Downside Risk and Volatility Dynamics in Financial Markets

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Certificate of Original Authorship

I, Alice Carole Thomas declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the School of Business (Finance Discipline Group) at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise reference or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

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Abstract

Adverse price movements in stock and energy markets threaten the stability and efficiency of financial markets. Devising more accurate risk measures is essential for protecting investment portfolios against these shocks. Energy futures markets have been shown to have volatility structures comparable to traditional stock markets, perhaps even more so after the financialization of commodities markets. Their interconnectedness means that macro-economic and energy-specific factors, through newly identified impact channels, can influence energy price.

The main contributions of this thesis include:

- *Forecasting with new measures of extreme downside risk – Chapter 2*. The first study proposes two alternative measures of stock-specific extreme downside risk, based on the downside realized semi-variances and cumulative returns. The suitability of these measures for improving the prediction of extreme downside risk is assessed against existing metrics in the literature. Their forecasting performance is evaluated by adopting a more industry-relevant forecasting horizon of one month. The proposed measures have better in-sample and out-of-sample forecasting performance. The performance of an investment strategy that precludes stocks with a high extreme downside risk is evaluated. Irrespective of the forecasting horizon, the new measures earn the highest risk-adjusted returns. This strategy may serve as a tool for fund managers to efficiently time the market.
- *The economic impact of daily volatility persistence on energy futures markets – Chapter 3*. The second study examines the role of daily volatility persistence in transmitting information from the macro-economy in the volatility of energy markets. Macro-economic factors, such as the VIX, the credit spread, and the Baltic Exchange Dirty Index, impact future volatility via the volatility persistence in crude oil markets. Conversely, the impact of these factors on the volatility persistence of natural gas markets is limited. There is also evidence that traditional market state variables, including returns and variances, are also transmitted to volatility via the volatility persistence channel. This variation in daily

volatility persistence is economically significant, contributing to a large proportion of future volatility. Based on the utility benefits of volatility forecasts, the volatility persistence-adjusted volatility models provide almost three times as much benefit to investors compared to competing volatility models, even after accounting for transaction costs and varying trading speeds. This chapter identifies a new transmission channel of macro-economic information in the volatility of energy markets with substantial economic impact in forecasting.

▷ *Liquidity provision channels and oil price volatility – Chapter 4*. The third study re-evaluates the role of hedgers and speculators as liquidity providers and their effects on weekly oil price volatility. By using two measures of hedging pressure that capture the liquidity provision by speculators and hedgers, hedging pressure driven by the speculators' liquidity provision decreases volatility, while hedging pressure induced by hedgers' liquidity provision increases volatility. Oil volatility tends to be more responsive to hedgers' short-term liquidity provision than variations induced by speculators' liquidity provisions. The liquidity provision by hedgers and speculators is significant determinant of volatility in inverted and normal markets with the effects being more pronounced in inverted markets. Further financial and business cycle risks have a measurable impact on how liquidity provision channels affect volatility. This chapter refines the role of hedgers and speculators in determining oil price volatility via two distinct liquidity provision channels with opposite effects on volatility.

CHAPTER 1

Introduction

1.1. Motivation and Literature Review

Effective risk assessment and management are essential for the accurate evaluation of financial risks and formation of robust models with practical relevance. This thesis focuses on three risk management topics related to the assessment of extreme downside risk in individual stocks, evaluation of the economic impact of volatility persistence on energy markets, and analysis of the relationship between liquidity provision channels and oil volatility.

1.1.1. Extreme downside risk. Single stock price crashes are events that remain widely misunderstood. These abrupt price declines are less common than expected and even when they do occur, it is mostly in times of crisis (e.g., the 2001 tech bubble and 2008 financial crisis). Hence, measures of extreme downside risk should reflect the fact that large stock price declines are sudden and, most importantly, infrequent. Accurately measuring extreme downside risk is crucial for a number of reasons. First, extreme downside risk can have a destabilizing effect on stock markets. It happens because adverse price movements in individual stocks can have a ripple effect on stock markets worldwide (Kim and Zhang (2014)). Second, extreme downside risk often has a negative impact on investors' portfolios and most certainly affects future risk management decisions (Ak et al. (2016)). It was apparent during the 2008 financial crisis when investment portfolios lost close to a third of their value.

The general concept behind extreme downside risk is rooted in the extreme value theory. In contrast, to the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1975), which does not differentiate between upside and downside betas (risks), the extreme value theory acknowledges that the normality and symmetric assumptions of stock returns are violated such that losses and gains are valued differently. The extreme downside risk explores the risk related to the extent of such losses. The economic mechanism behind the extreme downside risk is based on the premise that investors are homogeneous, that is they share the same opinion in pricing the underlying asset's fundamental value. Black (1976) and Christie (1982) argue that the leverage effect influences the extreme downside risk. The reasoning is that a decrease in stock prices raises both the operating and financial leverage of a firm, and hence increases the volatility of future returns. Another argument, referred to as the 'volatility feedback' mechanism, is that the impact of bad news in the market is amplified as investors reassess the market volatility and demand higher risk premium (Pindyck (1984), French et al. (1987), and Campbell and Hentschel (1992)). The stochastic bubble theory is also linked to the extreme downside risk. Blanchard and Watson (1982) argue that a market crash (or a collapsing bubble) is a rare event that ultimately causes large negative returns and more asymmetry in the return distribution. Hutton et al. (2009) introduce the concept of asymmetric information among firm managers. This unbalanced information structure leads managers to 'stockpile' bad news, and the sudden release of accumulated negative information causes a stock price crash.

Relaxing the assumption about investors' homogeneity (i.e., investors value the assets in their portfolios differently), Hong and Stein (1999) show that both constrained and unconstrained investors can affect extreme downside risk. The rationale is that constrained investors, those facing short selling restrictions, are driven out of the market. This prompts returns to be more negatively skewed, particularly after periods of heavy trading volume. Callen and Fang (2013) and Ak et al. (2016) argue that sophisticated investors (short sellers), who are better equipped to anticipate bad news that is not yet fully reflected in stock prices, have far less to lose when stock returns are skewed to the left. Hence, unsophisticated investors are the ones driving the extreme downside risk. The cumulative prospect theory of Barberis and Huang (2008) states that small probability events are overweighted, and thus, stocks with extreme negative returns have a greater chance of crashing in the future. The positive link between stocks at the left tail of return distribution and extreme downside risk is more persistent in a constrained financial environment with limited arbitrage and short selling (Miller (1977) and Shleifer and Vishny (1997)).[1]

[1]Two behavioural effects also explain the negative asymmetry in stock returns (Shleifer and Vishny (1997) and Hibbert et al. (2008)). First, the representativeness effect causes investors to link certain activities to their emotional states. Hence, activities with a negative affect are categorised as bad and vice versa for those with a positive affect. This ultimately influences investors' risk attitude. Second, the extrapolation bias leads investors to extrapolate past occurrences to determine future events. If investors experience negative returns, they are more likely to demand higher premiums.

A few metrics have tried to encapsulate the essence of extreme downside risk in the accounting and corporate finance literature. Earlier measures have employed the negative asymmetry of return distribution to proxy for the extreme downside risk (Chen et al. (2001) and Kim and Zhang (2014)). However, these measures are often sensitive to outliers and lack persistence (Chen et al. (2001)). Another measure of extreme downside risk, considering stock volatility during both the up jump and down crash days, can potentially overstate stock price crashes (Ak et al. (2016)). This makes them less efficient metrics. More recent measures have used sharp decline rather than slow decrease in stock prices to measure extreme downside risk. By not using a lower tail threshold, these measures are likely to understate the probability of stock price crashes (Bradshaw et al. (2010) and Ak et al. (2016)).

This study, therefore, proposes alternative measures. The new measures do not use the third moment (skewness), but rather the second moment (variance) to capture extreme downside risk. As mentioned by Man (2016), skewness is highly sensitive to outliers and other estimations, particularly the variance, and is statistically more robust. A limitation of skewness is that it has no or little persistence compared to the variance (Chen et al. (2001)). The extreme downside risk is also quantified using the cumulative returns instead of raw or actual returns.

1.1.2. Volatility persistence in energy futures markets. Energy markets, such as crude oil and natural gas, play an important role in the global economy, while the oil market's volatility is strongly associated with key sectors of the macro-economy (Chiang et al. (2015), Basak and Pavlova (2016), Aromi and Clements (2019), and Kang, Nikitopoulos and Prokopczuk (2020)). Moreover, the financialization of the commodity market has caused the size of energy markets, particularly crude oil, to skyrocket, from a volume of 20,000 futures contracts 10 years ago to almost 2 million contracts per day in recent times. Crude oil daily volatility was, on average, three times that of equity markets over the last decade. Therefore, managing risk exposures in energy markets is critical for many market participants, from fund managers and institutional investors and traders, to oil producers and consumers. Bollerslev et al. (2018) also show that many asset classes, including commodity futures, share similarities in volatility patterns. Energy markets, therefore, play an equally as important role in financial markets as other asset classes.

One of the key determinants of future volatility is its persistence, which is captured by the correlation between today's and tomorrow's volatility. Volatility persistence has been modeled and analyzed by several models, such as the autoregressive conditional heteroskedasticity (GARCH) and heterogeneous autoregressive model (HAR) models, with mixed empirical support on its nature and characteristics. A partial list of factors that explain volatility persistence includes volatility regime shifts (Lamoureux and Lastrapes (1994)), persistence of information arrivals (Laux and Ng (1993) and Andersen and Bollerslev (1997)), parameter uncertainty and investor learning (Brock and LeBaron (1996) and Johnson (2001)), heterogeneous trading frequencies (Müller et al. (1997) and Xue and Gençay (2012)), and investors' sensitivity to information (Liesenfeld (2001) and Berger et al. (2009)). As Bollerslev et al. (2018) state, the economic forces behind volatility clustering remain poorly understood. This echoes an observation by Diebold and Lopez (1995) that "a consensus economic model producing persistence in conditional variance does not exist." Goodhart and O'Hara (1997) note that "[P]erhaps the most serious problem of GARCH modeling is that we do not yet have a good theory to explain such persistence."

Most literature has failed to capture the dynamic features of volatility persistence, for example, the classical HAR model by Corsi (2009) assumes that volatility persistence is constant over time. By allowing volatility persistence to be time-varying, some studies show that specific market conditions can affect volatility persistence, particularly in equity markets. Patton and Sheppard (2015) and Bollerslev et al. (2016) demonstrate that volatility persistence is driven by the negative semivariance (i.e., the sum of squared negative intra-day returns) and measurement errors in daily volatility that reduce its information content. Wang and Yang (2018) also provide empirical evidence that specific market conditions, such as returns and volatility, can affect volatility persistence. The underlying mechanism is that if the unexpected shocks in these market conditions increase (decrease) volatility, this reflects more (less) priced information in the market and the arrival of new information is likely to be less (more) correlated suggesting lower (higher) volatility persistence (Ross (1989)). This study analyzes the importance of macro-economic factors – beyond the standard factors such as returns and volatility – in determining volatility persistence in energy markets.

There is also increasing evidence that accommodating macro-economic variables in economic models improves volatility forecasts, particularly in the crude oil market. These studies extend on the GARCH model to include macro-economic variables with mixed frequencies. Pan et al. (2017) use a GARCH-MIDAS (mixed-data sampling) model to show that macro-economic variables improve oil volatility forecasts, while macro-economic uncertainty is a strong predictor of volatility in energy markets (Bakas and Triantafyllou (2019)). Nonejad (2020) notes that the informational affinity between macro-economic variables and monthly oil volatility was stronger after 2008, while Nguyen and Walther (2020) focus on longer-term forecasting and use MIDAS to accommodate macro-economic variables at different frequencies. Emerging literature using high-frequency data analyzes short-term realized volatility forecasting in commodity markets (Degiannakis and Filis (2017), Zhang, Ma, Shi and Huang (2018), Degiannakis and Filis (2018), Ma et al. (2018), Prokopczuk et al. (2019), Alam et al. (2019), Luo et al. (2020), and Bissoondoyal-Bheenick et al. (2020)). Degiannakis and Filis (2017) demonstrate that stocks, Forex, commodities, and macro-economic information enhance the predictability of oil price volatility, and Degiannakis and Filis (2018) find predictive benefits in oil market volatility by using volatility and returns of financial markets. Alam et al. (2019) study sources of volatility asymmetries in the oil market and show that bad volatility dominates good volatility in terms of shock transmissions. Charles and Darnè (2014) filter out the impact of specific economic, political, and financial events from the crude oil return series and estimate the persistence of the corrected return series, while Andriosopoulos et al. (2017) estimate the energy volatility persistence with multiple macro-economic variables included in the variance equation. Although the two studies examine volatility persistence using GARCH type models, they do not allow volatility persistence to depend explicitly on known macro-economic variables. There is also growing literature on volatility forecasting that explores its utility benefits. This is because volatility forecasts presented on their own are often very difficult to interpret. By assuming there are varying transaction costs and trading speeds in the market, this reflects the fact that trading is costly and adversely affects traders' utility benefits (Gârleanu and Pedersen (2013), Gârleanu and Pedersen (2016), and Bollerslev et al. (2018)). This study, therefore, captures a relatively unexplored aspect of volatility forecasting, its economic significance, in energy markets.

By considering that volatility persistence and its determinants are priced factors in driving volatility, this study extends this concept in three directions. First, it analyzes the dynamic nature of volatility persistence in energy markets. Second, it identifies the macro-economic determinants of daily volatility persistence in energy markets. Third, this study assesses the economic significance of the new channels of macro-economic information, via volatility persistence, in determining volatility through various forecasting applications.

1.1.3. Liquidity provision channels in oil markets. Speculators are considered the traditional liquidity providers in the oil futures market. The theory of normal backwardation by Keynes (1930) and Hicks (1939) provides a clear explanation for why speculators use the oil futures markets. This theory postulates that as hedgers seek protection against price changes, they tend to hold short futures positions, while speculators engage in long futures positions and require compensation for bearing the risk. Then, the futures price trades below the expected future spot price, which implies an increasing trend in futures prices over time. As a result, on average, hedgers make losses and speculators make gains, which reflects their compensation for the risk. Hence, the trading behavior of both hedgers and speculators are likely to influence oil prices, as demonstrated by Hirshleifer (1988), Hirshleifer (1990), Bessembinder (1992), De Roon et al. (2000), Basu and Miffre (2013), and Bosch and Smimou (2022). Kang, Rouwenhorst and Tang (2020) have recently demonstrated that, in the short term, long hedgers earn higher returns than long speculators, implying that hedgers receive a risk premium as they become liquidity providers to satisfy trading demand from momentum traders (i.e., the speculators). This means that hedgers can also act as liquidity providers. Existing literature has focused primarily on exploring the relationship between hedging pressure and oil returns (Keynes (1930), Hicks (1939), and De Roon et al. (2000)) or risk premiums (Basu and Miffre (2013)). However, there is no empirical evidence that assesses the impact of these two liquidity provision channels, induced by speculators and hedgers, on oil price volatility.

The providers of liquidity in oil markets are usually the ones who dictate future oil price volatility. The market microstructure literature first demonstrates that market makers are rewarded with higher returns for providing liquidity to 'noninformational' traders in equity markets (Grossman and Miller (1988) and Campbell et al. (1993)). Recently, Kang, Rouwenhorst and Tang (2020) assess the profit/loss potential of three components of hedger activities, namely hedging demand, liquidity provision, and momentum trading. They find that the speculator's losses generated by their short-term momentum trading partly offsets the insurance premium earned, while hedgers benefit more from liquidity provision than momentum trading. They empirically demonstrate that hedgers can also act as liquidity providers. Hedgers and speculators have interchangeable roles as either market makers or 'noninformational' traders. While hedgers have traditionally been to known to consume liquidity and pay a premium to speculators to facilitate trade (Hirshleifer (1988), Hirshleifer (1990), and Bessembinder (1992)), hedgers become the liquidity providers in the short term and require a premium instead (Kang, Rouwenhorst and Tang (2020)). Furthermore, Anand et al. (2013) show that liquidity providers act as contrarians and decrease their trading positions after a positive return or premium. They provide evidence that liquidity providers decrease their trading positions after a price increase (positive return or premium). Similarly, Chang et al. (1997) demonstrate how trading positions and volatility are related, that is, higher trading position/volume, particularly for trading caused by investors' speculative motives, is associated with higher price volatility. Kahraman and Tookes (2017) also show that liquidity providers follow contrarian strategies implying that changes in trading positions are negatively related to stock returns.

This study tests the hypotheses that hedging pressure guided by trading driven by speculators', and hedgers' liquidity provision motives affect volatility but in opposite directions. Speculators are known to influence oil volatility in different ways. While De Long et al. (1990) show that irrational traders drive assets' prices away from its fundamental value, the rational arbitrageurs (fearing that the asset price will return to its fundamental value too slowly) drive volatility higher by reducing their trading positions. Hence, this study postulates that speculators, also, affect price volatility, particularly through their immediate demand for liquidity in the short term (Kang, Rouwenhorst and Tang (2020)), thereby, contradicting studies by Bryant et al. (2006) and Bohl and Stephan (2013) that indicate that speculators do not destabilize markets.

De Roon et al. (2000), Basu and Miffre (2013) and Bosch and Smimou (2022) have acknowledged that hedgers' demands for price insurance is highly influenced by the theory of normal backwardation. However, they fail to account for the contemporaneous effect of hedgers' short-term liquidity provision on volatility. This study, for first time, gauges the impact of liquidity provision channels on volatility under different oil market conditions. Oil futures markets have been attracting more financial traders with no interest in the physical commodity market since the financialization of commodity markets (Fattouh et al. (2013) and Büyükşahin and Robe (2014)). This implies that oil markets are highly responsive to equity-market uncertainty nowadays. While Bloom (2009) shows that uncertainty in equity market affecting hiring and investment indirectly influences the production decisions of oil-producing firms, Ajmi et al. (2015) argue that equity-market uncertainty, via economic policy uncertainty in the U.S, influences oil markets. This study provides evidence of yet another channel through which the equity-market uncertainty and/or recessionary pressure from the U.S, by interacting with the two liquidity provision channels, affect oil price volatility (Kang and Ratti (2013) and Antonakakis et al. (2014)).

1.2. Thesis Structure

This thesis consists of three studies that investigate downside risk and volatility dynamics in financial markets. The first study, presented in Chapter 2, proposes two new measures of extreme downside risk and assesses the performance of prediction models using a range of methods and metrics. The second study, covered in Chapter 3, identifies a new transmission channel of macro-economic information, via volatility persistence, in energy volatility and evaluates its forecasting and economic benefits. The final study, discussed in Chapter 4, analyzes the role of the liquidity provision induced by speculators and hedgers in determining oil volatility. Chapter 5 concludes and suggests directions for further research.

1.2.1. Forecasting with new measures of extreme downside risk. This study makes several contributions in the measurement and forecasting assessment of extreme downside risk. It begins by giving a general overview of existing extreme downside risk measures in the literature and introduces two new measures. The latter are built using exclusively the second moment of stock returns distribution in an attempt to make the new metrics more robust and efficient than their predecessors (Man (2016)).

Emulating the dynamic models in Harvey and Siddique (2000), Chen et al. (2001), Hutton et al. (2009), and Ak et al. (2016), this study predicts extreme downside risk six months ahead. We also adopt a more industry-relevant forecasting horizon of one month, an approach that has not been considered in the literature before. We then compare the out-of-sample forecasting performance of the new extreme downside risk measures with existing measures. The results reveal that the proposed measures have better predictive power over a shorter forecasting horizon. Another contribution of this study is that it develops an investment strategy based on the extreme downside risk measures introduced in Ak et al. (2016). The premise of this strategy is that stocks with the highest probability of crashing are shorted and the returns on portfolios (net of these stocks) are then estimated. We find that portfolios constructed using the new metrics as a benchmark are much more profitable than portfolios benchmarked on existing measures. This strategy serve as a diversification tool for portfolio managers to manage their risk, particularly in extreme market conditions.

1.2.2. The economic impact of daily volatility persistence on energy futures markets. This study proposes time-varying dynamics for daily volatility persistence, within the class of heterogeneous autoregressive models (Corsi (2009) and Sévi (2014)), and identifies the drivers of daily volatility persistence in the crude oil and natural gas markets. We test the hypothesis that macro-economic variables, together with known traditional market conditions such as returns and volatility (Wang and Yang (2018)), can impact daily volatility persistence in these markets. This study reveals significant statistical evidence that volatility persistence transmits macro-economic information to the volatility of energy markets. While credit spread, Baltic Index and VIX impact volatility persistence in the crude oil market, Treasury bill influences volatility persistence in the natural gas market.

This study also compares the out-of-sample forecasting performance of the volatility models accommodating information from the macro-economic variables with standard volatility models in the literature. The economic value of daily volatility forecasts are derived by estimating the average realized utility per unit of wealth in the energy markets (Bollerslev et al. (2018)). We also assess the sensitivity of realized utility to transaction costs and trading speeds in the market. The results show that for the volatility models accommodating information from macro-economic variables, the utility benefit to investors in oil markets can reach up to 160 basis points. To put this in a risk management perspective, this is a significant benefit that is marginally below the institutional fees typically required for active asset management.

1.2.3. Liquidity provision channels and oil price volatility. The contribution of this study is to present the effects of the liquidity provision by hedgers and speculators in determining crude oil volatility. This is achieved by disentangling the liquidity provision of speculators from the liquidity provision of hedgers by using two distinct measures of hedging pressure (Kang, Rouwenhorst and Tang (2020)). We describe two key results: First, in line with microstructure theory, hedging pressure induced by hedgers in the short term has a positive effect on volatility, while hedging pressure induced by speculators has an inverse relationship with volatility. Second, volatility is more responsive to hedgers' short-term liquidity provision.

This study recognizes the importance of the hedging pressure hypothesis by Hirshleifer (1990) and how the shape of future curve, representing either normal or inverted market, determines the demand for hedging. Specifically, it investigates the sensitivity of volatility to the liquidity provision channels in these two markets. It further assesses whether high/low market risk and economic boom/bust conditional on the two liquidity provision channels influence volatility. The results show that market risk and economic cycle, by affecting the propensity for either speculators or hedgers to provide liquidity, significantly impact oil volatility. This study reinforces the role of hedgers as insurance seekers, and most importantly, establishes the role of hedgers as liquidity providers in oil markets and evaluates the significance of these liquidity channels in determining volatility.

CHAPTER 2

Forecasting with New Measures of Extreme Downside Risk

2.1. Introduction

Extreme negative stock returns (events) are devastating, but because they are rare, we have little understanding of them. These events are usually considered to be unanticipated. The probability of extreme negative returns, across 3,000 U.S. firms, was around 2.5% during turbulent times in 2000 and 2008. However, this figure was revised downwards and stood at only 0.25% between 2000 and 2017.[1] Despite rare occurrences, sharp drops in stock prices can also have devastating effects on investors' portfolios. For instance, if someone had invested $1,000 in General Electric at the beginning of the century, they would be $10.7 million richer.[2] However, their investment could have doubled or tripled assuming the same investor avoided say its ten biggest stock price crashes at the time.[3] Moreover, the 2008 financial crisis not only caused investors' portfolios to drop by more than 30%, but also led to the collapse of financial institutions worldwide. Accurately measuring the extreme downside risk (EDR)[4], defined as the probability of sudden and infrequent large stock price decline, is essential.

This study presents two new measures that act as a substitute for capturing the probability of crashes in stocks. Specifically, we capture the EDR at the firm level (Chen et al. (2001), Kim and Zhang (2014), and Callen and Xiaohua (2015)) not at the market level (Amihud et al. (1990) and Schwert (1990)). A new class of volatility estimators proposed

[1]See Figure 2.1.1. Even when we randomly select five individual stocks (General Electric, Microsoft, CSX, Walmart, and Newmont Mining) representative of the top five industries in the sample, the probability of daily returns of less than -10% averaged only 1% over the last 17 years (See Figure 2.1.2). General Electric, Microsoft, CSX, Walmart, and Newmont Mining belong to manufacturing, services, transportation and public utilities, retail-trade, and mining industries, respectively.

[2]See https://www.fool.com/investing/2019/12/02/if-you-invested-1000-in-ges-ipo-this-is-how-much-m.aspx.

[3]The compounded cumulative monthly returns on General Electric stocks with (without) its ten biggest stock price crashes amounted to -1% (-10%) between 1980 and 2017.

[4]The terms 'extreme downside risk', 'crash risk', and 'tail risk' have been used interchangeably in earlier literature. However, in this study, we are referring to the probability of extreme negative stock returns as the extreme downside risk.

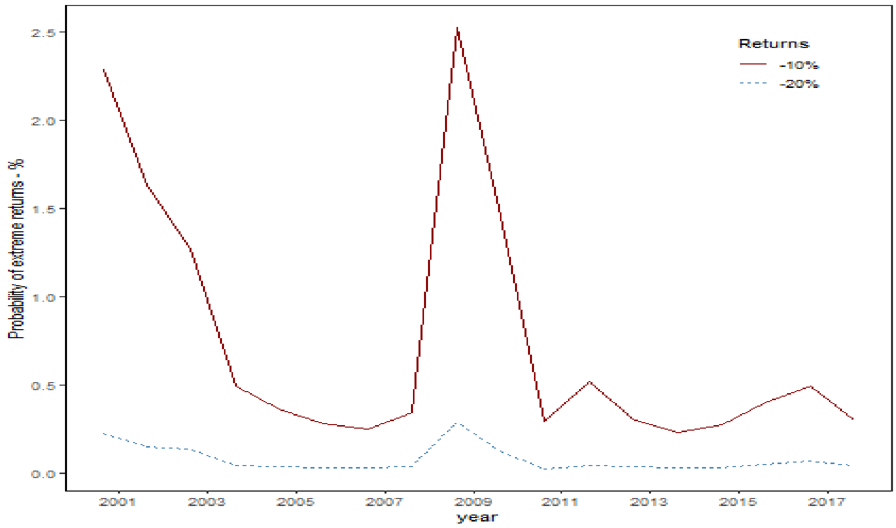


FIGURE 2.1.1. **Probability of Extreme Negative Returns in U.S. Stocks**

The figure shows the probability of daily returns of less than -10% and -20% in 3057 U.S. stocks between 2000 and 2017.

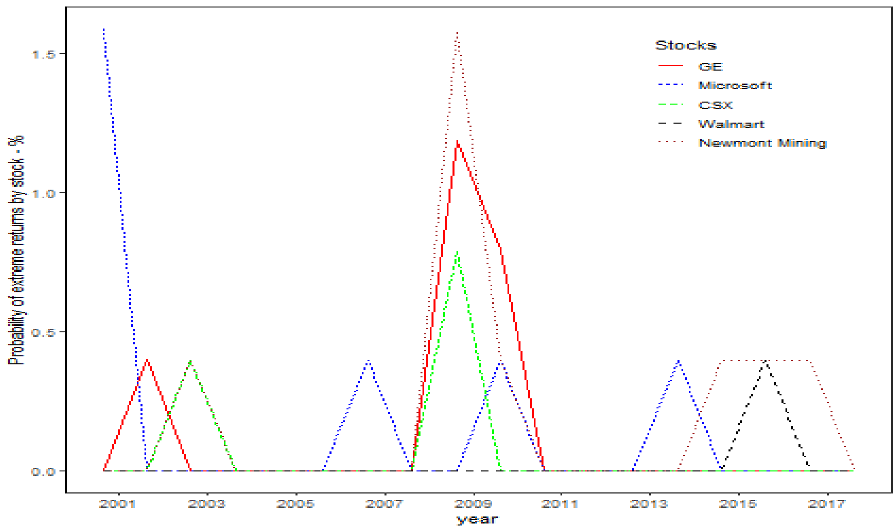


FIGURE 2.1.2. **Probability of Extreme Negative Returns for General Electric, Microsoft, CSX, Walmart, and Newmont Mining**

The figure shows the probability of daily returns of less than -10% for General Electric, Microsoft, CSX, Walmart, and Newmont Mining between 2000 and 2017. Each stock represents the top five industries (Manufacturing, services, transportation and public utilities, retail-trade, and mining) in the sample.

by Barndorff-Neilsen et al. (2010), namely the realized semivariance, disentangles the continuous-time volatility contributions from the contribution of positive and negative returns, and provides superior forecasting ability. Motivated by these findings, we propose a new measure of EDR based on the downside realized semivariance: the ratio of downside realized semivariance to realized variance (RDRS).[5] Further, we suggest a left tail risk measure based on the cumulative returns, the minimum cumulative return (MinCR), which better captures stock portfolio value and thus offers a more realistic reflection of EDR for portfolio managers.

The new EDR measures differ from existing measures in three ways. First, the new measures do not use higher-order moments to measure the thickness of the left tail. The appeal of the RDRS as a measure of EDR is its ability to forecast over a shorter horizon. Second, by introducing a predetermined threshold, we are looking at the most extreme negative returns. In comparison to existing EDR measures, adding a 'new threshold' to the new measure makes it closer to the true definition of an EDR. Thus, it reduces the likelihood of overstating the probability of crashes. Third, the proposed measure, the MinCR, offers a more conservative approach to defining EDR, that is, it measures how much an investor would have earned holding a stock.

Forecasting the EDR is important not only to academics, but also to practitioners. Since portfolio rebalancing occurs for most on a monthly basis, forecasting over a shorter horizon is deemed more realistic. We contribute to the growing literature using EDR measures to mitigate portfolio risk. This is acheived by introducing an investment strategy that builds portfolios benchmarked on these EDR measures. We then retrieve the return on investments for the stocks with the least EDR across the different portfolios.

We adopt a panel and time series approach to accurately identify external determinants of EDR. The purpose of these models is to effectively forecast the probability of crashes in individual U.S. stocks using the existing and new EDR measures. We show that the new EDR measures have better predictability than existing measures over one-month and six-month forecasting horizons. Large capitalization and high-returns stocks are the two external factors that have consistently increased the EDR over the last two decades.

We test the out-of-sample predictive accuracy of the new EDR measures against the existing measures over the two forecasting horizons. The results show that the new EDR measures are consistently outperforming the competing measures. We also assess whether

[5]The downside realized semivariance is commonly used as a measure of volatility within the market microstructure literature (Campbell and Hentschel (1992) and Patton and Sheppard (2015)).

their out-of-sample forecasting performance is sensitive to different market conditions, such as bear and bull markets. We find that the RDRS, forecasted six months ahead, has the most predictive accuracy, particularly under bearish (high volatility) market conditions. Similarly, the ability of the RDRS to correctly forecast the EDR one month ahead over existing EDR measures is not affected by these different market conditions.

We show that an investment strategy using high EDR stocks works best using the new EDR measures (RDRS and MinCR) as benchmarks. These portfolios, benchmarked on their in-sample and out-of-sample estimations, earn the highest returns and risk-adjusted returns over the two forecasting horizons. We find that this strategy is the most profitable, particularly when the new EDR measures are benchmarked on the in-sample estimations. For instance, the monthly return on the portfolio benchmarked on the new measures is twice as high, 12% versus 7%, as the portfolio benchmarked on the existing measures. The results for the monthly risk-adjusted returns are comparatively similar to the monthly returns estimations.

Many arguments have been proposed to explain the negative asymmetry of returns distribution. We acknowledge that the economic mechanism of EDR is driven by investors' behavior. Investors can either share the same opinion in pricing the underlying asset's fundamentals or value the assets in their portfolios differently. Black (1976) and Christie (1982) demonstrate that a drop in stock prices is more likely to increase the operating and financial leverage of firms and increase the volatility of future returns. Pindyck (1984), French et al. (1987), and Campbell and Hentschel (1992) show that the impact of bad news in the market is amplified as investors reassess market volatility and demand higher risk premiums, that is, the 'volatility feedback' mechanism. The asymmetric information among firm managers also leads them to 'stockpile' bad news, and the sudden release of accumulated negative information increases the EDR (Hutton et al. (2009)). Moreover, the cumulative prospect theory states that small probability events are overweighted, and thus, stocks with extreme negative returns have a greater chance of crashing in the future. This effect is the strongest in a constrained financial environment with limited arbitrage and short selling (Miller (1977), Shleifer and Vishny (1997), and Barberis and Huang (2008)). There is also an increasing amount of literature that has empirical tested whether the leverage effect, 'volatility feedback' mechanism, asymmetric information among firm managers, and cumulative prospect theory – the underlying economic mechanisms – help better explain stock price crashes (Harvey and Siddique (2000), Chen et al. (2001), Hutton et al. (2009), Kim and Zhang (2014), Callen and Xiaohua (2015), and Ak et al. (2016)).

We make several novel contributions on the measurement and forecasting assessment of EDR measures. There are four non-parametric measures, namely the negative conditional skewness (NCSKEW), down-to-up volatility (DUVOL), extreme sigma (EXSIGMA), and modified binary crash risk (MCRASH) measures, that are used to capture EDR in the accounting and corporate finance literature. The fat left tail measure NCSKEW captures the negative asymmetry in stock returns via the third moment of the return distribution (Chen et al. (2001) and Kim and Zhang (2014)). Compared to other measures, it captures the less extreme negative stock returns. Among the shortcomings of this measure is that skewness is sensitive to outliers, and other estimations (the second moment) are statistically more robust. Higher frequency data (as opposed to lower frequency data), collected on returns are more likely to capture the full effect of skewness (Man (2016)). The jump tail risk measure DUVOL considers the stock volatility during both the up jump and down crash days, but like the NCSKEW, lacks forecasting accuracy (Chen et al. (2001)). Bradshaw et al. (2010) and Ak et al. (2016) use minimum average returns to construct EDR measures, namely the EXSIGMA and MCRASH, respectively. The EXSIGMA favors sharp decline rather than slow decrease in stock prices, while MCRASH uses past returns to identify crashes (Bradshaw et al. (2010) and Ak et al. (2016)). However, the EXSIGMA and MCRASH do not have a lower tail threshold, thereby potentially understating the probability of stock price crashes.[6] We add to this literature by providing two alternative EDR measures that have better forecasting accuracy than the existing measures.

We also consider a more realistic forecasting horizon to detect crashes, to account for the fact that most investment portfolios are revised over shorter periods of time. Previous studies have focused on a longer forecasting horizon (Chen et al. (2001) and Ak et al. (2016)). Assessing the predictive accuracy of the existing and proposed EDR measures via out-of-sample testing reflects more 'real time' information. We provide further evidence that the EDR measures can act as benchmark to efficiently time the market by extending on the work of Bali et al. (2011) and Ak et al. (2016).

[6]Even though we are looking at continuous measures of EDR in this study, we acknowledge the Hutton et al. (2009) binary measure used in the literature.

The rest of the study is organized as follows. Section 2.2 describes the EDR measures, and proposes two new EDR measures. The data and preliminary analysis are presented in Section 2.3. In Section 2.4, we forecast the EDR and discuss the empirical results. Section 2.5 evaluates the performance of an investment strategy that avoids high EDR stocks. Section 2.6 presents some robustness tests, and Section 2.7 concludes the analysis.

2.2. Measuring Extreme Downside Risk

In this section, the economic mechanism behind measuring the EDR is explained, an account of existing EDR measures is discussed, and two new EDR measures are introduced.

2.2.1. Existing EDR measures.

2.2.1.1. *Negative conditional skewness (NCSKEW).* NCSKEW, the most widely used measures of EDR, is estimated by dividing the negative of the third moment of daily returns by its standard deviation, raised to the power of three (Chen et al. (2001)). It measures the conditional skewness caused by several less extreme negative returns. The NCSKEW, in other words, captures the fat left tail risk. Scaling NCSKEW by its standard deviation standardizes the EDR measure (Greene (1993)), and therefore allows the comparison across stocks with different variances. From a statistical standpoint, this measure estimates how many standard deviations the sample skewness is from zero. The addition of a negative sign to the third moment indicates that stocks with a more left-skewed distribution are more crash prone. A critique of this measure is that it eliminates stocks with longer tails, particularly those experiencing very extreme returns (Kim and Zhang (2014)). Henceforth, the negative conditional skewness ($NCSKEW_{i,\tau}$) for stock i in period τ for each sample year is given by:

$$NCSKEW_{i,\tau} = -\frac{\left[n\left(n-1\right)^{\frac{3}{2}}\sum r_{i,\tau}^{3}\right]}{\left[\left(n-1\right)\left(n-2\right)\left(\sum r_{i,\tau}^{2}\right)^{\frac{3}{2}}\right]}, \tag{2.2.1}$$

where $r_{i,\tau}$ is calculated by taking the stock i's daily returns and subtracting their mean returns over period τ, n is the number of observations in period τ, and τ represents a monthly and semi-annual sampling frequency. We use a similar approach to Chen et al. (2001) to quantify $r_{i,\tau}$, where the daily returns for each stock are aggregated to form semi-annual and monthly EDR measures. This differs from Hutton et al. (2009), who construct an annual EDR measure aggregated using weekly returns. Within the EDR literature, two approaches are normally used to estimate EDR returns: raw and firm-specific returns. Firm-specific returns are measured from the market model's residuals (Hutton et al. (2009)). Compared to using the raw returns, the expanded market model accounts for firm-specific factors instead of the broad market movement. We use the raw returns to minimize forecasting errors in the EDR measures. Hence, the higher the value of NCKSEW, the higher the probability of a stock crash.

2.2.1.2. *Down-to-up volatility (DUVOL).* The DUVOL is estimated by taking the logarithm of the ratio of the standard deviation on the 'down days' to the standard deviation on the 'up days' (Chen et al. (2001)). For any stock i over period τ, the down days refers to days with period τ returns below their period τ mean down days, and up days are those with returns above their period τ mean up days. Statistically, DUVOL is regarded as a jump tail risk measure. Thus, the down-to-up volatility ($DUVOL_{i,\tau}$) for stock i in period τ for each sample year is given by:

$$DUVOL_{i,\tau} = \log\left[\frac{(n_u - 1)\sum_{\text{DOWN}} r_{i,\tau}^2}{(n_d - 1)\sum_{\text{UP}} r_{i,\tau}^2}\right], \tag{2.2.2}$$

where n_u and n_d are the number of up and down days, respectively. Like the NCSKEW measure, high DUVOL is associated with high EDR. This measure, compared to the NCSKEW, considers both the up jump and down crash days (Ak et al. (2016)). Therefore, it can potentially understate the EDR.

2.2.1.3. *Extreme sigma (EXSIGMA).* Another EDR measure, EXSIGMA, estimates how many standard deviations the worst daily returns fall below their mean period τ returns (Bradshaw et al. (2010)). In contrast to the Hutton et al. (2009) binary EDR measure, extreme sigma (left tail risk measure) gives the magnitude of the EDR. Hence, the EXSIGMA for stock i in period τ for each sample year and is given by:

$$EXSIGMA_{i,\,\tau} = -\text{Min}\left[\frac{r_{i,\tau}}{\sqrt{\sum (r_{i,\tau})^2 / (n-1)}}\right]. \tag{2.2.3}$$

A high $EXSIGMA_{i,\,\tau}$ means there is a greater chance of stock i crashing in period τ. The EXSIGMA favors sharp decline rather than slow decrease in stock prices.

2.2.1.4. *Modified binary crash risk measure (MCRASH).* The MCRASH is defined as the negative ratio of the minimum daily returns in the current period τ to the standard deviation of the daily returns in the previous period $\tau - 1$ (Hutton et al. (2009) and Ak et al. (2016)). By using the past return variation to quantify the probability of EDR, this measure addresses the central limitation of the three EDR measures (NCSKEW, DUVOL, and EXSIGMA). The latter identifies crashes based on the actual distribution of returns, that is, the post-crash return distribution. The modified binary crash risk measure ($MCRASH_{i,\tau}$) for stock i in period τ for each sample year is given by:

$$MCRASH_{i,\tau} = \frac{-\text{Min}\left(r_{i,\tau}\right)}{\sqrt{\sum\left(r_{i,\tau-1}\right)^2 / \left(n-1\right)}}. \tag{2.2.4}$$

Similar to the aforementioned measures, the higher the MCRASH, the higher the EDR. One concern regarding EXSIGMA and MCRASH is that they may overstate the probability of EDR. The minimum return in the period τ is not necessarily an 'extreme return'.

2.2.2. New EDR measures. This study proposes two measures that act as a substitute for capturing the EDR. The likelihood of crashes is estimated using two approaches: the ratio of the downside realized semivariance to the realized variance (RDRS) and the minimum cumulative return (MinCR).

Earlier studies, including the study by Campbell and Hentschel (1992), have argued that volatility tends to increase slowly but decrease quickly in the volatility feedback model. Patton and Sheppard (2015) separate realized semivariance into upside and downside realized semivariance (from which the first new EDR measure emanates). They demonstrate empirically that downside realized semivariance is a better predictor of future volatility. While the downside realized semivariance is a volatility estimator, it also measures the left tail risk and/or EDR, making it an ideal candidate for estimating and forecasting the EDR. The MinCR is another tentative EDR measure. It focuses on the worst returns estimated cumulatively through the estimation period. MinCR shows how much an investor should have earned holding a stock. EXSIGMA and MCRASH use the minimum average return to compute EDR. The proposed measure, by looking at the cumulative returns, offers a more realistic definition of EDR for portfolio managers.

2.2.2.1. *Ratio of downside realized semivariance to realized variance (RDRS).* One of the new EDR measures is the ratio of downside realized semivariance to realized variance. Downside realized semivariance (DRS) measures the return variation below a predetermined benchmark/threshold (Barndorff-Neilsen et al. (2010)). Hence, the $DRS_{i,\tau}$ for stock i in period τ is estimated as:

$$DRS_{i,\tau} = \sum\nolimits_{j=1}^{n} r_{i,j}^2 I \left\{ r_{i,j} < \text{Cut-off}_k \right\}, \tag{2.2.5}$$

where n represents the total number of daily returns in each period τ. Instead of using a cut-off of 0, as in Barndorff-Neilsen et al. (2010), we introduce a lower threshold to accurately identify the 'extreme' negative returns. For the monthly measure, k represents a cut-off of -1% and -2%, while for the semi-annual measure, k stands for -3% and -4%.[7] There is, however, a trade-off between this cut-off and frequency of negative returns detected per period τ. For instance, a threshold lower than -4% detects fewer negative returns and vice versa for a higher threshold. DRS is scaled by realized variance (RV) to ensure the standardization of the EDR measure and is denoted by $RDRS_{i,\tau}$. Hence, the realized variance ($RV_{i,\tau}$) and the ratio of downside realized semivariance to realized variance ($RDRS_{i,\tau}$) for stock i in period τ for each sample year are given by:

$$RV_{i,\tau} = \sum\nolimits_{j=1}^{n} r_{i,j}^2 \tag{2.2.6}$$

and

$$RDRS_{i,\tau} = \frac{\text{DRS}_{i,\tau}}{\text{RV}_{i,\tau}}. \tag{2.2.7}$$

2.2.2.2. *Minimum cumulative return (MinCR).* We propose another EDR measure, which we call the minimum cumulative return. This measure does not consider the worst return in each period τ, as in EXSIGMA (Bradshaw et al. (2010)) and MCRASH (Ak et al. (2016)), but the minimum cumulative return. Statistically, the cumulative return represents the overall performance of the stock over the period τ, that is, how much an investor should have earned holding the stock. Thus, the minimum cumulative return

[7]For the monthly measure, a cut-off of 1% and 2% represent roughly 30% and 17% of the observations on daily returns in the sample, respectively. While for the semi-annual measure, a cut-off of 3% and 4% represent approximately 10% and 7% of the observations on daily returns in the sample, respectively. Compared to the other EDR measures, the returns $r_{i,\tau}$ are not demeaned.

($MinCR_{i,\tau}$) for stock i in period τ for each sample year and is given by:

$$MinCR_{i,\tau} = \left[\frac{-\text{Min}\left(\sum r^C_{i,\tau}\right)}{\sqrt{\sum \left(r^C_{i,\tau} - \bar{r}^C_{i,\tau}\right)^2 / (n-1)}} \right], \tag{2.2.8}$$

where $r^C_{i,\tau}$ is stock i's daily cumulative return in period τ, and $\bar{r}^C_{i,\tau}$ is the sample mean of the daily cumulative return in period τ. The higher the RDRS and MinCR, higher the probability of a stock price crash.

2.3. Data and Preliminary Analysis

2.3.1. Individual stocks. The sample consists of daily returns on NYSE, AMEX, and NASDAQ stocks, collected from the Center for Research in Security Prices' (CRSP) daily files. Firm-level accounting data is retrieved from CRSP/Compustat Merged annual and monthly files. The sample period starts on January 2000 and ends on December 2017. Excluded from this data set are stocks with SIC codes of 6000–6999 (financial stocks) and 4900–4999 (utility stocks). As explained by Fama and French (1992), financial stocks, compared to non-financial stocks, have high leverage which does not automatically indicate distress. Their exclusion ensures that the results are not skewed. In order to lessen the thin trading concern and improve the accuracy of the out-of-sample forecasts, only stocks with at least 96 months of data are included in the sample. Stocks with fewer trading months are subject to higher ups and downs in their share prices (Habib and Hasan (2017)). For the same reason, stocks with a yearly share price lower than \$1 are excluded (Kim et al. (2011)).

Manufacturing entities make up close to 50% of total stocks in the sample while the rest are divided among these industries: services (21%), transportation and public utilities (9%), retail trade (7%), mining (6%) and others (7%). While largecap stocks constitute close to 73% of the average market capitalization over the sample period, they represent only 9% of the total stocks.[8] Most stocks are smallcap that make up 4% of the total market capitalization (Table 2.3.1).

[8]Stocks with a market capitalisation above \$10 billion, between \$1 billion and \$10 billion and below \$1 billion are classified as largecap, midcap and smallcap, respectively.

TABLE 2.3.1. **Distribution of Stocks**

Panel A: Percentage of stocks by industry

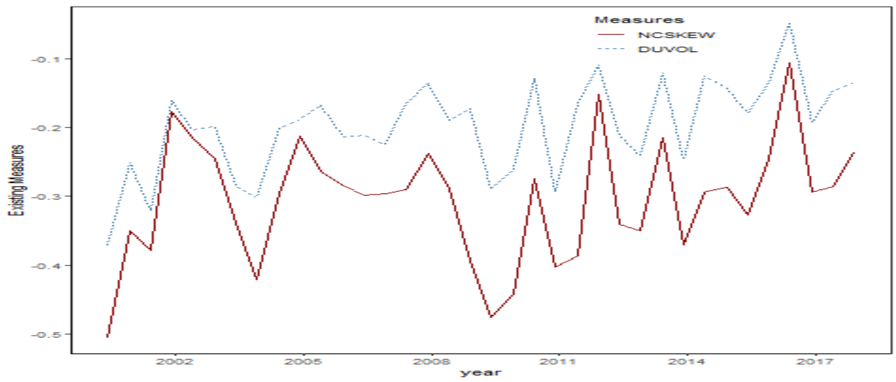
	Number of Stocks
Manufacturing	49.36%
Services	20.97%
Transportation and Public Utilities	8.83%
Retail-Trade	7.07%
Mining	6.87%
Wholesale-Trade	5.14%
Construction	1.67%
Other	0.10%

Panel B: Percentage of stocks by market capitalisation (size)

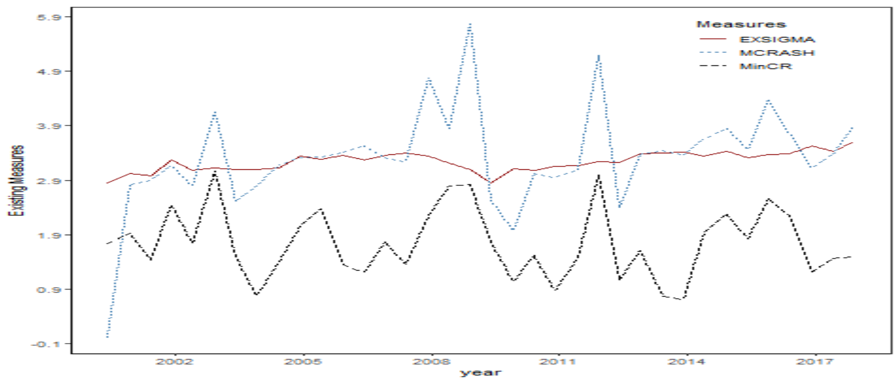
	Size ($ billion)	Size (%)	Nº stocks	Nº stocks (%)
Largecap	10,315	72.48%	272	8.90%
Midcap	3,318	23.32%	1035	33.86%
Smallcap	598	4.20%	1750	57.25%

This table provides details on the distribution of 3057 U.S. stocks from January 2000 to December 2017. Panel A presents the percentage of stocks categorised by industry. Stocks in the sample are grouped based on their first 2-digit Standard Industrial Classification (SIC) codes. Panel B categorizes stocks in the sample by market capitalisation. Total market capitalisation of all stocks is $14,231 billion. Largecap are stocks with a market capitalisation exceeding $10 billion. Midcap are stocks with a market capitalisation between $1 billion and $10 billion. Smallcap are stocks with a market capitalisation below $1 billion.

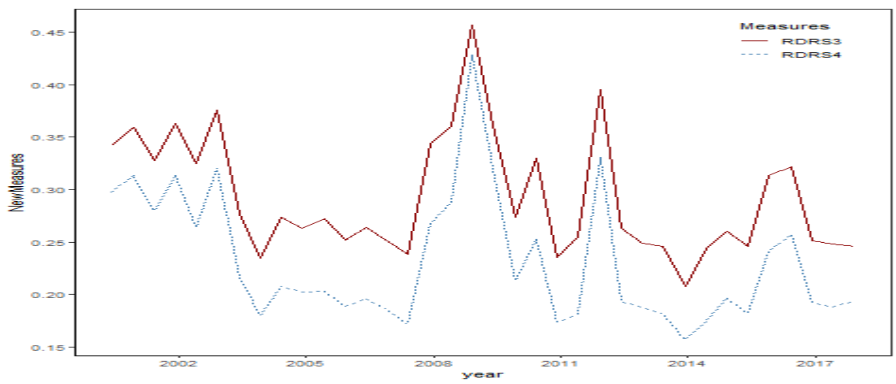
2.3.2. EDR measures. The time series of the EDR measures (NCSKEW, DUVOL, EXSIGMA, MCRASH, MinCR, and RDRS), averaged over six months, are depicted in Figure 2.3.1. They show how the measures can identify months with high and low EDR between 2000 and 2017. We observe that the time series of the new EDR measures, particularly the RDRS, correctly identify the Global Financial Crisis (GFC) crisis as a high EDR period. The existing EDR measures (NCSKEW, DUVOL, EXSIGMA, and MCRASH) potentially overstate EDR since they detect a larger number of high EDR months during relatively calm periods. Similarly, the time series of EXSIGMA failed to detect the high EDR period of 2008, experiencing instead its sharpest drop from 2008 to 2009. When aggregated over one month, the time series of EDR measures are much more volatile in comparison to their time series averaged over six months, as depicted in



(A) NCSKEW and DUVOL



(B) EXSIGMA, MCRASH and MinCR



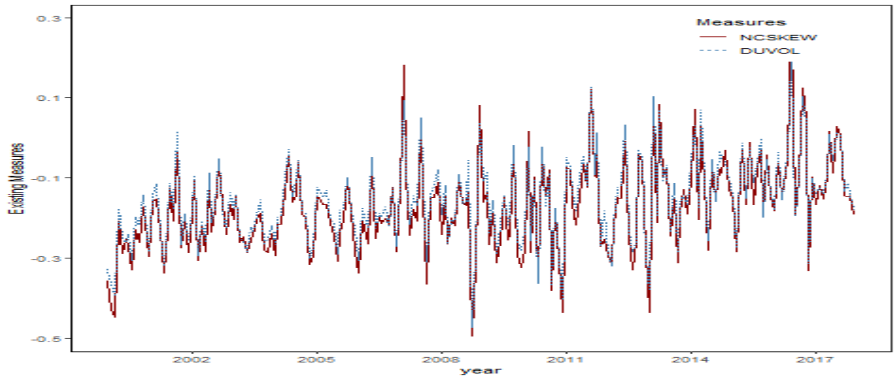
(C) RDRS3% and RDRS4%

FIGURE 2.3.1. **Semi-annual EDR Measures**

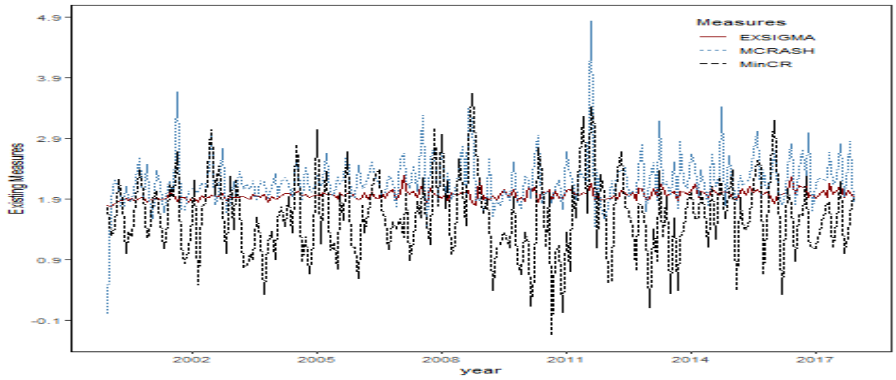
The figure shows the time series of NCSKEW, DUVOL, EXSIGMA, MCRASH, MinCR, RDRS3%, and RDRS4% sampled over six months between 2000 and 2017.

Figure 2.3.2. This is probably because the monthly EDR measures experience much more seasonal effects (month of the year effect).[9]

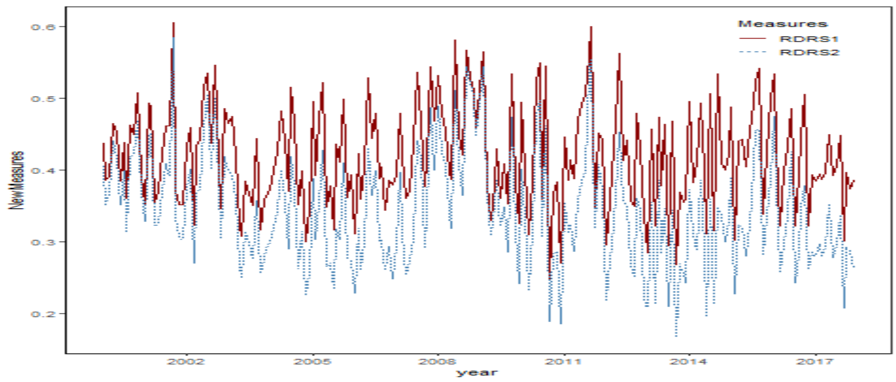
[9]We detailed how we deal with seasonality in the monthly EDR measures in Section 2.4.



