) skewness								
α	0.0012	0.0434***	0.0374***	0.0365***	0.0133	0.0199	0.0102	-0.0069
	(0.0023)	(0.0019)	(0.0026)	(0.0025)	(0.0358)	(0.0306)	(0.0458)	(0.0523)
Adjusted R^2	0.3569	0.5019	0.0424	0.1303	0.6841	0.7689	0.4796	0.3229
Appraisal Ratio, AR	0.0035	0.1594	0.0993	0.1028	0.0763	0.1337	0.0458	-0.0271

TABLE A.15: Spanning regressions for size-sorted portfolios

This table reports the univariate and multivariate predictive regressions of monthly excess returns for portfolios with risk timing onto the original portfolio counterparts, similarly to Table 3.6 in the main paper but for size-sorted portfolios. The sample includes 1,137 stocks. It reports the regression results for the original portfolios and those managed by RV, IV, MW, and GLB, constructed by the firm-level or aggregate-level risk-timing approach, respectively. Analyses compare the performance of volatility-managed entire sample portfolios with the original unscaled ones. The results when regressions control for the Fama and French (1993) and Carhart (1997) four factors are also reported. The equally-weighted size portfolio quartiles are: less than 25% is the quartile of firms with the lowest average level of size (Low), from 25% to 50% is the quartile with the second lowest(Q2), from 50% to 75% is the quartile with the second highest(Q3), and above 75% is the quartile of firms with the highest average level of size (High). The alpha and appraisal ratios are annualised. The R-squared is adjusted for the number of regressors. The superscripts * * *, **, and * indicate statistical significance at the 1%, 5%, and 10%-confidence levels, respectively.

	Firm-level				Aggregate-level					Firm-level				Aggregate-level			
Low	RV	IV	MW	GLB	RV	IV	MW	GLB	Q3	RV	IV	MW	GLB	RV	IV	MW	GLB
α	-0.0125***	0.0438***	0.0460***	0.0357***	-0.0157	0.0116	0.0007	-0.0114		-0.0050	0.0426***	0.0251***	0.0398***	0.0012	0.0238	0.0080	0.0177
	(0.0049)	(0.0039)	(0.0048)	(0.0046)	(0.0414)	(0.0308)	(0.0453)	(0.0517)		(0.0037)	(0.0030)	(0.0045)	(0.0042)	(0.0348)	(0.0310)	(0.0457)	(0.0509)
β	0.5125***	0.5305***	0.2060***	0.2879***	0.7417***	0.8654***	0.6767***	0.5431***		0.6290***	0.7280***	0.1824***	0.3558***	0.8283***	0.8661***	0.6765***	0.5718***
	(0.0029)	(0.0023)	(0.0028)	(0.0027)	(0.0382)	(0.0285)	(0.0418)	(0.0477)		(0.0026)	(0.0022)	(0.0032)	(0.0030)	(0.0319)	(0.0284)	(0.0418)	(0.0466)
Adjusted R^2	0.2625	0.3693	0.0536	0.1091	0.5487	0.7481	0.4561	0.2927		0.3973	0.5596	0.0322	0.1336	0.6850	0.7492	0.4559	0.3248
Appraisal Ratio, AR	-0.0314	0.1360	0.1175	0.0944	-0.0744	0.0738	0.0030	-0.0434		-0.0169	0.1710	0.0680	0.1152	0.0070	0.1519	0.0346	0.0689
Additional controls for Fama-French-Carhart four factors and Schneider et al. (2020) skewness																	
α	-0.0214***	0.0262***	0.0395***	0.0241***	-0.0278	0.0023	-0.0042	-0.0395		0.0060	0.0438***	0.0293***	0.0372***	0.0283	0.0264	0.0160	0.0038
	(0.0051)	(0.0041)	(0.0050)	(0.0049)	(0.0433)	(0.0320)	(0.0473)	(0.0539)		(0.0038)	(0.0032)	(0.0047)	(0.0044)	(0.0349)	(0.0322)	(0.0476)	(0.0530)
Adjusted R^2	0.2640	0.3724	0.0544	0.1107	0.5498	0.7517	0.4587	0.2960		0.4039	0.5643	0.0331	0.1348	0.7082	0.7496	0.4541	0.3236
Appraisal Ratio, AR	-0.0537	0.0817	0.1008	0.0639	-0.1321	0.0145	-0.0181	-0.1505		0.0201	0.1768	0.0796	0.1078	0.1671	0.1688	0.0691	0.0149
Q2									High								
α	-0.0018	0.0449	0.0366***	0.0431***	-0.0025	0.0243	0.0215	0.0163		-0.0040	0.0453***	0.0308***	0.0448***	0.0014	0.0340	0.0442	0.0379
	(0.0038)	(0.0031)	(0.0045)	(0.0042)	(0.0369)	(0.0294)	(0.0439)	(0.0512)		(0.0034)	(0.0030)	(0.0045)	(0.0041)	(0.0348)	(0.0327)	(0.0480)	(0.0504)
β	0.6080***	0.7019***	0.2051***	0.3711***	0.8011***	0.8784***	0.6998***	0.5523***		0.6645***	0.7309***	0.1232***	0.3534***	0.8270***	0.8482***	0.6289***	0.5777***
	(0.0027)	(0.0022)	(0.0032)	(0.0030)	(0.0341)	(0.0271)	(0.0406)	(0.0473)		(0.0025)	(0.0022)	(0.0033)	(0.0030)	(0.0320)	(0.0301)	(0.0442)	(0.0464)
Adjusted R^2	0.3707	0.5326	0.0427	0.1506	0.6406	0.7708	0.4881	0.3028		0.4433	0.5577	0.0127	0.1305	0.6830	0.7185	0.3936	0.3316
Appraisal Ratio, AR	-0.0058	0.1752	0.1001	0.1266	-0.0134	0.1636	0.0968	0.0630		-0.0143	0.1860	0.0848	0.1325	0.0079	0.2056	0.1819	0.1489
Additional controls for Fama-French-Carhart four factors and Schneider et al. (2020) skewness																	
α	0.0069*	0.0436***	0.0393***	0.0404***	0.0072	0.0225	0.0226	-0.0038		0.0130***	0.0481***	0.0346***	0.0431***	0.0326	0.0410	0.0593	0.0335
	(0.0040)	(0.0033)	(0.0047)	(0.0044)	(0.0382)	(0.0306)	(0.0459)	(0.0534)		(0.0036)	(0.0031)	(0.0047)	(0.0043)	(0.0348)	(0.0340)	(0.0498)	(0.0525)
Adjusted R^2	0.3753	0.5360	0.0436	0.1517	0.6446	0.7707	0.4845	0.3013		0.4514	0.5630	0.0133	0.1325	0.7079	0.7190	0.3986	0.3304
Appraisal Ratio, AR	0.0224	0.1706	0.1073	0.1185	0.0388	0.1513	0.1011	-0.0145		0.0468	0.1985	0.0951	0.1278	0.1929	0.2480	0.2452	0.1313

TABLE A.16: Spanning regressions for credit rating portfolios

This table reports the univariate and multivariate predictive regressions of monthly excess returns for portfolios with risk timing onto the original portfolio counterparts, similarly to Table 3.6 in the main paper but for credit rating portfolios. The sample includes 722 stocks. The results when regressions control for the Fama and French (1993) and Carhart (1997) four factors are also reported. The alpha and appraisal ratios are annualised. The R-squared is adjusted for the number of regressors. The superscripts * * *, **, and * indicate statistical significance at the 1%, 5%, and 10%-confidence levels, respectively.