(A) NCSKEW and DUVOL



(B) EXSIGMA, MCRASH and MinCR



(C) RDRS1% and RDRS2%

FIGURE 2.3.2. **Monthly EDR Measures**
The figure shows the time series of NCSKEW, DUVOL, EXSIGMA, MCRASH, MinCR, RDRS1%, and RDRS2% sampled over one month between 2000 and 2017.

Panel B of Table 2.3.2 shows the descriptive statistics of EDR measures estimated over one month and six month. The mean values of NCSKEW and DUVOL estimated over six months are negative, at -0.33 and -0.21, respectively. This is comparable to the averages reported by Chen et al. (2001) and Ak et al. (2016), and means that large positive events tend to outweigh negative ones. The mean values of the one-month averaged NCSKEW and DUVOL are higher than their six-month counterparts, implying that the monthly metrics are more crash prone. NCSKEW is, in general, more volatile than DUVOL. The volatility of NCSKEW is reduced when averaged over one month, while that of DUVOL is more persistent. The sample mean of EXSIGMA is 3.24, which indicates that the worst six-month returns are 3.24 standard deviations below the mean. The mean value of MCRASH is close to the EXSIGMA average. Compared to NCSKEW and DUVOL, the means and standard deviations of EXSIGMA and MCRASH averaged over one month are lower. In general, existing EDR measures, when averaged over one month, have much less variation, suggesting more persistence. Of the four existing EDR measures, MCRASH has the highest volatility throughout.

We find that a higher cut-off tend to reduce the mean value of the RDRS measures, that is, it decreases the probability of stock price crash. For instance, when averaged over six months, RDRS3% and RDRS4% have means of 0.30 and 0.24, respectively. While EXSIGMA and MCRASH all look at the minimum return within a six-month period, the MinCR considers instead the cumulative return. Thus, its mean/median values are lower than the EXSIGMA and MCRASH averages. The mean of the one-month MinCR measure is comparable to its six-month average. Based on the Ljung-Box test, the individual EDR measures have no serial autocorrelation over one month and six months. The Ljung-Box test, based on two lags (τ), is estimated for each stock and averaged throughout. However, we are not only relying on the past values of the EDR measures to determine future EDR. Different forecasting variables are also added to the forecasting models, as detailed in the next section.

2.3.3. Forecasting variables. According to Chen et al. (2001) and Zhu (2016), stock returns, stock volatility, stock value, and the intensity of disagreement among investor have a time-varying influence on EDR measures. Specifically, they are linked to the stochastic bubble theory, which predicts that a bubble built up causes the overinflation of stock prices and their eventual collapse. For instance, high returns and low volatility predict higher future EDR (Chen et al. (2001)). Due to their mispricing in the market, glamor stocks (those with low book-to-market value ratios) usually have a high EDR.

TABLE 2.3.2. **Statistics of Selected Variables**

Panel A: Description of forecasting variables

RET_{τ}	Mean of the daily returns at time τ, multiply by 100
SD_{τ}	Standard deviation of the daily returns at time τ
BM_{τ}	Total common/ordinary equity divided by market value of equity at time τ
$SIZE_{\tau}$	Log of the close market price times the common shares outstanding at time τ
$TURN_{\tau}$	Share turnover at time τ minus the share turnover at time $\tau - 1$ where turnover is calculated as the trading volume divided by the total number of shares outstanding at time τ
$FLEV_{\tau}$	Total long-term debt divided by total assets at time τ
ROA_{τ}	Net income divided by total assets at time τ
SI_{τ}	Number of shares sold short divided by total shares outstanding (sum of common shares outstanding, redeemable preference shares outstanding and non-redeemable preference shares outstanding) at time τ

Panel B: Descriptive statistics

	mean		st. dev.		median		Ljung-Box	
	1MTH	6MTH	1MTH	6MTH	1MTH	6MTH	1MTH	6MTH
EDR measures								
RDRS1%	0.423		0.215		0.416		0.275	
RDRS2%	0.348		0.224		0.333		0.175	
RDRS3%		0.298		0.146		0.293		0.246
RDRS4%		0.237		0.149		0.223		0.249
MinCR	1.971	1.764	0.600	1.497	1.902	1.555	0.301	0.391
NCSKEW	-0.184	-0.328	0.963	1.267	-0.155	-0.253	0.447	0.484
DUVOL	-0.166	-0.211	0.793	0.536	-0.148	-0.184	0.454	0.470
EXSIGMA	1.995	3.238	0.590	1.218	1.917	2.967	0.291	0.310
MCRASH	2.206	3.337	1.588	2.194	1.841	2.837	0.031	0.354
Forecasting variables								
RET	0.071	0.074	0.696	0.284	0.055	0.066	0.324	0.450
SD	0.029	0.030	0.018	0.015	0.024	0.027	0.001	0.019
TURN	0.000	0.002	0.082	0.063	-0.001	0.000	0.003	0.313
BM	0.585	0.546	2.574	1.590	0.516	0.516	0.000	0.005
FLEV	0.472	0.484	0.147	0.137	0.451	0.470	0.000	0.006
SIZE	6.541	6.472	0.844	1.012	6.650	6.639	0.000	0.012
ROA	0.012	0.012	0.124	0.114	0.018	0.018	0.015	0.031
SI	0.341	0.315	0.375	0.319	0.197	0.190	0.001	0.016

This table provides a description of the forecasting variables and details on the descriptive statistics of selected variables from January 2000 to December 2017. Panel A provides details on how the forecasting variables are estimated. Accounting variables such as the total long-term debt, total assets, total long-term debt, net income, common shares outstanding, redeemable preference shares outstanding, and non-redeemable preference shares outstanding are collected at a quarterly frequency from CRSP/Compustat. For the accounting variables collected quarterly, we set the same value for the three months of a quarter. τ represents a monthly (1MTH) and semi-annual (6MTH) sampling frequency. Panel B provides details on the statistical properties of selected variables. The variables are averaged across stocks, aggregated over one month (1MTH) and six month (6MTH). The p-values of the Ljung-Box test at lags 2 are reported.

Chen et al. (2001) also argue that high intensity of disagreement among investors (proxied by the detrended turnover) increases the probability of individual stocks crashing in future periods.

Stock size, degree of financial leverage, stock profitability, and short interest are four forecasting variables employed in this study to account for the firm-fixed effect. According to Chen et al. (2001), stock size is likely to increase future EDR. Large stocks face more public scrutiny, and the release of bad news in the market causes price shocks that create more uncertainty (Callen and Xiaohua (2015)). Black (1976), Christie (1982), and Callen and Xiaohua (2015) argue that a rise in financial leverage increases stock return volatility, and subsequently, future EDR. In contrast, Hutton et al. (2009) observe that stocks with high EDR have higher levels of indebtedness. They find that the stocks' operating performance is also known to negatively impact EDR. Therefore, stocks with poor profitability ratios have greater a chance of crashing. Ak et al. (2016) show that the presence of short sellers in the market increases the probability of stock price crashes. Accordingly, we include the stock's returns (RET), volatility (SD), value (BM), size (SIZE), volume (TURN), financial leverage (FLEV), profitability (ROA), and short interest (SI) as variables that aid in forecasting EDR. We provide a detailed description of the eight forecasting variables in Panel A of Table 2.3.2.[10]

2.3.4. Contemporaneous correlation. The contemporaneous correlation between the EDR measures and forecasting variables averaged across stocks, aggregated over six months and one month, are tabulated in Panels A and B of Table 2.3.3, respectively. Looking at the six-month averages, the NCSKEW–DUVOL pair of EDR measures has the highest cross-correlation (above 0.90). As noted by Chen et al. (2001), the two measures essentially reveal the same information. MCRASH has the lowest correlation (below 0.45) with the existing EDR measures (NCSKEW and DUVOL). This is probably because MCRASH is the only EDR metric looking at past returns variation. Since EXSIGMA and MCRASH share the same statistical properties, they also have a positive cross-correlation of 0.72. The strong positive contemporaneous correlation across the existing EDR measures is not lost when averaged over one month.

[10]The descriptive statistics of the forecasting variables are reported in Panel B of Table 2.3.2. The mean values of the forecasting variables namely the six-month returns, volatility and volume, are comparable to the averages reported by Chen et al. (2001), while financial leverage has similar average to Callen and Xiaohua (2015). Value and size have lower and higher mean values, respectively compared to the Chen et al. (2001) averages. The mean values of short interest and profitability differ to the statistics reported in Callen and Xiaohua (2015). Profitability and short interest have comparatively lower and higher mean values, respectively. Short interest and profitability are averaged over a year in Callen and Xiaohua (2015), this might explain why their mean values differ. Since most accounting variables are collected quarterly, the descriptive statistics of the one-month and six-month averages of the forecasting variables are very similar. Most of the forecasting variables are serially autocorrelated based on the Ljung-Box test.

TABLE 2.3.3. **Contemporaneous Correlation**

Panel A: Contemporaneous correlations of variables averaged over 3057 stocks and aggregated over six months

	EDR measures						
	NCSKEW	DUVOL	EXSIGMA	MCRASH	RDRS3%	RDRS4%	MinCR
EDR measures							
NCSKEW							
DUVOL	0.898						
EXSIGMA	0.645	0.564					
MCRASH	0.413	0.363	0.722				
RDRS3%	0.523	0.503	0.600	0.524			
RDRS4%	0.480	0.444	0.594	0.541	0.959		
MinCR	0.253	0.302	0.272	0.288	0.515	0.463	
Forecasting variables							
RET	-0.350	-0.425	-0.237	-0.258	-0.437	-0.392	-0.606
SD	-0.230	-0.274	0.032	0.206	0.440	0.513	0.141
TURN	-0.044	-0.055	0.027	0.153	0.029	0.041	-0.019
BM	-0.001	-0.001	-0.002	-0.001	0.001	0.001	0.000
FLEV	0.001	0.006	0.010	0.024	-0.022	-0.020	-0.006
SIZE	0.106	0.145	0.109	0.076	-0.148	-0.187	-0.008
ROA	0.009	0.012	0.012	0.009	-0.006	-0.009	0.000
SI	0.001	0.002	-0.002	-0.002	-0.017	-0.015	0.000

Panel B: Contemporaneous correlation of variables averaged over 3057 stocks and aggregated over one month

	EDR measures						
	NCSKEW	DUVOL	EXSIGMA	MCRASH	RDRS1%	RDRS2%	MinCR
EDR measures							
NCSKEW							
DUVOL	0.916						
EXSIGMA	0.738	0.654					
MCRASH	0.404	0.351	0.580				
RDRS1%	0.646	0.645	0.640	0.383			
RDRS2%	0.594	0.586	0.605	0.428	0.911		
MinCR	0.277	0.295	0.275	0.186	0.675	0.591	
Forecasting variables							
RET	-0.355	-0.373	-0.250	-0.160	-0.673	-0.597	-0.585
SD	-0.146	-0.162	0.052	0.291	0.098	0.267	0.072
TURN	-0.013	-0.025	0.033	0.210	0.000	0.022	-0.016
BM	0.000	0.000	-0.003	-0.001	-0.001	0.000	0.000
FLEV	0.003	0.003	0.001	0.003	-0.006	-0.013	-0.005
SIZE	0.046	0.045	0.095	0.024	-0.005	-0.106	-0.023
ROA	0.005	0.005	0.008	0.004	0.000	-0.006	-0.001
SI	-0.002	-0.002	-0.001	-0.001	-0.008	-0.012	-0.003

This table provides details on the contemporaneous correlation of key variables from January 2000 to December 2017. Panel A and Panel B report their contemporaneous correlation averaged over 3057 stocks and aggregated over six months and one month, respectively. The contemporaneous correlation between the forecasting variables (RET, SD, TURN, BM, FLEV, SIZE, ROA, and SI) are reported in Appendix 2.1.

The new EDR measures are positively correlated with the existing measures. RDRS3%–EXSIGMA having the highest pairwise correlation (0.60). Due to their conservative way of defining extreme returns, the correlation between MinCR and other tail risk measures (EXSIGMA and MCRASH) is much lower, around 0.25 on average. When the new measures are averaged over one month, their correlation is stronger with the existing measures (except MCRASH). Thus, RDRS and MinCR appear to be good candidates to measure the EDR.

We also examine the cross-correlation between the EDR measures and the forecasting variables in Table 2.3.3. We find that returns have a negative relationship with all EDR measures, averaged over six months. The findings are comparable to those in Chen et al. (2001). The correlation of returns with the EDR measures, averaged over one month, is still negative and the strongest with NCSKEW, EXSIGMA, and RDRS. Moreover, value is negatively correlated with existing EDR measures, but not with the new measures. Looking at the one-month averages, low-value stocks are negatively correlated with almost all EDR measures, but not NCSKEW and DUVOL. However, their correlation is rather low, below -0.01, particularly with the existing EDR measures. Volume, which effectively proxies for investors' disagreement around trading volume, demonstrates a positive relationship with most EDR measures averaged over one month and six months.

Leverage, the baseline measure of stocks' indebtedness, relates to firms' ability to repay their debt obligations. The existing EDR measures are positively correlated with leverage. This relationship is sustained across the two different time horizons. The positive correlation between size and the existing EDR measures reveals that large stocks have greater EDR than small ones. However, the new EDR measures are inversely related to size. Aggregating the variables over one month does not affect the relationship between size and the EDR measures. Profitability (firms' future operating performance), which proxies for the stock's profitability, is positively correlated with almost all EDR measures. However, the proposed EDR measures and profitability are negatively correlated over one month and six months. Short interest is viewed as managerial bad news hoarding activities. Most of the EDR measures are were negatively correlated with short interest, apart from NCSKEW, DUVOL, and MinCR. However, when the measures are constructed over one month, short interest is negatively correlated with almost all EDR measures. There is mixed evidence on the relationship between volatility and the EDR measures. Chen et al. (2001) show that the EDR measures and volatility are positively related. We find that NCSKEW and DUVOL have a negative correlation with volatility, while the other EDR measures share a very strong positive correlation with the same variable averaged over one month and six months.[11]

[11]We report the cross-correlation between the forecasting variables (return, volatility, volume, size, financial leverage, size, profitability, and short interest) in Appendix 2.1. The results reveal that forecasting variables have a fairly low cross-correlation, less than 0.70 on average, between each other.

Averaged over either one month or six months, the new EDR measures generally have a high contemporaneous correlation with the existing EDR measures. The relationship between the new measures and their predictors is comparable to what is observed in the existing EDR literature, except for size, short interest, and profitability. As expected, volatility and returns have the highest contemporaneous correlation with the EDR measures.

2.3.5. Stationarity and long memory tests. We test for stationarity in the time series of the EDR measures and the forecasting variables using the Im-Pesaran-Shin (IPS) unit-root test (Im et al. (2003)). The results are reported in Panel A of Table 2.3.4.[12] One advantage of the IPS test over other stationarity tests is that it works well in panel with shorter time series and more observations. We find that this test rejects the null hypothesis of non-stationarity (individual time series follows a unit root process) for all the time series aggregated over one month and six months.

We also test whether individual stocks have persistence (long memory processes). The Geweke and Porter-Hudak (GPH) test, Lo Modified rescaled range (R/S) test, and Modified rescaled variance (V/S) test are used to identify stocks with long memory processes (Giraitis et al. (2003)). Under the null hypothesis, the time series of individual stocks has no long memory (no persistence) and has long memory (persistence) otherwise. The percentage of stocks for which we reject the null hypothesis is shown in Panel B of Table 2.3.4. The GPH test reveals that the new EDR measures have the most persistence, at most 10% of the stocks included in the sample, when averaged over a month. Similarly, the R/S test confirms that the RDRS has the most persistence (the null hypothesis is rejected for approximately 59% of the stocks) over six months. In comparison, the existing EDR measures have no long memory over six months or one month. The V/S test indicates the presence of long memory in the new EDR measures for most stocks over one month and six months. These results reveal that the new EDR measures potentially have more forecasting power than the existing measures.

[12]The Im et al. (2003) (IPS) unit root test is calculated by estimating the individual ADF statistics at the cross-section and averaging their t-statistics to form a standardised t-statistic.

TABLE 2.3.4. **Stationarity and Long-memory Tests**

Panel A: Im-Pesaran-Shin Unit-Root Test

	1MTH z statistics	6MTH z statistics
EDR measures		
NCSKEW	-427.62 [0.00]	-151.07 [0.00]
DUVOL	-429.17 [0.00]	-151.52 [0.00]
EXSIGMA	-430.30 [0.00]	-140.22 [0.00]
MCRASH	-484.93 [0.00]	-195.48 [0.00]
RDRS1%	-441.05 [0.00]	
RDRS2%	-362.95 [0.00]	
RDRS3%		-157.61 [0.00]
RDRS4%		-141.55 [0.00]
MinCR	-410.54 [0.00]	-149.01 [0.00]
Forecasting variables		
RET	-394.66 [0.00]	-164.52 [0.00]
SD	-115.30 [0.00]	-61.66 [0.00]
TURN	-340.34 [0.00]	-179.89 [0.00]
BM	-32.77 [0.00]	-26.01 [0.00]
FLEV	-12.97 [0.00]	-12.30 [0.00]
SIZE	-2.49 [0.00]	-6.33 [0.00]
ROA	-30.69 [0.00]	-38.18 [0.00]
SI	-48.36 [0.00]	-45.26 [0.00]

Panel B: Long-memory Tests

	GPH test		R/S test		V/S test	
	1MTH	6MTH	1MTH	6MTH	1MTH	6MTH
EDR measures						
NCSKEW	3%	10%	0%	0%	2%	1%
DUVOL	3%	11%	0%	0%	2%	1%
EXSIGMA	3%	12%	0%	0%	4%	1%
MCRASH	2%	4%	0%	0%	0%	0%
RDRS1%	3%		0%		2%	
RDRS2%	10%		0%		19%	
RDRS3%		7%		60%		0%
RDRS4%		10%		58%		2%
MinCR	1%	5%	0%	0%	1%	0%

This table provides details on the stationarity and long-memory tests. Panel A reports the Im-Pesaran-Shin unit-root test tested on the variables aggregated over one month (1MTH) and six months (6MTH). The selection of lags (between 0 and 10) is made using the Akaike information criteria (AIC) and individual intercepts are added as exogenous variables. The p-values are reported in parentheses. The rejection of the null hypothesis indicates stationarity. Panel B reports the proportion of stocks in the sample, which EDR measures monthly (1MTH) and semi-annual (6MTH) time series, that has a long memory using the Geweke and Porter-Hudak (GPH), Lo Modified rescaled range (R/S), and Modified rescaled variance (V/S) tests. Total number of stocks in the sample is 3057.

2.4. Forecasting Extreme Downside Risk

We compare the in-sample and out-of-sample forecasting performance of four existing and two new EDR models over one-month and six-month forecasting horizons. While the in-sample estimates are derived using panel and time series estimations, the out-of-sample forecasts are obtained using a fixed rolling window estimation.

2.4.1. In-sample estimation.

2.4.1.1. *Forecasting EDR in the cross-section.* Using a cross-sectional regression specification, the EDR measures in period τ for each stock i are forecasted using information available at the end of period $\tau - 1$. Specifically, $EDR_{i,\tau}$ is regressed on its own lagged value and predictors (forecasting variables) in period $\tau - 1$. This model, which provides an estimate of the EDR determinants, is defined as:

$$\begin{aligned} EDR_{i,\tau} = {} & \beta_{EDR} EDR_{i,\tau-1} + \beta_{RET} RET_{i,\tau-1} + \beta_{SD} SD_{i,\tau-1} + \beta_{TURN} TURN_{i,\tau-1} \\ & + \beta_{BM} BM_{i,\tau-1} + \beta_{FLEV} FLEV_{i,\tau-1} + \beta_{SIZE} SIZE_{i,\tau-1} + \beta_{ROA} ROA_{i,\tau-1} \\ & + \beta_{SI} SI_{i,\tau-1} + \sum_{1}^{11} \beta_M^{11} M_\tau^{11} + \epsilon_{i,\tau}, \end{aligned} \tag{2.4.1}$$

where $EDR_{i,\tau}$ represents the six EDR measures[13] and $\epsilon_{i,\tau}$ is the error term. We also control for the impact of eight forecasting variables: the stock's returns (RET), volatility (SD), value (BM), size (SIZE), volume (TURN), financial leverage (FLEV), profitability (ROA), and short interest (SI). The forecasting variables are presented in Section 2.3.3. We add monthly (M_τ^{11}) dummies to the one-month model specifications to control for seasonal patterns in the EDR measures. M_τ^{11} represents the months January to November.[14]

Tables 2.4.1 and 2.4.2 present the in-sample panel data regression results estimated over six-month and one-month forecasting horizons, respectively. The lagged value of the EDR (represented by β_{EDR}), particularly for the new EDR measures (RDRS and MinCR), always increases the current EDR across the two forecasting horizons. However, we also find that the observed NCSKEW over the past six months can decrease its current value.

[13] NCSKEW, DUVOL, EXSIGMA, MCRASH, RDRS, and MinCR.

[14] The regressions are first tested for any panel effect using the Breush-Pagan Lagrange multiplier test. A fixed-effect with unbalanced panel regression is then estimated for each model. While related studies use a pooled OLS model, we adopt a fixed effect model. We are assuming that individual stocks behave differently in each time period.

MCRASH always remains negatively correlated with its own lagged value. We discover that predicting the EDR over shorter periods of time introduces more persistence.[15]

TABLE 2.4.1. **Forecasting EDR in the Cross-Section (Six Months Ahead**

	Existing EDR measures				New EDR measures		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	NCSKEW	DUVOL	EXSIGMA	MCRASH	RDRS3%	RDRS4%	MinCR
β_{EDR}	-0.020***	0.007	0.073***	-0.063***	0.138***	0.097***	0.027***
	(-4.227)	(1.382)	(12.369)	(-14.086)	(23.778)	(17.848)	(5.578)
β_{RET}	0.255***	0.160***	0.181***	-0.253***	0.053***	0.034***	0.331***
	(12.732)	(17.834)	(10.177)	(-9.066)	(21.140)	(14.688)	(13.450)
β_{SD}	-0.086***	-0.043***	0.004	-0.145***	0.009***	0.012***	0.006
	(-21.048)	(-23.822)	(0.917)	(-16.698)	(12.407)	(15.495)	(1.237)
β_{SI}	-0.165***	-0.088***	0.081**	0.125**	0.001	0.001	0.009
	(-45.794)	(-22.112)	(2.587)	(2.390)	(0.445)	(0.674)	(0.454)
β_{SIZE}	0.112***	0.053***	0.200***	0.370***	0.014***	0.012***	0.195***
	(24.316)	(23.122)	(33.593)	(43.981)	(21.805)	(19.785)	(35.768)
β_{BM}	-0.054**	-0.028*	0.088**	0.239***	0.010*	0.009**	0.050
	(-2.425)	(-1.907)	(1.962)	(3.523)	(1.835)	(2.280)	(0.915)
β_{FLEV}	-0.028	-0.014	0.007	0.119*	-0.001	0.000	-0.051
	(-1.260)	(-1.316)	(0.686)	(1.703)	(-1.119)	(0.104)	(-1.614)
β_{ROA}	-0.524***	-0.218***	-0.046	0.065	-0.028	-0.021	-0.141
	(-3.907)	(-4.275)	(-0.148)	(0.088)	(-0.735)	(-0.732)	(-0.424)
β_{TURN}	0.145**	0.053**	-0.112**	-0.23***	-0.003	-0.004	-0.008
	(2.137)	(2.126)	(-2.756)	(-3.665)	(-0.568)	(-0.818)	(-0.179)
$adjR^2$	-0.014	0.004	0.025	0.182	0.169	0.184	0.178
AIC	317,543	152,693	303,693	398,357	-107,492	-106,585	319,488

This table reports the estimation results of the following regression:

$$\begin{aligned}EDR_{i,\tau} &= \beta_{EDR}EDR_{i,\tau-1} + \beta_{RET}RET_{i,\tau-1} + \beta_{SD}SD_{i,\tau-1}\\ &+ \beta_{TURN}TURN_{i,\tau-1} + \beta_{BM}BM_{i,\tau-1} + \beta_{FLEV}FLEV_{i,\tau-1}\\ &+ \beta_{SIZE}SIZE_{i,\tau-1} + \beta_{ROA}ROA_{i,\tau-1} + \beta_{SI}SI_{i,\tau-1} + \epsilon_{i,\tau},\end{aligned}$$

where EDR represents NCSKEW, DUVOL, EXSIGMA, MCRASH, and RDRS. This table presents the in-sample panel data regression results using seven EDR measures. The fixed-effect regressions are estimated at a semi-annual frequency. AIC is the Akaike information criteria. All regressions also contain the time fixed effect (not shown) and the t-statistics are in parentheses, are adjusted for heteroskedasticity. We do not report any serial correlation in residuals test for the fixed-effect regression at a six-month frequency because these tests apply primarily to panels with long time series (Baltagi et al. (1992) and Baltagi (2005)). *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

Models 1 and 2 in Tables 2.4.1 and 2.4.2 reveal that most of the forecasting variables correctly predict the next period's (one month and six months) EDR. Among the forecasting

[15]Each model corresponds to the seven EDR measures considered in this analysis, where the two models are estimated using RDRS with two different thresholds. Callen and Xiaohua (2015) also observe that the NCSKEW and DUVOL in the past twelve months decrease, rather than increase, the current EDR.

TABLE 2.4.2. **Forecasting EDR in the Cross-Section (One Month Ahead)**

	Existing EDR measures				New EDR measures		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	NCSKEW	DUVOL	EXSIGMA	MCRASH	RDRS1%	RDRS2%	MinCR
β_{EDR}	0.013***	0.015***	0.036***	-0.134***	0.048***	0.089***	0.023***
	(8.819)	(9.832)	(17.175)	(-57.060)	(18.900)	(37.017)	(12.269)
β_{RET}	0.059***	0.053***	0.034***	-0.093***	0.019***	0.024***	0.117***
	(24.236)	(26.725)	(23.737)	(-19.532)	(24.451)	(30.077)	(24.746)
β_{SD}	-0.024***	-0.020***	-0.011***	-0.171***	0.000	0.005***	0.004**
	(-26.012)	(-23.226)	(-19.219)	(-27.441)	(1.622)	(11.787)	(2.272)
β_{SI}	-0.001	-0.047***	0.080***	0.059	-0.025***	-0.021***	-0.245***
	(-0.049)	(-10.657)	(5.381)	(1.461)	(-8.165)	(-3.245)	(-14.099)
β_{SIZE}	0.056***	0.046***	0.041***	0.042***	0.016***	0.012***	0.087***
	(27.497)	(26.443)	(34.762)	(12.147)	(38.384)	(22.899)	(29.132)
β_{BM}	0.000	-0.008	0.005	0.103	0.052***	0.060**	0.283***
	(0.001)	(-0.074)	(0.063)	(0.267)	(3.406)	(2.492)	(5.301)
β_{FLEV}	-0.066	-0.067	0.005	0.312*	-0.007	0.005	-0.021
	(-1.307)	(-1.509)	(0.326)	(1.826)	(-1.046)	(0.843)	(-0.397)
β_{ROA}	-0.142***	-0.132***	0.002	-0.017	0.000	-0.001	0.153
	(-3.536)	(-3.361)	(0.048)	(-0.093)	(-0.010)	(-0.035)	(0.908)
β_{TURN}	0.008	-0.004	-0.025***	-0.080**	-0.018***	-0.034***	-0.045**
	(0.593)	(-0.335)	(-3.656)	(-2.203)	(-6.022)	(-7.494)	(-2.177)
$adjR^2$	0.014	0.018	0.166	0.158	0.168	0.168	0.189
AIC	1,516,800	1,294,430	923,019	2,009,600	-226,845	-182,830	1,994,828
Wooldridge test	3.975*	3.310*	154.310***	36.111***	0.447	4.013*	3.464*
(p-value)	[0.05]	[0.07]	[0.00]	[0.00]	[0.50]	[0.05]	[0.06]

This table reports the estimation results of the following regression:

$$\begin{aligned} EDR_{i,\tau} = {} & \beta_{EDR}EDR_{i,\tau-1} + \beta_{RET}RET_{i,\tau-1} + \beta_{SD}SD_{i,\tau-1} \\ & + \beta_{TURN}TURN_{i,\tau-1} + \beta_{BM}BM_{i,\tau-1} + \beta_{FLEV}FLEV_{i,\tau-1} \\ & + \beta_{SIZE}SIZE_{i,\tau-1} + \beta_{ROA}ROA_{i,\tau-1} + \beta_{SI}SI_{i,\tau-1} \\ & + \sum_{1}^{11} \beta_M^{11} M_\tau^{11} + \epsilon_{i,\tau}, \end{aligned}$$

where EDR represents NCSKEW, DUVOL, EXSIGMA, MCRASH, and RDRS. This table presents the in-sample panel data regression results using seven EDR measures. The fixed-effect regressions are estimated at a monthly frequency, respectively. AIC is the Akaike information criteria. All regressions also contain the time fixed effect and monthly seasonal dummies (M_τ^{11}) (not shown) and the t-statistics are in parentheses, are adjusted for heteroskedasticity. All regressions are tested for serial correlation in their residuals using the Wooldridge test for AR(1) errors in fixed effect panel models, the p-values are reported (in parentheses). *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

variables that increase the next-month and six-month EDR are returns and size. High returns increase the probability of a stock price crash in the NCSKEW and DUVOL models (Harvey and Siddique (2000), Chen et al. (2001), Hutton et al. (2009), and Callen and Xiaohua (2015)). Similarly, the EDR literature acknowledges that small stocks (captured by their size), expose to less public scrutiny, are less likely to hide bad news and thus have less chance of a sharp drop in stock prices (Chen et al. (2001) and Ak et al. (2016)). We find that size significantly impacts the EDR in the NCSKEW and DUVOL models.

Volume causes a rise in the next six-month EDR, implying that higher trading volume triggers higher future EDR (Chen et al. (2001)).

Volatility, value, and profitability are negative and statistically significant in the NCSKEW and DUVOL models over the two forecasting horizons. Volatility and value are all precursors of lower EDR (Chen et al. (2001) and Kim and Zhang (2014)). Hutton et al. (2009) and Kim and Zhang (2014) explain the negative coefficient of profitability in the EDR models by arguing that low-productivity stocks are more crash prone. The similar behavior of the forecasting variables in the two models suggests that NCSKEW and DUVOL as measures are close substitutes (Chen et al. (2001)). This explains their very high cross-correlation when averaged over one month and six months (Table 2.3.3).

EXSIGMA and MCRASH are both measures of left tail risk that capture sharp declines in prices. We find that they have a statistically significant relationship with most forecasting variables in Models 3 and 4. For instance, size appears in the EXSIGMA and MCRASH models with the correct sign, as the existing EDR literature predicts. High returns increase the probability of a stock price crash in the EXSIGMA model, while high volatility decreases EDR in the MCRASH model. These results hold over six-month and one-month forecasting horizons. A high financial leverage in the past six months is expected to increase EDR (Hutton et al. (2009)). However, the coefficient of financial leverage is positive and statistically significant only in the MCRASH model. Volume appears significantly in the EXSIGMA and MCRASH models. However, it decreases next month EDR instead of increasing next month EDR.[16]

Models 5 to 7 in Tables 2.4.1 and 2.4.2 show the impact of the forecasting variables on the new EDR measures. Compared to the existing EDR measures, the thresholds in the RDRS measures ensure that we capture the most extreme negative returns. Also, by looking at the minimum cumulative returns, MinCR has a more conservative approach to measuring the left tail risk. Both high returns and size are likely to increase the probability of a stock price crash one month and six months ahead in the RDRS and MinCR models. We also observe that high volatility and value stocks are expected to increase future EDR over

[16]There is ample empirical evidence that volume positively impacts the EDR whilst the NCKSEW and DUVOL are employed as EDR's proxy (Chen et al. (2001) and Callen and Xiaohua (2015)). However, few studies have formally analyzed the impact of volume on the EDR using the left tail risk EDR measures (EXSIGMA and MCRASH).

the two forecasting horizons. Volume decreases next month's EDR as observed in the existing models (EXSIGMA and MCRASH).

The R^2 of the new EDR measures (RDRS and MinCR) are comparatively higher than for the existing measures. This suggests that the models fit the data best. The low akaike information criterion (AIC) of the new EDR measures (RDRS) reveal that they are likely to provide better forecasting accuracy either one month or six months ahead.

To summarize, we identify stocks with high market capitalization and returns as consistently increasing the future EDR over one-month and six-month forecasting horizons. The new EDR models better fit the data and have better predictive ability than the existing models.

2.4.1.2. *Forecasting EDR in the time series.* We estimate the time-series regressions in Equation (2.4.1) over the two forecasting horizons. This approach differs from the one used by Chen et al. (2001), since they estimate the time-series regressions of all stocks at different points in time. The mean of the estimated regression coefficients and adjusted t-statistics across all stocks for each EDR models are reported in Tables 2.4.3 and 2.4.4. The adjusted t-statistics are estimated using the Newey–West standard errors. The latter are corrected for cross-equation correlations by following the same procedure used by Chordia et al. (2000) and Hameed et al. (2010).[17]

Tables 2.4.4 and 2.4.3 present the in-sample time-series regression results estimated over one-month and six-month forecasting horizons, respectively. The lagged coefficients of the dependent variables, averaged over six months, are negative and statistically insignificant in most regression models (except the NCSKEW, DUVOL, and MCRASH models). Over the one-month forecasting horizon, in comparison, negative persistence is statistically relevant in the MCRASH model only.

[17]The standard errors are estimated using the following specification:

$$se\left(\bar{\beta}\right) = se\left(\frac{1}{N}\sum_{i=1}^{N}\beta_i\right) = \frac{1}{N}\sqrt{\sum_{i=1}^{N}Var\left(\beta_i\right) + \sum_{i=1}^{N}\sum_{j=1,j\neq i}^{N} p_{i,j}\sqrt{Var\left(\beta_i\right)Var\left(\beta_j\right)}},$$

where $p_{i,j}$ is the empirical correlation between the regression residuals for stocks i and j, $Var\left(\beta\right)$ is the variance of each estimated coefficients retrieved from the individual EDR time series, and N is the number of stocks in the sample.

TABLE 2.4.3. **Forecasting EDR in the Time Series (Six Months Ahead)**

		Existing EDR measures				New EDR measures		
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
		NCSKEW	DUVOL	EXSIGMA	MCRASH	RDRS3%	RDRS4%	MinCR
β_{EDR}	Average	-0.127***	-0.110*	-0.084	-0.132**	-0.059	-0.102	-0.077
	t-stat	(-3.471)	(-1.880)	(-0.547)	(-2.029)	(-0.310)	(-0.597)	(-0.038)
	%(t≤-1.96)	16%	14%	15%	19%	11%	14%	9%
	%(t≥1.96)	3%	4%	5%	3%	7%	5%	7%
β_{RET}	Average	0.250***	0.173**	0.153	-0.657***	0.009	-0.018	0.379
	t-stat	(3.452)	(2.194)	(0.468)	(-3.465)	(0.740)	(-0.151)	(1.112)
	%(t≤-1.96)	5%	4%	6%	12%	7%	9%	6%
	%(t≥1.96)	11%	14%	11%	5%	11%	8%	11%
β_{SD}	Average	-0.005	-0.013	-0.009	-0.564***	0.029	0.032	0.054
	t-stat	(-0.139)	(-0.346)	(-0.060)	(-6.441)	(0.473)	(0.566)	(0.385)
	%(t≤-1.96)	11%	12%	10%	40%	3%	2%	8%
	%(t≥1.96)	7%	7%	10%	2%	28%	30%	12%
β_{SI}	Average	-8.541***	0.048	-4.704**	2.337**	0.322	0.442	-2.042
	t-stat	(-18.358)	(0.107)	(-2.485)	(2.213)	(0.463)	(0.698)	(-1.321)
	%(t≤-1.96)	8%	9%	10%	8%	8%	8%	7%
	%(t≥1.96)	9%	11%	12%	14%	15%	15%	13%
β_{SIZE}	Average	0.966***	0.394***	5.149***	7.474***	0.456**	0.357*	5.207***
	t-stat	(8.061)	(3.124)	(9.130)	(24.812)	(2.215)	(1.949)	(11.030)
	%(t≤-1.96)	6%	7%	1%	1%	2%	3%	1%
	%(t≥1.96)	13%	15%	59%	54%	44%	35%	46%
β_{BM}	Average	-8.300***	-3.763***	1.750	-0.294	-0.949**	-0.981**	-15.212***
	t-stat	(-29.543)	(-12.680)	(1.407)	(-0.440)	(-2.366)	(-0.804)	(-14.375)
	%(t≤-1.96)	15%	18%	7%	7%	15%	15%	19%
	%(t≥1.96)	5%	6%	15%	14%	8%	7%	4%
β_{FLEV}	Average	-1.403***	-0.631***	0.499	1.247***	-0.038	-0.040	-1.965***
	t-stat	(-10.721)	(-3.465)	(0.846)	(3.885)	(-0.173)	(-0.200)	(-3.896)
	%(t≤-1.96)	13%	16%	7%	7%	12%	12%	17%
	%(t≥1.96)	6%	6%	15%	16%	11%	11%	6%
β_{ROA}	Average	1.062***	0.695***	0.605	-3.762***	-0.110	-0.169	-4.896***
	t-stat	(5.633)	(3.447)	(0.696)	(-7.925)	(-0.344)	(-0.589)	(-6.488)
	%(t≤-1.96)	7%	7%	8%	11%	11%	11%	14%
	%(t≥1.96)	9%	10%	9%	7%	7%	8%	7%
β_{TURN}	Average	6.204***	3.918***	-1.898**	-19.630***	0.424	-0.029	5.459***
	t-stat	(28.801)	(18.016)	(-2.038)	(-36.961)	(1.235)	(-0.093)	(7.063)
	%(t≤-1.96)	7%	8%	8%	6%	8%	8%	8%
	%(t≥1.96)	9%	10%	9%	9%	10%	11%	10%
$adjR^2$		0.109	0.173	0.854	0.772	0.762	0.676	0.572
AIC		304,073	151,619	330,075	394,660	-60,781	-64,570	359,230
Ljung Box test		0.548	0.527	0.571	0.785	0.459	0.474	0.510
(p-value)		[0.63]	[0.63]	[0.61]	[0.56]	[0.64]	[0.63]	[0.63]

This table reports the estimation results of the following regression:

$$\begin{aligned} EDR_{i,\tau} &= \beta_{EDR} EDR_{i,\tau-1} + \beta_{RET} RET_{i,\tau-1} + \beta_{SD} SD_{i,\tau-1} \\ &+ \beta_{TURN} TURN_{i,\tau-1} + \beta_{BM} BM_{i,\tau-1} + \beta_{FLEV} FLEV_{i,\tau-1} \\ &+ \beta_{SIZE} SIZE_{i,\tau-1} + \beta_{ROA} ROA_{i,\tau-1} + \beta_{SI} SI_{i,\tau-1} + \epsilon_{i,\tau}, \end{aligned}$$

where EDR represents NCSKEW, DUVOL, EXSIGMA, MCRASH, and RDRS. This table presents the in-sample OLS regressions estimated at a six-month frequency using seven EDR measures. The adjusted R^2 is estimated for each stock and averaged across stocks. AIC is the Akaike information criteria. The t-statistics (in parentheses), are estimated using the Newey–West standard errors and corrected for adjusted cross-equation correlations (Hameed et al. (2010)). %(t≤-1.96) and %(t≥1.96) is the percentage of stocks with t≤-1.96 or t≥1.96, respectively. All regressions are tested for serial correlation in their residuals using the Ljung Box test (estimated for each stock and averaged across stocks) for AR(1) errors, the p-values are reported (in parentheses). *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

TABLE 2.4.4. **Forecasting EDR in the Time Series (One Month Ahead)**

		Existing EDR measures				New EDR measures		
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
		NCSKEW	DUVOL	EXSIGMA	MCRASH	RDRS1%	RDRS2%	MinCR
β_{EDR}	Average	-0.011	-0.010	0.071	-0.102**	0.076	0.071	0.042
	t-stat	(-0.624)	(-0.478)	(1.395)	(-2.817)	(0.564)	(1.062)	(0.620)
	%(t≤-1.96)	4%	4%	2%	46%	3%	2%	2%
	%(t≥1.96)	3%	3%	17%	3%	15%	14%	10%
β_{RET}	Average	0.026	0.027	0.036	-0.188***	0.025	0.012	0.058
	t-stat	(1.152)	(1.178)	(0.737)	(-3.371)	(0.610)	(0.314)	(0.511)
	%(t≤-1.96)	2%	2%	2%	26%	3%	2%	4%
	%(t≥1.96)	6%	7%	12%	1%	14%	11%	7%
β_{SD}	Average	-0.006	-0.006	0.012	-0.262***	0.016	0.028	0.102
	t-stat	(-0.423)	(-0.426)	(0.368)	(-6.588)	(0.700)	(1.218)	(1.535)
	%(t≤-1.96)	8%	9%	5%	80%	1%	0%	1%
	%(t≥1.96)	3%	3%	13%	3%	28%	48%	23%
β_{SI}	Average	-1.139***	-1.516***	-0.793*	1.715***	-0.092	-0.025	-0.187
	t-stat	(-6.430)	(-8.687)	(-1.929)	(3.783)	(-0.355)	(-0.098)	(-0.258)
	%(t≤-1.96)	4%	5%	11%	9%	5%	5%	4%
	%(t≥1.96)	5%	5%	6%	8%	9%	10%	8%
β_{SIZE}	Average	0.229***	0.187***	2.360***	3.615***	0.573***	0.416***	2.771***
	t-stat	(4.246)	(3.444)	(18.236)	(25.324)	(6.647)	(5.016)	(11.445)
	%(t≤-1.96)	4%	4%	0%	0%	0%	1%	0%
	%(t≥1.96)	8%	8%	91%	79%	82%	67%	67%
β_{BM}	Average	-3.944***	-3.320***	2.233***	6.059***	-0.553**	-0.539**	-1.351***
	t-stat	(-31.344)	(-26.230)	(8.217)	(18.649)	(-2.986)	(-2.966)	(-13.980)
	%(t≤-1.96)	15%	16%	2%	2%	12%	12%	18%
	%(t≥1.96)	1%	1%	31%	37%	7%	6%	2%
β_{FLEV}	Average	-3.099***	-2.668***	5.607***	13.487***	0.400	0.490*	-1.937**
	t-stat	(-16.738)	(-14.344)	(13.510)	(27.525)	(1.436)	(1.785)	(-2.386)
	%(t≤-1.96)	9%	11%	4%	3%	7%	7%	8%
	%(t≥1.96)	3%	3%	23%	32%	14%	14%	6%
β_{ROA}	Average	-0.489***	-0.429***	-0.126	-0.057	-0.206*	-0.174	-1.529***
	t-stat	(-5.983)	(-5.224)	(-0.699)	(-0.266)	(-1.684)	(-1.446)	(-4.268)
	%(t≤-1.96)	6%	6%	8%	7%	12%	13%	10%
	%(t≥1.96)	3%	4%	5%	4%	3%	2%	2%
β_{TURN}	Average	0.906***	0.519***	0.669***	0.348	-0.014	-0.100	0.762**
	t-stat	(11.046)	(6.474)	(3.646)	(1.578)	(-0.114)	(-0.826)	(2.181)
	%(t≤-1.96)	4%	5%	8%	9%	8%	11%	7%
	%(t≥1.96)	4%	4%	3%	3%	2%	1%	3%
$adjR^2$		0.049	0.056	0.917	0.702	0.800	0.713	0.507
AIC		1,516,379	1,302,921	995,008	1,974,867	-126,129	-89,720	2,104,659
Ljung Box test		0.049	0.049	1.624	1.146	0.503	0.444	0.177
(p-value)		[0.87]	[0.87]	[0.67]	[0.66]	[0.73]	[0.73]	[0.82]

This table reports the estimation results of the following regression:

$$\begin{aligned} EDR_{i,\tau} = {} & \beta_{EDR}EDR_{i,\tau-1} + \beta_{RET}RET_{i,\tau-1} + \beta_{SD}SD_{i,\tau-1} \\ & + \beta_{TURN}TURN_{i,\tau-1} + \beta_{BM}BM_{i,\tau-1} + \beta_{FLEV}FLEV_{i,\tau-1} \\ & + \beta_{SIZE}SIZE_{i,\tau-1} + \beta_{ROA}ROA_{i,\tau-1} + \beta_{SI}SI_{i,\tau-1} + \epsilon_{i,\tau}, \end{aligned}$$

where EDR represents NCSKEW, DUVOL, EXSIGMA, MCRASH, and RDRS. This table presents the in-sample OLS regressions estimated at a one-month frequency using seven EDR measures. The adjusted R^2 is estimated for each stock and averaged across stocks. AIC is the Akaike information criteria. The t-statistics (in parentheses), are estimated using the Newey–West standard errors and corrected for adjusted cross-equation correlations (Hameed et al. (2010)). %(t≤-1.96) and %(t≥1.96) is the percentage of stocks with t≤-1.96 or t≥1.96, respectively. All regressions are tested for serial correlation in their residuals using the Ljung Box test (estimated for each stock and averaged across stocks) for AR(1) errors, the p-values are reported (in parentheses). *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

Models 1 and 2 show the impact of the forecasting variables on the two existing EDR measures (NCSKEW and DUVOL) over the two forecasting horizons. Almost all forecasting variables have the correct sign and are statistically significant, apart from financial leverage and short interest, over the one-month horizon. Very similar results are observed over the six-month horizon (with a sign reversal for profitability from negative to positive). Although NCSKEW and DUVOL have higher adjusted R^2 over six month than over one month, they perform poorly compared to the other models.

The in-sample time-series regression models of EXSIGMA and MCRASH are presented in Models 3 and 4, respectively. Most of the forecasting variables are statistically significant in the MCRASH model. We find that returns and volume (returns and profitability) enter the models, predicting the EDR six months (one month) ahead, with the wrong signs. The forecasting variables predicting higher EXSIGMA in future periods are size, financial leverage, and volume. We discover that financial leverage, and volume are statistically significant in the one-month EXSIGMA model only. While size increases the next six-month EDR, volume decreases it in the EXSIGMA model. Even though the two models have the highest adjusted R^2, they have poor predictive accuracy.

Models 5 to 6 show the time series estimations of the new EDR models. Over the six-month forecasting horizon, size, value, and volume enter the MinCR model significantly with the correct sign. All coefficients in RDRS3% and RDRS4% are either statistically insignificant or wrongly signed (except for size and value). However, over a one-month forecasting horizon, short interest, value, financial leverage, and profitability are strong predictors of EDR in the new models. Based on their AIC, we conclude that the new measures potentially have better forecasting accuracy compared to competing models over the two forecasting horizons.

To summarize, more forecasting variables are correctly signed and statistically significant in the in-sample time series estimations over the one-month forecasting horizon than the six-month horizon. It is also confirmed that the forecasting variables value, financial leverage, profitability, and volume significantly impact the EDR using two different estimation techniques (time series and panel).

2.4.2. Out-of-sample Estimation. The in-sample forecasting exercise primarily help identify the drivers of EDR. We use the out-of-sample estimation to determine which measures consistently and accurately predict the EDR. This involves splitting the time series of individual stocks into two sub samples. Hence, the in-sample period represents three-quarter of the time series for each stock, and the other quarter is the out-of-sample period. We again make predictions over the one- and six-month horizons. The advantage of forecasting over multiple periods is that it accounts for the structural change of data over time. Using a fixed rolling window estimation involves dropping the first observation in each iteration and estimating the same window size recursively for each EDR model.

We follow a similar approach to Patton and Sheppard (2015) by applying an 'insanity filter' to the negative forecasts of RDRS. Since the semivariances are strictly positive processes, the RDRS should always be greater than zero. The negative forecasts are substituted by the minimum positive forecasts in each fixed rolling window. For the other EDR measures (NCSKEW, DUVOL, EXSIGMA, MCRASH, and MinCR), we use the Swanson and White (1995), Terasvirta et al. (2005), and Patton and Sheppard (2015) 'insanity filter' instead. Whenever an EDR forecast exceeds the maximum EDR observed in the fixed rolling window, the forecast is substituted by the latest observed EDR in the respective rolling window.

2.4.2.1. *Out-of-sample forecasting performance.* We compare the out-of-sample performance of the new measures at predicting future EDR against existing measures by computing their out-of-sample R^2 (R^2_{OOS}) (Campbell and Thompson (2008), Welch and Goyal (2008), and Patton (2011)). The R^2_{OOS} is estimated as:

$$R^2_{OOS,\tau} = 1 - \left(\frac{MSE^N_\tau}{MSE^B_\tau}\right), \tag{2.4.2}$$

where mean squared error ($MSE_{m,\tau}$) measures the average squared difference between the actual values of the EDR and their forecasted values from the estimated EDR models[18], N represents the new EDR measures (RDRS and MinCR), and B represents the existing EDR measures (NCSKEW, DUVOL, EXSIGMA, and MCRASH). If the out-of-sample R^2 is greater than zero, then the new measure performs better than the existing

[18]The mean squared error ($MSE_{m,\tau}$) is estimated as:

$$MSE_{m,\tau} = \frac{1}{j}\sum_{i=1}^{j}\left[\frac{1}{n}\left(\sum_{i=1}^{n}\left(EDR_{m,\tau} - \widehat{EDR}_{m,\tau}\right)^2\right)\right].$$

where n is the number of fixed rolling windows, j is the number of stocks in the sample, and m are the seven EDR models.

measure. If the out-of-sample R^2 is smaller than zero, then the new measure performs worse than the existing measure.

Panel A of Table 2.4.5 shows the estimates of the out-of-sample R^2 over the six-month forecasting horizon. We find that the out-of-sample R^2 are primarily positive and reveal that the new EDR measures (RDRS3% and RDRS4%) outperform existing skewness measures (NCSKEW and DUVOL) and tail risk measures (EXSIGMA and MCRASH), as reported in the first two columns. The other new EDR measure, MinCR, also have better out-of-sample predictive accuracy than the NCSKEW and MCRASH. This shows the superior performance of the new measures compared to existing ones in predicting the EDR.

TABLE 2.4.5. **Out-of-sample Forecasting Performance**

Panel A: Out-of-sample R^2 at a six-month frequency

	New EDR measures		
	RDRS3%	RDRS4%	MinCR
Existing EDR measures			
NCSKEW	0.991	0.991	0.203
DUVOL	0.949	0.951	-3.424
EXSIGMA	0.986	0.987	-0.199
MCRASH	0.996	0.996	0.612

Panel B: Out-of-sample R^2 at a one-month frequency

	New EDR measures		
	RDRS1%	RDRS2%	MinCR
Existing EDR measures			
NCSKEW	0.951	0.948	-1.804
DUVOL	0.928	0.923	-3.139
EXSIGMA	0.888	0.881	-5.435
MCRASH	0.984	0.983	0.105

This table reports the out-of-sample R^2 for pairs of EDR measures over six-month and one-month forecasting horizons. Panel A and Panel B report the out-of-sample R^2 over six-month and one-month forecasting horizons, respectively. If the out-of-sample R^2 is greater than zero, then the new EDR measures (RDRS and MinCR) perform better than existing measure (NCSKEW, DUVOL, EXSIGMA, and MCRASH). If the out-of-sample R^2 is smaller than zero, then the new EDR measures perform worse than existing measures.

The out-of-sample R^2 for the 12 pairs of EDR models estimated over a one-month forecasting horizon are summarized in Panel B of Table 2.4.5. Since RDRS1% and RDRS2% have mostly a positive out-of-sample R^2, they have more predictive accuracy than the four existing measures. However, in their six-month forecasts, the RDRS is slightly inferior to the existing EDR measures. MinCR only out-perform MCRASH. In general, the RDRS consistently outperform existing measures and the out-of-sample performance of the MinCR is negligible.

2.4.2.2. *Out-of-sample forecast performance under different market conditions.* We reassess the out-of-sample performances of pairs of EDR models via the out-of-sample R^2 under the different market conditions (Xiao et al. (2018)). Bearish market conditions are indicated by periods of low monthly returns and high volatility, while bullish market conditions reflect periods of high monthly returns and low volatility. Using this analogy, we analyse four market scenarios in which combinations of low and high monthly returns and volatility varies accordingly. These scenarios include the LRLV, HRLV, LRHV, and HRHV. For instance, low return (LR) and high return (HR) are defined as the monthly returns in the lower and upper quartiles over the full sample, respectively. Low volatility (LV) and high volatility (HV) are the standard deviations of the monthly returns in the lower and upper quartiles.[19]

Panels A and B of Table 2.4.6 report the results of the out-of-sample R^2 under the different market conditions over six-month and one-month forecasting horizons, respectively. The RDRS3% and RDRS4% models still outperform the existing EDR models under all four market conditions. We observe that the new EDR models perform better than existing models, excluding DUVOL, during periods of high volatility (LRHV and HRHV). This shows that the new measures are not sensitive to high pressure market environments. Xiao et al. (2018) point out that bearish market conditions (high volatility) signal that the economy has become weak and there are potentially less positive spikes in the EDR. Chen et al. (2001) and Kim and Zhang (2014) also state that high volatility, at the firm level, reduces EDR. These bearish market conditions make the new measure easier to forecast six months ahead.

Panel B of Table 2.4.6 reveals that the new model (RDRS), which forecasts the EDR one month ahead, outperforms competing models, such as the NCSKEW, DUVOL, EXSIGMA,

[19]Returns and volatility are measured by RET and SD, see Table 2.3.2 for a detailed description of these variables.