	Firm-level				Aggregate-level			
AAA	RV	IV	MW	GLB	RV	IV	MW	GLB
α	0.0632	0.1205***	0.0420	0.1253**	0.0454	0.1268**	-0.0037	0.1607**
	(0.0528)	(0.0445)	(0.0498)	(0.0494)	(0.0744)	(0.0586)	(0.0922)	(0.0807)
β	0.5690***	0.3587***	0.0216	0.1066***	0.6210***	0.7855***	0.2288***	0.5232***
	(0.0234)	(0.0197)	(0.0220)	(0.0219)	(0.0446)	(0.0351)	(0.0553)	(0.0484)
Adjusted R^2	0.3206	0.2076	-0.0010	0.0148	0.3836	0.6158	0.0493	0.2714
Appraisal Ratio, AR	0.1229	0.2774	0.0865	0.2603	0.1200	0.4245	-0.0079	0.3906
Additional controls for Fama-French-Carhart four factors and Schneider et al. (2020) skewness								
α	0.0695	0.1108**	0.0333	0.1484***	0.0419	0.1319**	-0.0127	0.1589*
	(0.0555)	(0.0464)	(0.0522)	(0.0519)	(0.0780)	(0.0611)	(0.0966)	(0.0849)
Adjusted R^2	0.3210	0.2228	0.0058	0.0156	0.3799	0.6170	0.0432	0.2618
Appraisal Ratio, AR	0.1352	0.2575	0.0688	0.3084	0.1102	0.4421	-0.0270	0.3839
AA	RV	IV	MW	GLB	RV	IV	MW	GLB
α	-0.0138	0.0292***	0.0389***	0.0375***	-0.0224	0.0195	0.0341	0.0818
	(0.0107)	(0.0087)	(0.0138)	(0.0129)	(0.0380)	(0.0334)	(0.0550)	(0.0514)
β	0.6575***	0.7653***	0.1361***	0.3572***	0.8034***	0.8515***	0.5031***	0.5906***
	(0.0082)	(0.0067)	(0.0106)	(0.0099)	(0.0339)	(0.0298)	(0.0491)	(0.0458)
Adjusted R^2	0.4333	0.6081	0.0163	0.1311	0.6443	0.7242	0.2507	0.3467
Appraisal Ratio, AR	-0.0513	0.1330	0.1122	0.1155	-0.1172	0.1165	0.1234	0.3167
Additional controls for Fama-French-Carhart four factors and Schneider et al. (2020) skewness								
α	0.0107	0.0365***	0.0427***	0.0381***	0.0099	0.0311	0.0587	0.0762
	(0.0111)	(0.0091)	(0.0144)	(0.0135)	(0.0387)	(0.0347)	(0.0566)	(0.0535)
Adjusted R^2	0.4424	0.6109	0.0166	0.1335	0.6601	0.7242	0.2667	0.3462
Appraisal Ratio, AR	0.0404	0.1669	0.1231	0.1174	0.0533	0.1852	0.2144	0.2951
A	RV	IV	MW	GLB	RV	IV	MW	GLB
α	-0.0084*	0.0420***	0.0312***	0.0429***	-0.0013	0.0279	0.0259	0.0267
	(0.0044)	(0.0036)	(0.0056)	(0.0051)	(0.0372)	(0.0327)	(0.0475)	(0.0518)
β	0.6441***	0.7484***	0.1310***	0.3799***	0.8065***	0.8536***	0.6539***	0.5650***
	(0.0033)	(0.0027)	(0.0042)	(0.0038)	(0.0336)	(0.0296)	(0.0430)	(0.0469)
Adjusted R^2	0.4157	0.5847	0.0149	0.1517	0.6493	0.7277	0.4257	0.3171
Appraisal Ratio, AR	-0.0298	0.1795	0.0866	0.1299	-0.0067	0.1690	0.1080	0.1021
Additional controls for Fama-French-Carhart four factors and Schneider et al. (2020) skewness								
α	0.0092**	0.0449***	0.0342***	0.0396***	0.0304	0.0354	0.0460	0.0183
	(0.0046)	(0.0038)	(0.0059)	(0.0054)	(0.0374)	(0.0339)	(0.0490)	(0.0538)
Adjusted R^2	0.4251	0.5890	0.0153	0.1533	0.6735	0.7301	0.4351	0.3185
Appraisal Ratio, AR	0.0329	0.1929	0.0950	0.1199	0.1675	0.2154	0.1931	0.0699
BBB	RV	IV	MW	GLB	RV	IV	MW	GLB
α	-0.0132***	0.0337***	0.0220***	0.0333***	-0.0016	0.0225	0.0115	0.0068
	(0.0031)	(0.0026)	(0.0041)	(0.0038)	(0.0351)	(0.0307)	(0.0454)	(0.0513)
β	0.6700***	0.7476***	0.1529***	0.3561***	0.8238***	0.8672***	0.6776***	0.5554***
	(0.0023)	(0.0019)	(0.0029)	(0.0027)	(0.0323)	(0.0283)	(0.0418)	(0.0472)
Adjusted R^2	0.4511	0.5910	0.0216	0.1335	0.6775	0.7513	0.4574	0.3063
Appraisal Ratio, AR	-0.0466	0.1416	0.0599	0.0970	-0.0092	0.1448	0.0502	0.0261
Additional controls for Fama-French-Carhart four factors and Schneider et al. (2020) skewness								
α	0.0026	0.0377***	0.0256***	0.0330***	0.0243	0.0258	0.0216	-0.0093
	(0.0033)	(0.0027)	(0.0043)	(0.0040)	(0.0354)	(0.0320)	(0.0473)	(0.0534)
Adjusted R^2	0.4592	0.5959	0.0222	0.1344	0.6971	0.7514	0.4569	0.3056
Appraisal Ratio, AR	0.0094	0.1595	0.0698	0.0961	0.1414	0.1657	0.0941	-0.0359
BB	RV	IV	MW	GLB	RV	IV	MW	GLB
α	-0.0110*	0.0443***	0.0506***	0.0348***	-0.0022	0.0349	0.0396	0.0250
	(0.0063)	(0.0054)	(0.0076)	(0.0072)	(0.0356)	(0.0314)	(0.0457)	(0.0501)
β	0.6235***	0.7060***	0.2470***	0.3537***	0.8114***	0.8563***	0.6593***	0.5660***
	(0.0041)	(0.0035)	(0.0049)	(0.0047)	(0.0333)	(0.0293)	(0.0427)	(0.0468)
Adjusted R^2	0.3904	0.5349	0.0627	0.1345	0.6572	0.7323	0.4328	0.3181
Appraisal Ratio, AR	-0.0330	0.1576	0.1271	0.0917	-0.0120	0.2192	0.1709	0.0985
Additional controls for Fama-French-Carhart four factors and Schneider et al. (2020) skewness								
α	-0.0018	0.0427***	0.0570***	0.0344***	0.0077	0.0291	0.0361	0.0053
	(0.0066)	(0.0056)	(0.0080)	(0.0076)	(0.0364)	(0.0325)	(0.0475)	(0.0521)
Adjusted R^2	0.3962	0.5404	0.0642	0.1361	0.6695	0.7349	0.4325	0.3182
Appraisal Ratio, AR	-0.0056	0.1530	0.1433	0.0907	0.0435	0.1835	0.1558	0.0210
B	RV	IV	MW	GLB	RV	IV	MW	GLB
α	-0.0234**	0.0584***	0.0606***	0.0477***	-0.0267	0.0499	0.0872*	0.0413
	(0.0116)	(0.0097)	(0.0129)	(0.0122)	(0.0423)	(0.0358)	(0.0511)	(0.0552)
β	0.5552***	0.6495***	0.2338***	0.3393***	0.7551***	0.8300***	0.6066***	0.5115***
	(0.0066)	(0.0055)	(0.0073)	(0.0069)	(0.0373)	(0.0317)	(0.0452)	(0.0488)
Adjusted R^2	0.3090	0.4649	0.0577	0.1290	0.5688	0.6880	0.3659	0.2592
Appraisal Ratio, AR	-0.0580	0.1723	0.1352	0.1123	-0.1243	0.2733	0.3349	0.1468
Additional controls for Fama-French-Carhart four factors and Schneider et al. (2020) skewness								
α	-0.0219*	0.0521***	0.0635***	0.0488***	-0.0354	0.0424	0.0834	0.0202
	(0.0122)	(0.0102)	(0.0135)	(0.0128)	(0.0437)	(0.0370)	(0.0533)	(0.0574)
Adjusted R^2	0.3125	0.4687	0.0590	0.1319	0.5791	0.6956	0.3700	0.2681
Appraisal Ratio, AR	-0.0544	0.1544	0.1418	0.1152	-0.1668	0.2351	0.3213	0.0721
CCC	RV	IV	MW	GLB	RV	IV	MW	GLB
α	0.0256	0.1054***	0.0722	0.1290***	0.1038	0.0806	0.2098***	0.1057
	(0.0437)	(0.0389)	(0.0486)	(0.0470)	(0.0635)	(0.0516)	(0.0785)	(0.0777)
β	0.5446***	0.6119***	0.2540***	0.3284***	0.6821***	0.8032***	0.4229***	0.4423***
	(0.0212)	(0.0189)	(0.0235)	(0.0228)	(0.0416)	(0.0338)	(0.0515)	(0.0509)
Adjusted R^2	0.2961	0.4017	0.0664	0.1146	0.4636	0.6439	0.1762	0.1931
Appraisal Ratio, AR	0.0538	0.2486	0.1365	0.2520	0.3219	0.3072	0.5256	0.2676
Additional controls for Fama-French-Carhart four factors and Schneider et al. (2020) skewness								
α	0.0103	0.0776*	0.0775	0.1114**	0.0898	0.0696	0.2088**	0.0979
	(0.0459)	(0.0408)	(0.0511)	(0.0495)	(0.0670)	(0.0541)	(0.0826)	(0.0821)
Adjusted R^2	0.2975	0.4045	0.0643	0.1134	0.4591	0.6445	0.1711	0.1816
Appraisal Ratio, AR	0.0216	0.1836	0.1464	0.2175	0.2772	0.2656	0.5214	0.2460