TABLE 2.4.6. **Out-of-sample Forecasting Performance under Bearish and Bullish Market Conditions**

Panel A: Out-of-sample R^2 at a six-month frequency

	New EDR measures					
	RDRS3%	RDRS4%	MinCR	RDRS3%	RDRS4%	MinCR
	LRLV			HRLV		
Existing EDR measures						
NCSKEW	0.976	0.982	-0.320	0.979	0.984	-0.182
DUVOL	0.869	0.903	-6.175	0.887	0.914	-5.472
EXSIGMA	0.992	0.994	0.557	0.992	0.994	0.514
MCRASH	0.995	0.996	0.711	0.995	0.996	0.704
	LRHV			HRHV		
Existing EDR measures						
NCSKEW	0.989	0.990	0.169	0.990	0.991	0.161
DUVOL	0.941	0.945	-3.661	0.944	0.948	-3.681
EXSIGMA	0.988	0.989	0.074	0.988	0.989	0.021
MCRASH	0.995	0.996	0.641	0.996	0.996	0.624

Panel B: Out-of-sample R^2 at a one-month frequency

	New EDR measures					
	RDRS1%	RDRS2%	MinCR	RDRS1%	RDRS2%	MinCR
	LRLV			HRLV		
Existing EDR measures						
NCSKEW	0.864	0.892	-3.051	0.864	0.893	-3.063
DUVOL	0.799	0.841	-4.966	0.799	0.842	-4.981
EXSIGMA	0.944	0.955	-0.675	0.944	0.956	-0.674
MCRASH	0.976	0.981	0.285	0.976	0.981	0.292
	LRHV			HRHV		
Existing EDR measures						
NCSKEW	0.862	0.895	-3.119	0.864	0.896	-3.093
DUVOL	0.797	0.845	-5.065	0.800	0.847	-5.023
EXSIGMA	0.946	0.959	-0.622	0.946	0.959	-0.623
MCRASH	0.976	0.982	0.291	0.976	0.982	0.292

This table reports the out-of-sample R^2 for pairs of EDR models under different market conditions over six-month and one-month forecasting horizons. Panel A and Panel B report the out-of-sample R^2 over six-month and one-month forecasting horizons, respectively. If the out-of-sample R^2 greater than zero, then the new EDR measures (RDRS and MinCR) perform better than existing measure (NCSKEW, DUVOL, EXSIGMA, and MCRASH). If the out-of-sample R^2 is smaller than zero, then the new EDR measures perform worse than existing measures. LRLV, HRLV, LRHV, and HRHV represents the four market conditions. Low return (LR) and high return (HR) are defined as the monthly returns in the lower and upper quartiles over the full sample, respectively. Low volatility (LV) and high volatility (HV) are the standard deviations of the monthly returns in the lower and upper quartiles.

and MCRASH. There is, however, a minor dip in the out-of-sample R^2. Other EDR measures however, including the NCSKEW, DUVOL, and EXSIGMA, perform better than the MinCR. Compared to the six-month results, bearish or bullish market conditions have no apparent effect on the predictive accuracy of the different estimated models. The MinCR's worst performance vis-a-vis DUVOL is during periods of high volatility.

2.5. Investment Strategy

We evaluate the performance of an investment strategy that avoids stocks with a high probability of crashing (high EDR) by creating a market timing tactic for the six EDR measures. This will determine whether the new EDR measures achieve superior investment returns over the existing measures. We revisit the approach of Bali et al. (2011) and Ak et al. (2016) to classify high EDR stocks.

The forecasted EDR, retrieved from the estimated models in Section 2.4 for each stock across the different time intervals, are ranked into deciles (Portfolio 1 to 10) to obtain 10 thresholds. If the forecasted EDR fall below these thresholds, they are considered to be stocks with a low probability of crashing in the next period. The benchmark is set so that stocks with a high EDR (above their respective thresholds) are shorted. Then, the profitability and risk-adjusted returns of the low EDR stocks are computed.[20] The lower the threshold, the higher the number of stocks over each interval (one month and six months) are shorted. The assumption is that investors pick low EDR stocks over riskier ones when rebalancing their portfolios. Stocks with a low probability of crashing are expected to earn higher returns than those with a high probability of crashing. Hence, Portfolio 1 contains the stocks with the lowest return (least profitable) and Portfolio 10 contains the stocks with the highest return (most profitable). We also estimate the returns (risk-adjusted returns) difference between Portfolios 1 and 10. This represents the zero-cost spread portfolio (long/short strategy) in which an investor goes long on Portfolio 1 and short on Portfolio 10 to maximize their returns. We assess the statistical significance of the risk-adjusted returns for the different measures by computing their t-statistics.[21]

We evaluate the performance of the in-sample EDR forecasts, estimated over six-month and one-month forecasting horizons, via the market timing strategy and the results are reported in Panels A and B of Table 2.5.1. As expected, low EDR stocks, benchmarked

[20]The profitability is measured by returns averaged over one month and six months. The risk-adjusted return (Sharpe ratio) is calculated by dividing the average returns by standard deviation of returns over one month and six months.

[21]The latter is estimated as Sharpe ratio times the square root of the total number of months (one month and six months) in the sample (Sharpe (1994)). Using the Pinto et al. (2014) approach, we derive the critical Sharpe ratio (SR^c_τ) at the 1%, 5%, and 10% level of significance on a two-tailed test for the two sample of monthly and semi-annual returns as $SR^c_\tau = \text{Lev}_{\text{sig}}/\sqrt{\tau}$. Lev_{sig}, which represent the 1%, 5%, and 10% level of significance of the two-tailed test, are equal to 2.32, 1.96, and 1.64, respectively. τ represents the number of months (one month and six months) in the sample.

on the new EDR measures, earn, on average, the highest monthly returns in Portfolio 10 (see Panel B of Table 2.5.1). Investors using the new measures as benchmarks in lieu of existing measures will earn twice as much returns (12% versus 7%) in Portfolio 10. While the RDRS earns the highest average monthly returns in Portfolio 10, MinCR earns the highest returns in Portfolio 1. The zero-cost spread portfolio is the most profitable (in terms of returns) when we use the new EDR measures as benchmarks. The new measures outperform the existing ones, which means RDRS1% has the highest return and risk-adjusted return in most portfolios. However, the zero-cost spread portfolio offers the higher risk-adjusted returns if it is benchmarked on the existing EDR measures.

TABLE 2.5.1. **Market Timing using the In-sample EDR Forecasts**

Panel A: Market timing strategy using the six month ahead in-sample forecasts

		New EDR measures			**Existing EDR measures**			
	Portfolio	RDRS3%	RDRS4%	MinCR	NCSKEW	DUVOL	EXSIGMA	MCRASH
Profitability	1	0.77%	0.76%	1.81%	1.69%	1.89%	1.22%	1.86%
	10	8.18%	7.80%	8.49%	7.23%	7.36%	7.07%	8.51%
	10-1	7.41%	7.04%	6.68%	5.55%	5.47%	5.84%	6.65%
Risk-adjusted returns	1	0.118***	0.131***	0.158***	0.099***	0.109***	0.085***	0.123***
		(1.188)	(1.326)	(1.004)	(1.097)	(0.859)	(1.245)	(1.592)
	10	0.301***	0.295***	0.296***	0.241***	0.245***	0.237***	0.299***
		(3.039)	(2.980)	(2.435)	(2.472)	(2.392)	(3.017)	(2.994)
	10-1	0.183***	0.164***	0.139***	0.142***	0.136***	0.152***	0.175***
		(1.852)	(1.654)	(1.402)	(1.431)	(1.375)	(1.534)	(1.772)

Panel B: Market timing strategy using the one month ahead in-sample forecasts

		New EDR measures			**Existing EDR measures**			
	Portfolio	RDRS1%	RDRS2%	MinCR	NCSKEW	DUVOL	EXSIGMA	MCRASH
Profitability	1	2.60%	1.33%	3.08%	2.25%	2.39%	1.04%	1.13%
	10	11.55%	11.56%	11.06%	7.41%	7.60%	7.05%	8.63%
	10-1	8.95%	10.23%	7.99%	5.16%	5.21%	6.01%	7.50%
Risk-adjusted returns	1	0.118***	0.132***	0.138***	0.056***	0.060***	0.030***	0.034***
		(1.701)	(1.894)	(0.805)	(0.860)	(0.425)	(0.490)	(1.984)
	10	0.174***	0.182***	0.165***	0.104***	0.107***	0.099***	0.127***
		(2.497)	(2.610)	(1.491)	(1.532)	(1.426)	(1.816)	(2.373)
	10-1	0.056***	0.050***	0.027***	0.048***	0.047***	0.070***	0.092***
		(0.797)	(0.717)	(0.389)	(0.687)	(0.672)	(1.001)	(1.326)

This table reports the market timing strategy that uses the seven EDR measures as benchmarks. Panel A and Panel B report the market timing strategy using the EDR measures forecasted (in-sample) over six months and one month, respectively. Portfolio (decile) 1 contains the stocks with the lowest returns and Portfolio 10 contains the stocks with the highest returns. Portfolio 10-1 is the return (risk-adjusted return) difference between Portfolios 1 and 10. Profitability and risk-adjusted returns are measured by the average returns and Sharpe ratio. The critical Sharpe ratio (SR^c_τ) at the 1%, 5%, and 10% level of significance on a two-tailed test for the two sample of monthly and semi-annual returns as $SR^c_\tau = \text{Lev}_{\text{sig}}/\sqrt{\tau}$. Lev_{sig}, which represent the 1%, 5%, and 10% level of significance of the two-tailed test, are equal to 2.32, 1.96, and 1.64, respectively. τ represents the number of months (1MTH and 6MTH) in the sample. There are 102 6MTH and 206 1MTH. SR^c_{6MTH} at the 1%, 5%, and 10% level of significance is equal to 0.230, 0.194, and 0.162, respectively. SR^c_{1MTH} at the 1%, 5%, and 10% level of significance is equal to 0.162, 0.137, and 0.114, respectively. The t-statistics are in parentheses. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

Looking at a longer forecasting horizon (six months), the profitability (average returns) of low EDR stocks is comparable to the returns obtained over the one-month forecasting horizon (see Panel A of Table 2.5.1). Over a six-month forecasting horizon, the MinCR outperforms the other EDR measures in most portfolios. Similarly, the low EDR stocks using the MinCR as the benchmark earn higher risk-adjusted returns in Portfolio 1. Across the six-month forecasting horizon, MinCR and RDRS earn the highest risk-adjusted returns in Portfolio 1 and Portfolio 10, respectively. If we benchmark the EDR using the new measures, there is also a bigger return (risk-adjusted return) differential between Portfolios 1 and 10.

This market timing exercise is also replicated by using the out-of-sample EDR forecasts, estimated six months and one month ahead, as shown in Panels A and B of Table 2.5.2, respectively. Using the one-month forecasts renders the market timing tactic less profitable, meaning a drop in the risk-adjusted returns across the seven EDR measures. However, the risk-adjusted returns are homogeneous across the new and existing EDR measures, as reported in Panel B of Table 2.5.2. Portfolios benchmarked on the new measures nevertheless offer the highest risk-adjusted returns. While the zero-cost spread portfolio is not as profitable (in terms of returns) with the new EDR measures, this strategy offers decent risk-adjusted returns for the two classes of measures.

The average returns and risk-adjusted returns are also revised downwards when we use the (out-of-sample) six-month EDR forecasts. Specifically, the new EDR measures are earning higher average risk-adjusted returns than the existing measures in Portfolio 1 (see Panel A of Table 2.5.2). We also find that the zero-cost spread portfolio is equally profitable (in terms of returns only) when it is benchmarked on the new and existing EDR measures. Therefore, a strategy of avoiding high EDR stocks works best using the RDRS and MinCR as benchmarks. They consistently outperform the other EDR measures across the different portfolios and forecasting horizons.

TABLE 2.5.2. **Market Timing using the Out-of-sample EDR Forecasts**

Panel A: Market timing strategy using the six month ahead out-of-sample forecasts

		New EDR measures			**Existing EDR measures**			
	Portfolio	RDRS3%	RDRS4%	MinCR	NCSKEW	DUVOL	EXSIGMA	MCRASH
Profitability	1	0.49%	0.50%	0.51%	0.62%	0.63%	0.45%	0.39%
	10	5.25%	5.19%	5.23%	5.30%	5.26%	5.26%	5.23%
	10-1	4.76%	4.69%	4.72%	4.68%	4.63%	4.82%	4.84%
Risk-adjusted returns	1	0.082***	0.083****	0.058*	0.051*	0.047*	0.048	0.044**
		(0.412)	(0.414)	(0.253)	(0.234)	(0.240)	(0.218)	(0.292)
	10	0.180***	0.180***	0.180***	0.180***	0.178***	0.180***	0.180***
		(0.901)	(0.899)	(0.900)	(0.892)	(0.899)	(0.902)	(0.898)
	10-1	0.098***	0.097***	0.121***	0.129***	0.132***	0.132***	0.137***
		(0.490)	(0.484)	(0.606)	(0.646)	(0.658)	(0.659)	(0.684)

Panel B: Market timing strategy using the one month ahead out-of-sample forecasts

		New EDR measures			**Existing EDR measures**			
	Portfolio	RDRS1%	RDRS2%	MinCR	NCSKEW	DUVOL	EXSIGMA	MCRASH
Profitability	1	0.48%	0.49%	0.49%	0.54%	0.50%	0.64%	0.47%
	10	5.31%	5.29%	5.30%	5.31%	5.24%	5.33%	5.21%
	10-1	4.84%	4.80%	4.82%	4.77%	4.74%	4.69%	4.74%
Risk-adjusted returns	1	0.025	0.034*	0.020	0.022	0.022	0.030	0.023
		(0.179)	(0.245)	(0.143)	(0.160)	(0.159)	(0.216)	(0.166)
	10	0.084***	0.084***	0.082***	0.082***	0.082***	0.083***	0.082***
		(0.607)	(0.609)	(0.589)	(0.591)	(0.591)	(0.596)	(0.590)
	10-1	0.059***	0.050***	0.062***	0.060***	0.060***	0.053***	0.059***
		(0.428)	(0.364)	(0.445)	(0.431)	(0.432)	(0.380)	(0.424)

This table reports the market timing strategy that uses the seven EDR measures as benchmarks. Panel A and Panel B report the market timing strategy using the EDR measures forecasted (out-of-sample) over six months and one month, respectively. Portfolio (decile) 1 contains the stocks with the lowest returns and Portfolio 10 contains the stocks with the highest returns. Portfolio 10-1 is the return (risk-adjusted return) difference between Portfolios 1 and 10. Profitability and risk-adjusted returns are measured by the average returns and Sharpe ratio. The critical Sharpe ratio (SR^c_τ) at the 1%, 5%, and 10% level of significance on a two-tailed test for the two sample of monthly and semi-annual returns as $SR^c_\tau = \text{Lev}_{\text{sig}}/\sqrt{\tau}$. Lev_{sig}, which represent the 1%, 5%, and 10% level of significance of the two-tailed test, are equal to 2.32, 1.96, and 1.64, respectively. τ represents the number of months (1MTH and 6MTH) in the sample. There are 25 6MTH and 52 1MTH. SR^c_{6MTH} at the 1%, 5%, and 10% level of significance is equal to 0.464, 0.392, and 0.328, respectively. SR^c_{1MTH} at the 1%, 5%, and 10% level of significance is equal to 0.322, 0.272, and 0.227, respectively. The t-statistics are in parentheses. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

2.6. Robustness Tests

Additional robustness tests are conducted for completeness. First, we exclude the year 2008 (GFC period) from the sample period and are left with two subsamples: the PRE-GFC and POST-GFC periods.[22] This time period is characterized by excess market volatility, which can potentially skew forecasting results.

The in-sample panel regression models are re-estimated over a one-month forecasting horizon for the two subsample periods. The results are comparable to the full sample estimations. We also reassess the forecasting accuracy of the EDR models using the

[22]The GFC is commonly referred to a period of extreme stress in global financial markets, particularly in the U.S. economy. Even though the GFC started in mid 2007 and ended in early 2009, we choose to focus on the most turbulent year i.e., 2008.

out-of-sample R^2. Again, there is no major difference in the predictive accuracy of the forecasts in the two subsample periods. Similarly, the market timing exercise provides comparable results in the PRE-GFC period. During the POST-GFC period, the existing and new EDR measures are equally profitable when use as benchmarks. These results are reported in Appendix 2.2.

Second, we alter the thresholds, used to estimate the monthly and semi-annual RDRS measures, to ensure that the current thresholds are not driving the results. We use six thresholds (0, -0.005%, -1%, -2%, -3%, and -4%) in total. As a comparison, Barndorff-Neilsen et al. (2010) use a threshold of 0 to measure the downside realized semivariance.

Changing the threshold does not affect either the one-month or six-month in-sample panel estimations. The predictive accuracy of the out-of-sample estimates is unaltered by the thresholds in use over both forecasting horizons. The results obtained using the investment strategy, benchmarked on the in-sample and out-of-sample EDR forecasts, reveal that higher threshold mostly attracts higher risk-adjusted returns (see Appendix 2.3).

2.7. Conclusion

The aim of this study is to devise effective measures that act as a substitute for capturing EDR. By using a sample of 3,000 U.S. stocks over the past two decades, we find that the ratio of downside realized semivariance to realized variance and the minimum cumulative returns have better forecasting abilities than four well-known measures used in the literature. While existing studies have focused on predicting the EDR over longer periods, we use a more realistic forecasting horizon of month, which is in line with common portfolio rebalancing practices. An important contribution of this study is that we make out-of-sample forecasts by using a fixed rolling window estimation over the two forecasting horizons. This approach allows us to obtain not only one-period-ahead but multi-period-ahead forecasts. Moreover, we assess the sensitivity of the measures for predicting EDR under different market conditions, including bull and bear conditions. We evaluate the performance of these measures by creating an investment strategy that avoids stocks with the most extreme downside risk and estimate the risk-adjusted returns for different portfolios.

In line with the existing literature, the in-sample panel and time series regression models identify large market capitalization and high-return stocks as external factors that are likely to increase EDR one month and six months ahead. By assessing the goodness-of-fit of these models to accurately forecast EDR, we show that the new measures outperform existing ones. The ratio of downside realized semivariance to realized variance has better predictive accuracy over the two forecasting horizons. Under different market environments, the ratio of downside realized semivariance to realized variance still outperform other measures. Benchmarking the EDR measures to mimic a investment strategy that avoids stocks with high EDR shows that using the new metrics provide the highest risk-adjusted returns across different portfolios.

Forecasting the probability of crashes over a shorter time horizon, deemed a more realistic investment horizon for portfolio investors, shows promising results. This investment strategy can serve as a diversification tool for investors to protect and preserve their wealth during turbulent times. Practitioners can better mitigate their portfolio risk using this strategy, and potentially to reduce financial instability. Given that markets price risk differently, this study should be replicated in different countries. This investment strategy could also account for the fact that financial markets are incomplete, and include instead a utility-based valuation approach to quantify EDR.

Appendix 2.1. Cross-correlation between Forecasting Variables

To recap, the forecasting variables RET, SD, TURN, BM, FLEV, SIZE, ROA, and SI stand for returns, volatility, size, volume, financial leverage, profitability, and short interest, respectively. These variables have a fairly low cross-correlation (less than 0.70 on average) between each other, reported in Table A.2.1.1. While volume and volatility has the strongest positive cross-correlation, financial leverage and profitability has the strongest negative cross-correlation. William (1989) and Gallant et al. (1992) also confirm the positive relation between volume and volatility. It is because higher number of transactions translates to higher volatility. There is mixed evidence on the relationship between financial leverage and profitability at the firm level. For instance, Gale (1972) and Hurdle (1974) argue that low and high financial leverage attract high profitability.

TABLE A.2.1.1. **Contemporaneous Correlation between Forecasting Variables**

Panel A: Contemporaneous correlation between forecasting variables (six months)

	RET	SD	TURN	BM	FLEV	SIZE	ROA	SI
RET								
SD	0.114							
TURN	0.077	0.123						
BM	-0.001	0.002	0.002					
FLEV	0.011	0.001	0.005	-0.016				
SIZE	-0.025	-0.299	0.013	-0.004	0.063			
ROA	-0.002	-0.026	0.003	0.001	-0.134	0.021		
SI	-0.001	-0.010	0.000	0.000	0.009	-0.043	0.000	

Panel B: Contemporaneous correlation between forecasting variables (one month)

	RET	SD	TURN	BM	FLEV	SIZE	ROA	SI
RET								
SD	-0.146							
TURN	0.087	0.173						
BM	-0.001	0.000	0.000					
FLEV	0.006	-0.004	0.000	-0.007				
SIZE	0.019	-0.241	0.001	-0.004	0.090			
ROA	0.000	-0.021	0.001	0.000	-0.112	0.020		
SI	0.000	-0.009	0.000	0.000	-0.006	-0.044	0.000	

This table provides details on the contemporaneous correlation between forecasting variables from January 2000 to December 2017. Panel A and Panel B report their contemporaneous correlation averaged over 3057 stocks and aggregated over six months and one month, respectively.

Appendix 2.2. Excluding GFC Period

We exclude the year 2008 (GFC) from the sample period and are left with two subsamples: the PRE-GFC (2000-2007) and POST-GFC (2009-2017) periods. This time period (2008) is characterized by excess market volatility, which can potentially skew the forecasting results. The in-sample panel regression models are re-estimated over a one-month forecasting horizon for the two subsample periods (PRE-GFC and POST-GFC) (Tables A.2.2.1 and A.2.2.2). The results are comparable to the full sample estimations.

We also reassess the forecasting accuracy of the EDR models using the out-of-sample R^2 in the PRE-GFC and POST-GFC periods (see Panels A and B of Table A.2.2.3). Again, there is no major difference in the predictive accuracy of the forecasts in the two subsample periods.

Similarly, the market timing exercise provides comparable results in the PRE-GFC period (Table A.2.2.4). During the POST-GFC, period the existing and new EDR measures are equally profitable when used as benchmarks (Table A.2.2.5).

TABLE A.2.2.1. **Forecasting Monthly EDR in the Cross-Section during the PRE-GFC Period**

	Existing EDR measures				New EDR measures		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	NCSKEW	DUVOL	EXSIGMA	MCRASH	RDRS1%	RDRS2%	MinCR
β_{EDR}	0.004*	0.006**	0.031***	-0.121***	0.020***	0.064***	0.015***
	(1.896)	(2.515)	(10.813)	(-47.298)	(5.617)	(17.998)	(5.407)
β_{RET}	0.053***	0.051***	0.029***	-0.085***	0.018***	0.024***	0.138***
	(15.393)	(17.881)	(14.887)	(-16.735)	(15.713)	(20.318)	(19.891)
β_{SD}	-0.022***	-0.018***	-0.011***	-0.213***	0.000	0.004***	0.003
	(-15.809)	(-15.333)	(-12.265)	(-38.520)	(0.532)	(10.237)	(1.147)
β_{SI}	0.075	0.060	0.123	-0.018	-0.037**	-0.011	-0.392***
	(0.345)	(0.565)	(0.660)	(-0.059)	(-2.059)	(-0.171)	(-3.494)
β_{SIZE}	0.055***	0.043***	0.049***	0.124***	0.019***	0.017***	0.103***
	(19.601)	(18.235)	(24.950)	(20.159)	(29.798)	(23.613)	(21.480)
β_{BM}	-0.117**	-0.105**	0.017	0.231*	-0.030**	-0.037**	-0.208**
	(-2.425)	(-2.257)	(1.594)	(1.654)	(-2.442)	(-2.228)	(-2.268)
β_{FLEV}	-0.045	-0.058	0.010	0.182**	-0.017	-0.013	-0.095
	(-0.764)	(-1.083)	(1.015)	(2.824)	(-1.056)	(-1.025)	(-0.828)
β_{ROA}	-0.317	-0.381*	0.251**	0.654	-0.065	-0.033	-0.618
	(-1.322)	(-1.783)	(2.700)	(1.548)	(-0.858)	(-0.526)	(-1.069)
β_{TURN}	0.013	0.003	-0.027**	-0.032	-0.012***	-0.025***	-0.029
	(1.012)	(0.282)	(-2.450)	(-0.735)	(-2.853)	(-3.839)	(-1.138)
$adjR^2$	0.002	0.005	0.105	0.148	0.126	0.132	0.144
AIC	684,261	586,755	417,814	905,650	-104,011	-86,764	913,672
Wooldridge test	15.496***	13.568***	30.277***	10.546***	5.703**	2.858*	15.946***
(p-value)	[0.00]	[0.00]	[0.00]	[0.00]	[0.02]	[0.09]	[0.00]

This table reports the estimation results of the following regression:

$$\begin{aligned}EDR_{i,\tau} = {} & \beta_{EDR}EDR_{i,\tau-1} + \beta_{RET}RET_{i,\tau-1} + \beta_{SD}SD_{i,\tau-1} \\ & + \beta_{TURN}TURN_{i,\tau-1} + \beta_{BM}BM_{i,\tau-1} + \beta_{FLEV}FLEV_{i,\tau-1} \\ & + \beta_{SIZE}SIZE_{i,\tau-1} + \beta_{ROA}ROA_{i,\tau-1} + \beta_{SI}SI_{i,\tau-1} \\ & + \sum_{1}^{11} \beta_M^{11} M_\tau^{11} + \epsilon_{i,\tau},\end{aligned}$$

where EDR represents NCSKEW, DUVOL, EXSIGMA, MCRASH, and RDRS. This table presents the in-sample panel data regression (fixed-effect) results using seven monthly EDR measures during the PRE-GFC period (2000-2007). AIC is the Akaike information criteria. All regressions also contain the time fixed effect and monthly seasonal dummies (M_τ^{11}), not shown and the t-statistics are in parentheses, are adjusted for heteroskedasticity. All regressions are tested for serial correlation in their residuals using the Wooldridge test for AR(1) errors in fixed effect panel models, the p-values are reported (in parentheses). *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

TABLE A.2.2.2. **Forecasting Monthly EDR in the Cross-Section during the POST-GFC Period**

	Existing EDR measures				New EDR measures		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	NCSKEW	DUVOL	EXSIGMA	MCRASH	RDRS1%	RDRS2%	MinCR
β_{EDR}	0.009***	0.009***	0.023***	-0.146***	0.046***	0.064***	0.007**
	(4.166)	(4.253)	(8.157)	(-33.521)	(12.841)	(20.196)	(2.634)
β_{RET}	0.061***	0.051***	0.033***	-0.071***	0.017***	0.017***	0.075***
	(15.440)	(15.876)	(14.412)	(-9.710)	(14.264)	(15.244)	(10.327)
β_{SD}	-0.022***	-0.019***	-0.009***	-0.174***	-0.001*	0.002***	0.003
	(-14.973)	(-12.722)	(-10.062)	(-12.830)	(-1.781)	(4.003)	(0.962)
β_{SI}	0.046**	-0.033***	0.196***	0.106	-0.024***	-0.055***	-0.001
	(2.918)	(-3.942)	(4.289)	(1.398)	(-6.761)	(-5.518)	(-0.010)
β_{SIZE}	0.082***	0.068***	0.064***	0.031***	0.025***	0.019***	0.132***
	(20.352)	(20.046)	(27.337)	(4.754)	(28.549)	(20.925)	(22.217)
β_{BM}	-0.069	-0.048	-0.037	-0.077	0.036	0.045	0.197**
	(-0.368)	(-0.313)	(-0.389)	(-0.116)	(1.305)	(0.773)	(2.583)
β_{FLEV}	-0.125	-0.141	0.280***	1.846***	0.126***	0.246***	0.513**
	(-0.747)	(-1.028)	(2.874)	(5.878)	(3.394)	(5.741)	(2.022)
β_{ROA}	-0.025	-0.039	-0.016	-0.149	-0.002	-0.005	0.142
	(-0.280)	(-0.680)	(-0.186)	(-0.519)	(-0.088)	(-0.166)	(1.595)
β_{TURN}	0.003	-0.008	-0.023**	-0.030	-0.015***	-0.025***	-0.037
	(0.122)	(-0.470)	(-2.572)	(-0.580)	(-4.270)	(-5.517)	(-1.219)
$adjR^2$	0.009	0.015	0.100	0.147	0.156	0.150	0.192
AIC	742,430	631,359	450,098	972,673	-104,005	-83,496	957,726
Wooldridge test	14.150***	12.604***	10.777***	9.087***	3.131*	2.803*	12.711***
(p-value)	[0.00]	[0.00]	[0.00]	[0.00]	[0.08]	[0.09]	[0.00]

This table reports the estimation results of the following regression:

$$\begin{aligned} EDR_{i,\tau} = \; & \beta_{EDR}EDR_{i,\tau-1} + \beta_{RET}RET_{i,\tau-1} + \beta_{SD}SD_{i,\tau-1} \\ & + \beta_{TURN}TURN_{i,\tau-1} + \beta_{BM}BM_{i,\tau-1} + \beta_{FLEV}FLEV_{i,\tau-1} \\ & + \beta_{SIZE}SIZE_{i,\tau-1} + \beta_{ROA}ROA_{i,\tau-1} + \beta_{SI}SI_{i,\tau-1} \\ & + \sum_{1}^{11} \beta_M^{11} M_\tau^{11} + \epsilon_{i,\tau}, \end{aligned}$$

where EDR represents NCSKEW, DUVOL, EXSIGMA, MCRASH, and RDRS. This table presents the in-sample panel data regression (fixed-effect) results using seven monthly EDR measures during the POST-GFC period (2009-2017). AIC is the Akaike information criteria. All regressions also contain the time fixed effect and monthly seasonal dummies (M_τ^{11}), not shown and the t-statistics are in parentheses, are adjusted for heteroskedasticity. All regressions are tested for serial correlation in their residuals using the Wooldridge test for AR(1) errors in fixed effect panel models, the p-values are reported (in parentheses). *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

TABLE A.2.2.3. **Out-of-sample Forecasting Performance during PRE-GFC and POST-GFC Periods**

Panel A: Out-of-sample R^2 at a one-month frequency (PRE-GFC period)

	New EDR measures		
	RDRS1%	RDRS2%	MinCR
Existing EDR measures			
NCSKEW	0.953	0.947	-1.565
DUVOL	0.928	0.919	-2.956
EXSIGMA	0.887	0.873	-5.166
MCRASH	0.984	0.982	0.132

Panel B: Out-of-sample R^2 at a one-month frequency (POST-GFC period)

	New EDR measures		
	RDRS1%	RDRS2%	MinCR
Existing EDR measures			
NCSKEW	0.955	0.952	-1.426
DUVOL	0.930	0.925	-2.792
EXSIGMA	0.888	0.881	-5.042
MCRASH	0.986	0.985	0.223

This table reports the out-of-sample R^2 for pairs of EDR models over one-month forecasting horizon. Panel A and B report the out-of-sample R^2 during the PRE-GFC period (2000-2007) and the POST-GFC period (2009-2017), respectively. If the out-of-sample R^2 is greater than zero, then the new EDR measures (RDRS and MinCR) perform better than existing measure (NCSKEW, DUVOL, EXSIGMA, and MCRASH). If the out-of-sample R^2 is smaller than zero, then the new EDR measures perform worse than existing measures.

TABLE A.2.2.4. **Market Timing using the One Month Ahead EDR Forecasts during the PRE-GFC Period**

Panel A: Market timing strategy using the one month ahead in-sample forecasts

		New EDR measures			Existing EDR measures			
	Portfolio	RDRS1%	RDRS2%	MinCR	NCSKEW	DUVOL	EXSIGMA	MCRASH
Profitability	1	2.51%	1.05%	2.94%	2.92%	3.29%	1.82%	1.21%
	10	12.78%	12.55%	11.78%	8.78%	9.06%	8.09%	9.66%
	10-1	10.26%	11.51%	8.84%	5.85%	5.77%	6.27%	8.44%
Risk-adjusted returns	1	0.110***	0.103***	0.137***	0.076***	0.085***	0.054***	0.038***
		(1.007)	(0.948)	(1.257)	(0.693)	(0.781)	(0.495)	(0.345)
	10	0.190***	0.194***	0.171***	0.121***	0.125***	0.111***	0.139***
		(1.742)	(1.777)	(1.568)	(1.106)	(1.144)	(1.020)	(1.276)
	10-1	0.080***	0.090***	0.034***	0.045***	0.040***	0.057***	0.102***
		(0.735)	(0.829)	(0.311)	(0.412)	(0.363)	(0.525)	(0.931)

Panel B: Market timing strategy using the one month ahead out-of-sample forecasts

		New EDR measures			Existing EDR measures			
	Portfolio	RDRS1%	RDRS2%	MinCR	NCSKEW	DUVOL	EXSIGMA	MCRASH
Profitability	1	0.77%	0.58%	0.78%	0.82%	0.61%	0.61%	0.87%
	10	5.04%	4.96%	5.26%	5.21%	5.11%	5.00%	5.24%
	10-1	4.27%	4.39%	4.48%	4.39%	4.50%	4.40%	4.37%
Risk-adjusted returns	1	0.050**	0.043*	0.041*	0.043*	0.035	0.039*	0.057***
		(0.229)	(0.198)	(0.190)	(0.199)	(0.161)	(0.181)	(0.261)
	10	0.100***	0.100***	0.103***	0.102***	0.100***	0.099***	0.104***
		(0.460)	(0.459)	(0.470)	(0.466)	(0.460)	(0.453)	(0.475)
	10-1	0.050**	0.057***	0.061***	0.058***	0.065***	0.059***	0.047**
		(0.231)	(0.262)	(0.281)	(0.267)	(0.299)	(0.272)	(0.214)

This table reports the market timing strategy that uses the seven EDR measures as benchmarks during the PRE-GFC period (2000-2007). Panel A and Panel B report the market timing strategy using the one month ahead EDR measures in-sample and out-of-sample forecasts, respectively. Portfolio (decile) 1 contains the stocks with the lowest returns and Portfolio 10 contains the stocks with the highest returns. Portfolio 10-1 is the return (risk-adjusted return) difference between Portfolios 1 and 10. Profitability and risk-adjusted returns are measured by the average returns and Sharpe ratio. The critical Sharpe ratio (SR^c_τ) at the 1%, 5%, and 10% level of significance on a two-tailed test for the two sample of monthly and semi-annual returns as $SR^c_\tau = \text{Lev}_{\text{sig}}/\sqrt{\tau}$. Lev_{sig}, which represent the 1%, 5%, and 10% level of significance of the two-tailed test, are equal to 2.32, 1.96, and 1.64, respectively. τ represents the number of months (1MTH) in the sample. There are 84 1MTH in the in-sample PRE-GFC period and 21 1MTH in the out-of-sample PRE-GFC period. SR^c_{1MTH}, in the in-sample PRE-GFC period, at the 1%, 5%, and 10% level of significance is equal to 0.253, 0.214, and 0.179, respectively. SR^c_{1MTH}, in the out-of-sample PRE-GFC period, at the 1%, 5%, and 10% level of significance is equal to 0.506, 0.428, and 0.358, respectively. The t-statistics are in parentheses. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

TABLE A.2.2.5. **Market Timing using the One Month Ahead EDR Forecasts during the POST-GFC Period**

Panel A: Market timing strategy using the one month ahead in-sample forecasts

		New EDR measures			Existing EDR measures			
	Portfolio	RDRS1%	RDRS2%	MinCR	NCSKEW	DUVOL	EXSIGMA	MCRASH
Profitability	1	2.79%	1.50%	1.73%	1.61%	0.50%	1.07%	3.39%
	10	11.09%	11.21%	6.85%	7.02%	6.69%	8.13%	10.84%
	10-1	8.29%	9.71%	5.12%	5.41%	6.19%	7.05%	7.45%
Risk-adjusted returns	1	0.127***	0.142***	0.044***	0.041***	0.014***	0.034***	0.144***
		(1.241)	(1.395)	(0.428)	(0.402)	(0.132)	(0.331)	(1.408)
	10	0.171***	0.181***	0.099***	0.101***	0.097***	0.122***	0.167***
		(1.672)	(1.771)	(0.967)	(0.992)	(0.950)	(1.198)	(1.633)
	10-1	0.044	0.038***	0.055***	0.060***	0.083***	0.088***	0.023***
		(0.432)	(0.376)	(0.539)	(0.590)	(0.818)	(0.867)	(0.225)

Panel B: Market timing strategy using the one month ahead out-of-sample forecasts

		New EDR measures			Existing EDR measures			
	Portfolio	RDRS1%	RDRS2%	MinCR	NCSKEW	DUVOL	EXSIGMA	MCRASH
Profitability	1	0.65%	0.54%	0.78%	0.80%	0.67%	1.16%	0.68%
	10	6.48%	6.37%	6.66%	6.67%	6.76%	6.71%	6.58%
	10-1	5.83%	5.83%	5.88%	5.87%	6.09%	5.55%	5.89%
Risk-adjusted returns	1	0.036*	0.034*	0.032	0.033	0.030	0.054***	0.035*
		(0.176)	(0.168)	(0.157)	(0.162)	(0.148)	(0.266)	(0.173)
	10	0.111***	0.111***	0.108***	0.108***	0.113***	0.111***	0.111***
		(0.542)	(0.542)	(0.528)	(0.529)	(0.553)	(0.542)	(0.541)
	10-1	0.075***	0.076***	0.076***	0.075***	0.083***	0.056***	0.075***
		(0.366)	(0.374)	(0.371)	(0.366)	(0.405)	(0.276)	(0.369)

This table reports the market timing strategy that uses the seven EDR measures as benchmarks during the POST-GFC period (2009-2017). Panel A and Panel B report the market timing strategy using the one month ahead EDR measures in-sample and out-of-sample forecasts, respectively. Portfolio (decile) 1 contains the stocks with the lowest returns and Portfolio 10 contains the stocks with the highest returns. Portfolio 10-1 is the return (risk-adjusted return) difference between Portfolios 1 and 10. Profitability and risk-adjusted returns are measured by the average returns and Sharpe ratio. The critical Sharpe ratio (SR^c_τ) at the 1%, 5% and 10% level of significance on a two-tailed test for the two sample of monthly and semi-annual returns as $SR^c_\tau = \text{Lev}_{\text{sig}}/\sqrt{\tau}$. Lev_{sig}, which represent the 1%, 5%, and 10% level of significance of the two-tailed test, are equal to 2.32, 1.96, and 1.64, respectively. τ represents the number of months (1MTH) in the sample. There are 56 1MTH in the in-sample POST-GFC period and 24 1MTH in the out-of-sample POST-GFC period. SR^c_{1MTH}, in the in-sample PRE-GFC period, at the 1%, 5%, and 10% level of significance is equal to 0.237, 0.200, and 0.167, respectively. SR^c_{1MTH}, in the out-of-sample PRE-GFC period, at the 1%, 5%, and 10% level of significance is equal to 0.474, 0.400, and 0.335, respectively. The t-statistics are in parentheses. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

Appendix 2.3. Alternative Thresholds in RDRS Measure

We alter the thresholds, used to estimate the monthly and semi-annual RDRS measures, to ensure that the current thresholds are not driving the results. We use six thresholds (0, -0.005%, -1%, -2%, -3%, and -4%) in total. In comparison, Barndorff-Neilsen et al. (2010) use a threshold of 0 to measure the downside realized semivariance.

Changing the threshold does not affect either the one month or six months ahead in-sample panel estimations (see Tables A.2.3.2 and A.2.3.1). The predictive accuracy of the out-of-sample estimates is unaltered by the thresholds in use over both forecasting horizons (Table A.2.3.3).

The results obtained using the investment strategy, benchmarked on the in-sample and out-of-sample EDR forecasts, reveal that higher threshold mostly attracts higher risk-adjusted returns (Tables A.2.3.4 and A.2.3.5).

TABLE A.2.3.1. **Forecasting EDR in the Cross-Section using Different RDRS Thresholds (Six Months Ahead)**

	(1) RDRS0%	(2) RDRS0.005%	(3) RDRS1%	(4) RDRS2%
β_{RDRS}	0.133***	0.147***	0.152***	0.162***
	(11.181)	(12.691)	(14.394)	(21.877)
β_{RET}	0.063***	0.064***	0.065***	0.065***
	(16.272)	(16.901)	(18.030)	(22.107)
β_{SD}	0.001*	0.001	0.002***	0.005***
	(1.913)	(1.574)	(2.991)	(7.829)
β_{SI}	0.008*	0.007	0.005	0.004
	(1.753)	(1.597)	(1.300)	(1.377)
β_{SIZE}	0.024***	0.024***	0.023***	0.018***
	(28.499)	(29.129)	(28.849)	(25.566)
β_{BM}	0.009	0.009	0.009	0.009
	(1.179)	(1.265)	(1.329)	(1.467)
β_{FLEV}	-0.005*	-0.005*	-0.005*	-0.004*
	(-1.740)	(-1.740)	(-1.757)	(-1.778)
β_{ROA}	-0.026	-0.027	-0.033	-0.042
	(-0.802)	(-0.811)	(-0.922)	(-1.181)
β_{TURN}	-0.013***	-0.017***	-0.018***	-0.015***
	(-2.949)	(-4.020)	(-4.110)	(-3.639)
$adjR^2$	0.085	0.089	0.093	0.128
AIC	-119,201	-117,980	-116,736	-111,720

This table reports the estimation results of the following regression:

$$\begin{aligned} RDRS_{i,\tau} = {} & \beta_{RDRS}RDRS_{i,\tau-1} + \beta_{RET}RET_{i,\tau-1} + \beta_{SD}SD_{i,\tau-1} \\ & + \beta_{TURN}TURN_{i,\tau-1} + \beta_{BM}BM_{i,\tau-1} + \beta_{FLEV}FLEV_{i,\tau-1} \\ & + \beta_{SIZE}SIZE_{i,\tau-1} + \beta_{ROA}ROA_{i,\tau-1} \\ & + \beta_{SI}SI_{i,\tau-1} + \epsilon_{i,\tau}, \end{aligned}$$

where RDRS represents RDRS0%, RDRS0.005%, RDRS1%, RDRS2%, RDRS3%, and RDRS4%. This table presents the in-sample panel data regression results using the RDRS measures with different thresholds. The fixed-effect regressions are estimated at a semi-annual frequency. AIC is the Akaike information criteria. All regressions also contain the time fixed effect (not shown) and the t-statistics are in parentheses, are adjusted for heteroskedasticity. We do not report any serial correlation in residuals test for the fixed-effect regression at a six-month frequency because these tests apply primarily to panels with long time series (Baltagi et al. (1992) and Baltagi (2005)). *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

TABLE A.2.3.2. **Forecasting EDR in the Cross-Section using Different RDRS Thresholds (One Month Ahead)**

	(1) RDRS0%	(2) RDRS0.005%	(3) RDRS3%	(4) RDRS4%
β_{RDRS}	0.104***	0.113***	0.095***	0.062***
	(14.965)	(17.192)	(37.085)	(25.040)
β_{RET}	0.030***	0.031***	0.019***	0.009***
	(18.719)	(19.977)	(25.331)	(13.501)
β_{SD}	0.004***	0.004***	0.012***	0.015***
	(8.116)	(8.411)	(20.028)	(23.367)
β_{SI}	0.035***	0.028***	-0.008	-0.010
	(4.741)	(4.348)	(-1.406)	(-1.463)
β_{SIZE}	0.031***	0.031***	0.016***	0.011***
	(36.568)	(38.011)	(23.257)	(18.375)
β_{BM}	0.037	0.042	0.056	0.047
	(0.337)	(0.395)	(0.650)	(0.651)
β_{FLEV}	0.006	0.006	0.029*	0.032*
	(0.694)	(0.720)	(1.695)	(1.881)
β_{ROA}	0.261	0.239	0.236	0.271
	(0.740)	(0.656)	(0.653)	(0.956)
β_{TURN}	-0.026***	-0.029***	-0.052***	-0.053***
	(-6.924)	(-7.213)	(-7.907)	(-8.021)
$adjR^2$	0.130	0.132	0.161	0.161
AIC	-218,551	-214,946	-166,599	-202,707
Wooldridge test	0.637	0.766	10.109***	21.009***
(p-value)	[0.42]	[0.38]	[0.00]	[0.00]

This table reports the estimation results of the following regression:

$$\begin{aligned} RDRS_{i,\tau} = {} & \beta_{RDRS} RDRS_{i,\tau-1} + \beta_{RET} RET_{i,\tau-1} + \beta_{SD} SD_{i,\tau-1} \\ & + \beta_{TURN} TURN_{i,\tau-1} + \beta_{BM} BM_{i,\tau-1} + \beta_{FLEV} FLEV_{i,\tau-1} \\ & + \beta_{SIZE} SIZE_{i,\tau-1} + \beta_{ROA} ROA_{i,\tau-1} \\ & + \beta_{SI} SI_{i,\tau-1} + \sum_{1}^{11} \beta_M^{11} M_\tau^{11} + \epsilon_{i,\tau}, \end{aligned}$$

where RDRS represents RDRS0%, RDRS0.005%, RDRS1%, RDRS2%, RDRS3%, and RDRS4%. This table presents the in-sample panel data regression results using the RDRS measures with different thresholds. The fixed-effect regressions are estimated at a monthly frequency. AIC is the Akaike information criteria. All regressions also contain the time fixed effect and monthly seasonal dummies (M_τ^{11}) (not shown) and the t-statistics are in parentheses, are adjusted for heteroskedasticity. All regressions are tested for serial correlation in their residuals using the Wooldridge test for AR(1) errors in fixed effect panel models, the p-values are reported (in parentheses). *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

TABLE A.2.3.3. **Out-of-sample Forecasting Performance using Different RDRS Thresholds**

Panel A: Out-of-sample R^2 at a six-month frequency

	New EDR measures			
	RDRS0%	RDRS0.005%	RDRS1%	RDRS2%
Existing EDR measures				
NCSKEW	0.992	0.991	0.991	0.991
DUVOL	0.954	0.952	0.949	0.951
EXSIGMA	0.988	0.987	0.986	0.987
MCRASH	0.996	0.996	0.996	0.996

Panel B: Out-of-sample R^2 at a one-month frequency

	New EDR measures			
	RDRS0%	RDRS0.005%	RDRS3%	RDRS4%
Existing EDR measures				
NCSKEW	0.954	0.953	0.949	0.954
DUVOL	0.932	0.930	0.924	0.931
EXSIGMA	0.895	0.891	0.882	0.893
MCRASH	0.985	0.985	0.984	0.985

This table reports the out-of-sample R^2 for pairs of EDR models over six-month and one-month forecasting horizons. Panel A and Panel B report the out-of-sample R^2 over six-month and one-month forecasting horizons, respectively. If the out-of-sample R^2 is greater than zero, then the new measures (RDRS0%, RDRS0.005%, RDRS1%, RDRS2%, RDRS3%, and RDRS4%) perform better than the existing measure (NCSKEW, DUVOL, EXSIGMA, and MCRASH). If the out-of-sample R^2 is smaller than zero, then the new measures perform worse than the existing measures.

TABLE A.2.3.4. **Market Timing using the In-sample EDR Forecasts across Different Thresholds**

Panel A: Market timing strategy using the six months ahead in-sample forecasts

		New EDR measures				Existing EDR measures			
	Portfolio	RDRS0%	RDRS0.005%	RDRS1%	RDRS2%	NCSKEW	DUVOL	EXSIGMA	MCRASH
Profitability	1	1.77%	1.73%	1.53%	0.85%	1.69%*	1.89%	1.22%	1.86%
	10	8.31%	8.35%	8.48%	8.49%	7.23%	7.36%	7.07%	8.51%
	10-1	6.54%	6.62%	6.95%	7.64%	5.55%	5.47%	5.84%	6.65%
Risk-adjusted returns	1	0.115***	0.114***	0.110***	0.103***	0.099***	0.109***	0.085***	0.123***
		(1.160)	(1.151)	(1.110)	(1.038)	(1.097)	(0.859)	(1.245)	(1.592)
	10	0.285***	0.287***	0.295***	0.305***	0.241***	0.245***	0.237***	0.299***
		(2.879)	(2.899)	(2.979)	(3.077)	(2.472)	(2.392)	(3.017)	(2.994)
	10-1	0.170***	0.173***	0.185***	0.202***	0.142***	0.136***	0.152***	0.175***
		(1.719)	(1.748)	(1.868)	(2.039)	(1.431)	(1.375)	(1.534)	(1.772)

Panel B: Market timing strategy using the one month ahead in-sample forecasts

		New EDR measures				Existing EDR measures			
	Portfolio	RDRS0%	RDRS0.005%	RDRS3%	RDRS4%	NCSKEW	DUVOL	EXSIGMA	MCRASH
Profitability	1	3.29%	3.14%	1.26%	1.17%	2.25%	2.39%	1.04%	1.13%
	10	11.07%	11.17%	10.67%	9.87%	7.41%	7.60%	7.05%	8.63%
	10-1	7.78%	8.02%	9.40%	8.70%	5.16%	5.21%	6.01%	7.50%
Risk-adjusted returns	1	0.115***	0.112***	0.127***	0.124***	0.056***	0.060***	0.030***	0.034***
		(1.649)	(1.611)	(1.823)	(1.787)	(0.860)	(0.425)	(0.490)	(1.984)
	10	0.164***	0.166***	0.173***	0.165***	0.104***	0.107***	0.099***	0.127***
		(2.358)	(2.387)	(2.486)	(2.361)	(1.532)	(1.426)	(1.816)	(2.373)
	10-1	0.049***	0.054***	0.046***	0.040***	0.048***	0.047***	0.070***	0.092***
		(0.709)	(0.776)	(0.663)	(0.574)	(0.687)	(0.672)	(1.001)	(1.326)

This table reports the market timing strategy that uses the eight EDR measures as benchmarks. Panel A and Panel B report the market timing strategy using the EDR measures forecasted (in-sample) over six months and one month, respectively. Portfolio (decile) 1 contains the stocks with the lowest returns and Portfolio 10 contains the stocks with the highest returns. Portfolio 10-1 is the return (risk-adjusted return) difference between Portfolios 1 and 10. Profitability and risk-adjusted returns are measured by the average returns and Sharpe ratio. The critical Sharpe ratio (SR^c_τ) at the 1%, 5%, and 10% level of significance on a two-tailed test for the two sample of monthly and semi-annual returns as $SR^c_\tau = \text{Lev}_{\text{sig}}/\sqrt{\tau}$. Lev_{sig}, which represent the 1%, 5%, and 10% level of significance of the two-tailed test, are equal to 2.32, 1.96, and 1.64, respectively. τ represents the number of months (1MTH and 6MTH) in the sample. There are 102 6MTH and 206 1MTH. SR^c_{6MTH} at the 1%, 5%, and 10% level of significance is equal to 0.230, 0.194, and 0.162, respectively. SR^c_{1MTH} at the 1%, 5%, and 10% level of significance is equal to 0.162, 0.137, and 0.114, respectively. The t-statistics are in parentheses. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

TABLE A.2.3.5. **Market Timing using the Out-of-sample EDR Forecasts across Different Thresholds**

Panel A: Market timing strategy using the six month ahead out-of-sample forecasts

		New EDR measures				**Existing EDR measures**			
	Portfolio	RDRS0%	RDRS0.005%	RDRS1%	RDRS2%	NCSKEW	DUVOL	EXSIGMA	MCRASH
Profitability	1	0.47%	0.46%	0.49%	0.50%	0.62%	0.63%	0.45%	0.39%
	10	5.26%	5.28%	5.25%	5.19%	5.30%	5.26%	5.26%	5.23%
	10-1	4.80%	4.82%	4.76%	4.69%	4.68%	4.63%	4.82%	4.84%
Risk-adjusted returns	1	0.046	0.046	0.082**	0.083**	0.051*	0.047*	0.048	0.044**
		(0.230)	(0.229)	(0.412)	(0.414)	(0.234)	(0.240)	(0.218)	(0.292)
	10	0.179***	0.179***	0.180***	0.180***	0.180***	0.178***	0.180***	0.180***
		(0.894)	(0.897)	(0.901)	(0.899)	(0.892)	(0.899)	(0.902)	(0.898)
	10-1	0.133***	0.134***	0.098***	0.097***	0.129***	0.132***	0.132***	0.137***
		(0.664)	(0.669)	(0.490)	(0.484)	(0.646)	(0.658)	(0.659)	(0.684)

Panel B: Market timing strategy using the one month ahead out-of-sample forecasts

		New EDR measures				**Existing EDR measures**			
	Portfolio	RDRS0%	RDRS0.005%	RDRS3%	RDRS4%	NCSKEW	DUVOL	EXSIGMA	MCRASH
Profitability	1	0.46%	0.49%	0.47%	0.45%	0.54%	0.50%	0.64%	0.47%
	10	5.28%	5.29%	5.25%	5.26%	5.31%	5.24%	5.33%	5.21%
	10-1	4.82%	4.80%	4.77%	4.81%	4.77%	4.74%	4.69%	4.74%
Risk-adjusted returns	1	0.020	0.023	0.035*	0.037*	0.022	0.022	0.030	0.023
		(0.145)	(0.164)	(0.254)	(0.266)	(0.160)	(0.159)	(0.216)	(0.166)
	10	0.083***	0.083***	0.083***	0.084***	0.082***	0.082***	0.083***	0.082***
		(0.599)	(0.601)	(0.599)	(0.603)	(0.591)	(0.591)	(0.596)	(0.590)
	10-1	0.063***	0.061***	0.048***	0.047***	0.060***	0.060***	0.053***	0.059***
		(0.454)	(0.437)	(0.345)	(0.337)	(0.431)	(0.432)	(0.380)	(0.424)

This table reports the market timing strategy that uses the eight EDR measures as benchmarks. Panel A and Panel B report the market timing strategy using the RDRS measures forecasted (out-of-sample) over six months and one month, respectively. Portfolio (decile) 1 contains the stocks with the lowest returns and Portfolio 10 contains the stocks with the highest returns. Portfolio 10-1 is the return (risk-adjusted return) difference between Portfolios 1 and 10. Profitability and risk-adjusted returns are measured by the average returns and Sharpe ratio. The critical Sharpe ratio (SR^c_τ) at the 1%, 5%, and 10% level of significance on a two-tailed test for the two sample of monthly and semi-annual returns as $SR^c_\tau = \text{Lev}_{\text{sig}}/\sqrt{\tau}$. Lev_{sig}, which represent the 1%, 5%, and 10% level of significance of the two-tailed test, are equal to 2.32, 1.96, and 1.64, respectively. τ represents the number of months (1MTH and 6MTH) in the sample. There are 25 6MTH and 52 1MTH. SR^c_{6MTH} at the 1%, 5%, and 10% level of significance is equal to 0.464, 0.392, and 0.328, respectively. SR^c_{1MTH} at the 1%, 5%, and 10% level of significance is equal to 0.322, 0.272, and 0.227, respectively. The t-statistics are in parentheses. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

CHAPTER 3

The Economic Impact of Daily Volatility Persistence on Energy Markets

3.1. Introduction

The volatility of energy markets plays an integral role in the global economy. Information from asset classes, such as macro-economy and equity, has a material impact and carries significant predictive power for the future evolution of energy market volatility. According to Ross (1989), cross-market information is synonymous with volatility. Accordingly, empirical evidence has demonstrated the importance of this information transmission in modeling and forecasting volatility in commodity markets. Beyond the fundamentally important objective to ensure (statistical and economic) forecasting gain, this study further reveals the essential role of volatility persistence in transmitting this information in the volatility of energy markets. Although many studies find a wide range of variables affect future volatility, the information from lagged volatilities remains the most significant predictive channel (Patton and Sheppard (2015), Bollerslev et al. (2016), and Bollerslev et al. (2018)). The correlation between today's and tomorrow's volatility, captured by volatility persistence, is a fundamental block of future volatility. Therefore, examining the determinants and empirical characteristics of volatility persistence can lead to a more comprehensive understanding of how information is channeled in the volatility of energy markets.