TABLE A.17: The Frazzini and Pedersen (2014)'s betting-against-beta strategy

This table repeats Frazzini and Pedersen (2014)'s strategy for our 1,137 S&P 500 sampled stocks and our period as Table 3.10 in the main paper but using realised beta estimates. We follow Frazzini and Pedersen (2014) to sort our sample firms into deciles according to their betas. BAB represents the betting-against-beta factor. BAB is constructed by separating our sample stocks into either a low-beta portfolio or a high-beta portfolio and putting a long position on the low-beta portfolio and a short position on the high-beta portfolio. Stocks in either half of the portfolio are weighted by their ranked betas, with larger weights on high-beta stocks in the high-beta portfolio and low-beta stocks in the low-beta portfolio. The portfolios are rebalanced each month. This table reports alphas, robust standard errors in parentheses, R-squared adjusted for the number of predictors, and appraisal ratios of Fama and French (1993) 3-factor regressions. Panel A reports the Fama and French (1993) 3-factor regression results for each decile portfolio and the BAB portfolio, respectively. Panel A.1 reports the results when regressions are controlled for the Carhart (1997) Momentum factor and the ex-ante coskewness of Schneider et al. (2020). Panels B and C are similar to Panel A but refer to pre- and post-pandemic periods, not accounting for the ex-ante coskewness risk factor due to data limitation. The alpha and appraisal ratios are annualised. The appraisal ratio (AR) is the proportion of the estimated intercept and the standard error of the residuals of the regressions. The superscripts * * *, **, and * indicate statistical significance at the 1%, 5%, and 10%-confidence levels, respectively.

	Low	P2	P3	P4	P5	P6	P7	P8	P9	High	BAB
Panel A: January 1996 - December 2021											
α	0.1840***	0.1584**	0.1327**	0.1222**	0.1140*	0.0822	0.0634	0.0281	-0.0256	-0.1922	0.9476
	(0.0650)	(0.0634)	(0.0614)	(0.0599)	(0.0592)	(0.0589)	(0.0594)	(0.0566)	(0.0590)	(0.0659)	(0.8995)
Adjusted R^2	0.1182	0.0682	0.0540	0.0531	0.0581	0.0813	0.1202	0.1770	0.2943	0.5167	-0.0076
Appraisal Ratio, AR	0.5632	0.4969	0.4299	0.4059	0.3835	0.2777	0.2126	0.0988	-0.0864	-0.5805	0.2096
Panel A.1: Additional controls for Carhart's Momentum factor and Schneider et al. (2020) skewness											
α	0.0871	0.0793	0.0500	0.0367	0.0551	0.0067	0.0123	-0.0053	-0.0423	-0.1122	0.8448
	(0.0664)	(0.0658)	(0.0640)	(0.0624)	(0.0628)	(0.0624)	(0.0635)	(0.0623)	(0.0660)	(0.0775)	(1.3039)
Adjusted R^2	0.0830	0.0386	0.0334	0.0500	0.0782	0.1376	0.1979	0.2704	0.4008	0.5902	-0.0122
Appraisal Ratio, AR	0.3211	0.2952	0.1913	0.1440	0.2149	0.0262	0.0473	-0.0209	-0.1571	-0.3547	0.1587
Panel B: January 1996 - December 2019											
α	0.1609***	0.1365**	0.1136*	0.1022*	0.0940*	0.0606	0.0500	0.0208	-0.0327	-0.1845	0.9553
	(0.0616)	(0.0599)	(0.0582)	(0.0565)	(0.0558)	(0.0556)	(0.0561)	(0.0546)	(0.0570)	(0.0657)	(0.9707)
Adjusted R^2	0.0620	0.0111	0.0039	0.0101	0.0358	0.0791	0.1336	0.2051	0.3334	0.5391	-0.0075
Appraisal Ratio, AR	0.5405	0.4711	0.4040	0.3740	0.3483	0.2255	0.1842	0.0790	-0.1184	-0.5806	0.2036
Panel B.1: Additional controls for Carhart's Momentum factor											
α	0.1404**	0.1184*	0.0983*	0.0903	0.0830	0.0501	0.0452	0.0180	-0.0281	-0.1588	0.9532
	(0.0617)	(0.0602)	(0.0585)	(0.0570)	(0.0563)	(0.0560)	(0.0567)	(0.0552)	(0.0577)	(0.0656)	(0.9822)
Adjusted R^2	0.0768	0.0233	0.0122	0.0142	0.0388	0.0816	0.1317	0.2027	0.3318	0.5497	-0.0111
Appraisal Ratio, AR	0.4753	0.4111	0.3512	0.3313	0.3083	0.1866	0.1664	0.0680	-0.1018	-0.5056	0.2028
Panel C: January 2020 - December 2021											
α	0.1800	0.1424	0.1168	0.1063	0.1142	0.1233	0.0098	-0.0628	-0.0946	-0.3646	0.2920
	(0.3613)	(0.3504)	(0.3460)	(0.3320)	(0.3329)	(0.3427)	(0.3604)	(0.3230)	(0.3459)	(0.3609)	(0.6359)
Adjusted R^2	0.5083	0.4898	0.4442	0.4601	0.4125	0.3479	0.2711	0.2263	0.2044	0.3238	0.5170
Appraisal Ratio, AR	0.3793	0.3094	0.2570	0.2437	0.2612	0.2740	0.0207	-0.1482	-0.2082	-0.7693	0.3496
Panel C.1: Additional controls for Carhart's Momentum factor											
α	0.1849	0.1616	0.1441	0.1328	0.1423	0.1525	0.0342	-0.0358	-0.0659	-0.3384	0.3231
	(0.3726)	(0.3590)	(0.3520)	(0.3375)	(0.3379)	(0.3477)	(0.3680)	(0.3279)	(0.3513)	(0.3678)	(0.6525)
Adjusted R^2	0.4828	0.4702	0.4314	0.4481	0.4014	0.3359	0.2485	0.2114	0.1885	0.3051	0.4971
Appraisal Ratio, AR	0.3799	0.3446	0.3134	0.3012	0.3223	0.3357	0.0711	-0.0835	-0.1436	-0.7043	0.3791

TABLE A.18: Betting-against-implied-beta strategy

This table repeats Frazzini and Pedersen (2014)'s strategy for our 1,137 S&P 500 sampled stocks and our period as Table 3.10 in the main paper but using implied beta estimates. We follow Frazzini and Pedersen (2014) to sort our sample firms into deciles according to their implied betas. BAB represents the betting-against-implied-beta factor. BAB is constructed by separating our sample stocks into either a low-beta portfolio or a high-beta portfolio and putting a long position on the low-beta portfolio and a short position on the high-beta portfolio. Stocks in either half of the portfolio are weighted by their ranked implied betas, with larger weights on high-beta stocks in the high-beta portfolio and low-beta stocks in the low-beta portfolio. The portfolios are rebalanced each month. This table reports alphas, robust standard errors in parentheses, R-squared adjusted for the number of predictors, and appraisal ratios of Fama and French (1993) 3-factor regressions. Panel A reports the Fama and French (1993) 3-factor regression results for each decile portfolio and the BAB portfolio, respectively. Panel A.1 reports the results when regressions are controlled for the Carhart (1997) Momentum factor and the ex-ante coskewness of Schneider et al. (2020). Panels B and C are similar to Panel A but refer to pre- and post-pandemic periods, not accounting for the ex-ante coskewness risk factor due to data limitation. The alpha and appraisal ratios are annualised. The appraisal ratio (AR) is the proportion of the estimated intercept and the standard error of the residuals of the regressions. The superscripts * * *, **, and * indicate statistical significance at the 1%, 5%, and 10%-confidence levels, respectively.