In this study, we quantify and gauge the importance of volatility persistence in transmitting information from economic market variables to the daily volatility of two key energy markets: crude oil and natural gas. We study a heterogeneous autoregressive (HAR) model that allows volatility persistence to vary with returns, lagged volatility, and economic variables. The corresponding volatility persistence is termed conditional volatility persistence (CVP). As expected, we find that returns and realized variance are important determinants of volatility persistence in energy markets, while other economic variables also affect volatility persistence. The daily CVP of crude oil is negatively related to the credit spreads and the Baltic Exchange Dirty Tanker Index,[1] but positively related to the VIX.[2] Further, the impact of financial variables on the volatility persistence of natural gas markets is limited; only Treasury bills are positively related to CVP. These findings provide new evidence of the economic determinants of volatility persistence in energy markets.

Three (interrelated) results further underscore the economic significance of volatility persistence as the information-transmitting mechanism in the volatility dynamics of energy markets. First, the impact of returns is transmitted to future volatility via the volatility persistence channel. After accounting for volatility persistence, the direct impact of returns on future volatility is reduced considerably and/or becomes statistically insignificant (in natural gas). The impact of the economic variables is also transmitted to the energy volatility via the volatility persistence channel, rather than directly to the volatility level. Thus, CVP plays an important role in transmitting information from macro-economic and market conditions in future volatility. Second, the CVP determinants notably contribute to volatility variation. The VIX, credit spreads, and Baltic Exchange Dirty Tanker Index are particularly important for the volatility persistence in crude oil futures markets. Collectively, the CVP-based variables explain 15% to 23% of the variation in daily volatility across the two energy markets, accounting for 25% to 38% of the regression R^2.[3] Third, daily volatility persistence in energy markets is considerable and show large daily variations.[4] This evidence of a statistical and economic significance of daily CVP presents a challenge to models with constant volatility persistence and to the standard practice of

[1]Credit spreads and the Baltic Index are positively associated with energy market volatility. An unexpected increase in credit spreads or the tanker index tends to increase the energy market volatility. This volatility reflects the gross information flow over a short period of time (e.g., a day) associated with more priced information, thus the arrival of less correlated information, meaning low volatility persistence.

[2]Ross (1989) suggests that volatility reflects information flow, thus effects transmitted between different markets reflect cross-market information flows. Correlated information, defined as information urged by the same underlying economic change, e.g., a shock in the VIX, tends to arrive within a short period of time causing volatility clustering and thus increased volatility persistence.

[3]The contribution of these determinants is assessed by the means of the Shapley R^2. The Shapley R^2 measures the marginal contributions of a set of explanatory variables to the variation of the dependent variable. Thus, these variables are not only key determinants of volatility persistence but also transmit a material impact on future volatility that jointly accounts (via CVP) for almost one quarter of the variation in future volatility.

[4]The mean CVP is 54.6% in crude oil and 46.4% in natural gas, while the volatility of the CVP is 8.5% for crude oil and 7.7% for natural gas (which are larger than the standard deviations of daily volatility).

modeling and estimating the return impact on the volatility level, and not on its persistence.

Further, we demonstrate that models calibrating the correlation between current and future volatility and incorporating information from economic variables offer enhanced predictive accuracy for energy market volatility. In line with Bollerslev et al. (2018), we assess the economic value of the forecasting models by employing realized utility per unit of wealth, accounting for transaction costs and trading speed. The empirical results reveal superior statistical and economic benefits in incorporating information from macro-economic variables in the daily volatility persistence, particularly in the oil market (where macro-economic variables are important).[5]

The findings regarding the economic significance of volatility persistence contribute to two strands of literature. The first strand deals with modeling and analyzing the empirical characteristics of volatility persistence. Following the success of the generalized autoregressive conditional heteroskedasticity (GARCH) family models, a wide range of explanations have been proposed with mixed empirical support (Lamoureux and Lastrapes (1994), Andersen and Bollerslev (1997), Johnson (2001), Xue and Gençay (2012), and Berger et al. (2009)). However, as Bollerslev et al. (2018) state, "[T]he economic forces behind volatility clustering per se remain poorly understood." Several recent studies have explored the determinants of volatility persistence in equity markets (Patton and Sheppard (2015), Bollerslev et al. (2016), Wang and Yang (2018), Baur and Dimpfl (2019), and Chen and Wang (2020)). They find that factors such as the measurement errors in daily volatility, returns and volatility level can affect daily volatility persistence. We add to this literature by identifying key macro-economic determinants of daily CVP in energy markets and demonstrate that by linking volatility persistence to economic conditions, our models produce statistically and economically significant benefits relative to recent advances in modeling volatility dynamics.

Another strand of literature is associated with forecasting commodity market volatility (in particular, in the crude oil market) by conditioning on macro-economic variables. These studies extend on the GARCH model to include macro-economic variables with

[5]We compare the forecasting performance of our model against those of the Corsi (2009) HAR model, the Patton and Sheppard (2015) HAR with semivariance (HAR-SV) model, and the Bollerslev et al. (2016) HAR with realized quarticity (HAR-RQ) model.

mixed frequencies, and the enhanced model tends to improve forecasting ability in energy markets (Pan et al. (2017), Bakas and Triantafyllou (2019), Nguyen and Walther (2020), and Nonejad (2020)). There is an emerging literature using high-frequency data analyzes short-term realized volatility forecasting in commodity markets (Degiannakis and Filis (2017), Degiannakis and Filis (2018), Ma et al. (2018), Prokopczuk et al. (2019), Alam et al. (2019), and Bissoondoyal-Bheenick et al. (2020)). Degiannakis and Filis (2017) demonstrate that stocks, Forex, commodities, and macro-economic information enhances the predictability of oil price volatility, and Degiannakis and Filis (2018) find predictive benefits in oil market volatility by using volatility and returns of financial markets. Alam et al. (2019) study sources of volatility asymmetries in the oil market and show that bad volatility dominates good volatility in terms of shock transmissions.

This study underscores the economic importance of volatility persistence as an information-transmitting mechanism in energy markets, which infers material implications for several aspects of energy market dynamics. Since the financialization of commodity markets (Tang and Xiong (2012), Silvennoinen and Thorp (2013), and Cheng and Xiong (2014)), it has been argued that volatility in these markets, in particular, crude oil, has been integrated with equity markets, and volatility spillovers are evident between them (Chiang et al. (2015), Basak and Pavlova (2016), and Aromi and Clements (2019)). Energy market volatility also has a notable impact on the shape of futures curves, risk premiums and the asymmetric nature of the return-volatility relationship which has become more pronounced following the financialization of commodity markets.[6] Further, macro-economic and financial variables, such as industrial production, term and credit spreads, the US dollar index, and the VIX are key determinants of the dynamics in energy markets (in particular, oil markets) (Chiang et al. (2015), Prokopczuk et al. (2019), and Kang, Nikitopoulos and Prokopczuk (2020)). The magnitude of this impact differs across energy markets, so the economic determinants of volatility persistence and their impact may differ. Silvennoinen and Thorp (2013) show that macro-economic variables affect crude oil, but not natural gas. Recent empirical studies provide strong evidence of the decoupling of oil and gas prices, mainly due to the shale gas revolution (Zhang and Ji (2018) and Zhang, Shi and Shi (2018)). Ji et al. (2018) show that oil and its refining products act as

[6]See Chiarella et al. (2016), Nikitopoulos et al. (2017), Prokopczuk et al. (2017), Christoffersen and Pan (2018), Baur and Dimpfl (2018), and Prokopczuk et al. (2019) for related literature.

information transmitters, while natural gas markets act as information receivers. From a practical perspective, the physical energy markets have experienced significant structural changes in recent years, such as the expansion of the shale oil and gas markets (Kilian (2016)). Thus, investments in transportation facilities, production planning, and inventory management are affected by the determinants of the volatility dynamics and their transmission channels (e.g., volatility persistence). Moreover, volatility forecasting in energy markets is critical for trading and investment performance, derivatives pricing and hedging decisions. Accounting for information flows from economic variables in energy market volatility could potentially offer forecasting gains.

The remainder of the study is structured as follows. In Section 3.2, we outline the model specifications for conditional volatility persistence. Section 3.3 describes the data. We analyze volatility persistence in energy markets and identify its determinants in Section 3.4. Using forecasting considerations, the statistical and economic benefits of volatility persistence are further examined in Section 3.5. Section 3.6 concludes the study.

3.2. Modeling Volatility Persistence

The increasing availability of high-frequency data has improved the estimation and the forecasting of return-based realized variance (RV) measures (Bucci (2017)). The HAR model proposed by Corsi (2009) has emerged as the most popular model capturing the dynamics of daily RV. This model reproduces the empirically observed long memory of financial markets and has equal or better forecasting performance than more complicated models (Corsi (2009) and Sévi (2014)). We adapt HAR models to embed the feature of time-varying volatility persistence that may depend on market variables, such as returns, volatility, and macro-economic factors. Next, we discuss the formulation of volatility persistence in classical HAR models, and we introduce a novel approach to model conditional volatility persistence in HAR models.

3.2.1. Classical HAR models and volatility persistence. We denote as $RV_{t,D}$ the daily realized variance that is estimated as the sum of squared intra-day returns over a day, thus given by $RV_{t,D} = \sum_{i=1}^{M} r_i^2$ where M is the number of intra-day observations. The HAR model is based on the idea that the unobservable variance of returns is a linear function of the lagged squared return sampled over different time horizons, reflecting the impact of an investor with varying trading frequencies (Corsi (2009)). To account for the heterogenous effects of returns on volatility, namely the leverage effect, the lagged daily, weekly and monthly returns are also included in the model specifications.[7] Accordingly, the basic (leveraged) HAR model is estimated via the following regression:

$$RV_{t+1,D} = \alpha + \beta_D RV_{t,D} + Z_t + \epsilon_{t+1}, \tag{3.2.1}$$

where

$$Z_t = \beta_W RV_{t,W} + \beta_M RV_{t,M} + \theta_D^+ r_{t,D}^+ + \theta_D^- r_{t,D}^- + \theta_W r_{t,W} + \theta_M r_{t,M}, \tag{3.2.2}$$

with $RV_{t,W}$ and $RV_{t,M}$ representing the (non-overlapping)[8] averages of the lagged weekly and monthly realized variances, approximated by $RV_{t,W} = \frac{1}{4}\sum_{i=1}^{4} RV_{t-i,D}$, and $RV_{t,M} = \frac{1}{17}\sum_{i=5}^{21} RV_{t-i,D}$, respectively. The negative and positive daily returns are captured by $r_{t,D}^- = r_t I_{(r_t<0)}$ and $r_{t,D}^+ = r_t I_{(r_t>0)}$, respectively, and the lagged weekly and monthly returns are constructed as $r_{t,W} = \frac{1}{4}\sum_{i=1}^{4} r_{t-i,D}$ and $r_{t,M} = \frac{1}{17}\sum_{i=5}^{21} r_{t-i,D}$, respectively. The HAR model specifications (1)–(2) infer constant daily volatility persistence, represented by β_D, and ensure that statistically and economically significant variables impacting future daily RV are used as controls, including long-run dependence from weekly and monthly RV.

Patton and Sheppard (2015) introduce the negative semivariance (NSV) and the positive semivariance (PSV) which capture the influence of negative returns and positive returns on RV, respectively. They demonstrate empirically that in equity markets, negative shocks matter more for future volatility than positive shocks. The leveraged HAR model incorporating these semivariances is denoted as the HAR-SV model, and it is estimated as:

$$RV_{t+1,D} = \alpha + \beta_{PSV} PSV_{t,D} + \beta_{NSV} NSV_{t,D} + Z_t + \epsilon_{t+1}, \tag{3.2.3}$$

[7] In the seminal work by Corsi and Renò (2012) and subsequent work, the leverage effect is captured by the negative (daily, weekly, and monthly) returns. It is well documented that in equity markets the impact of negative returns on future volatility is more pronounced than positive returns; which motivates this representation. However, energy markets are known to react to either large negative or positive returns (Silvennoinen and Thorp (2013) and Baur and Dimpfl (2018)). This study aims to identify the impact of positive and negative returns on future RV. Accordingly, we consider a variation of the *classical* HAR model proposed in the literature by including the negative and positive daily returns (Wang and Yang (2018)).

[8] Non-overlapping averages allow to isolate the impact of $RV_{t,D}$ on $RV_{t+1,D}$.

where Z_t is given by (3.2.2), with $NSV_{t,D} = \sum_{i=1}^{n} r_{i,t}^2 I_{(r_{i,t}<0)}$ and $PSV_{t,D} = \sum_{i=1}^{n} r_{i,t}^2 I_{(r_{i,t}>0)}$. Although it is not directly inferred, the model's specifications entail a daily volatility persistence which is sensitive to the size and type of shocks – high negative shocks lead to high volatility persistence.[9]

The first explicit reference of the volatility persistence depending on market conditions was proposed by Bollerslev et al. (2016). The daily realized variance, which is computed using high-frequency returns, is influenced by market microstructure noise (e.g., bid-ask bounce and tick size) and new events (Barndorff-Nielsen and Shephard (2002) and Andersen et al. (2010)). The realized quad-power quarticity (RQ) captures the variance of these measurements errors and it is estimated as $RQ_{t,D} = \frac{n}{3}\sum_{i=1}^{n} r_{i,t}^4$. High $RQ_{t,D}$ means more noise and less information in $RV_{t,D}$, therefore less impact from $RV_{t,D}$ on $RV_{t+1,D}$. Thus, as documented by Bollerslev et al. (2016), this is a systemic variation associated with $RV_{t,D}$. The square root of $RQ_{t,D}$ interacts with the lagged realized variance, and it is added to the HAR model to produce the (leveraged) HAR-RQ model as:

$$RV_{t+1,D} = \alpha + (\beta_D + \beta_{RQ} RQ_{t,D}^{1/2}) RV_{t,D} + Z_t + \epsilon_{t+1}, \tag{3.2.4}$$

where Z_t is determined by (3.2.2).

Next, we propose a new class of HAR models with conditional volatility persistence.

3.2.2. HAR models with conditional volatility persistence.

The dynamic nature of daily volatility persistence is impacted by market conditions and macro-economic shocks and is captured by the so-called conditional volatility persistence (CVP). Empirical evidence in equity markets suggests that daily volatility persistence depends on observed market conditions, such as returns and volatility (Wang and Yang (2018)). The net price impact of an information event, following positive and negative returns, triggers the arrival of correlated information the next day, which leads to an increase in volatility persistence. A high-volatility market environment (high daily RV) is a signal that the market

[9] If we let $\theta_{t,D}^{-} = NSV_{t,D}/RV_{t,D}$, then model (3.2.3) can be rewritten as:

$$RV_{t+1,D} = \alpha + [\beta_{NSV}\theta_{t,D}^{-} + \beta_{PSV}(1-\theta_{t,D}^{-})]RV_{t,D} + Z_t + \epsilon_{t+1}.$$

Then, the daily volatility persistence of the HAR-SV model is expressed as $\beta_{NSV}\theta_{t,D}^{-} + \beta_{PSV}(1-\theta_{t,D}^{-}) = \beta_{PSV} + (\beta_{NSV} - \beta_{PSV})\theta_{t,D}^{-}$. Based on Patton and Sheppard (2015)'s findings for equity markets, $\beta_{NSV} \gg \beta_{PSV} > 0$, thus high $\theta_{t,D}^{-}$ will lead to high daily volatility persistence.

processes new information more rapidly, and there is less unpriced information, thus inducing a reduction in volatility persistence the next day (Andersen (1996)). Accordingly, daily volatility persistence, depending on returns and volatility, can be formulated by the following HAR-CVP model:

$$RV_{t+1,D} = \alpha + CVP_{t,D} RV_{t,D} + Z_t + \epsilon_{t+1}, \tag{3.2.5}$$

where

$$CVP_{t,D} = \beta_D + \beta_r^- r_{t,D}^- + \beta_r^+ r_{t,D}^+ + \beta_{RV} RV_{t,D}, \tag{3.2.6}$$

with β_r^-, β_r^+, and β_{RV} as the CVP coefficients and Z_t given again by (3.2.2). Note that the HAR-CVP model also includes non-overlapping long-run variances ($RV_{t,W}$ and $RV_{t,M}$) and returns ($r_{t,W}$ and $r_{t,M}$). Wang and Yang (2018) show that in equity markets, the coefficients $\beta_r^- < 0$, $\beta_r^+ > 0$, and $\beta_{RV} < 0$, inferring a positive relationship between daily returns and volatility persistence, and a negative relationship between volatility and volatility persistence.

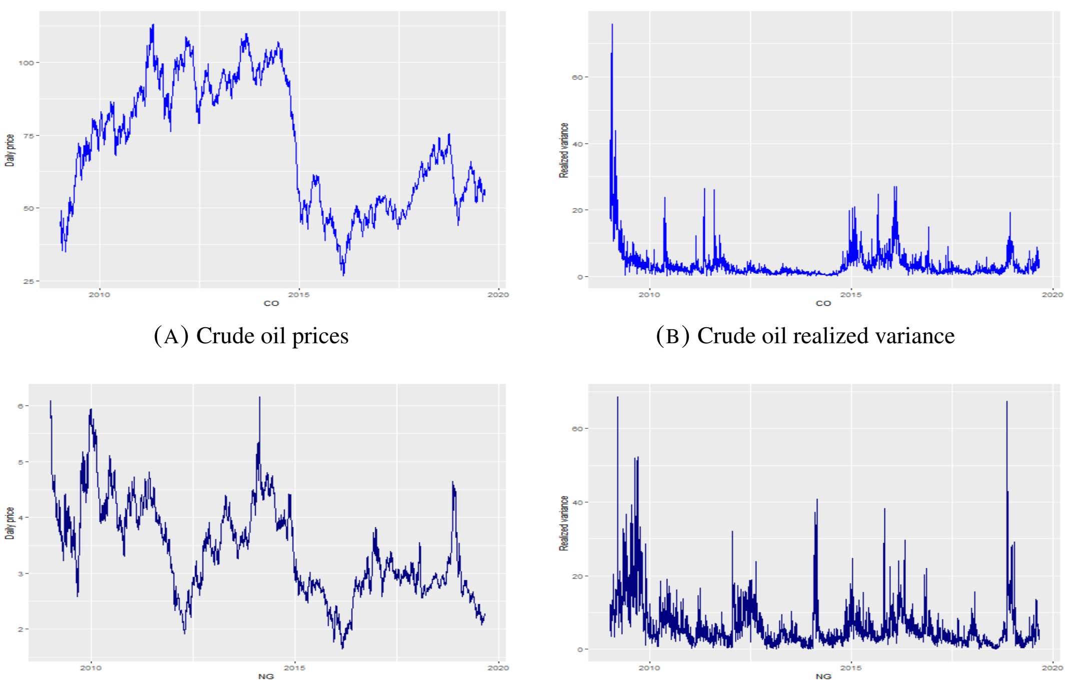
We hypothesize that volatility persistence is conditional, not only on market conditions such as returns and volatility, but also on macro-economic factors. Thus, we extend the aforementioned concept of CVP to include financial indicators, such as S&P 500 returns and credit spreads, and energy sector variables, such as the Baltic Exchange Dirty Tanker Index. Information about these macro-economic factors is represented by the set of conditioning variables $CV_{t,D}$. To identify the information transmission channels of these macro-economic factors, we further allow the set of conditioning variables to impact the dynamics of the volatility in two ways: by their direct effect on the daily realized variance and their indirect effect via volatility persistence. This model formulation can not only identify the macro-economic determinants of daily volatility persistence in energy markets, but also disentangle the information channels of these macro-economic factors on future volatility. Accordingly, we propose the following extension of model (3.2.5)–(3.2.6) to incorporate impact from economic factors, namely the HAR-CVP-CV model, which is estimated as:

$$RV_{t+1,D} = \alpha + CVP_{t,D} RV_{t,D} + Z_t + \delta_{CV} CV_{t,D} + \epsilon_{t+1}, \tag{3.2.7}$$

where the CVP (3.2.6) is extended and estimated by:

$$CVP_{t,D} = \beta_D + \beta_r^- r_{t,D}^- + \beta_r^+ r_{t,D}^+ + \beta_{RV} RV_{t,D} + \beta_{CV} CV_{t,D}, \tag{3.2.8}$$

with Z_t be represented in (3.2.2). The CVP now contains the market conditions variables $r_{t,D}^-$, $r_{t,D}^+$, $RV_{t,D}$, as well as the macro-economic conditioning variables $CV_{t,D}$; thus the corresponding regressors of CVP are $r_{t,D}^- RV_{t,D}$, $r_{t,D}^+ RV_{t,D}$, $RV_{t,D}^2$, and $CV_{t,D} RV_{t,D}$, respectively. Note that, δ_{CV} and β_{CV} represent vectors of the coefficients for the corresponding macro-economic conditioning variables in the daily realized variance dynamics and in its volatility persistence, respectively. This representation provides the flexibility to assess the direct impact of the conditioning variables on the realized variance and the contribution of the conditional volatility persistence on transmitting the (indirect) impact of the conditioning variables to the realized variance.



(A) Crude oil prices (B) Crude oil realized variance

(C) Natural gas prices (D) Natural gas realized variance

FIGURE 3.2.1. **Daily Prices and Realized Variances**
The figure plots the time series of the daily prices and the realized variances of the crude oil and natural gas front-month futures contracts between January 2009 and August 2019. RV is scaled by 10^4.

The HAR models can be estimated with OLS, as shown by Corsi (2009) and Corsi and Renò (2012). However, daily RV exhibits frequent spikes (see Figure 3.2.1). As pointed out by Patton and Sheppard (2015), these spikes tend to have a large influence on the estimated coefficients in the OLS estimation. Accordingly, we estimate the HAR models with weighted least squares (WLS), with the inverse of the fitted values of the error standard deviations, retrieved from the ordinary least square estimation, as the weights.[10]

3.3. Data and Preliminary Analysis

We study the volatility persistence of two key energy markets, crude oil and natural gas, from January 2009 to August 2019.[11] We employ the corresponding energy prices and a set of conditioning variables to estimate the daily realized variances using the different specifications of volatility persistence.

3.3.1. Energy futures. We use the prices of the nearest continuous futures contracts of the two energy commodities traded on the New York Mercantile Exchange (NYMEX). The daily RV, a measure of ex-post volatility, is constructed using the mid-quotations prices (average of bid and ask prices), sampled at five-minute intervals.[12] All futures prices are collected from Refinitiv Tick History (RTH). The data filter process for reducing the thin trading bias (Bollerslev et al. (2018)) is outlined in Appendix 3.2.

[10]Motivated by Neter et al. (2005), Montgomery et al. (2008), and Diebold (2015), we use a three-step approach to derive the WLS weights. First, we fit the regression model by OLS and carry out a residual analysis that determine the relationship between the OLS regression's residual and fitted values. We observe that the residual plot against the fitted values has a megaphone shape. This indicates that the constant variance assumption has been violated and also that the variability of the residuals increases with the fitted values. Second, we estimate the standard deviation function by regressing the absolute residuals on the fitted values. Using the absolute value of the residuals, rather than its squared value, is deemed more suitable because it is less affected by outliers in the data (Montgomery et al. (2008)). Thus, we run the regression $|\epsilon| \sim y$, where $|\epsilon|$ and y are the absolute values of the OLS regression's residuals and the OLS regression's fitted values, respectively. Third, we use the inverse of the squared fitted values from the standard deviation function as the WLS weights.

[11]We decided to start the analysis from 2009 based on liquidity considerations for energy contracts (see also Bissoondoyal-Bheenick et al. (2020)). The energy contracts were thinly traded (at a high-frequency level) prior to this period. Since the daily volatility measure (RV) is constructed using five-minute returns, we require that most contracts be traded over a five-minute window (with no major gaps in between). In Appendix 3.2. (Figure A.3.2.1.), we demonstrate that inclusion of thinly trading days can significantly overstate the average daily RV (four times more than its actual value), particularly for natural gas contracts. Similarly, during periods of low liquidity, we observe that the correlation between squared return (another proxy for daily volatility) and daily RV measure is weak. Hence, discarding the low liquidity periods removes noise in our volatility proxy.

[12]In the literature, the consensus is to aggregate returns into five-minute intervals as they usually provide the best RV approximation (Liu et al. (2015)).

We measure the daily volatility of the two energy markets by using the RV based on five-minute returns.[13] Some energy markets display seasonality, and failing to account for it may distort the pricing, hedging, and forecasting performance of the associated models (Suenaga et al. (2008), Martínez and Torró (2015), and Arismendi et al. (2016)). In line with Auer (2014), we test for seasonality in the RV time series using the Kruskal–Wallis (KW) test[14] and confirm that there is a day of the week and month of the year effect in natural gas volatility, but not in crude oil volatility.[15] Accordingly, we deseasonalize the natural gas RV time series based on the approach used by Hameed et al. (2010) and Wang (2013). This approach ensures that the adjusted and original RV time series mean and variance remain unchanged (i.e., they share the same statistical properties). Appendix 3.3. summarizes the details of the seasonality adjustments and tests.

The time series of the daily prices and the RV of the two energy markets are depicted in Figure 3.2.1. Between 2009 and 2014, energy prices trended upward, on average, as the economic recovery from the Global Financial Crisis and increasing demand from emerging economies drove oil prices up to $125 per barrel. However, by the end of 2014, oil and natural gas prices plummeted, driven by the slower economic growth of emerging countries and the rapid expansion of shale markets that led to a global oversupply of oil (oil glut). The impact of the oil glut was evident not only in the prices, but also in the RV series of the crude oil market. Interestingly, the RV time series reveal that natural gas had more clusters of volatility over the years than the other commodities. In recent years, natural gas markets have been uncorrelated to oil markets, which is evident from the price dynamics of these markets in Figure 3.2.1.[16] Unlike the oil market, natural gas prices are mainly determined by supply and demand controlled by weather and production levels, with less impact from economic growth conditions. Natural gas production has

[13]Alternative RV measures are also considered, namely the realized quad-power quarticity (RQ), the negative semivariance (NSV), and the positive semivariance (PSV). See Appendix 3.4. for a discussion of their statistical properties.

[14]See Kruskal and Wallis (1952).

[15]Crude oil markets display significant volatility spillovers and integration with equity markets, which may distort effects driven by potential oil market seasonal factors such as inventory (Cheng and Xiong (2014), Chiang et al. (2015), Basak and Pavlova (2016), Bampinas and Panagiotidis (2017), and Kang, Nikitopoulos and Prokopczuk (2020)).

[16]Following the liberation of natural gas prices from oil indexation, in recent years there is strong empirical evidence of the decoupling of crude oil and natural gas prices (particularly in the United States) (Geng et al. (2016*a*) and Zhang and Ji (2018)). The shale gas evolution has further affected the relation between the two markets (Geng et al. (2016*b*) and Caporin and Fontini (2017)).

increased dramatically with shale drilling, keeping natural gas prices low in recent years, with the occasional spikes driven mostly by extreme weather conditions, such as those in November 2018.[17]

3.3.2. Macro-economic variables. We hypothesize that general macro-economic factors, such as financial indicators and commodity sector variables, can affect the daily volatility persistence in energy markets and transmit this impact to the volatility of these markets. To capture these effects, we use HAR models for the RV of energy markets that integrate the direct impact of macro-economic factors on volatility, but also gauge their indirect impact on volatility via (conditional) volatility persistence. We term these factors conditioning variables, and we consider two groups: financial indicators and commodity sector variables. These factors are indicated by the empirical literature identifying key determinants of returns and volatility in energy markets.[18] Volatility is the main channel of volatility persistence, so they are likely to share the same determinants. We further aim to determine the importance of volatility persistence in transmitting this impact to volatility dynamics.

The first group of (volatility and) volatility persistence determinants is financial indicators. We consider the following six financial indicators: the S&P 500 return (SP500), VIX, US dollar index (USDI), credit spread (CS), 3-month Treasury bills (TB), and term spread (TS). The second group of conditioning variables is the commodity sector variables, including the S&P Goldman Sachs Commodity (non-energy) Index (SPGSCI), Commodity Research Bureau Raw Materials Index (CRB), and Baltic Exchange Dirty Tanker Index (BDI).[19] We report the summary statistics of the conditioning variables in

[17]See https://www.eia.gov/todayinenergy/detail.php?id=37713.

[18]See Morana (2013), Anzuini et al. (2015), Hitzemann (2016), Prokopczuk et al. (2019), and Kang, Nikitopoulos and Prokopczuk (2020).

[19]The data sources and the role of each determinant of energy markets dynamics are discussed with associated literature in Appendix 3.5. Other macro-economic factors could have been included in this study, such as inventory, hedging pressure, and industrial production. However, these factors are available on weekly or even monthly frequency. For this study, we focus on factors available in daily frequency. Inventory may have medium- to long-term effects on weekly/monthly volatility (Kogan et al. (2009), Haugom et al. (2014), and Nikitopoulos et al. (2017)). However, short-term volatility, e.g., daily volatility computed from high-frequency data, tends to be more sensitive to macro-economic factors (Kang, Nikitopoulos and Prokopczuk (2020)). Moreover, energy inventory data are avaible on weekly frequency, thus controlling for inventory in our models would compromise the reliability of the data as we will have to rely to some type of interpolation techniques. Thus, inventory is not included as a control variable.

TABLE 3.3.1. **Descriptive Statistics of Conditioning Variables**

	Mean	St. Dev.	Median	Skewness	Exc. Kurtosis	min	max	ADF
Financial indicators								
SP500(%)	0.045	1.046	0.063	0	5	-6.896	6.837	-14.466***
VIX	18.377	7.429	16.160	2	3	9.140	56.650	-4.495***
USDI	4.401	0.101	4.371	0	-2	4.220	4.573	-2.742
CS	1.064	0.441	0.960	3	9	0.530	3.350	-4.344***
TB	0.491	0.744	0.130	2	1	0.000	2.490	2.822
TS	2.019	0.918	2.010	0	0	-0.520	3.830	-2.583
Commodity sector variables								
SPGSCI	5.888	0.152	5.838	0	-1	5.551	6.245	-2.596
CRB	5.492	0.149	5.445	-1	1	5.154	5.864	-2.679
BDI	7.037	0.846	7.039	-5	40	0.000	8.447	-5.338***

This table details the descriptive statistics of the conditioning variables: SP500, VIX, USDI, CS, TB, TS, SPGSCI, CRB, and BDI. Based on results of the ADF test, we take the first difference of the USDI, TB, TS, SPGSCI, and CRB individual time series.

Table 3.3.1. Based on the results of the Augmented Dickey-Fuller (ADF) test, we take the first difference of the USDI, TB, TS, SPGSCI, and CRB individual time series.

3.4. The Role of Volatility Persistence in Energy Futures Markets

In this section, we identify the determinants and gauge the importance of volatility persistence in energy markets. First, we identify the macro-economic determinants of volatility persistence and discuss the role of volatility persistence in transmitting macro-economic information in volatility. Then, we reassess the role of two well-known determinants of volatility persistence: returns and variances. We also examine the economic significance of volatility persistence by evaluating the contribution of CVP determinants to volatility variation and by detecting the drivers of the CVP variation. Last, we discuss the statistical properties of the CVP.

3.4.1. Macro-economic information and volatility persistence. The impact of the macro-economic variables on future volatility and daily volatility persistence can be assessed by estimating the model HAR-CVP-CV (see equations (3.2.7)–(3.2.8)). While Tables 3.4.1 present the estimation results of this model in the crude oil markets, Tables 3.4.2 show the estimation results in the natural gas markets.[20]

[20]Even though some of the control variables are highly correlated, their coefficients have the appropriate sign, plausible magnitude, and are statistically significant. Accordingly, multicollinearity should not be a major concern, see page 173 of Brooks (2008). Further, the Ljung-box statistics for serial correlation in the residuals for the HAR-CVP-CV models validates that missing variables bias is not present in our model specifications (see the last two rows in Tables 3.4.1 and 3.4.2). Over-parameterization is also not a

TABLE 3.4.1. **The HAR-CVP-CV Models for Crude Oil**

β_{SP500}	-1.491									-0.138
	(-1.113)									(-0.113)
β_{VIX}		0.004*								0.009***
		(1.805)								(2.837)
β_{USDI}			3.732							2.059
			(1.189)							(0.607)
β_{CS}				-0.029						-0.098**
				(-1.198)						(-2.468)
β_{TB}					0.227					-0.035
					(0.236)					(-0.036)
β_{TS}						-0.500**				-0.290
						(-2.704)				(-1.347)
β_{SPGSCI}							-0.028			-0.049
							(-1.460)			(-1.056)
β_{CRB}								-0.025		0.047
								(-1.187)		(0.892)
β_{BDI}									-0.017*	-0.028***
									(-1.820)	(-2.834)
δ_{SP500}	-4.96E-04									-4.25E-04
	(-1.503)									(-1.249)
δ_{VIX}		-1.28E-06**								-1.77E-06**
		(-2.091)								(-2.166)
δ_{USDI}			-1.06E-03							-1.04E-03
			(-1.445)							(-1.267)
δ_{CS}				-9.67E-06						9.72E-06
				(-1.167)						(0.904)
δ_{TB}					5.73E-05					4.69E-05
					(0.331)					(0.256)
δ_{TS}						-2.59E-05				-3.62E-05
						(-0.549)				(-0.588)
δ_{SPGSCI}							-1.84E-04			4.79E-04
							(-0.423)			(0.524)
δ_{CRB}								-2.76E-04		-1.07E-03
								(-0.618)		(-1.061)
δ_{BDI}									1.67E-07	1.02E-06
									(0.150)	(0.872)
$adjR^2$	0.675	0.672	0.671	0.670	0.673	0.676	0.674	0.674	0.672	0.679
AIC	-40,486	-40,491	-40,454	-40,501	-40,470	-40,493	-40,492	-40,492	-40,469	-40,542
$LB(Q^*)$	5.04**	1.49	5.46**	7.42***	4.82**	7.01***	5.13**	4.56**	4.53**	3.41*
	(0.02)	(0.22)	(0.02)	(0.01)	(0.03)	(0.01)	(0.02)	(0.03)	(0.03)	(0.06)

This table reports the estimation results of the following regressions in the crude oil:

$$RV_{t+1,D} = \alpha + (\beta_D + \beta_r^- r_{t,D}^- + \beta_r^+ r_{t,D}^+ + \beta_{RV} RV_{t,D} + \beta_{CV} CV_{t,D}) RV_{t,D} \\ + Z_t + \delta_{CV} CV_{t,D} + \epsilon_{t+1,D},$$

where Z_t is defined by (3.2.2). The t-statistic (in parentheses), is estimated using the Newey–West standard errors. The following coefficients β_D, $\beta_r^- r_{t,D}^-$, $\beta_r^+ r_{t,D}^+$, $\beta_{RV} RV_{t,D}$, $\beta_{CV} CV_{t,D}$, and Z_t are reported in Table A.3.4.1 (Appendix 3.1.). AIC is the Akaike information criteria. $LB(Q^*)$ is the Ljung-Box test statistic and its p-value is reported in parentheses. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

We find that in oil markets, VIX and credit spreads are significant financial determinants of daily volatility persistence, and the Baltic Exchange Dirty Tanker Index is one of the

major concern because the estimated volatility models have at most 28 parameters and 2,500 (1,000) daily observations for the in-sample (out-of-sample) estimation. Models are likely to be over-parameterized particularly when working with short time series such as quarterly volatility (Smyth and Narayan (2015)).

TABLE 3.4.2. **The HAR-CVP-CV Models for Natural Gas**

β_{SP500}	-0.644									-0.591
	(-0.373)									(-0.368)
β_{VIX}		0.005								0.001
		(1.481)								(0.191)
β_{USDI}			-3.047							-2.789
			(-1.196)							(-0.950)
β_{CS}				0.131*						0.096
				(1.936)						(1.430)
β_{TB}					3.039***					3.162***
					(2.813)					(2.896)
β_{TS}						-0.227				-0.184
						(-0.707)				(-0.531)
β_{SPGSCI}							-0.005			0.044
							(-0.264)			(0.791)
β_{CRB}								-0.010		-0.056
								(-0.513)		(-0.933)
β_{BDI}									0.004	0.007
									(0.336)	(0.675)
δ_{SP500}	-1.10E-04									-3.93E-04
	(-0.128)									(-0.505)
δ_{VIX}		-2.13E-06								-8.09E-07
		(-1.463)								(-0.556)
δ_{USDI}			1.28E-03							1.20E-03
			(0.988)							(0.879)
δ_{CS}				-6.93E-05*						-4.56E-05
				(-1.911)						(-1.293)
δ_{TB}					-1.02E-03***					-1.11E-03***
					(-3.481)					(-3.548)
δ_{TS}						6.08E-05				5.70E-05
						(0.558)				(0.413)
δ_{SPGSCI}							1.21E-03**			1.94E-04
							(2.016)			(0.113)
δ_{CRB}								1.18E-03*		1.35E-03
								(1.839)		(0.728)
δ_{BDI}									1.21E-06	7.03E-07
									(0.211)	(0.176)
$adjR^2$	0.568	0.568	0.569	0.564	0.574	0.567	0.572	0.569	0.568	0.570
AIC	-34,892	-34,911	-34,893	-34,874	-34,923	-34,899	-34,909	-34,900	-34,901	-34,938
$LB(Q^*)$	2.34	0.95	2.91*	0.01	2.34	2.18	2.29	2.40	2.58	1.03
	(0.13)	(0.33)	(0.09)	(0.91)	(0.13)	(0.14)	(0.13)	(0.12)	(0.11)	(0.31)

This table reports the estimation results of the following regressions for the natural gas:

$$RV_{t+1,D} = \alpha + (\beta_D + \beta_r^- r_{t,D}^- + \beta_r^+ r_{t,D}^+ + \beta_{RV} RV_{t,D} + \beta_{CV} CV_{t,D}) RV_{t,D} + Z_t + \delta_{CV} CV_{t,D} + \epsilon_{t+1,D},$$

where Z_t is defined by (3.2.2). The following coefficients β_D, $\beta_r^- r_{t,D}^-$, $\beta_r^+ r_{t,D}^+$, $\beta_{RV} RV_{t,D}$, $\beta_{CV} CV_{t,D}$, and Z_t are reported in Table A.3.4.2 (Appendix 3.1.). The t-statistic (in parentheses), is estimated using the Newey-West standard errors. AIC is the Akaike information criteria. $LB(Q^*)$ is the Ljung-Box test statistic and its p-value is reported in parentheses. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

commodity sector determinants of volatility persistence (see Table 3.4.1). Specifically, the VIX impacts future oil volatility in two ways: directly by decreasing volatility levels and indirectly by increasing volatility persistence and consequently increasing volatility. Correlated information, driven by a shock in the VIX, tends to arrive within a short period of time triggering, volatility clustering and increased volatility persistence. As the impact of the indirect channel via volatility persistence is far more pronounced than the direct one, VIX positively affects oil volatility. Following the financialization of commodity markets, volatility spillovers, and co-movements between oil and equity markets are well documented (Tang and Xiong (2012) and Basak and Pavlova (2016)), providing compelling evidence of a positive relationship between VIX and oil market volatility (Silvennoinen and Thorp (2013), Kang, Nikitopoulos and Prokopczuk (2020), and Wang et al. (2020)). Credit spreads have also been identified as an important predictor of crude oil volatility (Hitzemann (2016) and Prokopczuk et al. (2019)). Worsening of credit conditions in the economy implies higher inflation compensation and volatility (Chen et al. (2014)). As a sudden increase in credit spreads would increase oil market volatility, this gross information flow over a short period of time (e.g., a day) is associated with more priced and thus less correlated information, reflecting a drop in volatility persistence (Hasbrouck (1995) and Andersen (1996)). This explains the negative relation between credit spreads and oil volatility persistence. The Baltic Exchange Dirty Tanker Index – which represents the physical factor that influences the supply of energy commodities – tends to decrease volatility persistence. Empirical literature suggests that BDI and future volatility are positively related (Breitenfellner et al. (2009), Kilian (2009), and Fan and Xu (2011)), and this impact is transmitted to volatility via a reduction in the oil market's volatility persistence.

The Treasury bills, a proxy for monetary policy, is the only financial factor affecting volatility persistence in the natural gas market. The indirect impact of the Treasury bills via the volatility persistence channel implies that the Treasury bills increases volatility persistence, that is, the $CVP_{t,D}$ variable, which subsequently indicates that the impact of volatility persistence on realized volatility is positive. There is also a direct negative impact of Treasury bills on volatility levels. Typically, low interest rates lead to high demand for inventories, which among other economic channels, puts upward pressure on future prices and potentially, volatility in energy markets (Arora and Tanner (2013), Frankel (2014), Cheng et al. (2018), and Kang, Nikitopoulos and Prokopczuk (2020)). Based on the argument that high volatility reflects better priced and thus less correlated information, a reduction in volatility persistence is stipulated. Another financial variable that directly affects the daily volatility levels in natural gas is the credit spreads, a well-accepted predictor of volatility in energy markets (Table 3.4.2). In contrast to the oil markets, commodity sector variables such as the S&P Goldman Sachs Commodity (non-energy) Index and CRB Index have a direct influence on daily volatility in the natural gas market.

Empirical studies demonstrate that financial indicators and commodity sector variables play an important role in determining volatility in energy markets (Robe and Wallen (2016), Prokopczuk et al. (2019), and Kang, Nikitopoulos and Prokopczuk (2020)). We find that the impact of these economic determinants is transmitted to future oil market volatility via its volatility persistence channel (and not directly to the volatility levels). Natural gas is less integrated with the oil market, and volatility is mostly driven by fundamentals,[21] so the impact of financial indicators on volatility is moderate (only via credit spreads and Treasury bills). Most of the macro-economic factors impact volatility directly in natural gas markets.[22]

3.4.2. Impact of returns and past volatility. Two well-known determinants of volatility include returns and past RV, so we reassess the impact of these two market conditions on volatility and the role of volatility persistence in transmitting this impact. For comparison purposes, we first consider the classical HAR model specifications, and then compare these with the conditional volatility persistence HAR models: the HAR-CVP and HAR-CVP-CV models (see Section 3.2.2). Recall that in the HAR models, the volatility persistence is constant (represented by β_D), while in the conditional volatility persistence HAR models, volatility persistence is modeled via the CVP that depends on the RV, (positive and negative) returns, and macro-economic variables. Reflecting an in-sample estimation, Panel A of Table 3.4.3 displays the impact of returns and RV on the next day's volatility for the classical HAR (see equations (3.2.1)–(3.2.2)) and HAR-CVP models. Tables 3.4.1 and 3.4.2 present the in-sample estimation results of the HAR-CVP-CV models inclusive of all macro-economic variables, financial variables, and commodity sector variables in the crude oil markets (natural gas markets), respectively. We find two main results. First, we confirm that daily returns and RV are important drivers of future volatility. Daily RV increases the next day's volatility, and daily returns decrease future volatility in the HAR

[21]Geng et al. (2016*a*) find that supply and demand are the main determinants of natural gas prices in the United States, while oil prices play a key role in determining natural gas prices in Europe and Japan.

[22]The addition of the macro-economic variables increases (adjusted) R^2 by 1.62% (from 66.8% to 67.9%) in the crude oil market and by 0.35% (from 56.8% to 57.0%) in the natural gas market when compared to the basic (leveraged) HAR models (Table 3.4.3).

models. Second and most importantly, the conditional volatility persistence HAR models estimation reveals that daily returns and RV are also significant determinants of volatility persistence and play a prominent role in transferring the impact of returns and RV to future volatility.

When using HAR models (see the first and third columns of Table 3.4.3), crude oil future volatility is determined by weekly returns and (positive and negative) daily returns, with the impact of negative daily returns much higher than positive daily returns and weekly returns. Past (positive and negative) daily returns are key determinants of future volatility in natural gas markets. The impact of positive daily returns is more pronounced than negative daily returns, a behavior reflecting the inverse leverage effect. This is consistent with the theory of storage and the impact of fundamental commodity supply and demand factors (Ng and Pirrong (1994) and Geng et al. (2016*a*)). In principle, low inventory (among other reasons and commodity shortages) drives commodity prices and volatility up, while high inventory drives prices and volatility down. Nevertheless, in the last decade, energy markets have been very actively traded markets and popular investment vehicles, explaining the similarity between the behavior of the crude oil market to the equity markets (Chiang et al. (2015) and Basak and Pavlova (2016)). Further, in the energy markets, past (daily, weekly, and monthly) RV is highly significant and positively related to the next day's volatility, with the impact of short-term volatilities more pronounced than the impact of monthly volatilities. Accordingly, short-term trading in energy markets seems to be more influential on future daily volatility than longer-term trading (Ma et al. (2018)).

The effects on volatility persistence are determined from the (in-sample) estimation of the HAR-CVP models reported in Panel A of Table 3.4.3 (see the second and forth columns). Daily returns and RV are important determinants of volatility persistence in energy markets. Negative returns affect volatility persistence in the crude oil market, and negative returns increase future oil volatility directly and indirectly via the volatility persistence channel. In the natural gas market, positive[23] and negative returns determine volatility

[23]The short-term effect of positive returns on natural gas volatility is consistent with the inverse leverage effect, thus for natural gas, fundamentals dominate in the short run.

persistence, and their impact is transmitted to future volatility entirely via volatility persistence. A negative return of 1% return leads to an average increase in daily volatility persistence of 28.6% in the crude oil market. In the natural gas market, a negative return of 1% increases (on average) volatility persistence by 13.6%, and a positive return of 1% increases volatility persistence by 15.4%.[24] Thus, the impact of positive returns on natural gas volatility persistence is marginally higher than the impact of negative returns. The RV was important for the volatility persistence of crude oil and natural gas, and is negatively associated with the CVP. On an average volatility day, volatility persistence is expected to decline by 4.4% in crude oil and 4.0% in natural gas.[25] Similar to the HAR models, past (daily, weekly, and monthly) RV remains highly significant and positively related to the next day's volatility. However, some of the RV impact is transmitted to future volatility via the CVP, and it has an inverse effect on volatility persistence. This can be explained by the argument that high volatility allows more information to be priced, resulting in lower volatility persistence (Andersen (1996)). Finally, results shown in Tables A.3.1.1 and Tables A.3.1.2 from Appendix 3.1 for the HAR-CVP-CV models reveal that the addition of the macro-economic variables does not affect the statistical significance of the other predictors of future volatility and daily volatility persistence, such as positive and negative returns and RV. Therefore, we conclude that volatility persistence plays an important role in transmitting the impact of returns and RV to volatility of energy markets.[26]

3.4.3. Economic significance of daily CVP. To further appreciate the contribution of the daily CVP to future volatility, we assess the economic significance of the daily CVP. We gauge the contribution of CVP determinants to the volatility variation, and then identify the drivers of the CVP variation.

3.4.3.1. *Contribution of CVP determinants to the volatility variation.* We have identified returns, RV and macro-economic variables such as the VIX, credit spreads, and

[24]In Table 3.4.3, $\beta_r^- = -0.156$ for crude oil and -0.077 for natural gas, while in Table 3.4.6, the mean level of CVP is 0.546 for crude oil and 0.464 for natural gas. Accordingly, the average increase in daily volatility persistence is $0.156/0.546 = 28.6\%$ for crude oil and $0.077/0.464 = 16.6\%$ for natural gas.

[25]This is computed by combining information from Table 3.4.3, Table 3.4.6 and Table A.3.3.2 from Appendix 3.4. For crude oil is computed as $0.006 \times 4.035/0.546 = 4.4\%$ and for natural gas, is $0.003 \times 6.206/0.464 = 4.0\%$, accordingly.

[26]The HAR-CVP model can be extended to include variations of the RV measure: the semivariances (SV) of Patton and Sheppard (2015) and the Bollerslev et al. (2016) realized quad-power quarticity (RQ). We use these extensions of the HAR-CVP model, namely, HAR-CVP-SV and HAR-CVP-RQ, as robustness tests and we find that the results are robust for these HAR-CVP model extensions (see Appendix 3.6. for details).

Treasury bills as significant determinants of CVP in the oil and natural gas markets. We use the Shapley-Owen decomposition of the regression R^2 to measure the marginal contribution (via their explanatory power) of each variable to the volatility variation captured by the HAR-CVP models.[27]

Panel B of Table 3.4.3 presents the decomposition of the CVP regressors, namely $r^+_{t,D}RV_{t,D}$, $r^-_{t,D}RV_{t,D}$, and $RV^2_{t,D}$ in the HAR-CVP models. We find that the CVP regressors explain 16.83% of future variations in crude oil's RV and 15.28% of future variations in natural gas's RV. Further, the CVP accounts for 25.05% of the model's explanatory power in crude oil and 26.91% in natural gas. Among the CVP regressors, RV^2 makes the stronger contribution (higher explanatory power) with a Shapley R^2 of 10.49% for crude oil and 9.43% for natural gas.[28] In addition, by comparing the HAR models to the HAR-CVP models, the direct influence of past short- and long-term returns and RV on future RV is significantly reduced in the two markets (with the effect more pronounced in the crude oil market). Moreover, $r^-_{t,D}$ has higher explanatory power than $r^+_{t,D}$ in the crude oil market, but $r^+_{t,D}$ is more important for natural gas. Thus, in the oil market, large negative returns have a greater impact on future volatility than large positive returns, a feature shared with equity markets, providing support for the concept of volatility spillovers between energy and equity markets.[29]

The Shapley decomposition of the regression R^2 for the HAR-CVP-CV models are presented in Table 3.4.4 for crude oil and natural gas, in Panel A and Panel B, respectively. The CVP regressors, $r^+_{t,D}RV_{t,D}$, $r^-_{t,D}RV_{t,D}$, $RV^2_{t,D}$, and $CV_{t,D}RV_{t,D}$, explain up to 18% of future variations in RV and account for up to 29% of the models' explanatory power. RV^2 generally has the most explanatory power (with a Shapley R^2 up to 10%), but the

[27]We follow the Lahaye and Neely (2020) and Wang and Yang (2018) approach to estimate the Shapley R^2. Henceforth, the total R^2 is the sum of the estimated Shapley R^2 for each variable. The Shapley R^2 decomposition helps to better assess the contribution of the CVP regresssors (as well as other regressors) to the HAR model. One advantage of the Shapley R^2 regression over the general linear regression technique is that it takes care of multicollinearity.

[28]Empirical evidence in equity markets shows that positive and negative returns (as CVP regresssors) have the more explanatory power than volatility (Wang and Yang (2018)).

[29]The explanatory power of CVP has also been considered for the HAR-SV and HAR-RQ models, and we found similar results (see Appendix 3.6. for details). Thus, these results are robust under the different HAR and HAR-CVP model specifications.

$CV_{t,D}RV_{t,D}$ reaches similar explanatory power for the models associated with key determinants of CVP, such as the VIX (7.47%), credit spreads (7.28%), and the Baltic Exchange Dirty Tanker Index (7.06%). This underscores the economic significance of the conditioning variables in explaining variation in future volatility, an effect that is channeled via volatility persistence. In fact, the indirect impact of each conditioning variable on future volatility (via CVP) reaches a Shapley R^2 of 7.5%, while comparatively, the direct impact of the same variables on future RV is much lower (reaching only 1%). Similar to the WLS regression results, the Shapley R^2 of the CVP regressors representing the conditioning variables is higher in the crude oil market than the natural gas market. Thus, the contribution of the conditioning variables is stronger to volatility persistence than the direct impact on volatility levels. This result is consistent with our previous findings, which indicates that these variables are key determinants of volatility persistence and transmit their impact to future volatility via the volatility persistence channel. This impact is considerable and accounts, via the CVP, for almost one quarter of the variation in future volatility.