	Low	P2	P3	P4	P5	P6	P7	P8	P9	High	BAB
Panel A: January 1996 - December 2021											
α	0.2316***	0.1991***	0.1683***	0.1562***	0.1177*	0.0941	0.0641	0.0229	-0.0704	-0.3311***	0.0599***
	(0.0651)	(0.0626)	(0.0617)	(0.0601)	(0.0600)	(0.0596)	(0.0584)	(0.0571)	(0.0592)	(0.0642)	(0.0206)
Adjusted R^2	0.1134	0.0932	0.0823	0.0766	0.0840	0.0873	0.1073	0.1618	0.2296	0.4162	0.1053
Appraisal Ratio	0.7090	0.6336	0.5434	0.5178	0.3909	0.3145	0.2188	0.0798	-0.2371	-1.0269	0.5791
Panel A.1: Controlling for the Carhart (1997) and Schneider et al. (2020) factors											
α	0.1512**	0.1180*	0.0864	0.0867	0.0511	0.0235	-0.0017	-0.0287	-0.0905	-0.3548***	0.0390*
	(0.0674)	(0.0657)	(0.0650)	(0.0637)	(0.0644)	(0.0626)	(0.0621)	(0.0602)	(0.0659)	(0.0738)	(0.0204)
Adjusted R^2	0.0719	0.0647	0.0722	0.0704	0.0984	0.1324	0.1592	0.2642	0.3313	0.5395	0.1233
Appraisal Ratio	0.5508	0.4415	0.3268	0.3341	0.1949	0.0923	-0.0067	-0.1172	-0.3371	-1.1813	0.4693
Panel B: January 1996 - December 2019											
α	0.2096***	0.1765***	0.1472**	0.1339**	0.0961*	0.0713	0.0517	0.0065	-0.0810	-0.3404***	0.0542***
	(0.0616)	(0.0596)	(0.0585)	(0.0570)	(0.0570)	(0.0561)	(0.0554)	(0.0537)	(0.0573)	(0.0634)	(0.0192)
Adjusted R^2	0.0503	0.0368	0.0366	0.0387	0.0597	0.0783	0.1010	0.1822	0.2577	0.4529	0.0599
Appraisal Ratio	0.7045	0.6132	0.5214	0.4866	0.3491	0.2633	0.1935	0.0249	-0.2927	-1.1115	0.5847
Panel B.1: Controlling for the Carhart (1997) factor											
α	0.1913***	0.1603***	0.1311**	0.1237**	0.0841	0.0623	0.0460	0.0089	-0.0678	-0.3175***	0.0481**
	(0.0619)	(0.0599)	(0.0588)	(0.0575)	(0.0574)	(0.0567)	(0.0560)	(0.0543)	(0.0577)	(0.0635)	(0.0193)
Adjusted R^2	0.0617	0.0459	0.0461	0.0407	0.0636	0.0792	0.0995	0.1796	0.2620	0.4635	0.0733
Appraisal Ratio	0.6469	0.5595	0.4665	0.4502	0.3062	0.2302	0.1721	0.0343	-0.2458	-1.0470	0.5226
Panel C: January 2020 - December 2021											
α	0.2193	0.2173	0.1888	0.2091	0.1504	0.1535	0.0010	0.0240	-0.0759	-0.2666	0.0434
	(0.3569)	(0.3401)	(0.3477)	(0.3434)	(0.3306)	(0.3433)	(0.3389)	(0.3361)	(0.3353)	(0.3487)	(0.1205)
Adjusted R^2	0.5267	0.4981	0.4505	0.4149	0.4315	0.3862	0.3583	0.3404	0.2602	0.2064	0.4738
Appraisal Ratio	0.4689	0.4876	0.4143	0.4647	0.3471	0.3414	0.0022	0.0545	-0.1729	-0.5836	0.2746
Panel C.1: Controlling for the Carhart (1997) factor											
α	0.2371	0.2437	0.2176	0.2332	0.1804	0.1881	0.0303	0.0417	-0.0591	-0.2592	0.0509
	(0.3666)	(0.3468)	(0.3540)	(0.3510)	(0.3356)	(0.3471)	(0.3445)	(0.3451)	(0.3444)	(0.3597)	(0.1234)
Adjusted R^2	0.5068	0.4845	0.4375	0.3962	0.4213	0.3803	0.3449	0.3133	0.2291	0.1661	0.4547
Appraisal Ratio	0.4968	0.5397	0.4720	0.5102	0.4128	0.4164	0.0677	0.0927	-0.1317	-0.5536	0.3164

Appendix 3. Out-of-sample forecast errors

This appendix reports the out-of-sample forecast errors similar to Table 3.12 in the main paper but uses the AR(1) model.

TABLE A.19: Out-of-sample forecast errors

As an extension of Table 3.12 in the main paper, this table reports the AR(1) forecast errors based on the data from the start of 1996 to the end of 2021, which includes the information on the pandemic shock.

	January 1996 to December 2019				January 1996 to December 2021			
	RV	IV	MW	GLB	RV	IV	MW	GLB
RMSE	0.0763	0.0899	0.0304	0.0580	0.0831	0.0917	0.0310	0.0523
MAE	0.0538	0.0671	0.0201	0.0372	0.0575	0.0685	0.0204	0.0334
MAPE	1.4765	3.0243	3.2232	2.2526	1.6309	3.2212	3.1833	2.7972

Appendix B

Additional Results in Liquidity of Central Stocks

TABLE B.1: Panel Regressions (Connectedness)

This table presents similar results to Table 4.2 but uses stock connectedness levels to replace CEWC measures and reports the coefficients for the primary lagged independent variables. Stock connectedness level is computed as the cross-sectional average of Antón and Polk (2014) common ownership measure in Equation (4.1). The lag is determined by the Akaike information criterion. Illiquidity is proxied as in Equation (4.3). The sample includes 608 stocks from 1999 Q1 to 2022 Q2. Robust standard errors are in parentheses. The superscripts ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Illiquidity			Connectedness	
	(1)	(2)		(1)	(2)
Panel A: Predictive regressions					
Connectedness	4.9693***	4.8637***	Illiquidity	0.1068***	0.1048***
	(0.0194)	(0.0198)		(0.0004)	(0.0004)
Volatility		-42.6787***	Volatility		-5.2991***
		(1.9212)			(0.2920)
VIX		0.0733***	VIX		0.0359***
		(0.0095)			(0.0014)
Money Shock		0.0001***	Money Shock		0.0000***
		(0.0001)			(0.0000)
Panel B: VAR regressions					
Connectedness	1.6908***		Connectedness	0.7997***	
	(0.1510)			(0.0202)	
Illiquidity	0.6056***		Illiquidity	0.0031	
	(0.0230)			(0.0029)	
Volatility	83.1468***		Volatility	-1.7725***	
	(6.3763)			(0.4108)	
VIX	0.0306***		VIX	0.0013*	
	(0.0066)			(0.0007)	
Money shock	-0.0001***		Money shock	0.0000***	
	(0.0000)			(0.0000)	

TABLE B.2: Connectedness Sorts

This table reports similar results to Table 4.3 but uses stock connectedness levels to replace CEWC measures. Stock connectedness level is computed as the cross-sectional average of Antón and Polk (2014) common ownership measure in Equation (4.1). Illiquidity is computed as in Equation (4.3). Size is proxied by the natural logarithm of stock market capitalisation. The excess returns are stocks' quarterly realised excess returns. The four-factor alphas are generated by regressions based on daily data in each quarter. 608 stocks from 1999 Q1 to 2022 Q2 are included in the portfolios. QL-QH represents the excess return improvement from the lowest to the highest connectedness quartiles. The t-statistic denotes the significance of the QL-QH excess returns.

Connectedness	Illiquidity	Size	Realised Return	α
QL	0.0855	16.8543	0.0302	0.0201
Q2	0.0713	16.9907	0.0247	0.0097
Q3	0.0617	17.1808	0.0256	0.0043
QH	0.0553	17.3942	0.0260	-0.0111
QL-QH	0.0302	-0.5400	0.0041	0.0312
t-stat.			2.8416	2.2813

TABLE B.3: Fama-Macbeth regression (Connectedness)

This table reports similar results to Table 4.4 but uses stock connectedness levels to replace CEWC measures. Stock connectedness level is computed as the cross-sectional average of Antón and Polk (2014) common ownership measure in Equation (4.1). Robust standard errors are in parentheses. The sample includes 608 stocks spanning from 1999 Q1 to 2022 Q2. The superscripts ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
$\beta^{Connectedness}$	-0.0105*	-0.0237***
	(0.0055)	(0.0059)
β^{Vol}		-4.5237***
		(0.6732)
β^{MKT}		0.0122*
		(0.0066)
β^{SMB}		-0.0006
		(0.0020)
β^{HML}		-0.0007
		(0.0017)
β^{UMD}		-0.0010
		(0.0031)
Constant	-0.0280	0.0014
	(0.0239)	(0.0016)
$Adjusted R^2$	0.0009	0.1869