3.4.3.2. *Determinants of CVP variation.* Beyond the determinants of the CVP, we also seek to identify the determinants of CVP variation. To this end, we decompose the variance of $CVP_{t,D}$ into the variances of its orthogonalized components $r^-_{t,D}$, $r^+_{t,D}$, and $RV_{t,D}$. The weights $w(r^-_{t,D})$, $w(r^+_{t,D})$, and $w(RV_{t,D})$ denote the contributions of $r^-_{t,D}$, $r^+_{t,D}$, and $RV_{t,D}$ to the variance of $CVP_{t,D}$.[30]

[30] We follow the Wang and Yang (2018) variance decomposition approach to assess the marginal contribution of return and volatility level on the CVP. We assume that $y = ax_1 + bx_2 + cx_3$. y represents the CVP, and x_i represents the three CVP regressors ($r^-_{t,D}RV_{t,D}$, $r^+_{t,D}RV_{t,D}$, and $RV^2_{t,D}$). As there are three regressors, $y = ax_1 + bx_2 + cx_3$ can be rewritten in 6 ways (3! = 6 permutations). We extract the residuals u_{21} and u_{31} from the following equations: (1) $x_2 = \alpha_0 + \alpha_1 x_1 + u_{21}$ and (2) $x_3 = \beta_0 + \beta_1 x_1 + u_{31}$. Then, $\widehat{u_{31}} = \lambda\widehat{u_{21}} + u_{32}$ is estimated, and u_{32} is retrieved. With the previously estimated coefficients and regressors, y can be further decomposed as:

$$y = ax_1 + b(\widehat{\alpha}_0 + \widehat{\alpha}_1 x_1 + \widehat{u}_{21}) + c(\widehat{\beta}_0 + \widehat{\beta}_1 x_1 + \widehat{u}_{31}).$$

Thus,

$$y = (a + b\widehat{\alpha}_1 + c\widehat{\beta}_1)x_1 + (b + c\widehat{\lambda})\widehat{u}_{21} + c\widehat{u}_{32} + \text{constant},$$

which simplifies to

$$= Ax_1 + B\widehat{u}_{21} + c\widehat{u}_{32} + \text{constant}.$$

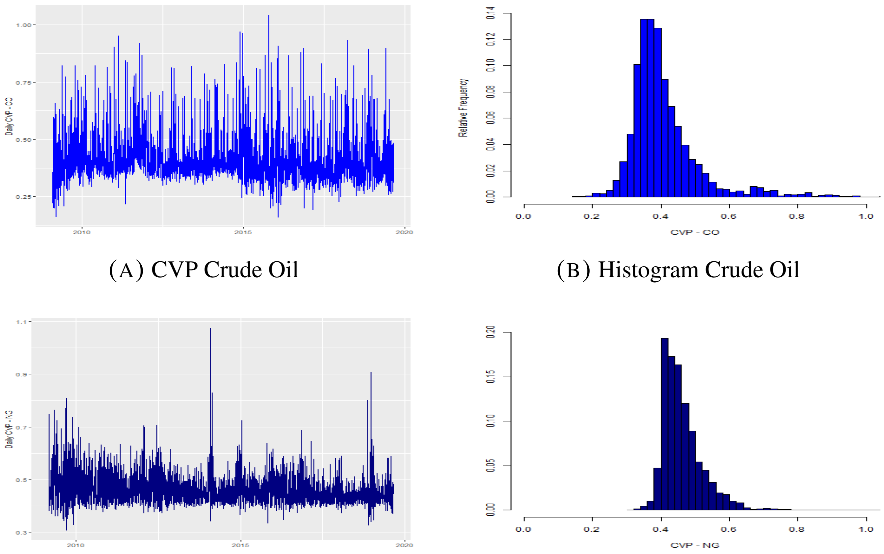
The variance of y is given by $var(y) = A^2 var(x_1) + B^2 var(\widehat{u}_{21}) + c^2 var(\widehat{u}_{32})$. The weights of each regressor are estimated as $w(x_1) \equiv \frac{A^2 var(x_1)}{var(y)}$, $w(x_2) \equiv \frac{B^2 var(x_2)}{var(y)}$, and $w(x_3) \equiv \frac{c^2 var(x_3)}{var(y)}$. Ultimately, $RV_{t,D}$ is replaced by $RQ^{1/2}_{t,D}$ as a CVP regressor in the HAR-CVP-RQ model.

The contribution of CVP variables ($r^-_{t,D}$, $r^+_{t,D}$, and $RV_{t,D}$) to the variance of CVP for the HAR-CVP models is reported in Table 3.4.5. Negative returns account for 87.1% and 52.5% of the CVP variance in the HAR-CVP models for crude oil and natural gas, respectively. The volatility level (RV) makes up approximately 7.5% of the CVP variance in the crude oil market, and 9.0% of the CVP variance in the natural gas market. The variance decomposition of the CVP variables reveals that negative return, rather than positive return, is the strongest driver of the variance of volatility persistence in the crude oil market. However, in natural gas markets, positive returns are the strongest driver of variation in volatility persistence. The combined effect of positive and negative returns accounts for 90-92% of the CVP variation across all markets.

3.4.4. Statistical properties of daily CVP. The daily CVP for the two energy markets are estimated by equation (3.2.7) and their statistical properties are reported in Table 3.4.6.[31] The time series and histogram of the daily CVP for each market are displayed in Figure 3.4.1.

Volatility persistence in energy markets fluctuates over time and exhibits significant variability. The mean of the daily CVP reaches 54.6% in the crude oil market and 46.4% in the natural gas market. The volatility persistence of the crude oil market also shows the highest variation (at 8.5%) followed by the natural gas markets (at 7.7%). The histograms in Figure 3.4.1 show that the mean CVP is larger than the median (long right-hand tail) in both energy markets. The crude oil market has a higher proportion of positive outliers (with 0.11% and 0.08% of the sample days having a CVP greater or equal to one, respectively). The cross-correlation between CVP and its components (r^-_D, r^+_D, RV_D, and $CV_{t,D}$) is presented in Panel B of Table 3.4.6. As expected, in the crude oil futures markets, the correlation between volatility persistence and negative returns is much stronger than the correlation between volatility persistence and positive returns. The reverse is true

[31] We identify the conditioning variables that have a significant impact (directly and indirectly) on future RV in Tables 3.4.1 and Tables 3.4.2 for the two energy commodities. The HAR-CVP-CV regression model is re-estimated, and their coefficients are extracted to compute $CVP_{t,D} = \beta_D + \beta^-_t r^-_{t,D} + \beta^+_t r^+_{t,D} + \beta_{RV} RV_{t,D} + \beta_{CV} CV_{t,D}$.



(A) CVP Crude Oil (B) Histogram Crude Oil

(C) CVP Natural Gas (D) Histogram Natural Gas

FIGURE 3.4.1. **Daily Conditional Volatility Persistence (CVP) and Histogram of CVP with Conditioning Variables**
The figure plots the daily conditional volatility persistence and the corresponding histogram for crude oil and natural gas front-month futures contracts between January 2009 and August 2019.

in the natural gas futures market. Positive returns play a larger role than negative returns. Daily volatility persistence is positively related (averaging 0.29) to RV in all markets.[32] The VIX and Treasury bills are positively correlated to volatility persistence, while credit spreads and the Baltic Exchange Dirty Tanker Index are negatively correlated with volatility persistence. These results are consistent with the results of the in-sample estimation of the HAR-CVP-CV models (see Tables 3.4.1 and Table 3.4.2).

3.5. Forecasting Performance

We assess the out-of-sample forecasting performance of the conditional volatility persistence HAR models in predicting daily volatility, compared to classical HAR models. Beyond the statistical significance of forecasting daily energy market volatility, we also consider a utility-based methodology to evaluate the economic significance of the forecasts.

[32] We rely on the Ljung-Box test to measure persistence over a day (Table 3.4.6).

3.5.1. Models and loss functions. Aiming to gauge the role of embedding macroeconomic information in improving predictive accuracy, we compare the out-of-sample performance of three classical HAR models (HAR, HAR-SV, and HAR-RQ) and two conditional volatility persistence HAR models (HAR-CVP and HAR-CVP-CV) (see Section 3.3 for model descriptions). We use the fixed rolling window out-of-sample forecast (Patton and Sheppard (2015) and Bollerslev et al. (2016)), in which the rolling window is set to 1,000 days representing approximately four years.[33] The HAR models are estimated using the WLS regressions. We use two loss functions (measuring the prediction error between two competing volatility models): the log of the mean squared errors (MSE-ln) and the quasi-likelihood ($QLIKE$) loss functions, defined as:

$$L(RV_{t+1,D}, \hat{RV}_{t+1,D}) = \begin{cases} (\ln RV_{t+1,D} - \ln \hat{RV}_{t+1,D})^2; \text{ for MSE} - \ln, \\ \frac{RV_{t+1,D}}{\hat{RV}_{t+1,D}} - RV_{t+1,D} \ln \frac{RV_{t+1,D}}{\hat{RV}_{t+1,D}}; \text{ for QLIKE,} \end{cases} \tag{3.5.1}$$

where $\hat{RV}_{t+1,D}$ is the forecast of $RV_{t+1,D}$. Derived from the mean squared errors loss function, the MSE-ln reduces the impact of large forecast errors $(RV_{t+1,D} - \hat{RV}_{t+1,D})$. Alternatively, $QLIKE$ measures the difference in the ratio of $RV_{t+1,D}/\hat{RV}_{t+1,D}$. The MSE-ln and QLIKE have been used extensively in the equity (Patton (2011)) and commodity (Byun and Cho (2013), Li and Li (2015), and Zhu et al. (2017)) literature. Using the loss functions, the forecasting accuracy is also assessed with the Diebold–Mariano (DM) test.[34] The pairwise loss difference ($d_{t+1,D}(HAR_k)$) against the two HAR-CVP models is defined as:

$$d_{t+1,D}(HAR_k) = L(RV_{t+1,D}, \hat{RV}_{t+1,D}; HAR - CVP) - L(RV_t, \hat{RV}_{t+1,D}; HAR_k),$$

[33] We use a fixed rolling window estimation that ensures that the rolling window and out-of-sample size stay constant. As we do not impose any restrictions on the parameters in the rolling window estimation, the forecasts can potentially be negative. Although negative forecasts rarely occur in this analysis, we apply an "insanity filter". This ensures that the negative forecasts are replaced by the minimum positive RV within each rolling window (Patton and Sheppard (2015)). We also replace the RV forecasts that exceed (fall behind) the maximum (minimum) observed RV in the rolling window with the mean observed RV in each rolling window (Swanson and White (1995), Bollerslev et al. (2016), and Bollerslev et al. (2018)). While the latter affects only 0.36% of the RV forecasts in the crude oil market, the natural gas market is unaffected by it. We reassess the out-of-sample forecasting performance of the HAR models without the Swanson and White (1995) filtering process or an alternative "insanity filter" where the "insane" forecasts are replaced with the dumb forecasts (Hyndman and Koehler (2006) and Lux and Kaizoji (2007)) and the results obtained are quantitatively similar.

[34] See Diebold and Mariano (2002). The DM test serves as a measure for comparing the forecasting accuracy of two competing models. It is a well-recognised forecasting evaluation statistic that has been widely used in empirical studies in equity markets (Han et al. (2015), Sharma and Vipul. (2016), and Wang and Yang (2018)) and commodity markets (Jiang et al. (2015), Herrera et al. (2018), and Gong and Lin (2018)).

where k represents the three classical HAR models (HAR, HAR-SV, and HAR-RQ). The DM test statistic, $DM[d_{t+1,D}(HAR_k)]$, is estimated via the following specification:

$$DM[\bar{d}_{t+1,D}(HAR_k)] = \frac{\bar{d}_{t+1,D}(HAR_k)}{\sqrt{(Var[d_{t+1,D}(HAR_k)]/T)}},$$

where $\bar{d}_{t+1,D}(HAR_k)$ is the mean value of $d_{t+1,D}(HAR_k)$, $Var[d_{t+1,D}(HAR_k)]$ is the variance of $d_{t+1,D}(HAR_k)$, and T is the number of forecasts.

3.5.2. Forecast comparison. We find that the conditional volatility persistence HAR models, on average, outperform the classical HAR models in forecasting accuracy (see Panel A of Table 3.5.1). The improvement in crude oil market is significant (with the lowest mean and median loss values for both loss functions (MSE-ln and QLIKE)), while the improvement in natural gas is marginal. The DM test statistics, reported in Panel B of Table 3.5.1, corroborate the loss function results in Panel A. These results confirm significant benefits in out-of-sample daily forecasting, when information from market and macro-economic variables is integrated in the model (Geng et al. (2016*a*) and Caporin and Fontini (2017)). In the crude oil market, the impact of macro-economic variables, such as the VIX and credit spreads, is substantial, and it is channeled in the oil price volatility via its persistence. Accounting for this information transmission channel brings significant forecasting gains. However, in the natural gas market, most of these macro-economic variables do not affect volatility persistence, meaning the proposed HAR-CVP-CV models would not improve forecasting performance. Prices and volatility in the natural gas market are predominantly driven by commodity sector factors, such as demand and inventory considerations and the recent shale gas expansion (Geng et al. (2016*a*) and Caporin and Fontini (2017)). This underscores the need for more robust forecasting models, which account for a wider range of macro-economic conditions that have a measurable impact on price dynamics of the oil and natural gas markets, such as demand and inventory (Geng et al. (2016*a*) and Caporin and Fontini (2017)).

Although conditional volatility persistence HAR models provide statistically stronger forecasts, from a practical perspective, the models should also outperform when these volatility forecasts are implemented in risk management investment strategies, as discussed next.

3.5.3. Economic significance of the forecasts. Motivated by Bollerslev et al. (2018), we employ a realized utility-based approach based on volatility forecasts to assess the economic benefit of implementing the proposed HAR models.[35] This approach assumes that rational investors[36] trade in a risky asset (i.e., energy asset) with time-varying volatility and earn a constant risk-adjusted return or Sharpe ratio (SR).[37] Investors seek to keep a constant level of risk and adjust their optimal portfolio size accordingly. Therefore, the risk/volatility target (RT) is set to reflect the annualized volatility in the respective market.[38] Bollerslev et al. (2018) assume that the coefficient of risk aversion, γ (metric of investors' degree of risk aversion), is the same across all asset classes. Gauging the actual degree of investors' risk aversion in different energy markets is not trivial; thus, we assume two levels of risk aversion; $\gamma = 2$ and 4. Because the RT is estimated by dividing the annualized SR by γ, the SR is retrieved accordingly. We use various combinations of the SR in the respective markets to derive the optimal γ.[39]

The expected return of an investor's strategy, optimal targeted position (OTP), is estimated by multiplying the SR by the RT. Because of the disutility of risk, as pointed out by Bollerslev et al. (2018), the net optimal targeted position (NOTP) is halved. Under a perfect risk model, the value of a risky asset is worth NOTP% of wealth. Assuming, for instance, that $\gamma = 2$, the NOTP are equal to 9% and 13% in the crude oil and natural gas markets, respectively.[40] Given that investors choose an initial investment position of $x^{\theta}_{t+1,D} = RT/\sqrt{E_t\left(RV^{\theta}_{t+1,D}\right)}$, the average realized utility per unit of wealth (UoW^{θ}) associated with each HAR model[41] is estimated for the crude oil and natural gas markets

[35] Commodity (with energy a commodity subclass) volatility is the highest among the different asset classes (such as equity or bond), and thus, is prone to more frequent shocks. Therefore, we use a dynamic approach to portfolio rebalancing and assume it happens daily. As Bollerslev et al. (2018) examine the aggregate volatility of different asset classes, they assume that portfolio rebalancing occurs monthly (less frequently).
[36] We assume that investors have mean-variance preferences, i.e., they want low risk and high return.
[37] In this setting, the SR is measured by $SR = E_t\left(r^e_{t+1,D}\right)/\sqrt{E_t\left(RV_{t+1,D}\right)}$, where the excess return ($r^e_{t+1,D}$) is equal to the return on the risky asset ($r_{t+1,D}$) less the return on a risk-free asset ($r^f_{t,D}$).
[38] In the crude oil and natural markets, the average annualized RV (over the sample period) stand at 30% and 36%, respectively.
[39] The estimated realized utility using a different SR in each market is reported in Appendix 3.7.
[40] Assuming that $\gamma = 4$ and SR is equal to 0.6 and 0.7, the NOTP are equal to 5% and 6% in the crude oil and natural gas markets, respectively.
[41] θ represents the HAR, HAR-SV, HAR-RQ, HAR-CVP, and HAR-CVP-CV models accordingly.

as follows:

$$UoW_{CO}^{\theta}=\frac{1}{T}\sum_{t,D}^{T}\left(18\%\frac{\sqrt{RV_{t+1,D}^{\theta}}}{\sqrt{E_t\left(RV_{t+1,D}^{\theta}\right)}}-9\%\frac{RV_{t+1,D}^{\theta}}{E_t\left(RV_{t+1,D}^{\theta}\right)}\right),$$

$$UoW_{NG}^{\theta}=\frac{1}{T}\sum_{t,D}^{T}\left(25\%\frac{\sqrt{RV_{t+1,D}^{\theta}}}{\sqrt{E_t\left(RV_{t+1,D}^{\theta}\right)}}-13\%\frac{RV_{t+1,D}^{\theta}}{E_t\left(RV_{t+1,D}^{\theta}\right)}\right),$$

where $RV_{t+1,D}^{\theta}$ and $E_t(RV_{t+1,D}^{\theta})$ represent the actual RV and the forecasted RV, respectively. The economic intuition behind the utility-based framework is that models with better forecasting accuracy provide a higher level of realized utility (economic benefit).

We also examine the effect of the transaction costs on realized utility by adopting an approach similar to Bollerslev et al. (2018). Palczewski et al. (2015) note that transaction costs can have a damaging effect on investors' positions, particularly for less informed (naïve) investors. Taking into account the actual cost of implementing risk-targeted positions causes a loss in utility. Transaction costs are estimated by using the 'full-spread' (median bid-ask spread)[42] and the 'half-spread' (half of the median bid-ask spread) over the previous nine months. Under this approach, the linear trading cost may vary with the absolute magnitude of the change in the positions, $\left|x_{t,D}^{\theta}-x_{t+1,D}^{\theta}\right|$. We emulate the trading strategy of Gârleanu and Pedersen (2013), Gârleanu and Pedersen (2016), and Bollerslev et al. (2018) and allow the investment positions to be rebalanced gradually. Only 15% of the positions are traded toward the zero-cost optimal target every day. This adjustment makes up for the fact that trading is done partially, and therefore, the loss in utility is not heavily penalized. The results of the average realized utility under five scenarios of transaction costs are reported in Table 3.5.2. Panel A shows the estimated realized utility with varying coefficients of risk aversion, and Panel B reports the differential in the realized utility between the classical HAR models and the conditional volatility persistence HAR models and their respective DM tests.

We find that the conditional volatility persistence HAR models consistently outperform the classical HAR models in the crude oil market. When $\gamma = 2$, the utility benefits of

[42] We calculate the spread by using the difference between the ask and bid prices divided by the midquote.

HAR-CVP and HAR-CVP-CV are approximately 8.5% and 8.6%, and these levels of utility benefits are 24.3 bps and 36.7 bps above the benefits of the basic HAR model (respectively and in the no transaction cost case) (see Panel A of Table 3.5.2). To put this in an economic perspective, the utility benefits of the model incorporating information from macro-economic variables (HAR-CVP-CV) imply that investors are willing to pay 36.7 bps to use the HAR-CVP-CV model for risk management rather than use the basic HAR models. This is a comparatively significant level of utility benefits for risk management that is marginally below the institutional fees typically required for active asset management (Bollerslev et al. (2018)).[43] The improvement the conditional volatility persistence HAR models offer compared to the HAR with semivariances is more than fivefold, reaching 144.9 bps for HAR-CVP and 157.2 bps for HAR-CVP-CV (no transaction cost and for $\gamma = 2$). Interestingly, the HAR with realized quarticity and the HAR-CVP provide very similar benefits to investors, potentially because both models accommodate time-varying volatility persistence that depends on market conditions. However, including the additional information from macro-economic variables (by using the HARR-CVP-CV model) improves the realized utility for crude oil by 17.5 bps under no transaction costs and even more than that when transaction costs are involved. Furthermore, when $\gamma = 4$, the utility benefits of HAR-CVP and HAR-CVP-CV are approximately 4.2% and 4.3%, respectively (in the no transaction cost case), which is 12.2 bps and 18.4 bps above the utility benefits of the basic HAR model. Although these benefits are lower than the benefits of a less risk-averse investor ($\gamma = 2$), this still represents a substantial level of utility benefits in the crude oil market. The results are quantitatively the same for the four scenarios concerning transaction costs and trading speed. Using the full-spread (as a proxy for the transaction costs) causes the largest reduction in realized utility in all markets. However, the utility benefit differential reaches 38.5 bps for the HAR-CVP-CV model (over the basic HAR) when $\gamma = 2$ and 19.2 bps when $\gamma = 4$. The 'Gradual' trading has a marginal impact on the utility benefits for all models. The DM tests, presented in Panel B of Table 3.5.2, confirm, further the validity of the results above. These findings underscore the substantial

[43]Based on the *Callan's 2019 Investment Management Fee Study Uncovers What Institutional Investors Are Actually Paying* (2019) Investment Management Fee Study, the weighted average institutional fees for active asset management ($423.4 billion total asset under management) were 41 basis points in 2018. This study looks at over 350 investment firms and 165 institutional investors globally.

economic benefits of embedding information from macro-economic factors in volatility forecasting applications, information that is transmitted in volatility via its persistence.

In the natural gas market, the benefits are marginal (and not statistically significant) between the models. Assuming different degrees of risk aversion and no transaction costs, the utility benefits are up to 1.4 bps higher for the conditional volatility persistence HAR models (compared to the HAR-SV and HAR-RQ models). At the different levels of trading speed, the utility benefits of the HAR-CVP or HAR-CVP-CV models over competing HAR models are (almost completely) lost, especially for the 'full' transaction costs scenarios where trading is the slowest. These results are mainly driven by the substantial impact of the relatively high transaction costs occurring in the natural gas market. The estimated transaction costs in the natural gas market (5.2 bps) is almost threefold higher than in the crude oil market (1.9 bps) (Bollerslev et al. (2018)).[44] Furthermore, the impact of the macro-economic variables (considered in this study) on the volatility of the natural gas market is marginal and mostly direct (as it is not channeled via the volatility persistence); thus, using models that incorporate information from the underlying market variables would not offer any benefits in forecasting performance.[45] When information from the macro-economy is important for volatility dynamics and is transmitted to the volatility via its persistence, as occurs in the crude oil market, then the conditional volatility persistence HAR models would provide substantial utility benefits. Thus, recognizing volatility persistence as an important information transmission channel in volatility forecasting brings statistically significant forecasting performance improvements, and substantial utility gains in risk management strategies.[46]

[44] We re-estimate the realized utility in the natural gas market, while assuming the same level of transaction costs as in the crude oil market, i.e., 1.9 bps, and we find that the transaction costs are no longer penalizing the realized utility to the same extent. These results are untabulated.

[45] While oil markets act as information transmitters, natural gas markets act as information receivers (Ji et al. (2018)).

[46] There is mixed evidence that volatility jumps improve forecasting accuracy in both the equity and commodity markets. Forsberg and Ghysels (2007), Wang and Yang (2018), and Caporin (2022) show that adding the volatility jumps to volatility models do not improve their predictive power, particularly in equity markets. While predicting the volatility of crude oil and heating oil one-day ahead, Prokopczuk et al. (2016) also observe that short-term volatility jumps have no statistical significance. Similarly, Asai et al. (2020) find that decomposing the realized variance into its continuous and jump components does not improve the volatility forecasts in oil markets. Hence, we test for the presence of jumps in realized volatility to determine their importance in each market. The realized variance time series ($RV_{t,D}$) is decomposed into two components its continuous component and jump component. While the continuous component, defined as the bipower variation, is estimated as $BV_{t,D} = \frac{\pi}{2}\sum_{i=2}^{n}|r_{i,t}|\,|r_{i-1,t}|$, the jump component is estimated as $JV_{t,D} = RV_{t,D} - BV_{t,D}$. We adopt the Barndorff-Nielsen and Shephard

3.6. Conclusion

We explore the role of daily volatility persistence in shaping the dynamics of future volatility in two energy markets: crude oil and natural gas. By allowing the daily volatility persistence to be time-varying in the HAR model, we identify the determinants of volatility persistence, and analyze its contribution to predicting future volatility. We further hypothesize that macro-economic variables impact daily volatility persistence, and we investigate the role of volatility persistence in transmitting the impact of these variables to future volatility. The ability of these models to forecast daily volatility in energy markets is examined, and their benefits for investment strategies are evaluated accordingly.

There is ample evidence that macro-economic variables strongly impact volatility in energy markets (Casassus and Collin-Dufresne (2005), Chiang et al. (2015), Miao et al. (2017), Cheng et al. (2018), and Nonejad (2020)). Although volatility persistence has the largest influence on future volatility, there is, however, no apparent channel linking volatility persistence and macro-economic variables together. This study shows the impact of macro-economic variables on daily volatility persistence. By first impacting volatility, the macro-economic variables then dictate the pace at which information is transmitted in the market and its likely effect on volatility persistence. We find that the Baltic Exchange Dirty Index and financial indicators, including the VIX, the credit spreads, and the 3-month Treasury bills, affect volatility persistence in energy markets. Returns and volatility levels also remain key determinants of volatility persistence. Negative returns impact volatility persistence in the crude oil market, while positive returns are more influential in volatility persistence in the natural gas market. In the crude oil market, volatility persistence plays a dominant role in diffusing the impact of returns, RV, and macro-economic conditions in future volatility. This impact is economically significant, as the variations in

(2006) test statistic (Z_t) which assumes under the null hypothesis that there is no jump in RV on day t. $Z_t = \frac{n^{1/2}(BV_{t,D}/RV_{t,D}-1)}{(\pi^2/4+\pi-5)^{1/2}\times\max\{1,QV_{t,D}^{1/2}/BV_{t,D}\}}$, where $QV_{t,D} = \frac{\pi^2 n}{4}\sum_{i=4}^{n}|r_{i,t}|\,|r_{i-1,t}|\,|r_{i-2,t}|\,|r_{i-3,t}|$. As in Prokopczuk et al. (2016), we use a significance level of 0.1% and find that volatility jumps occur on 7.4% and 5.8% of trading days in the crude oil and natural gas market, respectively. We also test whether the identified jumps days ($JV_{t,D}^{\text{sig}}$) have a significant impact on future daily volatility in the HAR, HAR-CVP, and HAR-CVP-CV models, where $JV_{t,D}^{\text{sig}}$ is captured by $JV_{t,D}^{\text{sig}} = JV_{t,D} I_{(\text{p-value}_{Z_t}<0.1\%)}$ (Andersen et al. (2007)). The results (untabulated) show that the identified jumps days have no significant impact on future volatility in these three models. Therefore, we believe that volatility jumps are not as important drivers of volatility in energy markets and choose not disentangle the realized volatility into its two components (continuous and jumps components) in this study.

daily volatility persistence contribute up to 18% of future volatility, accounting for 29% of the model's explanatory power. The statistical properties of daily CVP in the energy markets reveal that negative (positive) returns have a greater impact on oil (natural gas) volatility persistence, and that the mean volatility persistence reaches 50.5%. The out-of-sample forecasting analysis demonstrates that the conditional volatility persistence HAR models economically and statistically outperform the classical HAR models. The utility benefit can reach up to 160 bps (subject to the Sharpe ratio and risk target) for models accommodating information from macro-economic variables.

Several practical implications emerged from this study. The volatility of energy markets displays distinct characteristics, but energy markets are becoming more integrated with equity markets. The contribution of volatility persistence in forecasting daily realized variance (ex-post volatility) is measurable and indicative of volatility persistence being a priced risk factor. Thus, the modeling consideration of volatility persistence is important and provides useful insights for energy market participants, from institutional investors to energy producers and in particular, short-term traders. Based on the superior forecasting performance and economic gains achieved by the proposed daily CVP models, they offer a robust approach for assessing and managing short-term risk exposures relevant for momentum trading strategies and dynamic hedging applications. The COVID-19 pandemic underscores the role of energy markets in the stability of global economies, particularly as we witnessed negative oil prices at the climax of the outbreak.[47] As the aftermath of the COVID-19 pandemic is unfolding, the volatility of energy markets (along with the volatility of financial markets) is the main concern. Consequently, effective modeling and accurate forecasting of volatility are extremely important. These findings have also opened new directions for research, including the effects of volatility persistence on longer-term volatility forecasting and expanding to embed the effects of a wider range of macro-economic volatility determinants in energy markets.

[47]On 20 April 2020, for first time in history the US oil benchmark dropped into deep negative territory as a combined result of the sinking oil demand in a system with limited storage capacity and inability to take delivery of the long position of (deliverable) oil futures contracts.

TABLE 3.4.3. **The HAR and HAR-CVP Models**

Panel A: Model estimation

	Crude Oil		Natural Gas	
	HAR	HAR-CVP	HAR	HAR-CVP
α	9.79E-06***	1.45E-05***	1.37E-05*	2.76E-05**
	(3.265)	(4.276)	(1.957)	(2.716)
β_D	0.435***	0.436***	0.453***	0.415***
	(18.234)	(13.970)	(12.439)	(9.584)
β_r^-		-0.156***		-0.077***
		(-4.331)		(-3.400)
β_r^+		0.052		0.067***
		(1.531)		(3.309)
β_{RV}		-0.006**		-0.003*
		(-2.124)		(-2.208)
β_W	0.301***	0.299***	0.309***	0.311***
	(11.161)	(10.759)	(8.511)	(8.452)
β_M	0.159***	0.159***	0.140***	0.145***
	(6.608)	(6.455)	(4.809)	(4.485)
θ_D^-	-0.665***	-0.198*	-0.260**	0.040
	(-7.453)	(-1.910)	(-2.952)	(0.442)
θ_D^+	0.155*	0.009	0.592***	0.317*
	(1.705)	(0.094)	(5.780)	(2.499)
θ_W	-0.116*	-0.135**	-0.127	-0.145
	(-1.787)	(-2.078)	(-1.055)	(-1.161)
θ_M	-0.189	-0.208	-0.101	-0.110
	(-1.304)	(-1.464)	(-0.500)	(-0.565)
adj R^2	0.668	0.672	0.563	0.568
AIC	-40,448	-40,465	-34,885	-34,898

Panel B: Shapley R^2

	Crude Oil		Natural Gas	
	HAR	HAR-CVP	HAR	HAR-CVP
$RV_{t,D}$	25.50%	19.13%	25.34%	17.07%
$\Delta\%$		-24.98%		-32.62%
$r_{t,D}^- RV_{t,D}$		2.34%		2.68%
$r_{t,D}^+ RV_{t,D}$		3.99%		3.17%
$RV_{t,D}^2$		10.49%		9.43%
$\widehat{CVP}_{t,D}$		16.83%		15.28%
$RV_{t,W} + RV_{t,M}$	33.62%	26.99%	27.40%	22.01%
$\Delta\%$		-19.73%		-19.68%
$r_{t,D}^- + r_{t,D}^+$	6.24%	3.73%	3.51%	2.35%
$\Delta\%$		-40.19%		-32.97%
$r_{t,W} + r_{t,M}$	1.43%	0.48%	0.08%	0.06%
$\Delta\%$		-66.54%		-21.44%
R^2	66.80%	67.16%	56.33%	56.77%
$\widehat{CVP}_{t,D}/R^2$		25.05%		26.91%

This table reports the estimation results of the following regressions in the crude oil and natural gas markets:

$$\textbf{HAR}: \; RV_{t+1,D} = \alpha + \beta_D \, RV_{t,D} + Z_t + \epsilon_{t+1,D},$$
$$\textbf{HAR-CVP}: \; RV_{t+1,D} = \alpha + (CVP_{t,D})RV_{t,D} + Z_t + \epsilon_{t+1,D},$$

with $\widehat{CVP}_{t,D} = r_{t,D}^- RV_{t,D} + r_{t,D}^+ RV_{t,D} + RV_{t,D}^2$, $CVP_{t,D} = \beta_D + \beta_r^- r_{t,D}^- + \beta_r^+ r_{t,D}^+ + \beta_{RV} RV_{t,D}$, and Z_t is defined by (3.2.2). Panel A details the estimation results for two regression models in the crude oil and natural markets, outlined above. The t-statistic (in parentheses), is estimated using the Newey–West standard errors. AIC is the Akaike information criteria. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively. Panel B reports the Shapley decomposition of the regression R^2 in the HAR and HAR-CVP models. $\Delta\%$ is the percentage change of the Shapley R^2 in the HAR-CVP model compared to the HAR model.

TABLE 3.4.4. **Contribution of the CVP-CV Determinants to Volatility Variation (Shapley R^2)**

Panel A: HAR-CVP-CV model for Crude Oil

	SP500	VIX	USDI	CS	TB	TS	SPGSCI	CRB	BDI
$RV_{t,D}$	18.10%	16.43%	18.94%	17.02%	19.12%	18.35%	18.40%	18.32%	15.63%
$r^-_{t,D}RV_{t,D}$	2.68%	3.37%	3.74%	3.63%	3.95%	3.39%	3.33%	3.19%	3.38%
$r^+_{t,D}RV_{t,D}$	3.47%	1.93%	2.61%	1.89%	2.37%	2.90%	2.65%	2.64%	2.41%
$RV^2_{t,D}$	9.56%	8.65%	10.36%	8.53%	10.46%	9.70%	10.00%	9.89%	10.09%
$CV_{t,D}RV_{t,D}$	2.73%	7.47%	0.45%	7.28%	0.11%	2.78%	1.52%	1.86%	7.06%
$\widehat{CVP}_{t,D}$	18.44%	21.42%	17.16%	21.32%	16.90%	18.76%	17.49%	17.57%	22.94%
$CV_{t,D}$	1.03%	0.96%	0.04%	0.77%	0.05%	0.52%	0.24%	0.34%	1.11%
$RV_{t,W} + RV_{t,M}$	25.99%	24.27%	26.82%	23.98%	26.94%	25.08%	26.80%	26.58%	24.32%
$r^-_{t,D} + r^+_{t,D}$	3.93%	3.49%	3.63%	3.38%	3.77%	4.20%	3.81%	4.13%	2.86%
$r_{t,W} + r_{t,M}$	0.00%	0.59%	0.50%	0.57%	0.47%	0.67%	0.62%	0.48%	0.34%
R^2	67.50%	67.16%	67.08%	67.03%	67.26%	67.59%	67.36%	67.42%	67.20%
$\widehat{CVP}_{t,D}$/R^2	27.33%	31.89%	25.58%	31.81%	25.13%	27.76%	25.97%	26.05%	34.13%

Panel C: HAR-CVP-CV model for Natural Gas

	SP500	VIX	USDI	CS	TB	TS	SPGSCI	CRB	BDI
$RV_{t,D}$	17.06%	13.17%	17.07%	13.01%	16.89%	17.02%	17.14%	17.00%	12.57%
$r^-_{t,D}RV_{t,D}$	2.65%	2.14%	2.69%	1.92%	2.71%	2.68%	2.58%	2.36%	2.17%
$r^+_{t,D}RV_{t,D}$	3.15%	2.56%	3.17%	2.71%	3.20%	3.16%	3.12%	2.98%	2.69%
$RV^2_{t,D}$	9.41%	7.28%	9.44%	7.34%	9.43%	9.42%	9.34%	9.33%	8.39%
$CV_{t,D}RV_{t,D}$	0.04%	7.83%	0.08%	7.56%	0.34%	0.02%	0.38%	0.23%	8.20%
$\widehat{CVP}_{t,D}$	15.25%	19.80%	15.38%	19.53%	15.68%	15.28%	15.41%	14.91%	21.45%
$CV_{t,D}$	0.04%	0.65%	0.01%	0.11%	0.17%	0.01%	0.27%	0.01%	0.92%
$RV_{t,W} + RV_{t,M}$	22.09%	20.89%	22.00%	21.27%	22.06%	21.95%	21.92%	22.77%	19.60%
$r^-_{t,D} + r^+_{t,D}$	2.31%	1.73%	2.34%	2.00%	2.47%	2.34%	2.33%	2.08%	2.20%
$r_{t,W} + r_{t,M}$	0.04%	0.54%	0.06%	0.51%	0.10%	0.06%	0.08%	0.15%	0.03%
R^2	56.79%	56.77%	56.86%	56.43%	57.37%	56.67%	57.15%	56.91%	56.77%
$\widehat{CVP}_{t,D}$/R^2	26.85%	34.88%	27.04%	34.61%	27.33%	26.97%	26.96%	26.20%	37.78%

This table reports the Shapley decomposition of the regression R^2 in the HAR-CVP-CV models in the crude oil and natural gas market:

$$RV_{t+1,D} = \alpha + (CVP_{t,D})RV_{t,D} + Z_t + \delta_{CV}CV_{t,D} + \epsilon_{t+1,D},$$

with $\widehat{CVP}_{t,D} = r^-_{t,D}RV_{t,D} + r^+_{t,D}RV_{t,D} + RV^2_{t,D} + CV_{t,D}RV_{t,D}$, $CVP_{t,D} = \beta_D + \beta^-_r r^-_{t,D} + \beta^+_r r^+_{t,D} + \beta_{RV}RV_{t,D} + \beta_{CV}CV_{t,D}$, and Z_t is defined by (3.2.2).

TABLE 3.4.5. **CVP Variance Decomposition**

	HAR-CVP		
	$w(r^-_{t,D})$	$w(r^+_{t,D})$	$w(RV_{t,D})$
	Crude Oil		
Mean	87.1%	5.3%	7.5%
Median	86.7%	5.5%	7.8%
Min	76.0%	0.0%	0.1%
Max	99.9%	11.1%	15.4%
	Natural Gas		
Mean	52.5%	38.4%	9.0%
Median	52.7%	38.6%	8.8%
Min	29.4%	15.1%	0.1%
Max	75.2%	61.3%	18.2%

This table reports the summary statistics of the weights $w(r^-_{t,D})$, $w(r^+_{t,D})$, and $w(RV_{t,D})$ in the HAR-CVP model across six permutations in the orthogonalization process. The weights represent the percentages of the variance of $CVP_{t,D}$ decompose into the variances of its orthogonalized components $r^-_{t,D}$, $r^+_{t,D}$, and $RV_{t,D}$ in the HAR-CVP model.

TABLE 3.4.6. **Statistical properties of CVP**

Panel A: Descriptive Statistics

	Mean	St. Dev.	Median	Skewness	Exc. Kurtosis	Min	Max	$LB(1)$
Crude oil	0.546	0.085	0.521	2.071	7.384	0.373	1.336	400.111
Natural Gas	0.464	0.077	0.455	0.926	4.520	0.155	1.073	4.541

Panel B: Correlation

	r^+_D	r^-_D	RV_D	VIX_D	CS_D	TB_D	BDI_D
Crude oil	0.074***	-0.753***	0.429***	0.506***	0.160***	-	-0.238***
Natural gas	0.349***	-0.488***	0.146***	-	-	0.617***	-

The CVP is calculated as: $CVP_{t,D} = \beta_D + \beta^-_t r^-_{t,D} + \beta^+_t r^+_{t,D} + \beta_{RV} RV_{t,D} + \beta_{CV} CV_{t,D}$
This table reports the statistical properties of CVP in the crude oil and natural gas market. Panel A is the descriptive statistics of CVP in the energy markets. $LB(1)$ is the Ljung-Box test statistic at 1 lag. Panel B is the correlation between the CVP and individual components of the CVP. We only consider the conditional variables having a significant impact on future RV to construct $CVP_{t,D}$. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

TABLE 3.5.1. **Out-of sample Forecasting Performance**

Panel A: Loss functions comparison

	HAR	HAR-SV	HAR-RQ	HAR-CVP	HAR-CVP-CV
			Crude Oil		
MSE-ln					
Mean	0.236	0.294	0.211	0.185	0.155
Median	0.073	0.074	0.073	0.061	0.057
St. Dev.	0.558	1.054	0.419	0.420	0.333
QLIKE					
Mean	0.035	0.036	0.036	0.030	0.028
Median	0.037	0.034	0.037	0.033	0.032
St. Dev.	0.590	3.278	0.326	0.412	0.265
			Natural Gas		
MSE-ln					
Mean	0.287	0.310	0.291	0.287	0.289
Median	0.077	0.088	0.077	0.076	0.079
St. Dev.	0.810	0.894	0.803	0.778	0.773
QLIKE					
Mean	0.125	0.131	0.127	0.126	0.127
Median	0.039	0.042	0.039	0.038	0.040
St. Dev.	0.280	0.283	0.282	0.282	0.279

Panel B: DM tests

	Crude Oil			Natural Gas		
HAR-CVP						
	HAR	HAR-SV	HAR-RQ	HAR	HAR-SV	HAR-RQ
MSE-ln	-3.666***	-4.254***	-2.628**	-0.128	-3.991***	-1.777*
QLIKE	-2.537**	-2.532**	-1.261	0.968	-1.601	-1.071
HAR-CVP-CV						
	HAR	HAR-SV	HAR-RQ	HAR	HAR-SV	HAR-RQ
MSE-ln	-6.294***	-5.470***	-5.853***	0.383	-3.614***	-0.851
QLIKE	-4.303***	-2.819**	-3.819***	1.441	-1.281	-0.231

Panel A reports a comparison of loss functions, namely MSE-ln and QLIKE loss functions, across different HAR models for crude oil and natural gas market. Panel B reports the DM test statistics of the HAR_i against the HAR-CVP and the HAR-CVP-CV model, where i is the HAR, HAR-SV and HAR-RQ model. A negative value means that the HAR-CVP and/or HAR-CVP-CV model has lower loss values compared to the competing models. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

TABLE 3.5.2. **Realized Utility**

Panel A: Realized utility with varying coefficient of risk aversion

		HAR	HAR-SV	HAR-RQ	HAR-CVP	HAR-CVP-CV	HAR	HAR-SV	HAR-RQ	HAR-CVP	HAR-CVP-CV
		Crude Oil									
T.Costs	Spread	$\gamma = 2$					$\gamma = 4$				
Zero		8.243%	7.037%	8.435%	8.486%	8.610%	4.121%	3.519%	4.217%	4.243%	4.305%
Full	Full	8.189%	6.970%	8.381%	8.439%	8.574%	4.095%	3.485%	4.191%	4.219%	4.287%
Full	Half	8.216%	7.003%	8.408%	8.462%	8.592%	4.108%	3.502%	4.204%	4.231%	4.296%
Gradual	Full	8.235%	7.026%	8.426%	8.479%	8.604%	4.117%	3.513%	4.213%	4.239%	4.302%
Gradual	Half	8.238%	7.031%	8.430%	8.482%	8.607%	4.119%	3.516%	4.215%	4.241%	4.303%
		Natural Gas									
T.Costs	Spread	$\gamma = 2$					$\gamma = 4$				
Zero		11.518%	11.493%	11.500%	11.507%	11.501%	5.759%	5.746%	5.750%	5.753%	5.750%
Full	Full	11.423%	11.420%	11.398%	11.405%	11.391%	5.711%	5.710%	5.699%	5.702%	5.695%
Full	Half	11.470%	11.456%	11.449%	11.455%	11.445%	5.735%	5.728%	5.724%	5.728%	5.723%
Gradual	Full	11.503%	11.482%	11.484%	11.491%	11.484%	5.752%	5.741%	5.742%	5.745%	5.742%
Gradual	Half	11.511%	11.487%	11.492%	11.499%	11.492%	5.755%	5.744%	5.746%	5.749%	5.746%

Panel B: Differential in realized utility and DM tests

		HAR-CVP			HAR-CVP-CV			HAR-CVP			HAR-CVP-CV		
		HAR	HAR-SV	HAR-RQ	HAR	HAR-SV	HAR-RQ	HAR	HAR-SV	HAR-RQ	HAR	HAR-SV	HAR-RQ
		Crude Oil											
T.Costs	Spread	$\gamma = 2$						$\gamma = 4$					
Zero		24.321**	144.892**	5.147	36.663***	157.234**	17.489***	12.160**	72.446**	2.574	18.331***	78.617**	8.744***
		(2.275)	(2.363)	(0.880)	(3.858)	(2.575)	(3.244)	(2.275)	(2.363)	(0.880)	(3.858)	(2.575)	(3.244)
Full	Full	24.929**	146.872**	5.727	38.448***	160.392**	19.246***	12.464**	73.436**	2.864	19.224***	80.196**	9.623***
		(2.270)	(2.358)	(0.867)	(3.836)	(2.568)	(3.201)	(2.270)	(2.358)	(0.867)	(3.836)	(2.568)	(3.201)
Full	Half	24.632**	145.926**	5.438	37.566***	158.860**	18.373***	12.316**	72.963**	2.719	18.783***	79.430**	9.186***
		(2.286)	(2.371)	(0.911)	(3.906)	(2.590)	(3.341)	(2.286)	(2.371)	(0.911)	(3.906)	(2.590)	(3.341)
Gradual	Full	24.424**	145.264**	5.236	36.949***	157.788**	17.761***	12.212**	72.632**	2.618	18.475***	78.894**	8.881***
		(2.301)	(2.383)	(0.953)	(3.973)	(2.611)	(3.478)	(2.301)	(2.383)	(0.953)	(3.973)	(2.611)	(3.478)
Gradual	Half	24.380**	145.122**	5.193	36.817***	157.559**	17.630***	12.190**	72.561**	2.597	18.409***	78.779**	8.815***
		(2.273)	(2.361)	(0.874)	(3.848)	(2.572)	(3.223)	(2.273)	(2.361)	(0.874)	(3.848)	(2.572)	(3.223)
		Natural Gas											
T.Costs	Spread	$\gamma = 2$						$\gamma = 4$					
Zero		-1.144	1.378	0.647	-1.760	0.762	0.030	-0.572	0.689	0.323	-0.880	0.381	0.015
		(-1.216)	(0.595)	(0.708)	(-1.612)	(0.330)	(0.028)	(-1.216)	(0.595)	(0.708)	(-1.612)	(0.330)	(0.028)
Full	Full	-1.812*	-1.554	0.689	-3.216**	-2.958	-0.715	-0.906*	-0.777	0.345	-1.608**	-1.479	-0.357
		(-1.864)	(-0.664)	(0.721)	(-2.781)	(-1.264)	(-0.611)	(-1.864)	(-0.664)	(0.721)	(-2.781)	(-1.264)	(-0.611)
Full	Half	-1.478	-0.086	0.668	-2.489**	-1.097	-0.342	-0.739	-0.043	0.334	-1.244**	-0.549	-0.171
		(-1.550)	(-0.037)	(0.717)	(-2.222)	(-0.473)	(-0.304)	(-1.550)	(-0.037)	(0.717)	(-2.222)	(-0.473)	(-0.304)
Gradual	Full	-1.244	0.941	0.654	-1.980*	0.206	-0.082	-0.622	0.470	0.327	-0.990*	0.103	-0.041
		(-1.318)	(0.406)	(0.711)	(-1.800)	(0.089)	(-0.074)	(-1.318)	(0.406)	(0.711)	(-1.800)	(0.089)	(-0.074)
Gradual	Half	-1.194	1.161	0.651	-1.871*	0.485	-0.026	-0.597	0.581	0.325	-0.935*	0.242	-0.013
		(-1.267)	(0.501)	(0.710)	(-1.707)	(0.210)	(-0.024)	(-1.267)	(0.501)	(0.710)	(-1.707)	(0.210)	(-0.024)

Panel A report the average realized utility (UoW) with varying coefficient of risk aversion. The realized utility is estimated under five scenarios: no transaction costs ('Zero'), with transaction costs equal to the average full ('Full') and half ('Half') spreads with investment positions fully rebalanced at the close of each business day ('Full') and with transaction costs equal to the average full ('Full'), and half ('Half') spreads with investment positions rebalanced gradually ('Gradual'). The full and half spreads are the difference between the ask and bid prices divided by the midquote and half the full spread over the past nine months, respectively. The full spread is equal to 1.90 and 5.20 bps (basis points) in the crude oil and natural gas markets. The half spread stand at 0.95 and 2.60 bps in the respective markets. Panel B reports the reports the differential in realized utility between the classical HAR models and the HAR-CVP models and their respective DM tests (in parentheses). The differential in utility is reported in bps. A positive DM value means that the HAR-CVP and/or HAR-CVP-CV model has higher realized utility compared to the classical HAR models. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

Appendix 3.1. The HAR-CVP-CV Models - CVP Coefficients

TABLE A.3.1.1. **The HAR-CVP-CV Models for Crude Oil**

α	1.45E-05***	2.95E-05***	1.46E-05***	1.86E-05***	1.45E-05***	1.38E-05***	1.34E-05***	1.37E-05***	1.26E-05*	1.95E-05**
	(4.351)	(3.554)	(3.963)	(2.886)	(4.250)	(4.082)	(3.980)	(3.973)	(1.662)	(2.014)
β_D	0.436***	0.420***	0.438***	0.487***	0.435***	0.442***	0.429***	0.431***	0.562***	0.630***
	(14.176)	(11.551)	(14.339)	(14.591)	(14.084)	(14.477)	(14.126)	(14.143)	(8.073)	(9.089)
β_r^-	-0.136***	-0.143***	-0.152***	-0.153***	-0.156***	-0.134***	-0.139***	-0.142***	-0.159***	-0.117***
	(-3.974)	(-4.141)	(-3.967)	(-3.991)	(-4.272)	(-3.759)	(-4.213)	(-4.359)	(-4.178)	(-3.583)
β_r^+	0.050	0.050	0.055	0.051	0.051	0.055	0.056*	0.057	0.054	0.059*
	(1.426)	(1.547)	(1.511)	(1.528)	(1.504)	(1.609)	(1.646)	(1.633)	(1.534)	(1.948)
β_{RV}	-0.006**	-0.009***	-0.006**	-0.006**	-0.006**	-0.006**	-0.006**	-0.006**	-0.007**	-0.011***
	(-2.064)	(-2.944)	(-2.172)	(-2.023)	(-2.093)	(-2.124)	(-2.221)	(-2.328)	(-2.361)	(-3.332)
β_W	0.307***	0.291***	0.298***	0.288***	0.300***	0.305***	0.307***	0.306***	0.300***	0.292***
	(11.708)	(10.413)	(11.196)	(10.914)	(11.103)	(11.475)	(11.353)	(11.382)	(11.450)	(10.140)
β_M	0.159***	0.155***	0.160***	0.170***	0.159***	0.154***	0.163***	0.162***	0.155***	0.162***
	(6.680)	(6.165)	(6.892)	(6.816)	(6.604)	(6.552)	(6.657)	(6.665)	(6.541)	(6.846)
θ_D^-	-0.178*	-0.231**	-0.204*	-0.198*	-0.202*	-0.222**	-0.211**	-0.195*	-0.196*	-0.218**
	(-1.733)	(-2.277)	(-1.852)	(-1.853)	(-1.934)	(-2.114)	(-2.082)	(-1.928)	(-1.826)	(-2.160)
θ_D^+	0.027	0.019	0.002	0.012	0.009	0.019	0.039	0.031	0.012	0.059
	(0.280)	(0.215)	(0.016)	(0.124)	(0.101)	(0.199)	(0.418)	(0.324)	(0.128)	(0.659)
θ_W	-0.153**	-0.145**	-0.135**	-0.146**	-0.136**	-0.135**	-0.144**	-0.137**	-0.137**	-0.170**
	(-2.376)	(-2.285)	(-2.155)	(-2.361)	(-2.116)	(-2.104)	(-2.227)	(-2.120)	(-2.116)	(-2.734)
θ_M	-0.187	-0.206	-0.225	-0.134	-0.209	-0.206	-0.200	-0.196	-0.206	-0.172
	(-1.294)	(-1.474)	(-1.536)	(-0.935)	(-1.468)	(-1.465)	(-1.419)	(-1.391)	(-1.430)	(-1.265)
$adjR^2$	0.675	0.672	0.671	0.670	0.673	0.676	0.674	0.674	0.672	0.679
AIC	-40,486	-40,491	-40,454	-40,501	-40,470	-40,493	-40,492	-40,492	-40,469	-40,542
$LB(Q^*)$	5.04**	1.49	5.46**	7.42***	4.82**	7.01***	5.13**	4.56**	4.53**	3.41*
	(0.02)	(0.22)	(0.02)	(0.01)	(0.03)	(0.01)	(0.02)	(0.03)	(0.03)	(0.06)

This table reports the estimation results of the following regressions in the crude oil:

$$RV_{t+1,D} = \alpha + (\beta_D + \beta_r^- r_{t,D}^- + \beta_r^+ r_{t,D}^+ + \beta_{RV} RV_{t,D} + \beta_{CV} CV_{t,D}) RV_{t,D} + Z_t + \delta_{CV} CV_{t,D} + \epsilon_{t+1,D},$$

where Z_t is defined by (3.2.2). The t-statistic (in parentheses), is estimated using the Newey–West standard errors. AIC is the Akaike information criteria. $LB(Q^*)$ is the Ljung-Box test statistic and its p-value is reported in parentheses. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

TABLE A.3.1.2. **The HAR-CVP-CV Models for Natural Gas**

α	2.76E-05***	5.75E-05**	2.74E-05**	8.61E-05**	2.93E-05***	2.79E-05**	2.70E-05**	2.78E-05**	1.93E-05	7.34E-05*
	(3.022)	(2.458)	(2.763)	(2.645)	(3.153)	(2.796)	(2.697)	(2.758)	(0.492)	(1.884)
β_D	0.414***	0.346***	0.416***	0.311***	0.407***	0.414***	0.416***	0.413***	0.385***	0.281***
	(8.812)	(5.038)	(9.425)	(4.390)	(9.073)	(9.527)	(9.205)	(9.172)	(4.273)	(3.122)
β_r^-	-0.077***	-0.075***	-0.078***	-0.077***	-0.079***	-0.077***	-0.075***	-0.075***	-0.075***	-0.071***
	(-3.532)	(-3.443)	(-3.427)	(-3.559)	(-3.610)	(-3.392)	(-3.327)	(-3.308)	(-3.406)	(-3.361)
β_r^+	0.070***	0.067***	0.068***	0.067***	0.068***	0.066***	0.067***	0.067***	0.067***	0.068***
	(3.302)	(3.308)	(3.435)	(3.377)	(3.397)	(3.227)	(3.324)	(3.251)	(3.414)	(3.653)
β_{RV}	-0.003**	-0.005**	-0.003**	-0.005**	-0.003*	-0.003**	-0.003**	-0.003*	-0.003**	-0.005**
	(-2.004)	(-2.799)	(-2.341)	(-2.517)	(-1.935)	(-2.085)	(-2.011)	(-1.859)	(-2.106)	(-2.428)
β_W	0.314***	0.308***	0.313***	0.318***	0.312***	0.311***	0.311***	0.311***	0.311***	0.322***
	(8.293)	(8.381)	(8.250)	(8.124)	(8.256)	(8.430)	(8.268)	(8.289)	(8.298)	(8.365)
β_M	0.145***	0.144***	0.145***	0.137***	0.146***	0.145***	0.145***	0.145***	0.145***	0.131***
	(5.626)	(5.240)	(4.485)	(4.279)	(4.981)	(4.491)	(4.527)	(4.514)	(4.838)	(4.685)
θ_D^-	0.041	0.027	0.044	0.035	0.052	0.038	0.017	0.022	0.027	-0.021
	(0.447)	(0.295)	(0.477)	(0.392)	(0.575)	(0.423)	(0.189)	(0.244)	(0.305)	(-0.229)
θ_D^+	0.296**	0.319**	0.310**	0.304**	0.322**	0.322**	0.319**	0.323**	0.319**	0.300**
	(2.194)	(2.310)	(2.460)	(2.210)	(2.211)	(2.490)	(2.484)	(2.477)	(2.325)	(2.462)
θ_W	-0.142	-0.145	-0.148	-0.199	-0.142	-0.148	-0.138	-0.141	-0.132	-0.150
	(-1.219)	(-1.216)	(-1.184)	(-1.381)	(-1.125)	(-1.184)	(-1.113)	(-1.123)	(-1.083)	(-1.190)
θ_M	-0.122	-0.153	-0.102	-0.166	-0.099	-0.112	-0.136	-0.107	-0.091	-0.263
	(-0.589)	(-0.726)	(-0.515)	(-0.783)	(-0.489)	(-0.573)	(-0.701)	(-0.548)	(-0.423)	(-1.276)
$adjR^2$	0.568	0.568	0.569	0.564	0.574	0.567	0.572	0.569	0.568	0.570
AIC	-34,892	-34,911	-34,893	-34,874	-34,923	-34,899	-34,909	-34,900	-34,901	-34,938
$LB(Q^*)$	2.34	0.95	2.91*	0.01	2.34	2.18	2.29	2.40	2.58	1.03
	(0.13)	(0.33)	(0.09)	(0.91)	(0.13)	(0.14)	(0.13)	(0.12)	(0.11)	(0.31)

This table reports the estimation results of the following regressions for the natural gas:

$$RV_{t+1,D} = \alpha + (\beta_D + \beta_r^- r_{t,D}^- + \beta_r^+ r_{t,D}^+ + \beta_{RV} RV_{t,D} + \beta_{CV} CV_{t,D}) RV_{t,D} + Z_t + \delta_{CV} CV_{t,D} + \epsilon_{t+1,D},$$

where Z_t is defined by (3.2.2). The t-statistic (in parentheses), is estimated using the Newey-West standard errors. AIC is the Akaike information criteria. $LB(Q^*)$ is the Ljung-Box test statistic and its p-value is reported in parentheses. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

Appendix 3.2. Data Filtering

In comparison to other asset classes such as equity or foreign exchange, energy futures are less liquid. Hence, we follow a filter process that helps reduce the thin trading bias (Bollerslev et al. (2018)). Even though crude oil and natural gas futures trade over a 24-hour window (with 1-hour trading break), they have numerous periods of inactive trading. In order to determine the number of trading hours to keep in a day, we construct volatility signature plots (similar to the one used by Bollerslev et al. (2018)) in each market. The volatility signature plot allow us to assess whether slow trading periods affect the construction of daily RV. Hence, we include 5-minute intervals with at least K non-zero returns, even if there is no trade. K is let to vary between 1 and 5. If K = 1, all 5-minute intervals are included in the sample. When K = 2, 3, 4, and 5, we are assuming that trading days must contain at least one-quarter, mean, median, and three-quarters of the total number 5-minute intervals in day, respectively. The plots show that RV in the crude oil market is more sensitive to a high K; when more days are disregarded from the sample. If K is kept too low in the natural gas market, the RV construction suffers the most. Therefore, days with more than 8 and 10 trading hours data are kept in the crude oil and natural gas markets, respectively.[48]

We remove intra-day observations if the bid, ask and trade prices are less than zero and the ask price is less or equal to the bid price. In each five-minute interval, we delete observations for which the spread is negative and more than 50 times the median spread on that day. For each five-minute return, we estimate the standard deviation of the returns on the respective days (excluding the current observation) and remove returns that exceeds 7 standard deviations from zero (Barndorff-Nielsen et al. (2009)).[49]

[48]Moreover, keeping these thin days of trade in the sample also affects the relation between our constructed measure of realized variance and the squared returns (common proxy for volatility). It ensures that the relation between the RV and the squared returns is positive across all contracts.

[49]These represent 0.119% and 0.086% of the sample for crude oil and natural gas, respectively.

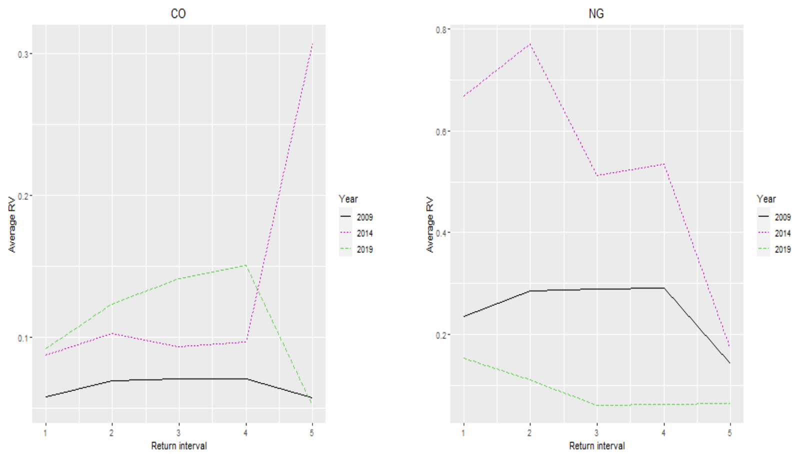


FIGURE A.3.2.1. **Volatility signature plots**

This figure shows how the average realized variance (RV) in the year 2009, 2014, and 2019 varies with the number of 5-minutes intervals included in the sample for crude oil (CO) and natural gas (NG) front-month futures contracts. If K = 1, there is no restrictions on the number of 5-minutes intervals in the sample. If K = 2, 3, 4, and 5, trading days must contain at least one-quarter, mean, median, and three-quarters of the total number 5-minute intervals in day, respectively.

Appendix 3.3. Seasonality Tests and Adjustments

According to Auer (2014), we test for seasonality in the RV time series using the Kruskal–Wallis (KW) test. Under the null hypothesis, the variance for all days of the week (months of the year) are drawn from the same population, or otherwise. The KW test confirms that there is a day of the week and month of the year effect in natural gas volatility but not in crude oil. The KW test results are reported in Table A.3.3.1.

TABLE A.3.3.1. **Seasonality Test**

	RV	
	Crude oil	Natural gas
KW test (DOW)	19.965 [0.05]	358.990 [0.00]
KW test (MOY)	5.624 [0.23]	11.983 [0.02]

This table reports the KW test seasonality test in the crude oil and natural gas markets. Under the null (alternative) hypothesis, there is no seasonal pattern (seasonal pattern) in the RV time series. DOW and MOY stand for the day of the week and month of the year effects, respectively. The p-values of the KW test are reported in brackets.

Table A.3.3.1 confirms that there is a day of the week and month of the year effect in natural gas volatility, but not in crude oil volatility. Accordingly, we deseasonalize the natural gas RV time series based on the approach used by Hameed et al. (2010) and Wang (2013). RV is regressed on a set of seasonality variables that removes the day of the week and month of the year effects in

$$RV_{t,D} = \beta_0 + \sum_{D=1}^{4} \beta_{1,D} DAY_{t,D} + \sum_{M=1}^{11} \beta_{2,M} MONTH_{t,M} + u_t,$$

where D is a dummy variable that represents the days of the week (Monday to Thursday) and M similarly represents the months of the year (January to November). We extract the residuals u_t from the above regression to construct the variance equation:

$$\log(u_t^2) = \beta_0 + \sum_{D=1}^{4} \beta_{1,D} DAY_{t,D} + \sum_{M=1}^{11} \beta_{2,M} MONTH_{t,M} + v_t.$$

The standardised residual is retrieved as such:

$$\hat{\epsilon}_t = \frac{\hat{u}_t}{exp(\beta_0 + \sum_{D=1}^{4} \beta_{1,D} DAY_{t,D} + \sum_{M=1}^{11} \beta_{2,M} MONTH_{t,M})\big/2}.$$

The adjusted realized variance is then estimated as $RV_{t,D}^{adj} = a + b\hat{\epsilon}_t$, where a is the mean value of $RV_{t,D}$ and b is equal to $\left[{}^{var(RV_{t,D})}\!/_{var(\hat{\epsilon}_t)}\right]^{(1/2)}$.

Appendix 3.4. RV Measures

We consider the realized quad-power quarticity (RQ), the negative semivariance (NSV), and the positive semivariance (PSV) as alternative RV measures. The descriptive statistics and cross-correlation of the return (r) and the four realized variance-based volatility measures, for crude oil and natural gas are reported in Panels A and B of Table A.3.4.1, respectively.

The mean and median of RV, NSV, PSV, and RQ in the natural gas market are the highest, standing on average at 6.2, 9.2, 3.1, and 3.1 respectively, than the crude oil markets. Furthermore, NSV has the highest mean/median across the two markets, while RQ has the lowest mean/median. The four measures are skewed to the right which is typical to RV measures. The descriptive statistics of returns in the two energy markets are close to a normal distribution. RV has the most serial correlation across all markets. This means that current variance of the futures contracts over 1, 20, 100, and 250 days is likely to predict future variance. As expected, all the RV-based volatility measures are positively correlated with each other, with cross correlations averaging 0.90. RV and RQ are positively associated with returns in the crude oil and natural gas markets consistent with the inventory effect linked to the theory of storage (Ng and Pirrong (1994) and Pindyck (2004)). In principle, low inventory (among other reasons and shortage in commodity markets) drives both commodity prices and volatility up, while high inventory drives both prices and volatility down.

TABLE A.3.4.1. **Descriptive Statistics of RV-based Volatility Measures**

Panel A: Descriptive Statistics

	Crude oil					Natural gas				
	RV	NSV	PSV	RQ	r	RV	NSV	PSV	RQ	r
mean	4.035	6.359	2.012	2.023	0.000	6.206	9.190	3.148	3.056	0.000
st. dev.	5.367	8.829	2.526	3.043	0.009	6.311	10.245	3.310	3.275	0.013
median	2.517	3.965	1.259	1.211	0.000	4.303	6.320	2.189	2.097	-0.001
skewness	6	8	4	10	2	3	6	5	5	0
Exc. Kurtos.	78	126	27	190	46	17	53	34	37	4
min	0.096	0.128	0.044	0.051	-0.056	0.015	0.651	0.210	0.194	-0.068
max	111.194	211.500	30.103	81.091	0.158	68.613	178.125	42.938	40.761	0.105
LB(1)	1,670	1,386	1,597	1,370	4	1,249	837	1,159	1,086	3
LB(20)	19,571	16,353	18,677	2,461	19	12,035	6,054	8,562	8,216	39
LB(100)	32,335	26,689	30,731	27,132	117	22,094	8,290	11,485	11,395	157
LB(250)	28,645	32,559	28,514	34,186	262	22,572	8,639	12,148	21,911	289

Panel B: Cross Correlations

	Crude oil					Natural gas				
	r	RV	RQ	NSV	PSV	r	RV	RQ	NSV	PSV
RV	0.143					0.060				
RQ	0.173	0.979				0.067	0.895			
NSV	-0.094	0.956	0.920			-0.175	0.881	0.910		
PSV	0.330	0.970	0.964	0.857		0.284	0.885	0.918	0.836	

Panel A and Panel B report the descriptive statistics and cross-correlations of the RV-based volatility measures (realized variance (RV), realized quad-power quarticity (RQ), negative semivariance (NSV), positive semivariance (PSV)) and return (r) in the crude oil and natural gas markets, respectively. LB(1), LB(20), LB(100), and LB(250) are the Ljung-Box test statistic at 1, 20, 100, and 250 lags, respectively. RV, RQ, PSV, and NSV are scaled by 10^4.

Appendix 3.5. Macro-economic Variables

We consider two categories of conditioning variables: financial indicators and commodity sector variables. The financial indicators are: the S&P 500 return (SP500), VIX, US dollar index (USDI), credit spreads (CS), 3-month Treasury bills (TB) and term spread (TS). The data sources are presented in Table A.3.5.1.

Many studies have explored the role of macro-economic variables in determining energy prices and volatility. Investors pursue trading strategies in energy futures market conditional to the states of equity markets. The lower equity returns (captured by the S&P 500 index), the higher the diversification benefits of investing in energy futures. This increase in demand for energy futures suggests higher price volatility. Based on weekly U.S. data Arouri et al. (2011) empirically show that unexpected shocks in equity market have a positive impact on oil price volatility. Similarly, Soucek and Todorova (2013) demonstrate that shocks in the S&P 500 index explain the variation in next day's oil price volatility.[50] Index returns tend to impact volatility via capital flows within markets (Tang and Xiong (2012) and Heath (2019)).

The VIX, defined as stock market's expectation of volatility implied by S&P 500 index options over the next 30-day period, measures equity market uncertainty. Following the financialization of commodity markets, commodity markets and equity markets have become more integrated (Basak and Pavlova (2016)). Chiang et al. (2015) identify the VIX as one of the persistent risk factors in oil markets. While Basak and Pavlova (2016) theoretically establish a positive link between equity market volatility and future commodity return volatility, Silvennoinen and Thorp (2013) provide the empirical evidence that high VIX index increases volatility in most energy markets.[51]

Energy contracts are often priced in U.S. dollars, and thus, making the currency the primary medium of exchange for investors rebalancing their portfolios in the short term. An appreciating U.S. dollar against U.S. key trading partners' currencies attracts capital flows and increases energy price volatility (Kang, Nikitopoulos and Prokopczuk (2020)). Jawadi et al. (2016) have empirically demonstrated that higher U.S. dollar/euro exchange rate raises future oil price volatility, but over longer forecasting horizon.

[50]The equity returns are estimated using high-frequency data (five-minute prices).
[51]These results in Silvennoinen and Thorp (2013) hold true in the crude oil and heating oil markets.

Credit spreads are considered strong predictors of future volatility (Chen et al. (2014), Hitzemann (2016), Prokopczuk et al. (2019), and Kang, Nikitopoulos and Prokopczuk (2020)). Chen et al. (2014) argue that worsening of credit conditions in an economy (measured by the default premium) leads to higher inflation compensation. With higher inflation expectations come larger shocks in energy volatility. Kang, Nikitopoulos and Prokopczuk (2020) and Nonejad (2020) empirically demonstrate that credit spreads increase short-term oil volatility and decrease long-term oil volatility. Macro-economic variables, such as the credit spreads, that provide forward-looking information about the future state of the economy, have better predictive power.

Earlier literature has shown that energy (primarily oil) prices and U.S. monetary policy are negatively correlated. An expansionary monetary policy, low interest rates, increases the demand for inventories and lowers the convenience yields. This causes the future term structure to be in backwardation and puts upward pressure on future oil prices and potentially volatility in energy markets (Frankel (2014), Cheng et al. (2018), and Kang, Nikitopoulos and Prokopczuk (2020)). Hammoudeh and Yuan (2008) analyze the impact of a contractionary monetary policy in commodity (metal) markets and discover that it reduces volatility. According to Casassus and Collin-Dufresne (2005), high interest rates (measured by the 3-month Treasury bills) increase the marginal cost of storage that ultimately raises the convenience yields and causes future term structure to be in backwardation.

The term spread (or yield curve spread) is regarded as a recession barometer that reflects direction of short-term monetary policy (Estrella and Mishkin (1998), Wheelock and Wohar (2009), and Bauer and Mertens (2018)). Nonejad (2020) shows that higher yield curve spreads reduce future monthly oil volatility. This variable is a robust predictor of volatility particularly during calmer periods such as the GFC.

Commodity sector variables include the S&P Goldman Sachs Commodity (non-energy) Index (SPGSCI), the Commodity Research Bureau Raw Materials Index (CRB), and the Baltic Exchange Dirty Tanker Index (BDI). The SPGSCI and CRB indices have become benchmarks for investing in commodity markets (Miao et al. (2017)). These two indices look at price movements of commodities, other than energy, which are sensitive to changes in economic conditions. Graham et al. (2013) analyze the contemporaneous correlation between the daily S&P GSCI (non-energy) Index returns and (energy) Index returns to reveal that the two indices are positively correlated. Even though Miao et al. (2017) are not looking specifically at forecasting oil volatility, they show that the CRB index is an important determinant of future weekly prices.[52] Given that the energy market is easily triggered by sudden changes in the global economy, the two indices can potentially affect volatility in energy prices.

The Baltic Exchange Dirty Tanker Index represents the physical factors that affect the supply of energy commodities and tracks the international shipping rates (Breitenfellner et al. (2009), Kilian (2009), and Fan and Xu (2011)). Lower index values imply lower energy prices and volatility. Miao et al. (2017) identify the tanker index as one of the strongest predictors of long-term oil prices. Moreover, Yuying et al. (2015) observe that unexpected shocks in the tanker index increase future oil (Brent) volatility. This effect disappeared after the GFC when the global economy had contracted and the demand for international shipping dropped.

The full list of conditioning variables and their data sources are presented in Table A.3.5.1.

TABLE A.3.5.1. **Conditioning Variables**

Indicator	Symbol	Description	Source
Financial indicators			
S&P 500 return	SP500	Continuously compounded return on the S&P 500 index	RTH
VIX level	VIX	CBOE volatility Index	FRED
US dollar index	USDI	Trade Weighted U.S. Dollar Index: Major Currencies, Goods	FRED
Credit spreads	CS	Excess yield of the Moody's seasoned Baa corporate bond	FRED
		over the Moody's seasoned Aaa corporate bond	FRED
3-month Treasury bills	TB	3-month treasury constant maturity rates	FRED
Term spread	TS	Difference between the 10-Year and 3-month treasury constant maturity rates	FRED
Commodity sector variables			
SPGSCI (log)	SPGSCI	S&P Goldman Sachs Commodity (non-energy) Index	RTH
CRB (log)	CRB	Commodity Research Bureau Raw Materials Index	RTH
Baltic Dirty (log)	BDI	Baltic Exchange Dirty Tanker Index	RTH

This table presents the conditioning variables and their data sources. The conditioning variables are classified into two main groups: financial indicators and commodity sector variables. FRED and RTH stand for the Federal Reserve Economic Data and Refinitiv Tick History, respectively.

[52]According to Miao et al. (2017), the S&P GSCI (non-energy) Index is not an important driver of oil prices.

Appendix 3.6. Alternative Models for CVP

We extend the HAR-CVP model to include two variations of the RV measure: the semivariances of Patton and Sheppard (2015) and the Bollerslev et al. (2016) realized quad-power quarticity (RQ).

First, we assess the impact of the positive (PSV) and negative (NSV) semivariances of Patton and Sheppard (2015) on future RV in the HAR-CVP model, via the HAR-CVP-SV model. Accordingly we decompose $RV_{t,D}$ into $PSV_{t,D}$ and $NSV_{t,D}$, and we estimate the HAR-CVP-SV model as:

$$RV_{t+1,D} = \alpha + \beta_{PSV} PSV_{t,D} + \beta_{NSV} NSV_{t,D} + CVP_{t,D} RV_{t,D} + Z_t + \epsilon_{t+1}, \quad (3.1)$$

where CVP is estimated as:

$$CVP_{t,D} = \beta_r^- r_{t,D}^- + \beta_r^+ r_{t,D}^+ + \beta_{RV} RV_{t,D}, \quad (3.2)$$

and Z_t is specified by equation (2), thus

$$Z_t = \beta_W RV_{t,W} + \beta_M RV_{t,M} + \theta_D^+ r_{t,D}^+ + \theta_D^- r_{t,D}^- + \theta_W r_{t,W} + \theta_M r_{t,M}. \quad (3.3)$$

Second, as RQ_t and RV_t can both be used as measures of volatility, we replace RV in the CVP model by the square root of RQ_t. Accordingly, the corresponding HAR-CVP-RQ model is estimated as:

$$RV_{t+1} = \alpha + CVP_{t,D} RV_{t,D} + Z_t + \epsilon_{t+1}, \quad (3.4)$$

where

$$CVP_{t,D} = \beta_D + \beta_r^- r_{t,D}^- + \beta_r^+ r_{t,D}^+ + \beta_{RQ} RQ_{t,D}^{1/2}, \quad (3.5)$$

and Z_t is given by (3.2.2). The CVP variables now include $r_{t,D}^-$, $r_{t,D}^+$, and $RQ_{t,D}^{1/2}$, the CVP regressors are $r_{t,D}^- RV_{t,D}$, $r_{t,D}^+ RV_{t,D}$, and $RQ_{t,D}^{1/2} RV_{t,D}$, and β_r^-, β_r^+, and β_{RQ} are the corresponding CVP coefficients.

The model estimation reveals that, in energy markets, both negative and positive semivariance is highly significant, with negative semivariance having a much greater impact on future volatility than positive semivariance in the HAR-SV model (see Panel A of Table A.3.6.1). Unlike equity markets (where only the negative semivariance is statistically significant (Patton and Sheppard (2015))), energy markets are more prone to high positive returns than high negative returns, the well known feature of inverse leverage effect (Sévi (2014)). Further, we see in Panel A of Table A.3.6.2 (i.e. the HAR-RQ model) that β_{RQ} is not statistically significant, thus we conclude that the impact of measurement errors on RV persistence is negligible in energy markets. When we add the CVP variables to the original HAR-SV and HAR-RQ models, we observe that these variables are still significantly impacting next day's future volatility. Also, β_{RQ} now appears significantly in the HAR-CVP-RQ models in both the crude oil and natural gas markets.

Panel B of Table A.3.6.1 presents the Shapley R^2 for the models with semivariance. As expected, negative semivariance has more explanatory power than the positive semivariance in explaining the next day's future volatility in the crude oil market. However, positive semivariance has more importance than the negative semivariance in the natural gas market. From Panel B of Table A.3.6.2, we conclude that the addition of the CVP variables in the HAR-CVP-SV and HAR-CVP-RQ models improves their the explanatory power.

TABLE A.3.6.1. **The HAR-SV and HAR-CVP-SV Models**

Panel A: Model estimation

	Crude oil		Natural gas	
	HAR-SV	HAR-CVP-SV	HAR-SV	HAR-CVP-SV
α	9.26E-06***	1.43E-05***	-1.15E-05	3.25E-05**
	(3.213)	(4.208)	(-1.314)	(2.565)
β_r^-		-0.153***		-0.095***
		(-4.284)		(-2.946)
β_r^+		0.053		0.071***
		(1.508)		(2.968)
β_{RV}		-0.006**		0.004**
		(-2.161)		(2.541)
β_{NSV}	0.562***	0.457***	0.444***	0.300**
	(6.251)	(4.697)	(4.522)	(2.724)
β_{PSV}	0.312***	0.416***	0.228**	0.131
	(3.698)	(4.356)	(2.223)	(1.220)
β_W	0.302***	0.300***	0.435***	0.391***
	(11.013)	(10.961)	(11.916)	(10.955)
β_M	0.161***	0.160***	0.168***	0.178***
	(6.740)	(6.522)	(5.104)	(5.098)
θ_D^-	-0.560***	-0.193*	-0.257**	0.122
	(-5.739)	(-1.707)	(-2.249)	(0.987)
θ_D^+	0.223**	0.015	0.727***	0.416***
	(2.177)	(0.149)	(6.221)	(3.064)
θ_W	-0.125*	-0.134**	-0.027	-0.064
	(-1.943)	(-2.069)	(-0.244)	(-0.555)
θ_M	-0.212	-0.210	-0.082	-0.167
	(-1.497)	(-1.481)	(-0.365)	(-0.749)
adj R^2	0.670	0.673	0.541	0.543
AIC	-40,454	-40,468	-34,724	-34,725

Panel B: Shapley R^2

	Crude Oil		Natural Gas	
	HAR-SV	HAR-CVP-SV	HAR-SV	HAR-CVP-SV
$r_{t,D}^- RV_{t,D}$		3.56%		2.39%
$r_{t,D}^+ RV_{t,D}$		2.13%		2.85%
$RV_{t,D}^2$		8.50%		7.74%
$\widehat{CVP}_{t,D}$		14.19%		12.98%
$PSV_{t,D}$	15.34%	12.14%	13.27%	9.53%
$\Delta\%$		-20.83%		-28.17%
$NSV_{t,D}$	17.74%	13.74%	13.14%	9.46%
$\Delta\%$		-22.53%		-27.96%
$PSV_{t,D} + NSV_{t,D}$	33.08%	25.89%	26.41%	18.99%
$\Delta\%$		-21.74%		-28.07%
$RV_{t,W} + RV_{t,M}$	27.63%	23.25%	24.22%	19.80%
$\Delta\%$		-15.84%		-18.23%
$r_{t,D}^- + r_{t,D}^+$	5.68%	3.75%	3.10%	2.17%
$\Delta\%$		-33.90%		-30.11%
$r_{t,W} + r_{t,M}$	0.65%	0.16%	0.34%	0.31%
$\Delta\%$		-74.61%		-10.27%
R^2	67.03%	67.25%	54.07%	54.26%
$\widehat{CVP}_{t,D}/R^2$		21.10%		23.93%

This table reports the estimation results of the following regressions in the crude oil and natural gas futures market:

$$\textbf{HAR-SV}: \ RV_{t+1,D} = \alpha + SV_{t,D} + Z_t + \epsilon_{t+1,D},$$
$$\textbf{HAR-CVP-SV}: \ RV_{t+1,D} = \alpha + SV_{t,D} + (CVP_{t,D})RV_{t,D} + Z_t + \epsilon_{t+1,D},$$

with $\widehat{CVP}_{t,D} = r_{t,D}^- RV_{t,D} + r_{t,D}^+ RV_{t,D} + RV_{t,D}^2$, $CVP_{t,D} = \beta_D + \beta_r^- r_{t,D}^- + \beta_r^+ r_{t,D}^+ + \beta_{RV} RV_{t,D}$, $SV_{t,D} = \beta_{PSV}\ PSV_{t,D} + \beta_{NSV}\ NSV_{t,D}$, and Z_t is defined by (3.2.2). Panel A details the estimation results for two regression models in the crude oil and natural gas markets, outlined above. The t-statistic (in parentheses), is estimated using the Newey–West standard errors. AIC is the Akaike information criteria. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively. Panel B reports the Shapley decomposition of the regression R^2 in the HAR-SV and HAR-CVP-SV models. $\Delta\%$ is the percentage change of the Shapley R^2 in the HAR-CVP-SV model compared to the HAR-SV model.

TABLE A.3.6.2. **The HAR-RQ and HAR-CVP-RQ Models**

Panel A: Model estimation

	Crude oil		Natural gas	
	HAR-RQ	HAR-CVP-RQ	HAR-RQ	HAR-CVP-RQ
α	9.58E-06**	1.48E-05***	1.49E-05*	2.85E-05***
	(2.763)	(4.536)	(1.905)	(2.939)
β_D	0.440***	0.452***	0.446***	0.418***
	(13.956)	(13.981)	(10.723)	(10.492)
β_r^-		-0.162***		-0.079***
		(-4.555)		(-3.580)
β_r^+		0.063*		0.074***
		(1.840)		(3.856)
β_{RQ}	-0.000	-0.005**	-0.005	-0.002***
	(-0.418)	(-2.445)	(-0.069)	(-3.220)
β_W	0.301***	0.291***	0.315***	0.307***
	(11.090)	(10.112)	(8.285)	(8.367))
β_M	0.161***	0.157***	0.141***	0.144***
	(6.624)	(6.371)	(4.709)	(4.516)
θ_D^-	-0.648***	-0.181*	-0.245***	0.037
	(-7.354)	(-1.740)	(-2.832)	(0.404)
θ_D^+	0.143	-0.021	0.579***	0.299**
	(1.628)	(-0.226)	(5.460)	(2.383)
θ_W	-0.108*	-0.137**	-0.139	-0.137
	(-1.668)	(-2.105)	(-1.083)	(-1.122)
θ_M	-0.181	-0.220	-0.074	-0.139
	(-1.228)	(-1.561)	(-0.348)	(-0.723)
adj R^2	0.670	0.671	0.565	0.567
AIC	-40,455	-40,451	-34,867	-34,909

Panel B: Shapley R^2

	Crude oil		Natural gas	
	HAR-RQ	HAR-CVP-RQ	HAR-RQ	HAR-CVP-RQ
$RV_{t,D}$	21.40%	19.24%	20.20%	17.88%
$\Delta\%$		-10.11%		-11.47%
$r_{t,D}^- RV_{t,D}$		4.05%		2.75%
$r_{t,D}^+ RV_{t,D}$		2.40%		3.25%
$RQ_{t,D}^{1/2} RV_{t,D}$	11.33%	9.93%	9.41%	7.80%
$\Delta\%$		-12.42%		-17.11%
$\widehat{CVP}_{t,D}$		16.37%		13.80%
$RV_{t,W} + RV_{t,M}$	28.53%	27.17%	23.81%	22.61%
$\Delta\%$		-4.79%		-5.04%
$r_{t,D}^- + r_{t,D}^+$	5.08%	3.77%	2.88%	2.36%
$\Delta\%$		-25.70%		-18.24%
$r_{t,W} + r_{t,M}$	0.69%	0.51%	0.16%	0.05%
$\Delta\%$		-26.84%		-67.84%
R^2	67.04%	67.06%	56.47%	56.70%
$\widehat{CVP}_{t,D}/R^2$		24.42%		24.33%

This table reports the estimation results of the following regressions in the crude oil and natural gas futures market:

$$\textbf{HAR-RQ}: \; RV_{t+1,D} = \alpha + (\beta_D + \beta_{RQ} RQ_{t,D}^{1/2})\, RV_{t,D} + Z_t + \epsilon_{t+1,D},$$
$$\textbf{HAR-CVP-RQ}: \; RV_{t+1,D} = \alpha + (CVP_{t,D}) RV_{t,D} + Z_t + \epsilon_{t+1,D},$$

with $\widehat{CVP}_{t,D} = r_{t,D}^- RV_{t,D} + r_{t,D}^+ RV_{t,D} + RQ_{t,D}^{1/2} RV_{t,D}, CVP_{t,D} = \beta_D + \beta_r^- r_{t,D}^- + \beta_r^+ r_{t,D}^+ + \beta_{RQ} RQ_{t,D}^{1/2}$, and Z_t is defined by (3.2.2). Panel A details the estimation results for two regression models in the crude oil and natural gas markets, outlined above. The t-statistic (in parentheses), is estimated using the Newey–West standard errors. AIC is the Akaike information criteria. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively. Panel B reports the Shapley decomposition of the regression R^2 in the HAR-RQ and HAR-CVP-RQ models. $\Delta\%$ is the percentage change of the Shapley R^2 in the HAR-CVP-RQ model compared to the HAR-RQ model.

Appendix 3.7. Sharpe Ratio

Table A.3.7.1 presents the realized utility results for varying Sharpe ratio.

TABLE A.3.7.1. **Realized Utility with Varying Sharpe Ratio**

Panel A: Realized utility with varying Sharpe ratio

		HAR	HAR-SV	HAR-RQ	HAR-CVP	HAR-CVP-CV	HAR	HAR-SV	HAR-RQ	HAR-CVP	HAR-CVP-CV
		Crude Oil									
T.Costs	Spread	$SR = 0.4$					$SR = 0.8$				
Zero		5.495%	4.691%	5.623%	5.657%	5.740%	10.991%	9.383%	11.246%	11.315%	11.479%
Full	Full	5.442%	4.625%	5.570%	5.610%	5.704%	10.937%	9.315%	11.193%	11.267%	11.444%
Full	Half	5.468%	4.658%	5.596%	5.634%	5.722%	10.963%	9.348%	11.219%	11.291%	11.461%
Gradual	Full	5.487%	4.681%	5.615%	5.650%	5.734%	10.982%	9.371%	11.238%	11.307%	11.474%
Gradual	Half	5.491%	4.686%	5.619%	5.654%	5.737%	10.986%	9.376%	11.242%	11.311%	11.476%
		Natural Gas									
T.Costs	Spread	$SR = 0.5$					$SR = 0.9$				
Zero		8.227%	8.209%	8.214%	8.219%	8.215%	14.809%	14.777%	14.786%	14.794%	14.786%
Full	Full	8.132%	8.137%	8.112%	8.117%	8.105%	14.714%	14.704%	14.683%	14.692%	14.676%
Full	Half	8.179%	8.173%	8.163%	8.168%	8.160%	14.761%	14.740%	14.734%	14.743%	14.731%
Gradual	Full	8.213%	8.198%	8.199%	8.204%	8.198%	14.794%	14.765%	14.770%	14.778%	14.769%
Gradual	Half	8.220%	8.203%	8.206%	8.211%	8.206%	14.801%	14.771%	14.778%	14.786%	14.778%

Panel B: DM tests

		HAR-CVP			HAR-CVP-CV			HAR-CVP			HAR-CVP-CV		
		HAR	HAR-SV	HAR-RQ	HAR	HAR-SV	HAR-RQ	HAR	HAR-SV	HAR-RQ	HAR	HAR-SV	HAR-RQ
		Crude Oil											
T.Costs	Spread	$SR = 0.4$						$SR = 0.8$					
Zero		16.214**	96.594***	3.431	24.442**	104.822***	11.659**	32.428**	193.189***	6.863	48.884**	209.645***	23.319**
		(2.270)	(3.836)	(0.867)	(2.358)	(3.201)	(2.568)	(2.270)	(3.836)	(0.867)	(2.358)	(3.201)	(2.568)
Full	Full	16.817**	98.546***	4.010	26.220**	107.949***	13.413**	33.040**	195.199***	7.444	50.676**	212.835***	25.080**
		(2.315)	(4.038)	(0.995)	(2.396)	(3.612)	(2.633)	(2.293)	(3.940)	(0.932)	(2.377)	(3.410)	(2.601)
Full	Half	16.520**	97.599***	3.722	25.338**	106.417***	12.540**	32.744**	194.253***	7.155	49.795**	211.303***	24.206**
		(2.293)	(3.940)	(0.932)	(2.377)	(3.410)	(2.601)	(2.282)	(3.889)	(0.900)	(2.368)	(3.307)	(2.584)
Gradual	Full	16.313**	96.937***	3.520	24.721**	105.345***	11.928**	32.536**	193.590***	6.953	49.178**	210.231***	23.594**
		(2.277)	(3.868)	(0.887)	(2.365)	(3.265)	(2.578)	(2.274)	(3.853)	(0.877)	(2.362)	(3.233)	(2.573)
Gradual	Half	16.268**	96.795***	3.477	24.589**	105.116***	11.797**	32.492**	193.448***	6.910	49.045**	210.002***	23.463**
		(2.274)	(3.853)	(0.877)	(2.362)	(3.233)	(2.573)	(2.272)	(3.845)	(0.872)	(2.360)	(3.217)	(2.571)
		Natural Gas											
T.Costs	Spread	$SR = 0.5$						$SR = 0.9$					
Zero		-0.817	0.984	0.462	-1.257	0.544	0.022	-1.470	1.772	0.832	-2.263	0.979	0.039
		(-1.216)	(0.595)	(0.708)	(-1.612)	(0.330)	(0.028)	(-1.216)	(0.595)	(0.708)	(-1.612)	(0.330)	(0.028)
Full	Full	-1.485**	-1.949	0.504	-2.712***	-3.177*	-0.723	-2.138*	-1.160	0.874	-3.719**	-2.740	-0.706
		(-2.101)	(-1.158)	(0.723)	(-3.188)	(-1.883)	(-0.837)	(-1.727)	(-0.386)	(0.720)	(-2.540)	(-0.914)	(-0.478)
Full	Half	-1.151*	-0.481	0.483	-1.985**	-1.316	-0.351	-1.805	0.308	0.853	-2.992**	-0.879	-0.334
		(-1.678)	(-0.289)	(0.719)	(-2.452)	(-0.791)	(-0.430)	(-1.477)	(0.103)	(0.715)	(-2.091)	(-0.295)	(-0.232)
Gradual	Full	-0.917	0.546	0.469	-1.476*	-0.013	-0.090	-1.571	1.336	0.839	-2.483*	0.424	-0.073
		(-1.358)	(0.329)	(0.712)	(-1.874)	(-0.008)	(-0.114)	(-1.296)	(0.448)	(0.711)	(-1.759)	(0.143)	(-0.052)
Gradual	Half	-0.867	0.767	0.466	-1.367*	0.266	-0.034	-1.521	1.556	0.835	-2.374*	0.703	-0.017
		(-1.288)	(0.463)	(0.710)	(-1.745)	(0.161)	(-0.044)	(-1.256)	(0.522)	(0.710)	(-1.686)	(0.237)	(-0.012)

Panel A report the average realized utility (UoW) with varying Sharpe ratio. The realized utility is estimated under five scenarios: no transaction costs ('Zero'), with transaction costs equal to the average full ('Full') and half ('Half') spreads with investment positions fully rebalanced at the close of each business day ('Full') and with transaction costs equal to the average full ('Full'), and half ('Half') spreads with investment positions rebalanced gradually ('Gradual'). The full and half spreads are the difference between the ask and bid prices divided by the midquote and half the full spread over the past nine months, respectively. The full spread is equal to 1.90 and 5.20 bps (basis points) in the crude oil and natural gas markets. The half spread stand at 0.95 and 2.60 bps in the respective markets. Panel B reports the reports the differential in realized utility between the classical HAR models and the HAR-CVP models and their respective DM tests (in parentheses). The differential in utility is reported in bps. A positive DM value means that the HAR-CVP and/or HAR-CVP-CV model has higher realized utility compared to the classical HAR models. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

CHAPTER 4

Liquidity Provision Channels and Oil Price Volatility

4.1. Introduction

Hedgers' motives are traditionally driven by demand for price insurance, aligned with the theory of normal backwardation by Keynes (1930) and Hicks (1939). Accordingly, hedgers in oil markets, typically risk-averse oil producers, stipulate a demand for short futures positions that has the effect of inducing speculators to provide liquidity and receive a premium for bearing the risk of oil price changes. However, insurance provision is not the only driver of hedgers' trading activity in oil futures markets. Kang, Rouwenhorst and Tang (2020) demonstrate that in the short term, long hedgers earn higher returns than long speculators, implying that hedgers receive a premium as they become the liquidity providers to satisfy the short-term trading demand of momentum speculators. Hedgers engaging in this short-term trading clearly do not seek price insurance, but rather serve, as liquidity providers. Therefore, liquidity provision in oil futures trading is administered both by speculators and oil hedgers in the short term. According to microstructure theory, as liquidity providers engage in contrarians strategies, they are rewarded with higher returns for providing liquidity. They ultimately decrease their trading positions and volatility spikes accordingly. This study explores the role of speculators and hedgers, as liquidity providers, in determining volatility in oil markets.

We hypothesize that the hedging pressure in oil futures markets is not guided exclusively by trading driven by hedgers' insurance provision motives, but also by hedgers' liquidity provision. Thus, the effect of changes in hedging pressure on oil volatility depends on the liquidity provision channels by either speculators or hedgers. When hedgers act as insurance seekers, hedging pressure increases (meaning the net short positions of hedgers increase), and long speculators are the liquidity providers receiving a premium. As liquidity providers, speculators behave as contrarians and their positive returns instigate a decrease in trading positions and, consequently, a decrease in volatility. Thus, when speculators are the liquidity providers, an increase in hedging pressure leads to a decrease in volatility. In contrast, in the short run, hedgers serve as liquidity providers, so as the hedging pressure decreases[1], long hedgers receive a premium and by executing contrarian trading strategies, their positive returns impose a decrease in trading positions and volatility. Consequently, in the short run, hedgers become liquidity providers, so a decrease in hedging pressure reduces volatility.

This study, for first time in the literature, provides empirical evidence to support the distinct impact of these liquidity provision channels in determining oil volatility. By using the weekly reports on hedgers' positions, published by the Commodity Futures Trading Commission (CFTC), we employ two measures of hedging pressure that effectively capture the liquidity provision by hedgers and speculators. We essentially disentangle the impact of these two liquidity provision channels from the hedging pressure that has been commonly studied in the literature (De Roon et al. (2000), Basu and Miffre (2013), and Bosch and Smimou (2022)). We then assess the effect of liquidity provision by hedgers and speculators on determining weekly crude oil volatility. We control for the impact of important determinants of weekly volatility, including past volatility, returns, and weekly information on inventory. We find that a 1% increase in the component of hedging pressure driven by speculators' liquidity provision decreases volatility by 16%, while in the short run, a 1% increase in the component of hedging pressure driven by hedgers' liquidity provision increases volatility by 68%. Thus, while liquidity provision by hedgers is likely to increase volatility, liquidity provision by speculators leads to a decrease in volatility stipulated by the notion that liquidity providers act as contrarians. Further, oil volatility tends to be more responsive to the hedgers' short-term liquidity provision compared to variations induced by speculators' liquidity provisions.

Motivated by the findings of Büyükşahin and Harris (2011) and Kang, Rouwenhorst and Tang (2020), we also investigate the impact of the liquidity provision channels on volatility, conditioned on falling and rising oil market conditions. We stipulate that oil markets conditions would have a distinctive effect on how the liquidity provision channels determine volatility. We find that liquidity provision by speculators would lead to an increase

[1]The net short positions of hedgers decrease, as hedgers take long positions in futures contracts and earn a premium compensating for their liquidity provision.

in volatility in rising markets. However, the short-term liquidity provision by hedgers decreases volatility in falling markets. This implies that trading by speculators has a substantial impact on volatility in rising markets, while trading by hedgers willing to provide liquidity to momentum speculators affects volatility by it both in falling and rising markets.

Crude oil markets have experienced substantial variation in recent years linked to supply inelasticity and global economic slowdown (Kilian and Murphy (2014)) that has been reflected to the shape of the futures curve. The impact of volatility on the shape of the futures curve has been established, and positive spreads tend to be more responsive to volatility shocks (Nikitopoulos et al. (2017)). Since normal and inverted markets respond differently to volatility shocks, we hypothesize that the impact of the liquidity provision channels on volatility would be affected by these markets conditions. First, we confirm the V-shaped relationship between the slope of the futures curve and the two market states (inverted and normal), increasing volatility by the same magnitude (Haugom et al. (2014) and Nikitopoulos et al. (2017)). The aggregate effects on volatility are negative for the liquidity provision by speculators and positive for the liquidity provision by hedgers, with the effects being more pronounced in inverted markets.

We also examine the responsiveness of the liquidity provisions by speculators and hedgers in oil futures markets (in determining volatility) to macro-economic shocks associated with market risk and business cycle risk. We find that independent the level of market risk, the aggregate effect of the liquidity provision by speculators on volatility is negative. However, the reduction in volatility is higher in low market risk conditions than in high market risk conditions, potentially because speculators are reluctant to provide liquidity in high market risk conditions. Inversely, the aggregate effect of the short-term liquidity provision by hedgers on volatility is positive in both high and low market risk environments. Yet, net trading tends to increase substantially volatility in low risk conditions as hedgers are inclined to facilitate liquidity provision in low rather than in high market risk conditions. Business cycles are likely to influence the demand for hedging via the liquidity provision by speculators (Baumeister and Kilian (2016) and Lang and Auer (2020)). We demonstrate that the aggregate effect on the volatility from liquidity provision by speculators remains negative and the aggregate effect from liquidity provision by hedgers remains positive irrespective of the signals of an economic boom or downturn.

This study offers new insights into the role of speculators, and, for first time in the literature, the role of hedgers as liquidity providers in determining weekly oil market volatility. We establish the dual role of hedgers in oil markets, which have a statistically and economically significant impact on oil price volatility and opposite effects on volatility. The hedgers' dual role as insurance seekers and short-term liquidity providers explains hedgers' excessive trading references, described by Cheng and Wei (2014) and Kang, Rouwenhorst and Tang (2020). Indeed, Kang, Rouwenhorst and Tang (2020) observe that hedgers, acting as the liquidity providers for momentum speculators in the short term, earn comparatively higher returns (premium). Their study shows that a considerable portion of speculators' trading is orthogonal to momentum, and the benefits to the hedgers of the 'immediate' liquidity provision are higher than the losses from facilitating momentum trading. They further note that the empirical evidence on the effect of speculative trading on volatility is mixed. While Danthine (1978) establishes that imperfectly informed speculators stabilize prices, Stein (1987) shows the opposite by demonstrating that speculators disrupt prices.[2] We find that speculators can indeed affect price volatility, particularly through their immediate demand for liquidity in the short term. This evidence contradicts Bryant et al. (2006) and Bohl and Stephan (2013), who empirically demonstrate that speculators do not destabilize markets. We find that demand for 'hedging' is driven by two liquidity provision channels that have opposite effects on volatility, thus providing an explanation for the contradictory evidence in terms of the influence of speculation on volatility.

Although many studies including De Roon et al. (2000), Basu and Miffre (2013), and Bosch and Smimou (2022), have acknowledged that hedgers' demand for price insurance is highly influenced by the theory of normal backwardation, they fail to account for the contemporaneous effect of hedgers' short-term liquidity provision. We demonstrate that the liquidity provision channels have different impacts on volatility in normal and inverted

[2]There is also a behavioral explanation for why speculators can potentially influence volatility. De Long et al. (1990) show that irrational traders drive an asset's price away from its fundamental value. However, it is the rational arbitrageurs (fearing that the asset price will return to its fundamental value too slowly) that drive volatility higher by reducing their trading positions.

markets and, most importantly, liquidity provision by speculators, conditioned on normal market conditions, affects volatility in the opposite direction.

Following the financialization of commodity markets, oil futures markets have been attracting more financial traders (with no interest per se in the physical commodity market) (Fattouh et al. (2013) and Büyükşahin and Robe (2014)). Further, Bloom (2009) has previously shown that uncertainty in equity markets affecting hiring and investment, indirectly influences the production decisions of oil-producing firms. Another channel through which equity-market uncertainty influences the oil market is via economic policy uncertainty in the U.S. (Ajmi et al. (2015)). We provide evidence of another channel through which the equity-market uncertainty affects oil price volatility. Specifically, high-volatility environments influence both the liquidity provision by speculators and hedgers. Recessionary pressure from the U.S. is known to influence oil price movements (Kang and Ratti (2013) and Antonakakis et al. (2014)).

The remainder of the study is structured as follows. Section 4.2 introduces the data utilized for capturing the impact of the liquidity provision channels on weekly oil volatility. In Section 4.3, we present the effects of the liquidity provision by hedgers and speculators on determining volatility. We further investigate the sensitivity of volatility to the liquidity provision channels in normal and inverted markets in Section 4.4, and then their effects in low/high market and business cycle risk environments in Section 4.5. Section 4.6 concludes this study.

4.2. Data and Preliminary Analysis

4.2.1. Oil realized variance. The data represent crude oil price dynamics and cover the period between January 2009 and December 2019. We use high-frequency prices of the front-month continuous futures contracts of crude oil traded on the NYMEX, collected from RTH, to construct the daily realized variance. The latter, which acts as a measure of ex-post volatility, is the mid-quotations prices (average of bid and ask prices) sampled at five-minute intervals.[3] Daily realized variance, estimated as the sum of squared intra-day returns over a day, is given by $RV_{t,d} = \sum_{i=1}^{m} r_{i,t}^2$ where m is the number of intra-day

[3]In the literature, the consensus is to aggregate returns into five-minute intervals as they usually provide the best RV approximation (Liu et al. (2015)).

observations. Similarly, the weekly volatility is measured by the sum of squared five-minute returns over a week, $RV_{t,w} = \sum_{i=1}^{s} r_{i,t}^2$ where s is the number of five-minute returns in a week. We adopt a data filter process similar to the one used by Bollerslev et al. (2018) to reduce the thin trading bias present in oil markets.[4]

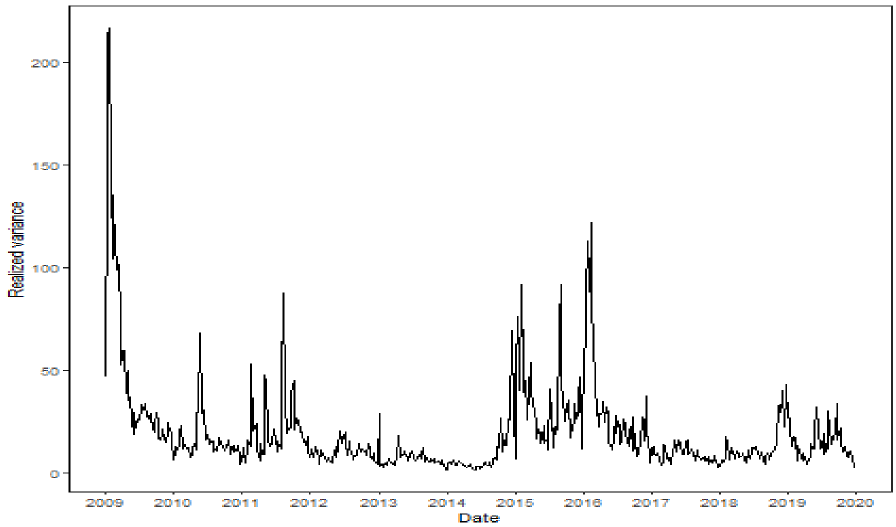
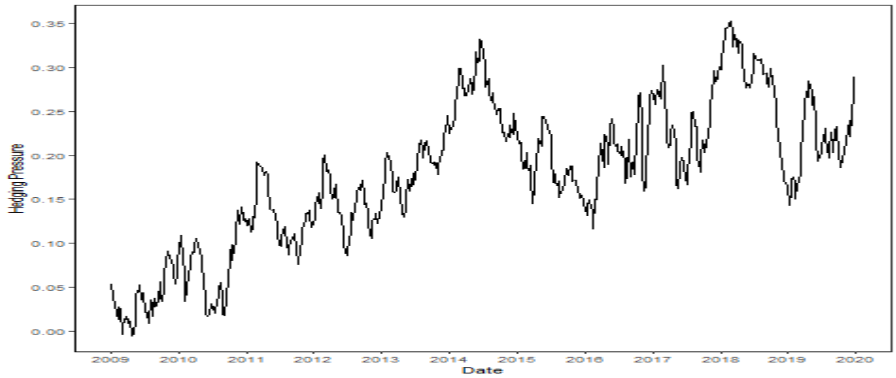


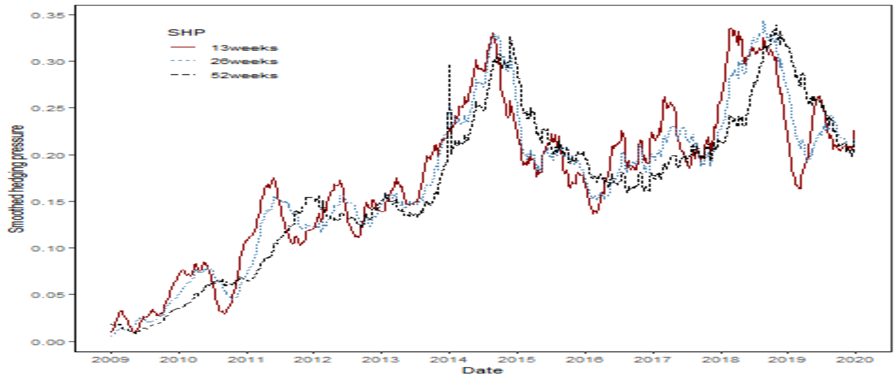
FIGURE 4.2.1. **Crude Oil Weekly Realized Variance**
The figure plots the time series of the weekly realized variance of crude oil front-month futures contracts between January 2009 and December 2019. RV is scaled by 10^4.

The time series of crude oil's RV is depicted in Figure 4.2.1. Oil price volatility tended to exhibit periods of relatively low variation and periods of high variation. For instance, despite the volatility spike during the GFC in 2008, volatility remained relatively high between 2015 and 2017. During these times, there was an oversupply of oil (referred to as the oil glut) in OCED countries, which reduced their economic growth during these years. The expansion of the shale industry among U.S. oil producers also contributed to the global oil oversupply.

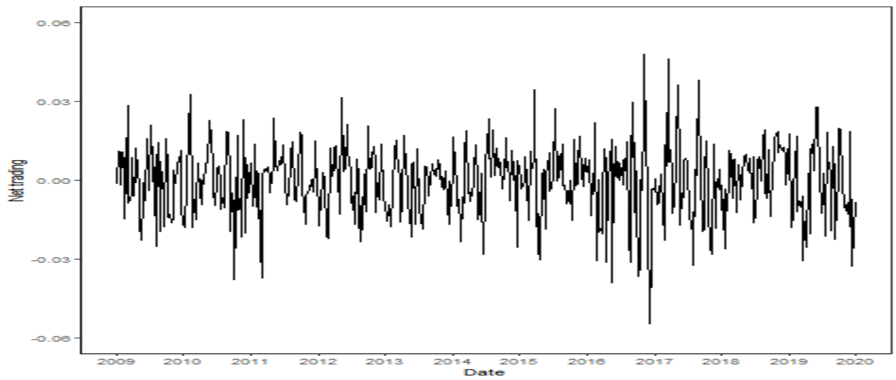
[4]Even though crude oil futures trade over a 24-hour window (with 1-hour trading break), they have numerous periods of inactive trading. Hence, we follow a filter process that helps reduce this thin trading bias (Bollerslev et al. (2018)). Days which have at least 10 active trading hours are kept in the sample and less than 20% of trading days are discarded. Similarly, we remove intraday observations if the bid, ask, and trade prices are less than zero and the ask price is less or equal to the bid price. In each five-minute interval, we delete observations for which the spread is negative and more than 50 times the median spread on that day. For each five-minute return, we estimate the standard deviation of the returns on the respective days (excluding the current observation) and remove returns that exceeds 8 standard deviations from zero (Barndorff-Nielsen et al. (2009)). This represents 0.065% of the data.



(A) Hedging pressure



(B) Smoothed hedging pressure



(C) Net trading

FIGURE 4.2.2. **Crude Oil: Hedging Pressure, Smoothed Hedging Pressure, and Net Trading**

The figure plots the time series of the weekly hedging pressure (HP) and its two components (smoothed hedging pressure (SHP) and net trading (NT)) of crude oil between January 2009 and December 2019. SHP is estimated using 13-week, 26-week, and 52-week moving average of hedgers' net short positions.

4.2.2. Hedging pressure. The CFTC, via their weekly Commitment of Traders (COT) reports, provides information on the long and short positions of different traders' type (commercials, noncommercials, and nonreportables).[5] In this study, we focus on hedging pressure from the commercial traders' perspective that we termed hedgers. Hedging pressure (HP), defined as the net short position of hedgers (commercial traders), is estimated as the number of contracts that hedgers are short, less the number of contracts that they are net long, divided by the open interest held in a week.[6] Open interest is the total number of short and long contracts jointly held by hedgers, speculators, and nonreportables traders.[7] Thus, hedging pressure is computed as:

$$HP_{t,w} = \frac{\text{Hedgers' short positions}_{t,w} \; - \; \text{Hedgers' long positions}_{t,w}}{\text{Open interest}_{t,w}} \tag{4.2.1}$$

$$= \frac{\text{-Hedgers' net long positions}_{t,w}}{\text{Open interest}_{t,w}}. \tag{4.2.2}$$

Kang, Rouwenhorst and Tang (2020) demonstrate empirically that variation in hedging pressure is driven by two components: the traditional liquidity provision of speculators to meet hedgers' demand for price insurance and the liquidity provision of hedgers to satisfy the short-term momentum trading of speculators. Following the concept and terminology used in Kang, Rouwenhorst and Tang (2020), we introduce net trading (NT) as the component of the hedging pressure that captures the behavior of hedgers with no palpable hedging motives, but rather, as liquidity providers for short-term speculative trading. This is estimated as the change in the net long position of hedgers in consecutive weeks, divided by the open interest held in the past week. Specifically, it measures the position change of hedgers (net long position of hedgers between weeks $t-1$ and t, normalized by the open interest in week $t-1$), and is defined as:

$$NT_{t,w} = \frac{\text{Hedgers' net long positions}_{t,w} \; - \text{Hedgers' net long positions}_{t-1,w}}{\text{Open interest}_{t-1,w}}. \tag{4.2.3}$$

To separate the impact of hedgers' liquidity provision from the impact of speculators liquidity provision, we introduce the smoothed hedging pressure. This captures the component of hedging pressure that is driven by the need of hedgers for price insurance and

[5]CFTC stands for the Commodity Futures Trading Commission. Commercial traders (e.g. oil producers or consumers) are hereafter defined as hedgers. Noncommercial traders represent speculators, while nonreportables are much smaller traders in the market. The long and short positions of commercial traders are measured each week on Tuesday, and are publicly released three days later, after the market close on Friday.