TABLE B.4: Connectedness and stock returns

This table reports similar results to Table 4.6 but uses stock connectedness levels to replace CEWC measures. Stock connectedness level is computed as the cross-sectional average of Antón and Polk (2014) common ownership measure in Equation (4.1). Robust standard errors are in parentheses. The R-squared is adjusted. The sample includes 608 stocks spanning from 1999 Q1 to 2022 Q2. The superscripts * * *, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively

	(1)	(2)	(3)
Connectedness	0.0121***	0.0122***	0.0118***
	(0.0026)	(0.0026)	(0.0026)
MKT		0.0051***	0.0018
		(0.0012)	(0.0013)
SMB		-0.0117***	-0.0141***
		(0.0022)	(0.0022)
HML		-0.0061***	-0.0091***
		(0.0014)	(0.0014)
UMD			-0.0086***
			(0.0012)
Constant	-0.0121***	-0.0117***	-0.0070*
	(0.0039)	(0.0039)	(0.0040)
Adjusted R^2	0.0010	0.0020	0.0028

TABLE B.5: Betting against connectedness

This table reports similar results to Table 4.8 but uses stock connectedness levels to replace CEWC measures. Stock connectedness level is computed as the cross-sectional average of Antón and Polk (2014) common ownership measure in Equation (4.1). The BAC denotes the betting-against-connectedness factor. BAC is constructed by putting a long position on the lowest connectedness quartile portfolio and a short position on the rest of the portfolios. Stocks are equally weighted. The portfolios are rebalanced each quarter. This table reports alphas, robust standard errors, adjusted R-squared, and appraisal rations of Carhart (1997) four-factor regressions. Robust standard errors are in parentheses. The superscripts ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel.A Betting Against Connectedness					
	Q1	Q2	Q3	Q4	BAC
α	-0.0735***	-0.0558***	-0.0249	-0.0510***	0.0675*
	(0.0051)	(0.0043)	(0.0039)	(0.0042)	(0.0094)
Adjusted R^2	0.7925	0.8288	0.8410	0.8067	0.7447
Appraisal Ratio	-1.3544	-1.2356	-0.6071	-1.1401	0.6778

FIGURE B.1: Impulse Response Function (Connectedness)

This figure displays the stock illiquidity or connectedness impulse responses to a one-standard-deviation orthogonalised shock to the connectedness or illiquidity. The solid line indicates the estimated impulse response, while the shades indicate the 95% confidence interval.

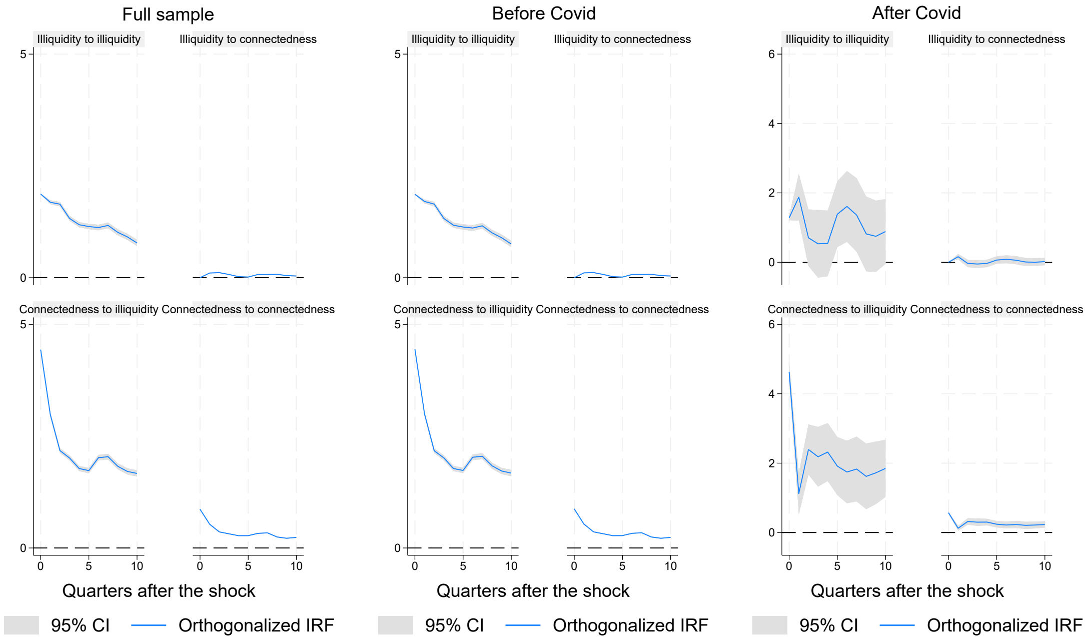


FIGURE B.2: Impulse Response Function: The GFC (Connectedness)

This figure displays the same stock illiquidity or connectedness impulse responses to a one-standard-deviation orthogonalised shock to the connectedness or illiquidity as those in Figure B.1 but focuses only on the period excluding the Global Financial Crisis (GFC) and GFC only from 2007 Q3 to 2009 Q2. The solid line indicates the estimated impulse response, while the shades indicate the 95% confidence interval.

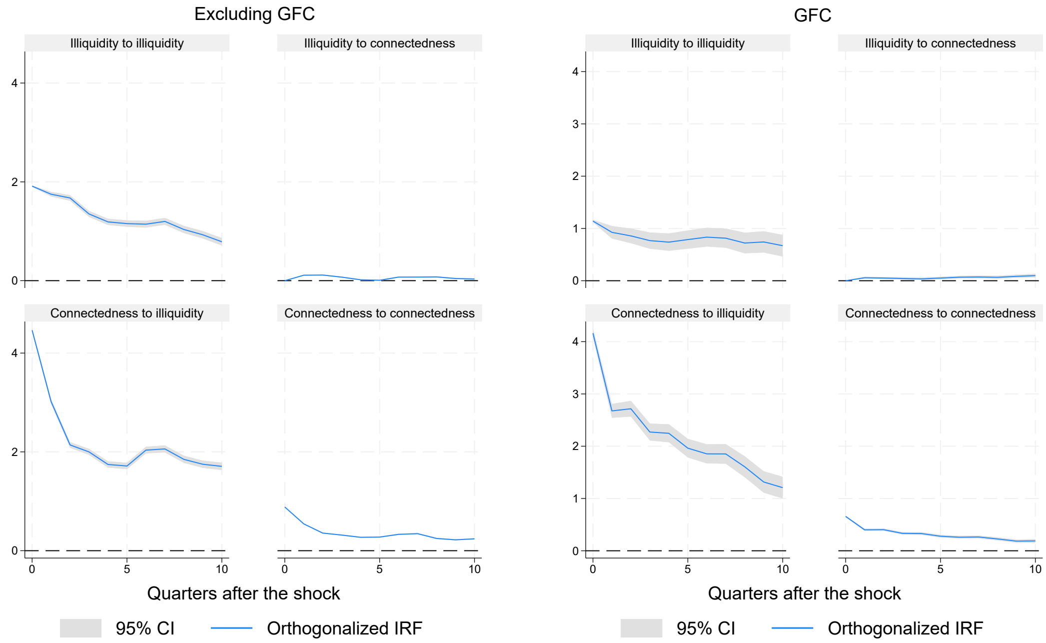
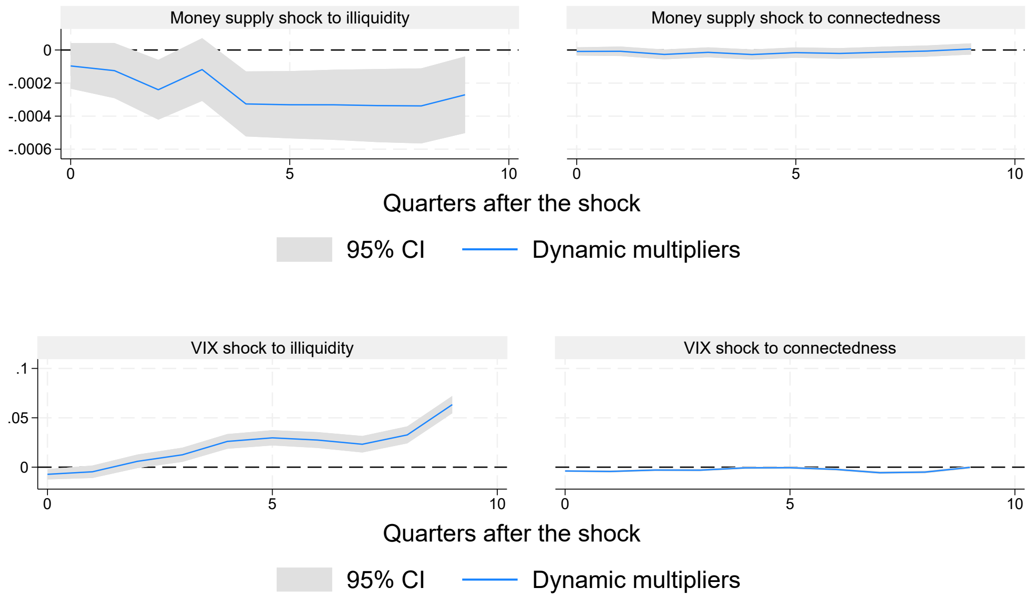


FIGURE B.3: Local Projection Impulse Response Function (Connectedness)

This figure displays the response of stock illiquidity and connectedness to a one-unit shock in the VIX index and money supply shock over a horizon of 10 quarters. The solid line indicates the estimated impulse response, while the shades indicate the 95% confidence interval.



Appendix C

Additional Results in Volatility Timing in Cryptocurrency Markets

TABLE C.1: Volatility timing premium correlations

This table reports the correlations between the premium created by RV-timing strategy and other market factors including Max, FFR, FGI, and SGI which have been discussed in Section 5.3. The sample period is from March 2017 to December 2023. The correlation table is made for BDMI, BDMLCI, BDMXLCI, and PSI in separate panels, respectively. The p-values are reported in the parenthesis.

Panel A: BDMI

	Premium	Max	FFR	FGI	SGI
Max	-0.0524	1.0000			
	(0.0279)				
FFR	-0.0011	-0.1446	1.0000		
	(0.9629)	(0.0000)			
FGI	-0.0541	0.1713	0.0159	1.0000	
	(0.0337)	(0.0000)	(0.5321)		
SGI	0.0151	0.0252	0.0818	0.2149	1.0000
	(0.5337)	(0.2998)	(0.0007)	(0.0000)	

Panel B: BDMLCI

	Premium	Max	FFR	FGI	SGI
Max	-0.0397	1.0000			
	(0.0960)				
FFR	0.0020	-0.1411	1.0000		
	(0.9315)	(0.0000)			
FGI	-0.0534	0.1853	0.0159	1.0000	
	(0.0359)	(0.0000)	(0.5321)		
SGI	0.0138	0.0178	0.0818	0.2149	1.0000
	(0.5687)	(0.4629)	(0.0007)	(0.0000)	

Panel C: BDMXLCI

	Premium	Max	FFR	FGI	SGI
Max	-0.0340	1.0000			
	(0.1538)				
FFR	-0.0104	-0.3203	1.0000		
	(0.6617)	(0.0000)			
FGI	-0.0250	0.0709	0.0159	1.0000	
	(0.3268)	(0.0054)	(0.5321)		
SGI	-0.0170	0.0557	0.0818	0.2149	1.0000
	(0.4842)	(0.0217)	(0.0007)	(0.0000)	

Panel D: PSI

	Premium	Max	FFR	FGI	SGI
Max	0.0758	1.0000			
	(0.0015)				
FFR	-0.0112	-0.2983	1.0000		
	(0.6371)	(0.0000)			
FGI	0.0163	0.1487	0.0159	1.0000	
	(0.5219)	(0.0000)	(0.5321)		
SGI	-0.0025	-0.0312	0.0818	0.2149	1.0000
	(0.9179)	(0.1989)	(0.0007)	(0.0000)	

Table C.2: VIX sorts

This table reports similar results to Table 5.3 but for VIX-sorted quartile subsamples. Corresponding VIX data is provided by Federal Reserve Bank of St. Louis. The sample period is from March 2017 to December 2023. Panel A reports the sorted results for the entire sample period, while Panel B and Panel C report similar results but for the period excluding the COVID and only for the COVID respectively.

	BDMI		BDMLCI		BDMXLCI		PSI	
	Unsclaed	RV-managed	Unsclaed	RV-managed	Unsclaed	RV-managed	Unsclaed	RV-managed
Panel A: March 2017 to December 2023								
Low	0.0059	0.0065	0.0051	0.0050	0.0068	0.0051	0.0001	0.0006
Q2	0.0008	-0.0008	0.0007	-0.0009	0.0010	-0.0014	0.0000	-0.0014
Q3	0.0024	0.0021	0.0024	0.0021	0.0028	0.0033	-0.0001	-0.0001
High	-0.0012	0.0011	-0.0011	0.0013	-0.0033	-0.0023	-0.0013	-0.0018
H-L	-0.0071	-0.0054	-0.0062	-0.0037	-0.0101	-0.0073	-0.0014	-0.0024
Panel B: Excluding January 2020 to December 2021								
Low	0.0082	0.0069	0.0071	0.0047	0.0099	0.0054	-0.0010	-0.0017
Q2	-0.0010	0.0017	-0.0011	0.0015	-0.0014	0.0006	0.0002	0.0007
Q3	0.0005	0.0003	0.0005	0.0005	-0.0005	-0.0018	-0.0006	-0.0014
High	-0.0040	-0.0047	-0.0039	-0.0046	-0.0058	-0.0076	-0.0013	-0.0025
H-L	-0.0122	-0.0116	-0.0110	-0.0094	-0.0157	-0.0130	-0.0002	-0.0008
Panel C: January 2020 to December 2021								
Low	0.0065	0.0052	0.0064	0.0051	0.0088	0.0074	0.0016	0.0014
Q2	0.0058	0.0040	0.0056	0.0037	0.0101	0.0063	-0.0002	0.0008
Q3	0.0051	0.0100	0.0053	0.0103	0.0023	0.0094	0.0022	0.0014
High	0.0005	0.0012	0.0006	0.0012	-0.0015	0.0010	-0.0017	-0.0010
H-L	-0.0060	-0.0040	-0.0058	-0.0039	-0.0102	-0.0064	-0.0033	-0.0024

TABLE C.3: VIX-sorted spanning regression

This table reports similar results to Table 5.4 but for VIX-sorted quartile subsamples. Panel B and Panel C report similar results to Panel A but for the period excluding the COVID and only for the COVID respectively. The appraisal ratio (AR) is computed by the ratio of alphas and regression errors. Both alphas and appraisal ratios are annualised. The coefficient standard errors are reported in parentheses. The superscript ***, **, and * indicate statistical significance at 1%, 5%, and 10% respectively.