[6]Hedgers' net short position is equal to the hedgers' short position less long position in week t normalized by the open interest held in week t.

[7]Open interest can be also estimated as the sum of hedgers' short and long positions. Both measures of open interest give qualitatively similar results.

reflects the impact of liquidity provision by speculators. The smoothed hedging pressure (SHP) is the trailing n-week moving average of the net short positions of hedgers divided by the open interest held in a week, and is estimated as:[8]

$$SHP_{t,w} = \frac{n\text{-weeks moving average of hedgers' net short positions}_{t,w}}{\text{Open interest}_{t,w}}. \tag{4.2.4}$$

Figure 4.2.2 shows the time series of hedging pressure, smoothed hedging pressure (over 52 weeks, 26 weeks and 13 weeks) and net trading from 2009 to 2019. The top panel, which represents hedging pressure, shows that hedgers were predominantly net short (i.e., HP was mainly positive). For example, in the last week of December 2011, hedging pressure was at 12%. This means that 12% of hedgers' positions were more short than long. The middle panel captures the component of hedging pressure driven by hedgers' demand for price insurance and emulates the dynamics of overall hedging pressure. Comparatively, the bottom panel (net trading), which depicts the component of hedging pressure driven by the short-term liquidity provision of hedgers, shows a rather noisy pattern.

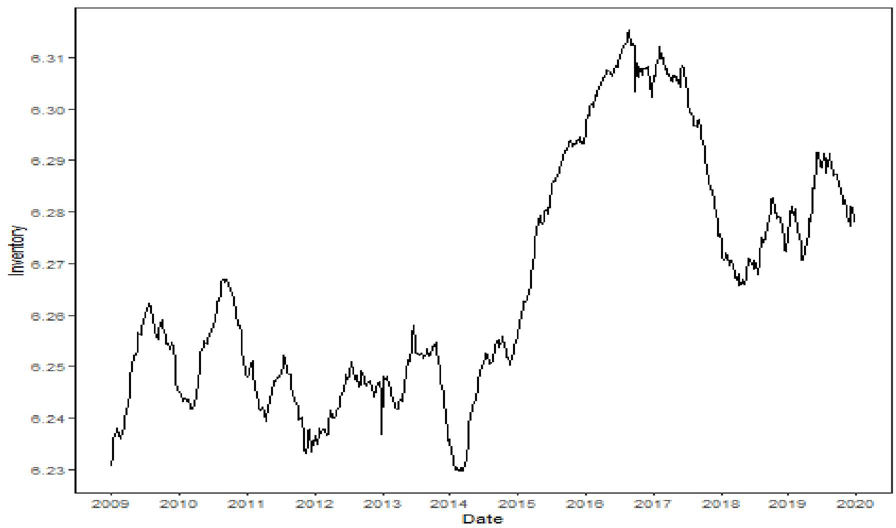


FIGURE 4.2.3. **Crude Oil and Petroleum Inventory**

The figure plots the weekly crude oil and petroleum inventory between January 2009 and December 2019.

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[8]Since we are looking at behavior of hedgers over the past ten years (not thirty years as reported in Kang, Rouwenhorst and Tang (2020)), we report a shorter moving average (26 weeks) of the net short positions of hedgers in this study. Alternative measures of SHP, which use a 52 weeks and 13 weeks moving average of the net short positions of hedgers, are also examined. n represents the 52 weeks, 26 weeks, and 13 weeks.

4.2.3. Crude oil and petroleum inventory. Inventory is known to influence oil volatility, and is proxied by the EIA weekly series on primary stocks of U.S. crude oil and petroleum inventory.[9] Nikitopoulos et al. (2017) demonstrate that the EIA's definition of inventory (as opposed to the OECD's definition, which include, petroleum inventory of non-U.S. countries) is more likely to influence short-term oil prices/volatility. Figure 4.2.3 show that inventory increased steadily after 2015 (increasing by roughly 1.72 million barrels per day, as reported by the EIA). The surplus inventory during the oil glut between 2014–2016 was also evident. Therefore, we decide to use inventory as a control variable to eliminate any exogeneity concerns.

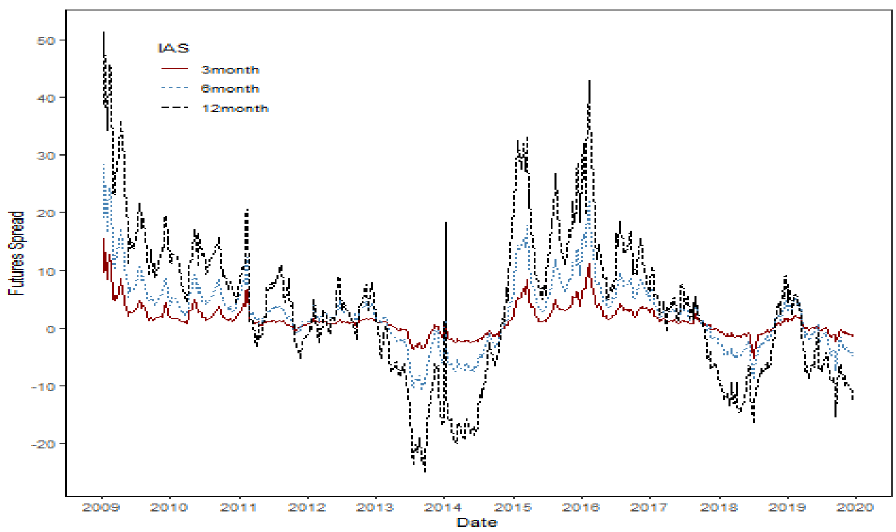


FIGURE 4.2.4. **3-month, 6-month and 12-month Futures Interest-adjusted Spreads**

The figure plots the weekly average of daily 3-month, 6-month, and 12-month interest-adjusted spreads the crude oil front-month futures contracts between January 2009 and December 2019.

4.2.4. Futures interest-adjusted spreads. We construct a weekly measure of futures spreads to gauge the impact of different oil market conditions, namely normal and inverted markets, on the power of hedgers' motives to determine volatility.[10] We use the daily prices of CME light sweet crude oil (WTI) futures prices for the nearest (first), fourth,

[9]The weekly U.S. ending stocks of crude oil and petroleum products (in thousand barrels). EIA stands for the U.S. Energy Information Administration.

[10]Oil markets are normal (or in contango) when futures prices exceed the spot price implying positive futures spreads and an upward-sloping futures curve. Oil markets are inverted (or in backwardation) when spot prices exceed futures prices implying negative futures spreads and a downward-sloping futures curve.

seventh, and thirteenth monthly contract expiry dates from RTH to build the weekly measure of futures spread. A crude oil futures contract represents 1000 bushels to be delivered to Cushing, Oklahoma. Each futures contract expires on the third business day prior to the 25^{th} calendar day of the month preceding the delivery month. After a contract expires, the n-month contract for the remainder of that calendar month is the contract for the second following month. The LIBOR rate is the U.S. dollar (USD) LIBOR interest rate in n-month maturities.[11] The 12-month futures interest-adjusted spread is estimated as:

$$IAS\,(n-1)_{t,d} = \frac{\mathrm{FP}\,(t_d, n) - \mathrm{FP}\,(t_d, 1)\left[1 + \frac{\mathrm{LIBOR}(t_d, n-1)(n-1)}{12}\right]}{\mathrm{FP}\,(t_d, 1)}$$

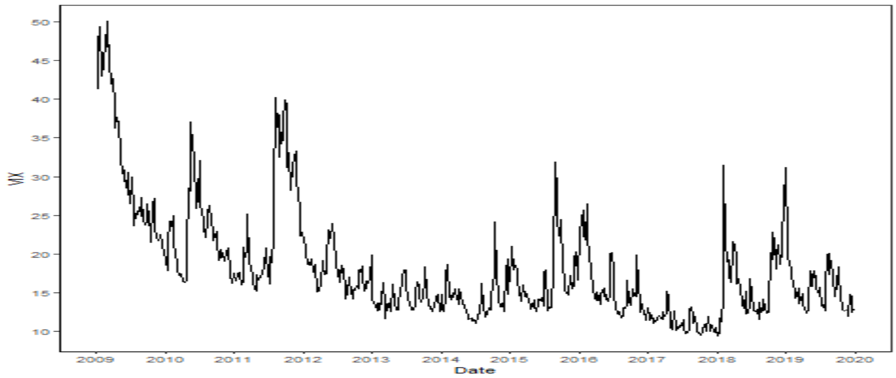
Given that $n = 12$, then $FP(t_d, n)$ is the 12^{th}-month nearest futures price on day t_d, $FP(t_d, 1)$ is the 1^{st}-month nearest futures price on day t_d, and LIBOR$(t_d, n-1)$ is the 12^{th}-month LIBOR rate on day t_d. Therefore, the futures interest-adjusted spread, $IAS12_{t,w}$, is the average of the daily 12^{th}-month $IAS12_{t,d}$ over a given week. Moreover, the negative interest-adjusted spread ($IAS12^{-}_{t,w}$), which represents an inverted market, is estimated as $IAS12_{t,w} < 0$ and zero otherwise. The positive interest-adjusted spread ($IAS12^{+}_{t,w}$), which represents a normal market, is estimated as $IAS12_{t,w} > 0$ and zero otherwise.

Figure 4.2.4 graphs the 3-month, 6-month, and 12-month IAS between 2009 and 2019. From 2009 to 2018, the IAS were primarily positive apart from between 2013 and 2015 (signaling that crude oil futures market was normal). After 2018, the crude oil market oscillated between normal state (positive spreads) and inverted state (negative spreads). Between 2009 and 2019, oil markets were more often normal rather than inverted, at 63% versus 37% (as measured by the weekly positive and negative 12-month interest-adjusted futures spread).[12]

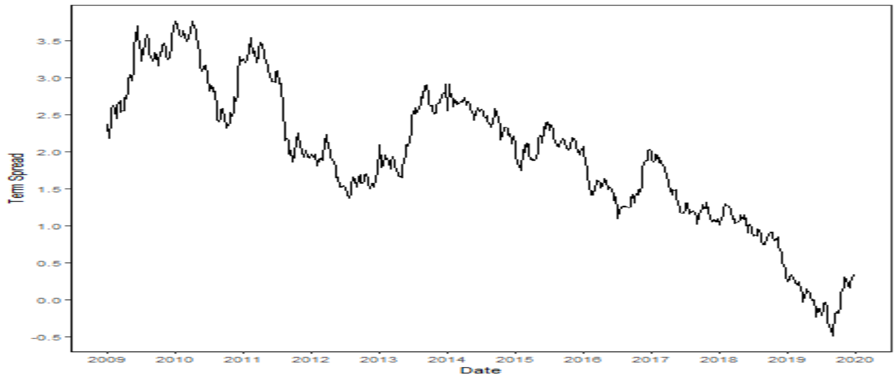
4.2.5. Financial sector risk. The financial sector risk is measured by the VIX index (CBOE volatility index), and the stock market's expectation of volatility implied by the S&P 500 index options over the next 30-day period. This is commonly referred to as the

[11]The LIBOR rate is the average interbank interest rate at which a large number of banks on the London money market are prepared to lend one another unsecured funds denominated in USD. The futures prices and LIBOR rate are collected from RTH.

[12]If we use the 3-month and 6-month interest-adjusted futures spread, then oil markets were much more normal than inverted (72% against 28% and 69% against 31%).



(A) VIX



(B) Term Spread (%)

FIGURE 4.2.5. **VIX and Term Spread**
Panel (a) plots the weekly CBOE VIX index, and Panel (b) plots the weekly term spread (difference between the weekly 10-Year and 3-month treasury bond constant maturity rates) between January 2009 and December 2019.

fear index or fear gauge. The daily VIX index is collected from the FRED. We retrieve the daily VIX and calculate their weekly averages. For instance, Silvennoinen and Thorp (2013) show that volatility in equity market can adversely effect oil futures volatility.

Panel (a) in Figure 4.2.5 shows a plot of the weekly CBOE VIX index (VIX) time series, from 2009 to 2019. A high VIX index – above 20 – is a signal that the equity market is under stress and an economic slowdown or recession is imminent. However, a low VIX index – below 20 – represents a normal and stable market. The VIX highest jump at 50.1 was on March, 2009.

4.2.6. Business cycle risk. The daily treasury bond constant maturity rates are collected from the FRED. We calculate the weekly 10-year and 3-month treasury bond constant maturity rates by averaging their respective daily rates. The business cycle risk is estimated using the weekly term spread (TS), which is the difference between the weekly 10-year and 3-month treasury bond constant maturity rates. By tracking the component of expected returns, the term spread effectively captures the short-term business cycles (Fama and French (1989)).[13] While a positive (yield curve is normal) term spread means that the long-term (10-year) rates are higher than the short-term (3-month) rates, a negative (yield curve is inverted) term spread indicates that the short-term rates are higher than the long-term rates.

Panel (b) in Figure 4.2.5 shows the weekly time series of the term spread between 2009 and 2019. It shows that the yield curve was primarily normal on most weeks. After the GFC (2007–2008), the yield curve increased at a rapid pace, with the term spread reaching close to 4% at its peak in 2010. This could be explained partially by the Federal Reserve conducting a more aggressive monetary policy through its long-term rates instead of the conventional short-term rates. They purchased longer-term treasuries and mortgage-backed debt and issued forward guidance regarding the future conduct of monetary policy (Kapinos and Musatov (2018)). Between 2014 and early 2019, the term spread gradually declined but remained positive. Interestingly, the term spread was negative for numerous weeks in mid-2019 (representing 4% of the sampled weeks).

Panel (A) of Table 4.2.1 reports the descriptive statistics of the variables as described above between 2009 and 2019. We observe that weekly oil volatility was five times as high as its daily volatility. A positive hedging pressure means that hedgers were primarily net short this last decade. If hedgers are net short, this ultimately implies that they are net sellers of oil futures contracts (Basu and Miffre (2013)). Assuming the open interest is constant, net trading also measures the decrease in hedging pressure. Net trading was negative (-0.056%) between 2009 and 2019, which indicates an overall decrease in hedgers' trading position in consecutive weeks. While weekly inventory was relatively stable, the three measures of futures spreads were more volatile. The longer the maturity of the futures contracts, the more variation there seemed to be in the IAS measures. Even though the positive and negative changes in the VIX have similar mean values (in absolute terms), the positive changes in the VIX were more pronounced. Given the term

[13]These business cycles are identified by the National Bureau of Economic Research (NBER).

TABLE 4.2.1. **Statistical Properties**

Panel A: Descriptive statistics

	mean	st. dev.	median	min	max	LB(1)	ADF
RV	19.844	23.472	12.675	1.475	216.810	369	-6.158***
HP	0.183	0.081	0.188	-0.005	0.352	495	-3.532**
SHP52	0.172	0.083	0.179	0.008	0.339	508	-1.577
SHP	0.177	0.081	0.189	0.005	0.343	509	-2.666
SHP13	0.180	0.080	0.189	0.009	0.335	508	-3.112
NT(%)	-0.056	1.331	0.025	-5.462	4.813	36	-6.769***
Inv	6.267	0.024	6.261	6.230	6.314	512	-1.926
IAS3(%)	1.277	2.616	1.076	-5.254	15.476	459	-3.172*
IAS6(%)	2.460	6.088	2.551	-10.705	28.279	472	-2.890
IAS12(%)	2.354	8.141	2.106	-13.097	32.194	468	-2.829
VIX	18.020	7.311	15.772	9.340	50.128	448	-5.161***
TS(%)	1.904	0.974	1.946	-0.492	3.768	509	-3.182*

Panel B: Correlation

	RV	HP	SHP52	SHP	SHP13	NT(%)
RV						
HP	-0.433***					
SHP52	-0.252***	0.109***				
SHP	-0.339***	0.865***	0.948***			
SHP13	-0.382***	0.796***	0.883***	0.963***		
NT	0.107***	-0.080*	0.115***	0.097**	0.068*	

This table provides details on the statistical properties of selected variables between 2009 and 2019. Panel A reports their descriptive statistics of these variables. They include the weekly realized variance (RV), hedging pressure (HP), 52-week smoothed hedging pressure (SHP52), 26-week smoothed hedging pressure (SHP), 13-week smoothed hedging pressure (SHP13), net trading (NT), inventory (Inv), 12-month futures interest-adjusted spread (IAS12), 6-month futures interest-adjusted spread (IAS6), 3-month futures interest-adjusted spread (IAS3), financial risk (VIX), and business cycle risk (TS). LB(1) is the Ljung-Box test statistic at 1 lag. RV is scaled by 10^4. ***, **, and * denote the rejection of the null hypothesis at 1%, 5%, and 10% significance levels, respectively. Panel B reports the 'Pearson' correlation between the RV, HP, variants of the SHP, and NT.

spread is biased toward positive spreads, its mean value reflects that. The autocorrelation (persistence) of the individual time series over a week is measured using the Ljung-Box test (LB(1)) in Panel (A) of Table 4.2.1. We report the correlation between the realized variance, variations of the smoothed hedging pressure, and net trading in Panel (B) of Table 4.2.1. The results show that realized variance is negatively (positively) correlated with hedging pressure and smoothed hedging pressure (net trading). Since hedging pressure and smoothed hedging pressure both capture the liquidity provision by speculators, they are highly correlated with each other. As net trading aims to proxy for the liquidity provision by hedgers, we observe that it has fairly low (negative) correlation with hedging pressure or smoothed hedging pressure.

4.3. The Role of Liquidity Provision in Determining Volatility

To assess the role of liquidity provision by hedgers and speculators in determining oil volatility, we first analyze the impact of net trading and smoothed hedging pressure on weekly volatility. Second, by acknowledging the importance of oil returns in establishing the liquidity provision channel (Kang, Rouwenhorst and Tang (2020)), we assess the impact of net trading and smoothed hedging pressure on volatility while conditioning on falling or raising oil market conditions.

4.3.1. The liquidity provision channels. We analyze the impact of variation in hedging pressure on determining future oil volatility. An increase in hedging pressure driven by hedgers' demand for price insurance, represented by an increase on their net short positions, is stipulated by speculators providing liquidity and earning the risk premium. When the liquidity providers are speculators, as they earn positive returns, they will adopt contrarian trading strategies and decrease their trading positions, causing a reduction in volatility. Thus, an increase in hedging pressure leads to a reduction in oil volatility.

Conversely, the liquidity provision argument put forward by Kang, Rouwenhorst and Tang (2020) stipulates that in the short run, hedging pressure is driven by the need to provide liquidity to the momentum trading of speculators. Hence, in the short run, hedgers become the liquidity providers and earn higher returns, reflecting the risk premium to provide liquidity to speculators. Guided by their positive returns, hedgers take more long positions, resulting in a reduction in hedging pressure, while as contrarians they reduce their trading position, which leads to a reduction in oil prices volatility. Therefore, when the liquidity provision is driven by hedgers, a decrease in hedging pressure leads to a decrease in volatility. This component of hedging pressure is captured by net trading.

We assess the overall impact of hedging pressure, $HP_{t,w}$, on weekly volatility as follows:

$$RV_{t+1,w} = \beta_0 + \beta_{\mathrm{HP}_w}\mathrm{HP}_{t,w} + \sum_{k=0}^{k=3} \beta_{\mathrm{RV}_{k,w}}\mathrm{RV}_{t-k,w} + \epsilon_{t+1,w}, \tag{4.3.1}$$

where $\sum_{k=0}^{k=3} RV_{t-k,d}$ represents an autoregressive process of order 4 for RV and the order selection criteria is based on the Aikaike's information criterion (AIC). This acknowledges that the current and lagged values of volatility (in the past weeks) can also influence future volatility.[14] Equation (4.3.1) and all other equations defined hereafter are estimated using the weighted least squares (WLS) estimation, with the inverse of the fitted values of the error standard deviations, retrieved from the ordinary least square estimation, as the weights.[15]

To capture the impact of liquidity provision on determining volatility, and disentangle the liquidity provision by speculators and hedgers, we use two measures of hedging pressure: smoothed hedging pressure and net trading. Smoothed hedging pressure represents the hedger's demand for insurance and reflects the component of the hedging pressure driven by liquidity provision by speculators. Net trading is the component of hedging pressure that is driven by hedgers' liquidity provision for short-term momentum trading. The effects of these two drivers of variations in hedging pressure on weekly volatility are captured by the following two regressions:

$$RV_{t+1,w} = \beta_0 + \beta_{\mathrm{SHP}_w}\mathrm{SHP}_{t,w} + \sum_{k=0}^{k=3} \beta_{\mathrm{RV}_{k,w}}\mathrm{RV}_{t-k,w} + \epsilon_{t+1,w}, \tag{4.3.2}$$

$$RV_{t+1,w} = \beta_0 + \beta_{\mathrm{NT}_w}\mathrm{NT}_{t,w} + \sum_{k=0}^{k=3} \beta_{\mathrm{RV}_{k,w}}\mathrm{RV}_{t-k,w} + \epsilon_{t+1,w}, \tag{4.3.3}$$

[14] The autoregressive process for RV can be re-written as:

$$\sum_{k=0}^{k=3} \beta_{RV_{k,w}} RV_{t-k,w} = \beta^*_{RV_{0,w}}[RV_{t,w}] + \sum_{k=1}^{k=3}(\beta_{RV_{0,w}} - \beta_{RV_{k,w}})[RV_{t,w} - RV_{t-k,w}],$$

$$\beta^*_{RV_{0,w}} = \beta_{RV_{0,w}} + \beta_{RV_{1,w}} + \beta_{RV_{2,w}} + \beta_{RV_{3,w}}.$$

We, henceforth, choose to report $\beta^*_{RV_{0,w}}$ as the joint influence of current (week t) and past volatility (weeks $t-1$, $t-2$, and $t-3$) on next week's volatility.

[15] Since the weekly RV time series experience numerous spikes which influences the estimated coefficients in the OLS estimation, the WLS is a better alternative. Motivated by Neter et al. (2005), Montgomery et al. (2008), and Diebold (2015), we use a three-step approach to derive the WLS weights. First, we fit the regression model by OLS and carry out a residual analysis that determine the relationship between the OLS regression's residual and fitted values. We observe that the residual plot against the fitted values has a megaphone shape. This indicates that the constant variance assumption has been violated and also that the variability of the residuals increases with the fitted values. Second, we estimate the standard deviation function by regressing the absolute residuals on the fitted values. Using the absolute value of the residuals, rather than its squared value, is deemed more suitable because it is less affected by outliers in the data (Montgomery et al. (2008)). Thus, we run the regression $|\epsilon| \sim y$, where $|\epsilon|$ and y are the absolute values of the OLS regression's residuals and the OLS regression's fitted values, respectively. Third, we use the inverse of the squared fitted values from the standard deviation function as the WLS weights.

where $SHP_{t,w}$ and $NT_{t,w}$ represent smoothed hedging pressure and net trading, respectively. To confirm that these two measures capture independent variations in hedging pressure, we assess the impact of both net trading and smoothed hedging pressure on weekly volatility by considering the following regression:

$$RV_{t+1,w} = \beta_0 + \beta_{\mathrm{SHP}_w}\mathrm{SHP}_{t,w} + \beta_{\mathrm{NT}_w}\mathrm{NT}_{t,w} + \sum_{k=0}^{k=3}\beta_{\mathrm{RV}_{k,w}}\mathrm{RV}_{t-k,w} + \epsilon_{t+1,w}. \qquad (4.3.4)$$

Table 4.3.1 presents the estimation results of these four models, and confirms the distinctive impact of the volatility provision channels on determining volatility. We find that hedging pressure (in Model (1)) are negatively associated with volatility. An increase in the net short position of hedgers, who act as insurance seekers, means that more long speculators are earning higher (positive returns), and they are likely to decrease their trading positions. This ultimately means a fall in oil volatility. A 1% increase in hedging pressure decreases future volatility by 18.5%. However, this change in hedging pressure is not always driven by hedgers seeking price protection, so the liquidity provision may not be offered only by speculators.

We find that a 1% increase in smoothed hedging pressure (see Model (2)) will lead to a decrease in weekly volatility of only 15.9%. This implies that smoothed hedging pressure can only capture a component of the (total) hedging pressure, and this component reflects the variation driven by hedgers seeking price protection and speculators offering liquidity provision. The other component of hedging pressure reflects the variations associated with hedgers becoming liquidity providers in the short run and requiring a compensation (higher returns). They usually take on more long positions, which causes them to reduce their trading position (net trading). Behaving as contrarian traders, this reduction in trading position from hedgers causes a reduction in oil futures volatility, as observed in Model (3) of Table 4.3.1. We see that a 1% increase in net trading is likely to increase volatility by 67.5%. Thus, two key results emerge from this analysis. First, liquidity provision by hedgers and speculators have opposite effects on volatility, with short-term hedgers' liquidity provision positively impacting volatility and speculators' liquidity provision negatively affecting volatility. Second, volatility is more sensitive to variations

TABLE 4.3.1. **The HP Models**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_0	0.065***	0.056***	0.027***	0.058***	0.065***	0.054***	0.027***	0.057***
	(5.808)	(5.415)	(6.728)	(5.682)	(5.941)	(5.297)	(7.164)	(5.685)
β_{HP_w}	-0.185***				-0.184***			
	(-4.875)				(-4.773)			
β_{SHP_w}		-0.159***		-0.162***		-0.150***		-0.156***
		(-4.099)		(-4.338)		(-3.816)		(-4.123)
β_{NT_w}			0.675***	0.706***			0.631***	0.678***
			(4.557)	(4.936)			(4.224)	(4.509)
β_{Inv_w}					0.450***	0.459***	0.449**	0.421***
					(3.074)	(2.979)	(2.714)	(2.868)
$\beta_{RV^*_{0,w}}$	0.820***	0.840***	0.838***	0.832***	0.816***	0.840***	0.838***	0.831***
	(22.219)	(22.487)	(24.044)	(22.747)	(22.572)	(22.562)	(24.363)	(22.837)
$adjR^2$	0.513	0.476	0.400	0.497	0.518	0.485	0.417	0.504
AIC	-1,249	-1,190	-1,079	-1,222	-1,261	-1,206	-1,105	-1,235

This table reports the estimation results of the following regressions in the crude oil futures market:

$$RV_{t+1,w} = \beta_0 + \beta_{\mathrm{HP}_w}\mathrm{HP}_{t,w} + \beta_{\mathrm{Inv}_w}\mathrm{Inv}_{t,w} + \sum_{k=0}^{k=3}\beta_{\mathrm{RV}_{k,w}}\mathrm{RV}_{t-k,w} + \epsilon_{t+1,w},$$

$$RV_{t+1,w} = \beta_0 + \beta_{\mathrm{SHP}_w}\mathrm{SHP}_{t,w} + \beta_{\mathrm{NT}_w}\mathrm{NT}_{t,w} + \beta_{\mathrm{Inv}_w}\mathrm{Inv}_{t,w} + \sum_{k=0}^{k=3}\beta_{\mathrm{RV}_{k,w}}\mathrm{RV}_{t-k,w} + \epsilon_{t+1,w},$$

The table details the estimation results for eight specifications of the HP model in the crude oil futures markets, outlined above. The t-statistic (in parentheses), is estimated using the Newey–West standard errors. AIC stands for the Akaike information criteria. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

driven by hedgers' liquidity provision than those induced by the speculators' liquidity provisions.

Further, we observe that the coefficient of smoothed hedging pressure and net trading remain the same among models assessing the individual impact of these measures and their combined impact when comparing Models (2), (3), and (4). Thus, net trading and smoothed hedging pressure capture independent components of hedging pressure. In addition, current and past three week volatility ($RV_{t,w}$), as an additional control variable, significantly increases next week's volatility.

Inventory is an important determinant of volatility in oil markets, and is likely to affect the relationship between volatility and demand for hedging. According to the theory of storage by Working (1949) and Brennan (1976), there is a monotonic relationship between inventory and volatility. Low inventories relate to the risks of inventory exhaustion, which leads to an increase in volatility. However, more recent research reveals an asymmetric V-shaped relationship between oil inventory and futures price volatility (Kogan et al. (2009), Haugom et al. (2014), and Nikitopoulos et al. (2017)). At high levels of inventory, supply becomes inelastic and hinders inventory adjustments that cause an increase in volatility. Thus, low or high levels of inventory may induce an increase in volatility. We investigate the effect of the liquidity provision in determining volatility while controlling for inventories (in the four above mentioned models). Table 4.3.1 presents the estimation results of these regressions and confirms that growth in inventory, as inventory levels, increases oil price volatility (see Models (5), (6), (7), and (8)). This is because inventory's supply becomes inelastic when there is an inventory accumulation (Nikitopoulos et al. (2017)). The statistical significance of the other predictors (including hedging pressure, smoothed hedging pressure, and net trading) of weekly volatility are not affected by the inclusion of inventory.[16]

4.3.2. Impact of rising and falling markets. Asymmetric volatility is an empirical feature of financial markets referring to the association of high volatility with negative returns that has been explained via the leverage effect, feedback effect, and behavioral effects.[17] In commodity markets, typically, a positive relationship between returns and volatility prevails (known as inverted asymmetric volatility), which can be explained by the theory of storage or the safe haven property of some commodities like gold.[18] However, recent empirical studies in oil markets have revealed an asymmetric volatility effect that could be attributed to the risk and information sharing between commodity markets and other financial markets following the financialization of commodity markets (Chiarella et al. (2016) and Baur and Dimpfl (2018)). Hence, we revisit the effects of oil price returns on volatility and investigate the role of the conditional impact of (positive or negative) returns on determining the effects of liquidity provision channels on volatility.

[16]We also use a longer (52-week) and shorter (13-week) trailing period to estimate the moving average of hedgers' net short positions (smoothed hedging pressure). This allows us to determine whether alternative trailing periods affect the relationship between smoothed hedging pressure and future volatility (see Appendix 4.1). The results reveal that longer and shorter trailing periods do not affect the statistical significance of smoothed hedging pressure and its combined impact with net trading.

[17]Black (1976) and Christie (1982) introduce the leverage effect argument where an increase in firms' financial leverage drives negative returns and high volatility. Campbell and Hentschel (1992) assert that increase in volatility induces a decrease in returns. A behavioral explanation to the positive relation between return shocks and volatility is that individuals (investors) perceive positive return and low risk investment as a good investment (particularly for safe-haven commodities such as gold) (Hibbert et al. (2008)).

[18]The theory of storage by Ng and Pirrong (1994) links positive commodity price returns with low levels of inventories and the uncertainty on inventory exhaustion with an increase in volatility. Further, Tully and Lucey (2007) and Baur (2012) explain the empirically observed positive return-volatility in gold via the safe haven argument.

The conditional impact of market states, that is falling or rising markets on the dynamic relationship between the liquidity provision channels and volatility is assessed by the effect of the 'combined' hedging pressure, smoothed hedging pressure, and net trading in determining volatility, conditional on negative or positive returns.[19] Note that the variations in the combined hedging pressure is driven by hedgers' two distinct motives: one motive as insurance seekers – establishing speculators as the liquidity providers – captured by the smoothed hedging pressure, and the other motive as liquidity providers for the short-term momentum trading captured by net trading.

In rising markets, hedgers are likely to unwind some of their hedging positions as they are not as concerned with oil price upturns. While they decrease their net short positions, speculators earn comparatively lower returns for providing liquidity. Speculators, as the contrarian traders, increase their trading positions, and thus volatility. Liquidity provision by speculators tends to increase volatility in rising markets. Conversely, hedgers are concerned about downside market risk and increase their net short positions to mitigate this risk in falling markets. Speculators are ultimately net long and earning comparatively higher returns. Volatility falls as speculators lower their trading positions. Therefore, liquidity provision by speculators causes a decrease in volatility in falling markets.

Hedgers act as the liquidity providers in the short run. In rising markets, hedgers are reluctant to provide liquidity. By decreasing their net short positions, they earn comparatively lower returns. As they are now trading as contrarians, they increase their trading positions, causing volatility to increase. Thus, liquidity provision by hedgers leads to an increase in volatility in rising markets. In falling markets, hedgers are eager to provide liquidity to speculators and increase their net short positions. Hedgers earn comparatively higher returns for doing so, and as they lower their trading positions, volatility is expected to decrease. Hence, liquidity provision by hedgers signals a decrease in volatility in falling markets.

We investigate the validity of these arguments by considering the conditional impact of positive and negative returns on hedging pressure, smoothed hedging pressure, and net trading, and how they influence weekly volatility. This impact is assessed by the following

[19] Rising (falling) futures market represents positive (negative) futures returns.

regressions:

$$\begin{aligned} RV_{t+1,w} = \beta_0 &+ \beta_{\mathrm{HP}_w}\mathrm{HP}_{t,w} + \beta_{\mathrm{HP}_w r_w^+}\mathrm{HP}_{t,w} r_{t,w}^+ + \beta_{\mathrm{HP}_w r_w^-}\mathrm{HP}_{t,w} r_{t,w}^- \\ &+ \sum_{k=0}^{k=3} \beta_{\mathrm{RV}_{k,w}}\mathrm{RV}_{t-k,w} + \beta_{r_w^+} r_{t,w}^+ + \beta_{r_w^-} r_{t,w}^- + \epsilon_{t+1,w}. \end{aligned} \tag{4.3.5}$$

$$\begin{aligned} RV_{t+1,w} = \beta_0 &+ \beta_{\mathrm{SHP}_w}\mathrm{SHP}_{t,w} + \beta_{\mathrm{SHP}_w r_w^+}\mathrm{SHP}_{t,w} r_{t,w}^+ + \beta_{\mathrm{SHP}_w r_w^-}\mathrm{SHP}_{t,w} r_{t,w}^- \\ &+ \sum_{k=0}^{k=3} \beta_{\mathrm{RV}_{k,w}}\mathrm{RV}_{t-k,w} + \beta_{r_w^+} r_{t,w}^+ + \beta_{r_w^-} r_{t,w}^- + \epsilon_{t+1,w}. \end{aligned} \tag{4.3.6}$$

$$\begin{aligned} RV_{t+1,w} = \beta_0 &+ \beta_{\mathrm{NT}_w}\mathrm{NT}_{t,w} + \beta_{\mathrm{NT}_w r_w^+}\mathrm{NT}_{t,w} r_{t,w}^+ + \beta_{\mathrm{NT}_w r_w^-}\mathrm{NT}_{t,w} r_{t,w}^- \\ &+ \sum_{k=0}^{k=3} \beta_{\mathrm{RV}_{k,w}}\mathrm{RV}_{t-k,w} + \beta_{r_w^+} r_{t,w}^+ + \beta_{r_w^-} r_{t,w}^- + \epsilon_{t+1,w}. \end{aligned} \tag{4.3.7}$$

$$\begin{aligned} RV_{t+1,w} = \beta_0 &+ \beta_{\mathrm{SHP}_w}\mathrm{SHP}_{t,w} + \beta_{\mathrm{NT}_w}\mathrm{NT}_{t,w} + \beta_{\mathrm{NT}_w r_w^+}\mathrm{NT}_{t,w} r_{t,w}^+ + \beta_{\mathrm{NT}_w r_w^-}\mathrm{NT}_{t,w} r_{t,w}^- + \beta_{\mathrm{SHP}_w r_w^+}\mathrm{SHP}_{t,w} r_{t,w}^+ \\ &+ \beta_{\mathrm{SHP}_w r_w^-}\mathrm{SHP}_{t,w} r_{t,w}^- + \sum_{k=0}^{k=3} \beta_{\mathrm{RV}_{k,w}}\mathrm{RV}_{t-k,w} + \beta_{r_w^+} r_{t,w}^+ + \beta_{r_w^-} r_{t,w}^- + \epsilon_{t+1,w}. \end{aligned} \tag{4.3.8}$$

where the weekly negative and positive returns are estimated as $r_w^- = r_{t,w} I_{(r_{t,w}<0)}$ and $r_w^+ = r_{t,w} I_{(r_{t,w}>0)}$, respectively. By adding the positive and negative returns to the model's specifications, they account for their heterogeneous effect on volatility.

We simultaneously test/control for the impact of returns on volatility, and the results are reported in Table 4.3.2. The asymmetric volatility effect is statistically significant in oil markets (Chiarella et al. (2016), Baur and Dimpfl (2018), and Kang, Nikitopoulos and Prokopczuk (2020)) where both negative and positive return shocks affect future volatility. Following a 1% increase in the negative and positive return shocks, future volatility will increase by 7.7% and decrease by 39.4%, respectively (see row 15 and 19 of Table 4.3.2). While negative return shocks consistently increase future volatility, positive shocks have no influence on future volatility (except in Model (3) where positive shocks decrease future volatility). Since the negative return shocks tend to have a significant impact on future volatility, the crude oil market seems to experience the leverage effect similarly to equity markets.

TABLE 4.3.2. **The HP Models with Returns Shocks**

	(1)	(2)	(3)	(4)
β_0	0.090***	0.083***	0.045***	0.081***
	(7.484)	(6.675)	(6.185)	(7.241)
β_{HP_w}	-0.274***			
	(-6.804)			
β_{SHP_w}		-0.258***		-0.247***
		(-5.525)		(-6.074)
β_{NT_w}			0.727***	0.642***
			(4.002)	(4.344)
β_{Inv_w}	0.422**	0.427**	0.441*	0.396**
	(2.489)	(2.344)	(1.829)	(2.268)
$\beta_{RV^*_{0,w}}$	0.680***	0.702***	0.686***	0.705***
	(17.050)	(17.611)	(14.473)	(18.616)
$\beta_{r^-_w}$	-0.092***	-0.087***	-0.046*	-0.083***
	(-3.856)	(-3.540)	(-1.887)	(-3.483)
$\beta_{r^+_w}$	-0.022	-0.115	-0.394**	-0.083
	(-0.141)	(-0.765)	(-2.643)	(-0.570)
$adjR^2$	0.493	0.440	0.262	0.466
AIC	-1,213	-1,127	-857	-1,164

This table reports the estimation results of the following regressions in the crude oil futures market:

$$
\begin{aligned}
RV_{t+1,w} &= \beta_0 + \beta_{\mathrm{HP}_w}\mathrm{HP}_{t,w} + \beta_{\mathrm{Inv}_w}\mathrm{Inv}_{t,w} + \sum_{k=0}^{k=3}\beta_{\mathrm{RV}_{k,w}}\mathrm{RV}_{t-k,w} \\
&\quad + \beta_{r^+_w} r^+_{t,w} + \beta_{r^-_w} r^-_{t,w} + \epsilon_{t+1,w}, \\
RV_{t+1,w} &= \beta_0 + \beta_{\mathrm{SHP}_w}\mathrm{SHP}_{t,w} + \beta_{\mathrm{NT}_w}\mathrm{NT}_{t,w} + \beta_{\mathrm{Inv}_w}\mathrm{Inv}_{t,w} \\
&\quad + \sum_{k=0}^{k=3}\beta_{\mathrm{RV}_{k,w}}\mathrm{RV}_{t-k,w} + \beta_{r^+_w} r^+_{t,w} + \beta_{r^-_w} r^-_{t,w} + \epsilon_{t+1,w},
\end{aligned}
$$

The table details the estimation results for four specifications of the HP model with returns shocks in the crude oil futures markets, outlined above. The t-statistic (in parentheses), is estimated using the Newey–West standard errors. AIC stands for the Akaike information criteria. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

The results, which determine whether rising and falling markets via the two liquidity provision channels impact oil price volatility, are tabulated in Table 4.3.3. In rising markets, liquidity provision by speculators will cause an (statistically significant) increase in volatility by 14.2% and an overall decrease in volatility by 54.8% (see Model (2)).[20] This implies that hedgers are highly sensitive to oil price increases and adjust their trading positions accordingly. In rising market conditions, the liquidity providers – speculators

[20]Since we are now conditioning the smoothed hedging pressure on rising state of oil markets, its effect on future volatility is estimated as $\beta_{SHP_w} + \beta_{SHP_w r^+_w} \times r^+_{t,d}$ (-0.690+0.142), assuming there is an increase in positive returns of 1%.

– are more sensitive to oil price changes and by adjusting their trading position, they increase volatility. The impact of the liquidity provision by speculators, conditioned on falling market conditions, is also significant. It decreases volatility by 18.4% as they are expected to make losses on their net long positions (volatility decreases (in total) by 87.4%).

In rising market conditions, short-term liquidity provision by hedgers significantly decreases volatility (see Model (3) of Table 4.3.3). An increase by 1% in net trading will lead to a decrease in volatility by 16.6% and an increase in volatility (in total) by 49.4%.[21] The liquidity provision by hedgers, conditioned on falling markets, does not have a significant effect.

We also consider the impact of rising and declining market conditions, conditioned on combined hedging pressure, on future volatility. Again, we observe that hedging pressure, conditioned on rising markets, increases volatility by 14.3% (see Model (1) in Table 4.3.3). The net impact of hedging pressure on volatility is negative, decreasing it by 56.5%. When hedging pressure is conditioned on falling market conditions, volatility decreases by 11.4% (84.6% in total). Rising market condition has a comparable impact on smoothed hedging pressure and combined hedging pressure, and falling market condition has a stronger impact on smoothed hedging pressure than combined hedging pressure.

Model (4) allows us to assess the importance of the two traders' motives concurrently in determining volatility. While liquidity provision by speculators will increase (decrease) volatility in rising (falling) markets, liquidity provision by hedgers will decrease volatility under both market conditions. These results confirm that liquidity provision by speculators (directly and indirectly) significantly impact volatility under rising and falling oil markets. However, liquidity provision by hedgers has a direct effect on volatility that is stronger than its indirect effect on volatility. As shown in Table 4.3.3, as inventory (as a key control variable) accumulates its supply becomes inelastic, which ultimately increases next week's oil price volatility.

[21]The effect of net trading on future volatility is estimated as $\beta_{NT_w} + \beta_{NT_w r_w^-} \times r_{t,d}^+$ (0.660+-0.166), assuming there is an increase in positive returns of 1%.

TABLE 4.3.3. **The HP Models Conditioned on Rising and Falling Market Conditions**

	(1)	(2)	(3)	(4)
β_0	0.194***	0.177***	0.047***	0.171***
	(9.313)	(9.535)	(6.498)	(9.020)
β_{HP_w}	-0.708***			
	(-9.443)			
$\beta_{HP_w r_w^-}$	-0.138***			
	(-4.393)			
$\beta_{HP_w r_w^+}$	0.143***			
	(7.815)			
β_{SHP_w}		-0.690***		-0.657***
		(-8.276)		(-8.137)
$\beta_{SHP_w r_w^-}$		-0.184***		-0.161***
		(-5.780)		(-5.472)
$\beta_{SHP_w r_w^+}$		0.142***		0.132***
		(6.543)		(6.452)
β_{NT_w}			0.660**	0.665**
			(2.380)	(2.103)
$\beta_{NT_w r_w^-}$			-0.119	-0.322*
			(-1.299)	(-1.889)
$\beta_{NT_w r_w^+}$			-0.166*	-0.099
			(-1.671)	(-0.826)
β_{Inv_w}	0.522**	0.532**	0.456*	0.506**
	(2.655)	(2.555)	(1.905)	(2.504)
$\beta_{RV^*_{0,w}}$	0.580***	0.635***	0.681***	0.635***
	(9.795)	(12.039)	(14.444)	(12.106)
$\beta_{r_w^-}$	0.190**	0.275***	-0.018	0.237*
	(2.445)	(3.790)	(-0.688)	(-1.665)
$\beta_{r_w^+}$	-0.294***	-0.282***	-0.048***	-0.265***
	(-7.449)	(-6.901)	(-2.953)	(-6.642)
$adjR^2$	0.445	0.407	0.249	0.418
AIC	-1,058	-988	-843	-1,019

This table reports the estimation results of the following regressions in the crude oil futures market:

$$\begin{aligned} RV_{t+1,w} &= \beta_0 + \beta_{\text{HP}_w}\text{HP}_{t,w} + \beta_{\text{HP}_w r_w^+}\text{HP}_{t,w} r_{t,w}^+ + \beta_{\text{HP}_w r_w^-}\text{HP}_{t,w} r_{t,w}^- + \beta_{\text{Inv}_w}\text{Inv}_{t,w} \\ &+ \sum_{k=0}^{k=3}\beta_{\text{RV}_{k,w}}\text{RV}_{t-k,w} + \beta_{r_w^+} r_{t,w}^+ + \beta_{r_w^-} r_{t,w}^- + \epsilon_{t+1,w}, \\ RV_{t+1,w} &= \beta_0 + \beta_{\text{SHP}_w}\text{SHP}_{t,w} + \beta_{\text{NT}_w}\text{NT}_{t,w} + \beta_{\text{NT}_w r_w^+}\text{NT}_{t,w} r_{t,w}^+ \\ &+ \beta_{\text{NT}_w r_w^-}\text{NT}_{t,w} r_{t,w}^- + \beta_{\text{SHP}_w r_w^+}\text{SHP}_{t,w} r_{t,w}^+ + \beta_{\text{SHP}_w r_w^-}\text{SHP}_{t,w} r_{t,w}^- \\ &+ \beta_{\text{Inv}_w}\text{Inv}_{t,w} + \sum_{k=0}^{k=3}\beta_{\text{RV}_{k,w}}\text{RV}_{t-k,w} + \beta_{r_w^+} r_{t,w}^+ + \beta_{r_w^-} r_{t,w}^- + \epsilon_{t+1,w}, \end{aligned}$$

The table details the estimation results for four specifications of the HP model conditioned on rising and falling market conditions in the crude oil futures markets, outlined above. The t-statistic (in parentheses), is estimated using the Newey–West standard errors. AIC stands for the Akaike information criteria. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

Overall, we conclude that liquidity provision channels indirectly impact volatility in two ways. First, liquidity provision by speculators, under rising (falling) market conditions, increases (decreases) volatility. Second, liquidity provision by hedgers, under falling and rising market conditions, is expected to decrease volatility. These direct effects tend to outweigh the indirect effects of liquidity provision by hedgers on volatility. Thus, when speculators profit by providing liquidity, their trading has a significant (and opposite) impact on weekly oil volatility.

4.4. Liquidity Provision and the Shape of the Futures Curve

We next investigate whether the impact of the liquidity provision channels on volatility is conditional to oil market conditions and evaluate this impact in inverted and normal markets.

The hedging pressure hypothesis by Hirshleifer (1990) underscores the importance of the shape of the futures curve in determining the demand for hedging. The downward sloping state of the futures curve, known as backwardation, which represents inverted markets, is associated with an increase in hedging pressure, while the upward sloping state of the futures curve, known as contango, represents normal markets and is associated with a decrease in hedging pressure.[22] Furthermore, according to the theory of storage, there is a monotonic relationship between the shape of the futures curve and volatility. Low (high) inventory is related to inverted (normal) markets and induces an increase (decrease) in volatility. However, recent research by Kogan et al. (2009) and Nikitopoulos et al. (2017) demonstrates that high inventories relate to inelastic demand and also lead to high volatility.

To validate the V-shaped relationship between volatility and futures spreads and examine the effects of the oil market conditions on the relationship between liquidity provision channels and volatility, we incorporate the positive and negative futures interest-adjusted

[22]Based on a hedging pressure measure that represents net short positions, markets are inverted when net short oil producers are seeking price insurance which subsequently increases hedging pressure and induces net long speculators to provide liquidity, and is linked to the market expectations of an appreciation of oil market price. Conversely, markets are normal when net long oil consumers are seeking price insurance which subsequently decreases hedging pressure and induces net short speculators to provide liquidity. This is linked to depreciating oil market price expectations that provide an insurance premium to the net short speculators.

spreads in the regressions.[23] Table 4.4.1 presents the results under inverted market conditions and Table 4.4.2 presents the results under normal market conditions. The results infer that normal oil markets (positive futures spread) and inverted oil markets (negative futures spread) increase oil price volatility. This is in line with previous studies by Kogan et al. (2009) and Symeonidis et al. (2012) that demonstrate positive and negative futures spreads induce higher oil volatility. A 1% increase in the negative and positive futures spreads would increase volatility by approximately 35% (see row 15 of Tables 4.4.1 and 4.4.2). However, we observe that normal oil markets (significantly) increase volatility, primarily in Model (3) (see Table 4.4.2). The magnitude of the increase in future oil volatility is the same under the two market states.

The relationship between liquidity provision channels and the volatility in inverted and normal oil markets is discussed next.

4.4.1. Liquidity provision in inverted markets. Markets in backwardation are associated with an expectation of price appreciation. Short position holders are expected to earn negative returns while long position holders are likely to earn positive returns. Hedgers, behaving as insurance seekers in the long run, earn negative returns for consuming liquidity. By providing liquidity, speculators take long positions and earn positive returns. Since speculators are the liquidity providers, they are the ones engaged in contrarian strategies. As they earn a premium (positive returns), they are likely to reduce their trading position, thereby lowering volatility. Thus, an increase in hedging pressure leads to a decrease in volatility. The prospect of rising oil prices impacts hedgers differently in the short term. As they increase their long positions to provide liquidity to speculators, they earn higher (positive) returns. Because they are now the contrarians traders, they are more likely to decrease their trading positions, which lowers volatility. Thus, this decrease in hedging pressure lowers future volatility.

We find that when oil markets are inverted, an increase in smoothed hedging pressure leads to a decrease in volatility, while an increase in net trading increases volatility (see

[23]The positive and negative futures spread ($IAS12^{+}_{w}$ and $IAS12^{-}_{w}$), which effectively capture normal and inverted oil markets, are added as additional variables to the regression models. We also let the positive and negative futures spread interact with liquidity provision channels to measure their joint effect on future volatility. Liquidity provision by speculators conditioned on the negative and positive futures spread is given by $SHP_{w}IAS12^{-}_{w}$ and $SHP_{w}IAS12^{+}_{w}$. Liquidity provision by hedgers conditioned on the negative and positive futures spread is given by $NT_{w}IAS12^{-}_{w}$ and $NT_{w}IAS12^{+}_{w}$.

Table 4.4.1). In inverted markets, liquidity provision by speculators has a negative effect on future volatility, while short-term liquidity provision by hedgers has a positive and statistically significant effect on future volatility. From Model (2), we infer that an increase in the smoothed hedging pressure by 1% will decrease future volatility by 47.5%.[24] From Model (3), we conclude that an increase in net trading would increase volatility by 90.1%.[25] Accordingly, short-term liquidity provision by hedgers has a three-fold stronger effect on future volatility, which underlines the importance of the liquidity channel by hedgers in determining future weekly volatility in inverted markets.

Model (1) reports the combined effect that hedging pressure has on determining volatility. The overall effect of hedging pressure on future volatility is negative in inverted markets, and decreases next week's volatility by 52.4%. This result implies that long-term liquidity provision by speculators tends to dominate the effect on volatility overall. Model (4) simultaneously assesses the influence of liquidity provision by hedgers and speculators on future volatility. As the coefficients remain almost unaffected compared to Models (2) and (3), we confirm that these two effects are distinct and capture the different components of the hedging pressure. Other predictors of volatility, including past volatility, returns, and inventory, behave as expected in the four models reported in Table 4.4.1.

These results highlight the importance of liquidity provision channels in determining future volatility. In inverted markets, liquidity provision by speculators tends to dominate and negatively impact next week's volatility. Short-term liquidity provision by hedgers has a statistically significant and positive effect on volatility, which has been overlooked by previous literature.

4.4.2. Liquidity provision in normal markets. Normal markets are associated with an expectation of price depreciation. Short position holders are expected to earn positive

[24]The net effect of smoothed hedging pressure on future volatility is estimated as $\beta_{SHP_w} + \beta_{SHP_w IAS12^-_w} \times SHP_{t,w} IAS12^-_{t,w}$ (-0.287+-0.188), assuming that the negative futures spread (capturing inverted oil markets) rise by 1%.

[25]The net effect of net trading on future volatility is estimated as $\beta_{NT_w} + \beta_{NT_w IAS12^-_w} \times NT_{t,w} IAS12^-_{t,w}$ (0.839+0.062), assuming that the negative futures spread (capturing inverted oil markets) rise by 1%.