	BDMI					BDMLCI					BDMXLCI					PSI				
	Low	Q2	Q3	High	Full sample	Low	Q2	Q3	High	Full sample	Low	Q2	Q3	High	Full sample	Low	Q2	Q3	High	Full sample
Panel A: March 2017 to December 2023																				
α	0.8392**	-0.3469	0.0554	0.4887	0.2251	0.5896*	-0.3630	0.0424	0.5255	0.1717	0.4980	-0.5708	0.2257	0.0556	0.0101	0.1334	-0.3394	-0.0213	-0.1638	-0.1262
	(0.3342)	(0.4056)	(0.4769)	(0.4087)	(0.2018)	(0.3024)	(0.4053)	(0.4828)	(0.4173)	(0.2009)	(0.3046)	(0.4810)	(0.5826)	(0.4786)	(0.2374)	(0.4231)	(0.2822)	(0.1859)	(0.1408)	(0.1373)
β	0.5362***	0.7410***	0.7974***	0.7164***	0.6855***	0.5262***	0.7389***	0.8026***	0.7257***	0.6853***	0.4552***	0.8487***	0.8423***	0.7463***	0.6867***	0.5256***	0.3480***	0.3412***	0.8536***	0.4596***
	(0.0259)	(0.0394)	(0.0442)	(0.0332)	(0.0174)	(0.0237)	(0.0394)	(0.0449)	(0.0339)	(0.0174)	(0.0187)	(0.0413)	(0.0452)	(0.0357)	(0.0173)	(0.0469)	(0.0379)	(0.0363)	(0.0450)	(0.0212)
Adjusted R^2	0.5001	0.4534	0.4322	0.5224	0.4696	0.5352	0.4521	0.4269	0.5181	0.4693	0.5798	0.4968	0.4482	0.5060	0.4713	0.2259	0.1636	0.1697	0.4576	0.2107
Appraisal Ratio, AR	1.9399	-0.6579	0.0894	0.9200	0.4223	1.5040	-0.6889	0.0676	0.9688	0.3235	1.2615	-0.9130	0.2981	0.0895	0.0161	0.2420	-0.9250	-0.0879	-0.8999	-0.3478
Panel B: Excluding January 2020 to December 2021																				
α	0.7658**	0.6133*	-0.0287	-0.3113	0.1337	0.3997	0.5908	-0.0030	-0.3118	0.0575	0.3674	0.4655	-0.3304	-0.4878	-0.2463	-0.3458	0.1027	-0.3150*	-0.1955*	-0.2110
	(0.3591)	(0.3694)	(0.5829)	(0.7086)	(0.2640)	(0.2678)	(0.3838)	(0.5844)	(0.7114)	(0.2604)	(0.3298)	(0.4099)	(0.6795)	(0.8119)	(0.3077)	(0.3943)	(0.4744)	(0.1848)	(0.1067)	(0.1764)
β	0.4657***	0.7378***	0.8944***	0.8722***	0.7031***	0.4470***	0.7495***	0.9044***	0.8744***	0.7003***	0.3981***	0.8564***	1.0054***	0.9822***	0.7080***	0.2969***	1.4132***	0.3182***	1.3413***	0.5389***
	(0.0253)	(0.0379)	(0.0579)	(0.0585)	(0.0226)	(0.0191)	(0.0394)	(0.0584)	(0.0588)	(0.0224)	(0.0181)	(0.0386)	(0.0596)	(0.0629)	(0.0226)	(0.0400)	(0.0885)	(0.0441)	(0.0633)	(0.0295)
Adjusted R^2	0.5293	0.5581	0.4423	0.4237	0.4383	0.6455	0.5464	0.4435	0.4223	0.4402	0.6148	0.6210	0.4860	0.4468	0.4414	0.1526	0.4586	0.1454	0.5982	0.2116
Appraisal Ratio, AR	1.9724	1.5224	-0.0452	-0.4034	0.2286	1.3767	1.4113	-0.0047	-0.4024	0.0998	1.0290	1.0412	-0.4456	-0.5533	-0.3613	-0.8029	0.1984	-1.5635	-1.7075	-0.5401
Panel C: January 2020 to December 2021																				
α	0.2411	0.2380	1.5218*	0.2326	0.4786*	0.2387	0.2127	1.5448*	0.2181	0.4760*	0.5445	0.3430	1.8953*	0.4755	0.6733**	0.2461	0.2069**	-0.2173	0.0104	0.1184
	(0.3040)	(0.2674)	(0.8487)	(0.5094)	(0.2664)	(0.3012)	(0.2639)	(0.9127)	(0.5110)	(0.2786)	(0.3441)	(0.3022)	(1.0339)	(0.6367)	(0.3269)	(0.3333)	(0.0838)	(0.5986)	(0.1867)	(0.1927)
β	0.6496***	0.5179***	0.7754***	0.5857***	0.6409***	0.6486***	0.5161***	0.7975***	0.5909***	0.6469***	0.5970***	0.4912***	0.8101***	0.6031***	0.6350***	0.2606***	0.1230***	1.0239***	0.6020***	0.3412***
	(0.0287)	(0.0224)	(0.0727)	(0.0428)	(0.0231)	(0.0284)	(0.0222)	(0.0782)	(0.0431)	(0.0242)	(0.0266)	(0.0205)	(0.0738)	(0.0473)	(0.0235)	(0.0279)	(0.0118)	(0.1147)	(0.0474)	(0.0255)
Adjusted R^2	0.8011	0.8111	0.4745	0.5980	0.5951	0.8037	0.8136	0.4520	0.5993	0.5769	0.7981	0.8226	0.4891	0.5642	0.5838	0.4042	0.4640	0.3862	0.5615	0.2547
Appraisal Ratio, AR	1.1308	1.2788	2.5616	0.6485	1.2534	1.1296	1.1573	2.4189	0.6061	1.1920	2.2623	1.6429	2.6051	1.0607	1.4365	1.0409	3.5218	-0.5183	0.0793	0.4271

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