TABLE 4.4.1. **The HP Models in Inverted Markets**

	(1)	(2)	(3)	(4)
β_0	0.100***	0.094***	0.067***	0.093***
	(7.923)	(6.718)	(11.789)	(7.131)
β_{HP_w}	-0.319***			
	(-6.474)			
$\beta_{HP_w IAS12^-_w}$	-0.205***			
	(-3.513)			
β_{SHP_w}		-0.287***		-0.284***
		(-4.843)		(-5.267)
$\beta_{SHP_w IAS12^-_w}$		-0.188**		-0.175**
		(-2.687)		(-2.764)
β_{NT_w}			0.839***	0.846***
			(3.454)	(4.051)
$\beta_{NT_w IAS12^-_w}$			0.062**	0.046**
			(2.578)	(2.345)
$\beta_{IAS12^-_w}$	0.548***	0.509***	0.311***	0.480***
	(3.920)	(3.323)	(7.331)	(3.417)
β_{Inv_w}	0.333*	0.367**	0.476***	0.331*
	(1.939)	(2.128)	(2.872)	(1.938)
$\beta_{RV^*_{0,w}}$	0.501***	0.506***	0.395***	0.469***
	(7.699)	(7.319)	(5.122)	(6.607)
$\beta_{r^-_w}$	-0.093***	-0.088***	-0.051**	-0.084***
	(-3.890)	(-3.652)	(-2.160)	(-3.629)
$\beta_{r^+_w}$	-0.002	-0.009	-0.020	-0.005
	(-0.117)	(-0.585)	(-1.398)	(-0.348)
$adjR^2$	0.506	0.464	0.344	0.477
AIC	-1,236	-1,156	-956	-1,184

This table reports the estimation results of the following regressions in the crude oil futures market:

$$\begin{aligned} RV_{t+1,w} = {} & \beta_0 + \beta_{\text{HP}_w}\text{HP}_{t,w} + \beta_{\text{HP}_w\text{IAS12}^-_w}\text{HP}_{t,w}\text{IAS12}^-_{t,w} + \beta_{\text{IAS12}^-_w}\text{IAS12}^-_{t,w} \\ & + \beta_{\text{Inv}_w}\text{Inv}_{t,w} + \sum_{k=0}^{k=3}\beta_{\text{RV}_{k,w}}\text{RV}_{t-k,w} + \beta_{r^+_w}r^+_{t,w} + \beta_{r^-_w}r^-_{t,w} + \epsilon_{t+1,w}, \end{aligned}$$

$$\begin{aligned} RV_{t+1,w} = {} & \beta_0 + \beta_{\text{SHP}_w}\text{SHP}_{t,w} + \beta_{\text{NT}_w}\text{NT}_{t,w} + \beta_{\text{SHP}_w\text{IAS12}^-_w}\text{SHP}_{t,w}\text{IAS12}^-_{t,w} \\ & + \beta_{\text{NT}_w\text{IAS12}^-_w}\text{NT}_{t,w}\text{IAS12}^-_{t,w} + \beta_{\text{IAS12}^-_w}\text{IAS12}^-_{t,w} + \beta_{\text{Inv}_w}\text{Inv}_{t,w} \\ & + \sum_{k=0}^{k=3}\beta_{\text{RV}_{k,w}}\text{RV}_{t-k,w} + \beta_{r^+_w}r^+_{t,w} + \beta_{r^-_w}r^-_{t,w} + \epsilon_{t+1,w}, \end{aligned}$$

The table details the estimation results for four specifications of the HP model in inverted oil futures markets, outlined above. The t-statistic (in parentheses), is estimated using the Newey–West standard errors. AIC stands for the Akaike information criteria. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

returns while long position holders are likely to earn negative returns. Hedgers acting as insurance seekers increase their long positions in normal markets while speculators (as providers of liquidity) take short positions and earn positive returns. Since speculators trade as contrarians, they lower their trading position, which reduces volatility. Thus, a decrease in hedging pressure decreases volatility. In the short run, hedgers become the

TABLE 4.4.2. **The HP Models in Normal Markets**

	(1)	(2)	(3)	(4)
β_0	0.096***	0.098***	0.051***	0.096***
	(6.731)	(6.728)	(6.501)	(7.059)
β_{HP_w}	-0.287***			
	(-5.862)			
$\beta_{HP_w IAS12_w^+}$	0.128**			
	(2.089)			
β_{SHP_w}		-0.306***		-0.298***
		(-5.241)		(-5.632)
$\beta_{SHP_w IAS12_w^+}$		0.193**		0.169**
		(2.416)		(2.206)
β_{NT_w}			0.523**	0.542***
			(2.406)	(3.187)
$\beta_{NT_w IAS12_w^+}$			0.049	0.053
			(1.388)	(1.585)
$\beta_{IAS12_w^+}$	-0.037	-0.113	0.386***	-0.093
	(-0.240)	(-0.590)	(3.697)	(-0.508)
β_{Inv_w}	0.438**	0.464**	0.451**	0.436**
	(2.744)	(2.598)	(1.983)	(2.534)
$\beta_{RV^*_{0,w}}$	0.455***	0.456***	0.321***	0.424***
	(5.586)	(5.312)	(3.173)	(4.904)
$\beta_{r_w^-}$	-0.081***	-0.072***	-0.027	-0.069***
	(-3.486)	(-2.997)	(-1.195)	(-2.980)
$\beta_{r_w^+}$	0.000	-0.012	-0.039***	-0.010
	(-0.006)	(-0.851)	(-2.830)	(-0.709)
$adjR^2$	0.491	0.425	0.266	0.443
AIC	-1,212	-1,098	-868	-1,128

This table reports the estimation results of the following regressions in the crude oil futures market:

$$RV_{t+1,w} = \beta_0 + \beta_{\mathrm{HP}_w}\mathrm{HP}_{t,w} + \beta_{\mathrm{HP}_w\mathrm{IAS12}_w^+}\mathrm{HP}_{t,w}\mathrm{IAS12}^+_{t,w} + \beta_{\mathrm{IAS12}_w^+}\mathrm{IAS12}^+_{t,w} + \beta_{\mathrm{Inv}_w}\mathrm{Inv}_{t,w} + \sum_{k=0}^{k=3}\beta_{\mathrm{RV}_{k,w}}\mathrm{RV}_{t-k,w} + \beta_{r_w^+}r^+_{t,w} + \beta_{r_w^-}r^-_{t,w} + \epsilon_{t+1,w},$$

$$RV_{t+1,w} = \beta_0 + \beta_{\mathrm{SHP}_w}\mathrm{SHP}_{t,w} + \beta_{\mathrm{NT}_w}\mathrm{NT}_{t,w} + \beta_{\mathrm{SHP}_w\mathrm{IAS12}_w^+}\mathrm{SHP}_{t,w}\mathrm{IAS12}^+_{t,w} + \beta_{\mathrm{NT}_w\mathrm{IAS12}_w^+}\mathrm{NT}_{t,w}\mathrm{IAS12}^+_{t,w} + \beta_{\mathrm{IAS12}_w^+}\mathrm{IAS12}^+_{t,w} + \beta_{\mathrm{Inv}_w}\mathrm{Inv}_{t,w} + \sum_{k=0}^{k=3}\beta_{\mathrm{RV}_{k,w}}\mathrm{RV}_{t-k,w} + \beta_{r_w^+}r^+_{t,w} + \beta_{r_w^-}r^-_{t,w} + \epsilon_{t+1,w},$$

The table details the estimation results for four specifications of the HP model in normal oil futures markets, outlined above. The t-statistic (in parentheses), is estimated using the Newey–West standard errors. AIC stands for the Akaike information criteria. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

liquidity providers, increase their short positions, and earn positive returns. While they provide liquidity to speculators, they reduce their trading position (trading as contrarians). The latter is likely to reduce future volatility. Accordingly, this increase in hedging pressure leads to a decrease in volatility.

Table 4.4.2 reveals that in normal markets, a decrease in the smoothed hedging pressure leads to a decrease in volatility, while an increase in net trading leads to an increase, not a decrease, in volatility. Liquidity provision by speculators is associated with a decrease in the smoothed hedging pressure that tends to decrease volatility by 11.3% (Model (2)),[26] while increasing liquidity provision by hedgers, conditioned on normal oil markets, has no influence on volatility (Model (3)).[27] As observed in inverted oil markets, liquidity provision by hedgers also plays an important role in determining future volatility. However, their impact on volatility is less pronounced in normal oil markets.

The effect of the combined hedging pressure on future volatility appears to not be statistically significant under normal market conditions (see Model (1) in Table 4.4.2). However, Model (4), which separates the impact of the hedgers and speculators as liquidity providers, reveals that these two components of hedging pressure (each driven by the liquidity provision of hedgers and speculators) have a measurable impact on volatility.[28]

Thus, short-term liquidity provision by hedgers is an important determinant of weekly oil volatility. Further, depending on the shape of the oil futures curve, liquidity provision by hedgers and speculators affects future (weekly) volatility differently. In inverted markets, liquidity induced by speculators reduces weekly volatility, while short-term liquidity induced by hedgers leads to a significant increase in volatility. In normal markets, liquidity provision by hedgers and speculators is also important in determining weekly volatility.

4.5. The Impact of Macro-economic Shocks

In this section, we determine whether the liquidity provision channels are affected by macro-economic shocks. We specifically test for the impact of financial market and business cycle shocks, conditioned on the liquidity provision channels, on future volatility.

[26]The net effect of smoothed hedging pressure on future volatility is estimated as $\beta_{SHP_w} + \beta_{SHP_w IAS12^+_w} \times SHP_{t,w} IAS12^+_{t,w}$ (-0.306+0.193), assuming that the positive futures spread (capturing normal oil markets) rise by 1%.

[27]The net effect of net trading on future volatility is estimated as $\beta_{NT_w} + \beta_{NT_w IAS12^+_w} \times NT_{t,w} IAS12^+_{t,w}$ (0.523+0.049), assuming that the positive futures spread (capturing normal oil markets) rise by 1%. Net trading increases future volatility by 57.2%

[28]We also test whether different maturity dates (three months and six months) affect the interest-adjusted spreads estimates. The latter indicates the extent to which oil futures markets are inverted or normal. We determine the sensitivity of the liquidity provision by hedgers and speculators to the two oil market states in Appendix 4.2.

Nagel (2012) and Kang, Rouwenhorst and Tang (2020) argue that financial market shocks influence the commodity futures market primarily via hedgers' liquidity provision. Thus, we assess the responsiveness of volatility to the two liquidity provision channels under high and low financial market risk environments. External (macro-economic) shocks to the market can either be perceived as negative or positive news, and are likely to influence the risk appetite of hedgers and speculators. We argue that these shocks incentivize them to either hold back or provide liquidity in the market, while business cycle shocks are likely to influence the demand for hedging via the liquidity provision by speculators. Negative business cycle shocks indicate weakening macro-economic conditions, and positive shocks signal a stable macro-economic environment.

4.5.1. Financial market risk. The level of uncertainty and risk aversion in equity markets, defined as the financial market risk, is known to impact oil price volatility. Silvennoinen and Thorp (2013) demonstrate that high financial risk has a detrimental effect on oil futures volatility. Specifically, an increase in financial risk would increase volatility in commodity markets. The financialization of the commodity market was a contributing factor for institutional investors entering the market. By building commodity futures and equity portfolios, Basak and Pavlova (2016) demonstrate that following the financialization of commodity markets, the correlation between the two markets has increased and shocks from equity markets are transmitted to futures and spot commodity markets. Financial market risk, measured by the weekly change in the VIX, is decomposed into its positive and negative components. If the positive (negative) change in the VIX is above its sample median in that week, it represents a negative (positive) shock to the VIX given by VIX_w^+ and VIX_w^-, which translates to high (low) financial market risk environment.

The results presented in Table 4.5.1 reveal that under a low financial market risk environment, VIX and oil markets volatility are positively related in line with Silvennoinen and Thorp (2013) and Basak and Pavlova (2016) (see row 15 from Models (5) to (8)). However, in high financial risk environment, this relation breaks down potentially due to the idiosyncratic nature of the shocks driving this extreme risk (or volatility) (see row 15 from Models (1) to (4)). We find evidence that the integration between equity and oil markets is stronger in low financial risk environments.

TABLE 4.5.1. **The HP Models Conditioned on Financial Sector Risk**

	(1)	(2)	(3)	(4)		(5)	(6)	(7)	(8)
β_0	0.090***	0.084***	0.048***	0.083***	β_0	0.076***	0.065***	0.039***	0.065***
	(6.528)	(6.713)	(6.423)	(7.410)		(6.305)	(5.469)	(6.647)	(5.657)
β_{HP_w}	-0.281***				β_{HP_w}	-0.236***			
	(-6.307)					(-5.540)			
$\beta_{HP_wVIX_w^+}$	0.048				$\beta_{HP_wVIX_w^-}$	-0.047***			
	(1.407)					(-2.945)			
β_{SHP_w}		-0.272***		-0.266***	β_{SHP_w}		-0.207***		-0.199***
		(-5.776)		(-6.600)			(-4.326)		(-4.466)
$\beta_{SHP_wVIX_w^+}$		0.077*		0.083*	$\beta_{SHP_wVIX_w^-}$		-0.060***		-0.058***
		(1.878)		(1.989)			(-3.450)		(-3.486)
β_{NT_w}			0.656***	0.595***	β_{NT_w}			0.818***	0.702**
			(2.899)	(3.177)				(4.313)	(2.550)
$\beta_{NT_wVIX_w^+}$			0.032	0.026	$\beta_{NT_wVIX_w^-}$			0.019**	0.024**
			(1.478)	(1.226)				(2.505)	(2.090)
$\beta_{VIX_w^+}$	-0.050	-0.103	0.032	-0.103	$\beta_{VIX_w^-}$	0.137***	0.156***	0.057***	0.155***
	(-0.576)	(-1.182)	(0.918)	(-1.165)		(3.514)	(4.299)	(4.973)	(4.454)
β_{Inv_w}	0.413**	0.418**	0.442*	0.386**	β_{Inv_w}	0.404**	0.418**	0.378*	0.406**
	(2.535)	(2.358)	(1.813)	(2.255)		(2.595)	(2.548)	(1.845)	(2.606)
$\beta_{RV^*_{0,w}}$	0.684***	0.710***	0.670***	0.711***	$\beta_{RV^*_{0,w}}$	0.737***	0.767***	0.735***	0.761***
	(16.394)	(17.931)	(13.882)	(18.651)		(20.545)	(23.149)	(18.609)	(22.986)
$\beta_{r_w^-}$	-0.084***	-0.077***	-0.033	-0.071***	$\beta_{r_w^-}$	-0.098***	-0.098***	-0.061**	-0.093***
	(-3.835)	(-3.378)	(-1.451)	(-3.209)		(-4.346)	(-4.261)	(-2.610)	(-4.113)
$\beta_{r_w^+}$	-0.003	-0.014	-0.047***	-0.012	$\beta_{r_w^+}$	0.011	0.009	-0.018	0.010
	(-0.171)	(-0.960)	(-3.168)	(-0.878)		(0.754)	(0.662)	(-1.322)	(0.715)
$adjR^2$	0.502	0.449	0.239	0.475	$adjR^2$	0.544	0.513	0.342	0.531
AIC	-1,223	-1,138	-819	-1,173	AIC	-1,309	-1,258	-983	-1,286

This table reports the estimation results of the following regressions in the crude oil futures market:

$$\begin{aligned} RV_{t+1,w} &= \beta_0 + \beta_{\text{HP}_w}\text{HP}_{t,w} + \beta_{\text{HP}_w\text{VIX}_w^+}\text{HP}_{t,w}\text{VIX}_w^+ + \beta_{\text{HP}_w\text{VIX}_w^-}\text{HP}_{t,w}\text{VIX}_w^- \\ &+ \beta_{\text{VIX}_w^-}\text{VIX}_w^- + \beta_{\text{VIX}_w^+}\text{VIX}_w^+ + \beta_{\text{Inv}_w}\text{Inv}_{t,w} \\ &+ \sum_{k=0}^{k=3}\beta_{\text{RV}_{k,w}}\text{RV}_{t-k,w} + \beta_{r_w^+}r_{t,w}^+ + \beta_{r_w^-}r_{t,w}^- + \epsilon_{t+1,w}, \end{aligned}$$

$$\begin{aligned} RV_{t+1,w} &= \beta_0 + \beta_{\text{SHP}_w}\text{SHP}_{t,w} + \beta_{\text{NT}_w}\text{NT}_{t,w} + \beta_{\text{SHP}_w\text{VIX}_w^+}\text{SHP}_{t,w}\text{VIX}_w^+ \\ &+ \beta_{\text{NT}_w\text{VIX}_w^+}\text{NT}_{t,w}\text{VIX}_w^+ + \beta_{\text{SHP}_w\text{VIX}_w^-}\text{SHP}_{t,w}\text{VIX}_w^- + \beta_{\text{SHP}_w\text{VIX}_w^-}\text{SHP}_{t,w}\text{VIX}_w^- \\ &+ \beta_{VIX_w^-}VIX_w^- + \beta_{VIX_w^+}VIX_w^+ + \beta_{\text{Inv}_w}\text{Inv}_{t,w} \\ &+ \sum_{k=0}^{k=3}\beta_{\text{RV}_{k,w}}\text{RV}_{t-k,w} + \beta_{r_w^+}r_{t,w}^+ + \beta_{r_w^-}r_{t,w}^- + \epsilon_{t+1,w}, \end{aligned}$$

The table details the estimation results for eight specifications of the HP model conditioned on the financial sector risk in the crude oil futures markets, outlined above. The t-statistic (in parentheses), is estimated using the Newey–West standard errors. AIC stands for the Akaike information criteria. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

The liquidity provision by speculators may be affected by financial market risk conditions in the following ways. High financial risk conditions make speculators more reluctant to provide liquidity, while low financial risk conditions make speculators more eager to act as liquidity providers. In a high market risk environment, hedgers are eager to get insurance cover causing an increase in hedging pressure. Speculators, as liquidity providers, are not very keen to provide liquidity so may earn comparatively lower returns but, as contrarians, would increase their trading positions inducing an increase in volatility. Otherwise, in low financial market risk environment, speculators are inclined to provide liquidity and as earners of higher returns would decrease their trading positions inducing a decrease in volatility. Therefore, liquidity provision channels may impact volatility differently under different levels of financial risk.[29]

Variations in the level of financial risk may also impact the propensity for hedgers to provide liquidity in the short term. High financial risk tends to decrease the desire for hedgers to provide liquidity because a volatile financial environment is detrimental to financial intermediaries (they represent swap dealers in oil markets).[30] Low financial risk represents an incentive for hedgers to provide liquidity. We argue that in a low market risk condition, hedgers decrease their long positions (i.e., they are net short). They are likely to earn comparatively lower returns for providing liquidity. Since they are trading as contrarians, they will increase their trade positions, which increases volatility. In high-risk market conditions, hedgers are not keen to provide liquidity, and the effects of liquidity provision by hedgers on volatility are not significant. They are hedgers after all.

However, when assessing the aggregate effect of liquidity provision, independent of the level of market risk (high or low financial risk conditions), the liquidity provision by speculators is negatively associated with volatility (see Models (2) and (6) in Table 4.5.1, respectively). In high market risk conditions, smoothed hedging pressure reduces volatility by 19.5%[31], while in low market risk conditions, it reduces volatility by 26.7%.[32] The impact of liquidity provision by speculators on volatility is higher in low market risk conditions than in high market risk conditions. This is potentially due to the inclination of speculators to provide liquidity in low risk environment than in high risk environment. As predicted by theory, the short-term 'aggregate' liquidity provision by hedgers is positively associated with volatility in both high or low financial risk conditions (see Models (3) and

[29]Hence, the model specifications include additional explanatory variables that capture the impact of the liquidity provision by speculators on volatility conditioned on the negative and positive financial shocks ($SHP_{t,w}VIX_w^+$ and $SHP_{t,w}VIX_w^-$).

[30]The impact of the liquidity provision by hedgers on volatility conditioned on the negative and positive financial shocks is given by $NT_{t,w}VIX_w^+$ and $NT_{t,w}VIX_w^-$. However, Kang, Rouwenhorst and Tang (2020) argue that the presence of large commodity producers (who do not rely on financial intermediaries) in the market reduces the financial sector risk to a tolerable level. Therefore, the financial risk by interacting with the net trading has no influence on volatility.

[31]The net effect of smoothed hedging pressure on future volatility is estimated as $\beta_{SHP_w} + \beta_{SHP_wVIX_w^+} \times SHP_{t,w}VIX_{t,w}^+$ (-0.272+0.077), assuming that there is a 1% rise in the positive changes in financial market risk.

[32]The net effect of smoothed hedging pressure on future volatility is estimated as $\beta_{SHP_w} + \beta_{SHP_wVIX_w^-} \times SHP_{t,w}VIX_{t,w}^-$ (-0.207+-0.060), assuming that there is a 1% rise in the negative changes in financial market risk.

(7) of Table 4.5.1, respectively). However, net trading increases volatility substantially in low market risk conditions (83.7%),[33] compared to the increase induced in high market risk conditions. Hedgers would be willing to provide liquidity only in low risk environment and be reluctant in high risk environment, where the effects are also insignificant (see Model (3)). Models (4) and (8) further confirm the robustness of these results.

Models (1) and (5) in Table 4.5.1 reveal that hedging pressure has (an overall) negative effect on volatility in line with theoretical predictions, independent of the level of market risk. Yet, hedging pressure reduces volatility marginally more in low market risk conditions.

In summary, the impact of liquidity provision by speculators and hedgers is not sensitive to different financial market risk environments, for example, liquidity provision by speculators decreases volatility, and liquidity provision by hedgers increases volatility. However, we find evidence that speculators and hedgers are motivated to provide liquidity in low markets risk conditions than in high market risk conditions, which is reflected to a more substantial impact on volatility.

4.5.2. Business cycle risk. The business cycle risk, by capturing the short-term pattern in economic activity, is known to impact oil volatility. As there is a negative correlation between the current GDP growth and future term spread, a 'normal' yield curve indicates a stronger future economy, and an inverted yield curve signals an impending recession (Estrella and Hardouvelis (1991), Estrella and Mishkin (1998), Wheelock and Wohar (2009), and Baur and Dimpfl (2018)). We therefore assume that negative business shock announces weakening macro-economic conditions. There is increasing investor pessimism in the market when the slope of the term spread is negative. Kang, Nikitopoulos and Prokopczuk (2020) show that lower term spread increases oil volatility, particularly since 2004. A positive business shock announces stable macro-economic conditions, which is likely to decrease volatility. Business cycle risk (term spread) is estimated as the difference between the 10-year and 3-month treasury bond constant maturity rates. If the positive (negative) change in the term spread is above its sample median in that week, it represents a positive (negative) business cycle shock given by TS_w^+ and TS_w^-.

[33]The net effect of net trading on future volatility is estimated as $\beta_{NT_w} + \beta_{NT_w VIX_w^-} \times NT_{t,w} VIX_{t,w}^-$ (0.818+0.019), assuming that there is a 1% rise in the negative changes in financial market risk.

Models (1) to (4) in Table 4.5.2 reveal that positive business cycle shocks significantly decrease future oil volatility. When the positive change in the term spread increases by 1%, future volatility decreases by approximately 7% (see row 15). Negative business cycle shocks, however, have no impact on future volatility.

TABLE 4.5.2. **The HP Models Conditioned on Business Cycle Risk**

	(1)	(2)	(3)	(4)		(5)	(6)	(7)	(8)
β_0	0.074***	0.060***	0.038***	0.060***	β_0	0.078***	0.068***	0.046***	0.065***
	(6.139)	(5.509)	(7.212)	(5.442)		(6.581)	(7.978)	(6.733)	(7.585)
β_{HP_w}	-0.234***				β_{HP_w}	-0.243***			
	(-5.834)					(-5.739)			
$\beta_{HP_wTS_w^+}$	0.049**				$\beta_{HP_wTS_w^-}$	-0.222			
	(2.656)					(-1.058)			
β_{SHP_w}		-0.189***		-0.185***	β_{SHP_w}		-0.223***		-0.206***
		(-4.517)		(-4.437)			(-6.648)		(-6.318)
$\beta_{SHP_wTS_w^+}$		0.039**		0.040**	$\beta_{SHP_wTS_w^-}$		-0.039*		-0.035*
		(2.942)		(2.310)			(-1.846)		(-1.659)
β_{NT_w}			0.740***	0.648***	β_{NT_w}			0.793***	0.572***
			(3.876)	(4.074)				(4.104)	(3.714)
$\beta_{NT_wTS_w^+}$			-0.131	-0.147*	$\beta_{NT_wTS_w^-}$			0.086	0.051
			(-1.467)	(-1.714)				(0.717)	(0.457)
$\beta_{TS_w^+}$	-0.117***	-0.094***	-0.036***	-0.097***	$\beta_{TS_w^-}$	0.146	0.388	0.057	0.330
	(-3.475)	(-5.059)	(-3.197)	(-3.273)		(0.303)	(0.750)	(0.255)	(0.656)
β_{Inv_w}	0.379**	0.350**	0.396**	0.307**	β_{Inv_w}	0.409**	0.418**	0.459*	0.420**
	(2.532)	(2.223)	(2.016)	(2.016)		(2.584)	(2.501)	(1.955)	(2.620)
$\beta_{RV^*_{0,w}}$	0.746***	0.772***	0.733***	0.770***	$\beta_{RV^*_{0,w}}$	0.706***	0.741***	0.687***	0.743***
	(21.074)	(22.784)	(19.248)	(22.935)		(17.932)	(22.061)	(14.889)	(22.190)
$\beta_{r_w^-}$	-0.098***	-0.099***	-0.062**	-0.096***	$\beta_{r_w^-}$	-0.092***	-0.088***	-0.047*	-0.085***
	(-4.398)	(-4.306)	(-2.618)	(-4.291)		(-3.952)	(-3.647)	(-1.909)	(-3.603)
$\beta_{r_w^+}$	0.010	0.007	-0.018	0.011	$\beta_{r_w^+}$	0.004	-0.004	-0.039**	-0.001
	(0.659)	(0.461)	(-1.305)	(0.810)		(0.242)	(-0.245)	(-2.724)	(-0.058)
$adjR^2$	0.547	0.517	0.342	0.538	$adjR^2$	0.515	0.482	0.260	0.512
AIC	-1,318	-1,271	-986	-1,303	AIC	-1,253	-1,203	-854	-1,241

This table reports the estimation results of the following regressions in the crude oil futures market:

$$\begin{aligned} RV_{t+1,w} = \beta_0 &+ \beta_{\text{HP}_w}\text{HP}_{t,w} + \beta_{\text{HP}_w\text{TS}_w^+}\text{HP}_{t,w}\text{TS}_w^+ + \beta_{\text{HP}_w\text{TS}_w^-}\text{HP}_{t,w}\text{TS}_w^- \\ &+ \beta_{\text{TS}_w^-}\text{TS}_w^- + \beta_{\text{TS}_w^+}\text{TS}_w^+ + \beta_{\text{Inv}_w}\text{Inv}_{t,w} \\ &+ \sum_{k=0}^{k=3}\beta_{\text{RV}_{k,w}}\text{RV}_{t-k,w} + \beta_{r_w^+}r_{t,w}^+ + \beta_{r_w^-}r_{t,w}^- + \epsilon_{t+1,w}, \end{aligned}$$

$$\begin{aligned} RV_{t+1,w} = \beta_0 &+ \beta_{\text{SHP}_w}\text{SHP}_{t,w} + \beta_{\text{NT}_w}\text{NT}_{t,w} + \beta_{\text{SHP}_w\text{TS}_w^+}\text{SHP}_{t,w}\text{TS}_w^+ \\ &+ \beta_{\text{NT}_w\text{TS}_w^+}\text{NT}_{t,w}\text{TS}_w^+ + \beta_{\text{SHP}_w\text{TS}_w^-}\text{SHP}_{t,w}\text{TS}_w^- + \beta_{\text{SHP}_w\text{TS}_w^-}\text{SHP}_{t,w}\text{TS}_w^- \\ &+ \beta_{TS_w^-}TS_w^- + \beta_{TS_w^+}TS_w^+ + \beta_{\text{Inv}_w}\text{Inv}_{t,w} \\ &+ \sum_{k=0}^{k=3}\beta_{\text{RV}_{k,w}}\text{RV}_{t-k,w} + \beta_{r_w^+}r_{t,w}^+ + \beta_{r_w^-}r_{t,w}^- + \epsilon_{t+1,w}, \end{aligned}$$

The table details the estimation results for eight specifications of the HP model conditioned on the business cycle risk in the crude oil futures markets, outlined above. The t-statistic (in parentheses), is estimated using the Newey–West standard errors. AIC stands for the Akaike information criteria. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

We hypothesize that business cycle shocks will impact the liquidity provision by speculators. If there are negative business cycle shocks, the probability of future recession is likely to be high. As a direct consequence, hedgers increase their net short positions. Hedgers will be net short (after increasing their net positions) and speculators will be net long. Speculators as liquidity providers to hedgers will earn positive returns (premium). As they are also trading as contrarians, they will lower their trading positions. This ultimately results in a general fall in future volatility. Positive business shocks means that the overall economy is in good shape and hedgers are likely to reduce their net short positions. While hedgers are net long, speculators are net short and earn comparatively lower returns. Since they trade as contrarians, they increase their trading positions. Volatility is likely to increase as a result.[34]

Business cycle shocks also influence hedgers' willingness to provide liquidity to speculators in the short term. Deep recessions have a pronounced negative impact on the oil industry. We argue that negative business cycle shocks will cause hedgers to provide more liquidity (i.e., they will be net long) and earn positive returns. As they are now the contrarian traders, they will lower their trading positions, and volatility will decrease as a result. Therefore, negative business cycle shocks are expected to decrease volatility. Otherwise, positive business cycle shocks will cause hedgers to provide less liquidity and they will earn comparatively lower returns. As hedgers increase their trading positions, volatility is expected to increase. Positive business cycle shocks are likely to increase volatility.[35]

The results confirm that positive business cycle shocks, conditioned on liquidity provision by speculators, increase next week's volatility (see Model (2) in Table 4.5.2). Smoothed hedging pressure, in total, is expected to decrease volatility by 15%.[36] Negative business cycle shocks, conditioned on smoothed hedging pressure, decrease next week's volatility (see Model (6)). In total, smoothed hedging pressure is expected to decrease volatility by 26.2%.[37] Both positive and negative business cycle shocks cause hedgers to rethink their trading strategy the most. When hedgers become liquidity providers, the positive (negative) business cycle shocks conditioned on net trading, decrease (increase) future

[34]The model specifications include additional explanatory variables that capture the impact of the liquidity provision by speculators on volatility conditioned on the negative and positive business cycle shocks ($SHP_{t,w}TS^-_w$ and $SHP_{t,w}TS^+_w$).

[35]The impact of the liquidity provision by hedgers on volatility conditioned on the negative and positive business cycle shocks is given by $NT_{t,w}TS^-_w$ and $NT_{t,w}TS^+_w$.

[36]The net effect of smoothed hedging pressure on future volatility is estimated as $\beta_{SHP_w} + \beta_{SHP_wTS^+_w} \times SHP_{t,w}TS^+_{t,w}$ (-0.189+0.039), assuming that there is a 1% rise in the positive business cycle shocks.

[37]The net effect of smoothed hedging pressure on future volatility is estimated as $\beta_{SHP_w} + \beta_{SHP_wTS^-_w} \times SHP_{t,w}TS^-_{t,w}$ (-0.207+-0.060), assuming that there is a 1% rise in the negative business cycle shocks.

volatility. However, these two variables lack statistical significance. This reveals that business shocks do not affect liquidity provision by hedgers. Net trading overall causes an increase of 87.9% and 60.9% in future volatility after negative and positive business cycle shock, respectively (see Models (7) and (3)).[38]

The combined effect of hedging pressure (which encapsulate the two components of hedging pressure), conditioned on positive business cycle shocks, also increases future volatility in Model (1). We find that hedging pressure is expected to decrease volatility by 18.5% in total. Model (4) captures the impact of positive business cycle shocks, via the two liquidity provision channels on future volatility. Model (8) shows the impact of negative business cycle shocks via the two liquidity provision channels on future volatility. While Model (4) again confirms that positive financial shocks, conditioned on smoothed hedging pressure, increase volatility, Model (8) reveals that negative financial shocks, conditioned on smoothed hedging pressure, decrease volatility.

Overall, we see that negative (positive) business cycle shocks, through liquidity provision by speculators, decreases (increases) volatility. This implies that the prospect of recessionary pressure (economic upturn) motivates commercials to hedge more (less) aggressively by taking more (less) short positions.

4.6. Conclusion

This study explores how hedging pressure influences speculators and hedgers in their roles as liquidity providers, and reveals that the two channels determine oil volatility in opposite directions. The role of speculators has traditionally been to provide liquidity to hedgers, thus implying that an increase in hedging pressure translates to lower volatility. However, as there is a role reversal in the short (hedgers become the providers of liquidity), hedger pressure instead increases volatility. By using two measures of hedging pressure, in lieu of the standard one, we effectively disentangle the two liquidity provisions channels. We further analyze the impact of the liquidity provision by speculators and hedgers on volatility conditioned on observable oil market conditions, such as falling

[38] The net effect of net trading on future volatility is estimated as $\beta_{NT_w} + \beta_{NT_w TS_w^-} \times NT_{t,w}TS_{t,w}^-$ (0.793+0.086), assuming that there is a 1% rise in the negative business cycle shocks. Similarly, the net effect of net trading on future volatility is estimated as $\beta_{NT_w} + \beta_{NT_w TS_w^+} \times NT_{t,w}TS_{t,w}^+$ (0.740+-0.131), assuming that there is a 1% rise in the positive business cycle shocks.

(rising) and normal (inverted) market states. As macro-economic shocks, including the market risk and business cycle risk, influence the responsiveness of hedging pressure to the liquidity provision channels, we also investigate their impact on oil volatility.

We find that hedging pressure driven by speculators' liquidity provision decreases volatility, while the hedging pressure driven by hedgers' short term liquidity provision increases volatility. Thus, while liquidity provision by hedgers leads to a increase in volatility, liquidity provision by speculators decreases volatility, explained by the concept that liquidity providers act as contrarians. Further, oil volatility tends to be more responsive to hedgers' short-term liquidity provision than variations induced by speculators' liquidity provisions. We observe that oil market conditions alter the relationship between liquidity provision channels and volatility. Specifically, liquidity provision by speculators (hedgers) increases (decreases) volatility in rising (rising and falling) markets. Liquidity provision by speculators decreases volatility, while the liquidity provision by hedgers is likely to increase volatility in inverted markets. In normal markets, liquidity provision by hedgers and speculators increases volatility. Speculators and hedgers are motivated to provide liquidity in low markets risk conditions than in high market risk conditions, which is reflected to a more substantial impact on volatility. Moreover, signals of a booming or bearish economy primarily affect the liquidity provision by speculators and increases volatility.

By offering a new perspective on the roles of speculators and hedgers as liquidity providers, we demonstrate that hedgers also influence volatility dynamics in oil markets. Speculators, through their immediate demand for liquidity in the short term, affect the speculative trading on volatility. We discover that liquidity provision channels are sensitive to oil-specific factors as well as macro-economic factors, and influence volatility differently. We reason that as hedgers become less weary about price upturns in rising oil markets, liquidity provision by speculators has the largest influence on volatility. In falling oil markets, hedgers are concerned about mitigating their downside risk, and liquidity provision by hedgers impacts volatility. We confirm that liquidity provision channels are built on the assumption that oil markets are inverted. As oil markets shift into a normal state, liquidity provision channels determine volatility in opposite direction. We have seen that macro-economic factors, via the liquidity provision channels, influence oil price volatility. Low market volatility environments rather than high volatility environments encourage both speculators and hedgers to provide liquidity. Similarly, an economic upturn (downturn) from the U.S. incentivize commercials to hedge less (more) aggressively and, as a result, influences predominantly liquidity provision by speculators.

Appendix 4.1. Alternative Smoothed Hedging Pressure Trailing Periods

We use a longer (52-week) and shorter (13-week) trailing period to estimate the moving average of hedgers' net short positions (smoothed hedging pressure). This allows us to determine whether alternative trailing periods affect the relationship between smoothed hedging pressure (SHP) and future volatility. As a comparison, Kang, Rouwenhorst and Tang (2020) use a trailing period of 52-week to compute smoothed hedging pressure.

Using a longer and shorter trailing period do not affect the statistical significance of smoothed hedging pressure and its combined impact with net trading in Models (1), (2), (5) and (6) in Table A.4.1.1. When we control for the impact of inventory on volatility, we find that the coefficient of smoothed hedging pressure and net trading remain unchanged in most model specifications (Models (3), (4), (7) and (8)). Smoothed hedging pressure will lead to a decrease in weekly volatility by approximately 16%.

TABLE A.4.1.1. **The HP Models using Different Smoothed Hedging Pressure Trailing Periods**

	SHP52				SHP13			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_0	0.057***	0.054***	0.059***	0.056***	0.049***	0.057***	0.052***	0.060***
	(5.299)	(5.244)	(5.831)	(5.577)	(5.114)	(5.495)	(5.236)	(5.915)
β_{SHP_w}	-0.174***	-0.159***	-0.175***	-0.162***	-0.130***	-0.158***	-0.135***	-0.162***
	(-3.942)	(-3.644)	(-4.327)	(-3.872)	(-3.972)	(-4.250)	(-4.070)	(-4.533)
β_{NT_w}			0.686***	0.651***			0.725***	0.671***
			(4.779)	(4.267)			(4.611)	(4.400)
β_{Inv_w}		0.459***		0.420**		0.478***		0.439***
		(2.833)		(2.673)		(3.171)		(3.041)
$\beta_{RV^*_{0,w}}$	0.840***	0.842***	0.832***	0.834***	0.859***	0.833***	0.852***	0.824***
	(21.512)	(22.271)	(22.257)	(22.585)	(21.446)	(22.669)	(21.833)	(22.956)
$adj R^2$	0.462	0.473	0.479	0.488	0.597	0.499	0.613	0.519
AIC	-1,167	-1,186	-1,194	-1,210	-1,176	-1,229	-1,200	-1,261

This table reports the estimation results of the following regressions in the crude oil futures market:

$$RV_{t+1,w} = \beta_0 + \beta_{\text{SHP}_w}\text{SHP}_{t,w} + \beta_{\text{NT}_w}\text{NT}_{t,w} + \beta_{\text{Inv}_w}\text{Inv}_{t,w} + \sum_{k=0}^{k=3}\beta_{\text{RV}_{k,w}}\text{RV}_{t-k,w} + \epsilon_{t+1,w},$$

The table details the estimation results for eight specifications of HP model in the crude oil futures markets, outlined above. The t-statistic (in parentheses), is estimated using the Newey–West standard errors. AIC stands for the Akaike information criteria. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

Appendix 4.2. Interest-adjusted Spreads with Different Maturity Date

We also determine the sensitivity of liquidity provision by hedgers and speculators to normal and inverted oil markets. However, we are using contracts with shorter maturities (3 months and 6 months) to estimate the futures interest-adjusted spreads. This allows us determine whether the results are sensitive to the maturity date of oil contracts.

First, we test whether positive and negative components of the 3-month futures spread ($IAS3_{t,w}$) and 6-month futures spread ($IAS6_{t,w}$) influence weekly volatility. Consistent with the previous findings, the negative component of the 3-month futures spread and 6-month futures spread is likely to increase future weekly volatility (see Tables A.4.2.1 and A.4.2.2). Its effect is much more pronounced (significant) on volatility than the positive component of 3-month futures spread and 6-month futures spread. The latter only increase future volatility in Model (3) (see Tables A.4.2.3 and A.4.2.4). Even though for more weeks the markets are normal in the sample (72% and 69% of weeks in the sample are normal when we use the 3-month futures spread and 6-month futures spread, respectively), we find that inverted oil markets impact the most volatility by increasing it. Dempster et al. (2012) and Nikitopoulos et al. (2017) find that trading variables and financial variables are primarily linked to the medium-term and long-term futures spread. Thus, explaining why future volatility is more responsive to the 12-month and 6-month futures spread than the 3-month futures spread.

Second, we observe that liquidity provision by hedgers, conditioned on inverted oil markets, decreases future volatility (see Models (2) and (4) in Tables A.4.2.1 and A.4.2.2). As expected, in inverted oil markets, liquidity provision by speculators increases future volatility (see Models (3) and (4)). This implies that shorter maturities futures contracts, as an input to construct the futures interest-adjusted spreads, conditioned on liquidity provision by hedgers and speculators are equally likely to influence future volatility.

When oil markets are normal, increase in smoothed hedging pressure is also associated with an increase in volatility (see Models (2) and (4) in Tables A.4.2.3 and A.4.2.4). However, we find that this effect tends to disappear when we compute the futures spreads using shorter maturities futures contracts (i.e., the 3-month futures spread).

TABLE A.4.2.1. **The HP Models in Inverted Markets using 3-month Futures Spread**

	(1)	(2)	(3)	(4)
β_0	0.096***	0.091***	0.057***	0.091***
	(6.390)	(5.955)	(9.056)	(6.523)
β_{HP_w}	-0.302***			
	(-5.699)			
$\beta_{HP_w IAS3^-_w}$	-0.118***			
	(-2.918)			
β_{SHP_w}		-0.295***		-0.289***
		(-4.656)		(-5.185)
$\beta_{SHP_w IAS3^-_w}$		-0.122***		-0.112***
		(-3.056)		(-2.995)
β_{NT_w}			0.878***	0.853***
			(4.181)	(4.524)
$\beta_{NT_w IAS3^-_w}$			0.054***	0.039***
			(2.987)	(3.038)
$\beta_{IAS3^-_w}$	0.313***	0.311***	0.177***	0.294***
	(3.112)	(3.438)	(5.256)	(3.439)
β_{Inv_w}	0.590**	0.597**	0.589**	0.589**
	(2.147)	(2.158)	(2.153)	(2.135)
$\beta_{RV^*_{0,w}}$	0.680***	0.695***	0.647***	0.694***
	(15.888)	(16.278)	(16.377)	(17.148)
$\beta_{r^-_w}$	-0.092***	-0.088***	-0.052**	-0.085***
	(-3.945)	(-3.636)	(-2.212)	(-3.680)
$\beta_{r^+_w}$	-0.010	-0.104	-0.236*	-0.058
	(-0.065)	(-0.709)	(-1.686)	(-0.414)
$adjR^2$	0.500	0.457	0.323	0.474
AIC	-1,226	-1,147	-935	-1,180

This table reports the estimation results of the following regressions in the crude oil futures market:

$$RV_{t+1,w} = \beta_0 + \beta_{\text{HP}_w}\text{HP}_{t,w} + \beta_{\text{HP}_w\text{IAS3}^-_w}\text{HP}_{t,w}\text{IAS3}^-_{t,w} + \beta_{\text{IAS3}^-_w}\text{IAS3}^-_{t,w} + \beta_{\text{Inv}_w}\text{Inv}_{t,w} + \sum_{k=0}^{k=3}\beta_{\text{RV}_{k,w}}\text{RV}_{t-k,w} + \beta_{r^+_w}r^+_{t,w} + \beta_{r^-_w}r^-_{t,w} + \epsilon_{t+1,w},$$

$$RV_{t+1,w} = \beta_0 + \beta_{\text{SHP}_w}\text{SHP}_{t,w} + \beta_{\text{NT}_w}\text{NT}_{t,w} + \beta_{\text{SHP}_w\text{IAS3}^-_w}\text{SHP}_{t,w}\text{IAS3}^-_{t,w} + \beta_{\text{NT}_w\text{IAS3}^-_w}\text{NT}_{t,w}\text{IAS3}^-_{t,w} + \beta_{\text{IAS3}^-_w}\text{IAS3}^-_{t,w} + \beta_{\text{Inv}_w}\text{Inv}_{t,w} + \sum_{k=0}^{k=3}\beta_{\text{RV}_{k,w}}\text{RV}_{t-k,w} + \beta_{r^+_w}r^+_{t,w} + \beta_{r^-_w}r^-_{t,w} + \epsilon_{t+1,w},$$

The table details the estimation results for four specifications of the HP model in inverted oil futures markets, outlined above. The t-statistic (in parentheses), is estimated using the Newey–West standard errors. AIC stands for the Akaike information criteria. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

TABLE A.4.2.2. **The HP Models in Inverted Markets using 6-month Futures Spread**

	(1)	(2)	(3)	(4)
β_0	0.097***	0.091***	0.061***	0.090***
	(6.116)	(5.510)	(7.607)	(7.110)
β_{HP_w}	-0.311***			
	(-5.469)			
$\beta_{HP_w IAS6^-_w}$	-0.454**			
	(-2.771)			
β_{SHP_w}		-0.286***		-0.282***
		(-4.100)		(-5.374)
$\beta_{SHP_w IAS6^-_w}$		-0.413**		-0.379**
		(-2.330)		(-2.622)
β_{NT_w}			0.870***	0.861***
			(3.794)	(4.365)
$\beta_{NT_w IAS6^-_w}$			0.018**	0.013**
			(2.806)	(2.608)
$\beta_{IAS6^-_w}$	0.120***	0.108***	0.068***	0.103***
	(2.999)	(2.852)	(4.939)	(3.224)
β_{Inv_w}	0.346**	0.380**	0.491**	0.342**
	(1.994)	(2.103)	(2.706)	(1.963)
$\beta_{RV^*_{0,w}}$	0.680***	0.691***	0.631***	0.692***
	(15.497)	(15.175)	(14.065)	(17.556)
$\beta_{r^-_w}$	-0.093***	-0.088**	-0.051***	-0.085***
	(-3.978)	(-3.618)	(-2.182)	(-3.648)
$\beta_{r^+_w}$	-0.010	-0.090	-0.210	-0.045
	(-0.067)	(-0.595)	(-1.517)	(-0.316)
$adjR^2$	0.503	0.459	0.332	0.475
AIC	-1,232	-1,150	-944	-1,183

This table reports the estimation results of the following regressions in the crude oil futures market:

$$RV_{t+1,w} = \beta_0 + \beta_{\mathrm{HP}_w}\mathrm{HP}_{t,w} + \beta_{\mathrm{HP}_w\mathrm{IAS6}^-_w}\mathrm{HP}_{t,w}\mathrm{IAS6}^-_{t,w} + \beta_{\mathrm{IAS6}^-_w}\mathrm{IAS6}^-_{t,w}$$
$$+ \beta_{\mathrm{Inv}_w}\mathrm{Inv}_{t,w} + \sum_{k=0}^{k=3}\beta_{\mathrm{RV}_{k,w}}\mathrm{RV}_{t-k,w} + \beta_{r^+_w}r^+_{t,w} + \beta_{r^-_w}r^-_{t,w} + \epsilon_{t+1,w},$$
$$RV_{t+1,w} = \beta_0 + \beta_{\mathrm{SHP}_w}\mathrm{SHP}_{t,w} + \beta_{\mathrm{NT}_w}\mathrm{NT}_{t,w} + \beta_{\mathrm{SHP}_w\mathrm{IAS3}^-_w}\mathrm{SHP}_{t,w}\mathrm{IAS6}^-_{t,w}$$
$$+ \beta_{\mathrm{NT}_w\mathrm{IAS6}^-_w}\mathrm{NT}_{t,w}\mathrm{IAS6}^-_{t,w} + \beta_{\mathrm{IAS6}^-_w}\mathrm{IAS6}^-_{t,w} + \beta_{\mathrm{Inv}_w}\mathrm{Inv}_{t,w}$$
$$+ \sum_{k=0}^{k=3}\beta_{\mathrm{RV}_{k,w}}\mathrm{RV}_{t-k,w} + \beta_{r^+_w}r^+_{t,w} + \beta_{r^-_w}r^-_{t,w} + \epsilon_{t+1,w},$$

The table details the estimation results for four specifications of the HP model in inverted oil futures markets, outlined above. The t-statistic (in parentheses), is estimated using the Newey–West standard errors. AIC stands for the Akaike information criteria. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

TABLE A.4.2.3. **The HP Models in Normal Markets using 3-month Futures Spread**

	(1)	(2)	(3)	(4)
β_0	0.094***	0.099***	0.043***	0.096***
	(7.240)	(7.369)	(6.136)	(7.677)
β_{HP_w}	-0.286***			
	(-6.264)			
$\beta_{HP_w IAS3_w^+}$	0.336			
	(1.080)			
β_{SHP_w}		0.548**		0.589***
		(2.499)		(3.244)
$\beta_{SHP_w IAS3_w^+}$		0.748*		0.688
		(1.672)		(1.631)
β_{NT_w}			0.528	0.141
			(0.192)	(0.510)
$\beta_{NT_w IAS3_w^+}$			0.138	0.137
			(0.985)	(1.004)
$\beta_{IAS3_w^+}$	-0.022	-0.096	0.103**	-0.084
	(-0.263)	(-0.924)	(2.346)	(-0.842)
β_{Inv_w}	0.463***	0.507***	0.477**	0.469**
	(3.044)	(2.932)	(2.309)	(2.816)
$\beta_{RV^*_{0,w}}$	0.648***	0.663***	0.616***	0.665***
	(12.201)	(11.794)	(11.216)	(12.662)
$\beta_{r_w^-}$	-0.091***	-0.084***	-0.047***	-0.080***
	(-3.951)	(-3.493)	(-2.102)	(-3.466)
$\beta_{r_w^+}$	0.019	-0.109	-0.291**	-0.075
	(0.133)	(-0.750)	(-2.197)	(-0.541)
$adjR^2$	0.492	0.424	0.287	0.445
AIC	-1,216	-1,097	-907	-1,130

This table reports the estimation results of the following regressions in the crude oil futures market:

$$\begin{aligned} RV_{t+1,w} &= \beta_0 + \beta_{\text{HP}_w}\text{HP}_{t,w} + \beta_{\text{HP}_w\text{IAS3}_w^+}\text{HP}_{t,w}\text{IAS3}_{t,w}^+ + \beta_{\text{IAS3}_w^+}\text{IAS3}_{t,w}^+ \\ &\quad + \beta_{\text{Inv}_w}\text{Inv}_{t,w} + \sum_{k=0}^{k=3}\beta_{\text{RV}_{k,w}}\text{RV}_{t-k,w} + \beta_{r_w^+}r_{t,w}^+ + \beta_{r_w^-}r_{t,w}^- + \epsilon_{t+1,w}, \end{aligned}$$

$$\begin{aligned} RV_{t+1,w} &= \beta_0 + \beta_{\text{SHP}_w}\text{SHP}_{t,w} + \beta_{\text{NT}_w}\text{NT}_{t,w} + \beta_{\text{SHP}_w\text{IAS3}_w^+}\text{SHP}_{t,w}\text{IAS3}_{t,w}^+ \\ &\quad + \beta_{\text{NT}_w\text{IAS3}_w^+}\text{NT}_{t,w}\text{IAS3}_{t,w}^+ + \beta_{\text{IAS3}_w^+}\text{IAS3}_{t,w}^+ + \beta_{\text{Inv}_w}\text{Inv}_{t,w} \\ &\quad + \sum_{k=0}^{k=3}\beta_{\text{RV}_{k,w}}\text{RV}_{t-k,w} + \beta_{r_w^+}r_{t,w}^+ + \beta_{r_w^-}r_{t,w}^- + \epsilon_{t+1,w}, \end{aligned}$$

The table details the estimation results for four specifications of the HP model in normal oil futures markets, outlined above. The t-statistic (in parentheses), is estimated using the Newey–West standard errors. AIC stands for the Akaike information criteria. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

TABLE A.4.2.4. **The HP Models in Normal Markets using 6-month Futures Spread**

	(1)	(2)	(3)	(4)
β_0	0.098***	0.103***	0.047***	0.100***
	(7.248)	(6.965)	(5.720)	(7.689)
β_{HP_w}	-0.300***			
	(-6.330)			
$\beta_{HP_w IAS6_w^+}$	0.222*			
	(1.693)			
β_{SHP_w}		-0.335***		-0.321***
		(-5.481)		(-6.204)
$\beta_{SHP_w IAS6_w^+}$		0.413**		0.372**
		(2.163)		(2.093)
β_{NT_w}			0.550**	0.587***
			(2.510)	(3.204)
$\beta_{NT_w IAS6_w^+}$			0.063	0.069
			(0.990)	(1.098)
$\beta_{IAS6_w^+}$	-0.201	-0.510	0.547**	-0.451
	(-0.569)	(-1.134)	(2.796)	(-1.066)
β_{Inv_w}	0.461***	0.505***	0.470**	0.468**
	(2.938)	(2.850)	(2.069)	(2.754)
$\beta_{RV^*_{0,w}}$	0.642***	0.651***	0.585***	0.657***
	(11.881)	(10.905)	(9.456)	(12.173)
$\beta_{r_w^-}$	-0.087***	-0.078***	-0.039*	-0.075***
	(-3.758)	(-3.300)	(-1.717)	(-3.269)
$\beta_{r_w^+}$	0.005	-0.125	-0.341**	-0.092
	(0.034)	(-0.847)	(-2.483)	(-0.649)
$adjR^2$	0.487	0.420	0.270	0.440
AIC	-1,203	-1,085	-876	-1,119

This table reports the estimation results of the following regressions in the crude oil futures market:

$$\begin{aligned} RV_{t+1,w} &= \beta_0 + \beta_{\mathrm{HP}_w}\mathrm{HP}_{t,w} + \beta_{\mathrm{HP}_w\mathrm{IAS6}_w^+}\mathrm{HP}_{t,w}\mathrm{IAS6}_{t,w}^+ + \beta_{\mathrm{IAS6}_w^+}\mathrm{IAS6}_{t,w}^+ \\ &\quad + \beta_{\mathrm{Inv}_w}\mathrm{Inv}_{t,w} + \sum_{k=0}^{k=3}\beta_{\mathrm{RV}_{k,w}}\mathrm{RV}_{t-k,w} + \beta_{r_w^+}r_{t,w}^+ + \beta_{r_w^-}r_{t,w}^- + \epsilon_{t+1,w}, \end{aligned}$$

$$\begin{aligned} RV_{t+1,w} &= \beta_0 + \beta_{\mathrm{SHP}_w}\mathrm{SHP}_{t,w} + \beta_{\mathrm{NT}_w}\mathrm{NT}_{t,w} + \beta_{\mathrm{SHP}_w\mathrm{IAS6}_w^+}\mathrm{SHP}_{t,w}\mathrm{IAS6}_{t,w}^+ \\ &\quad + \beta_{\mathrm{NT}_w\mathrm{IAS6}_w^+}\mathrm{NT}_{t,w}\mathrm{IAS6}_{t,w}^+ + \beta_{\mathrm{IAS6}_w^+}\mathrm{IAS6}_{t,w}^+ + \beta_{\mathrm{Inv}_w}\mathrm{Inv}_{t,w} \\ &\quad + \sum_{k=0}^{k=3}\beta_{\mathrm{RV}_{k,w}}\mathrm{RV}_{t-k,w} + \beta_{r_w^+}r_{t,w}^+ + \beta_{r_w^-}r_{t,w}^- + \epsilon_{t+1,w}, \end{aligned}$$

The table details the estimation results for four specifications of the HP model in normal oil futures markets, outlined above. The t-statistic (in parentheses), is estimated using the Newey–West standard errors. AIC stands for the Akaike information criteria. *, **, and *** denote the 10%, 5%, and 1% level of significance, respectively.

CHAPTER 5

Conclusion and Directions for Future Research

This thesis considers three studies on risk assessment and management with an emphasis on the downside risk of individual stocks and volatility dynamics in energy markets. Estimating the extreme downside risk in individual stocks is known to be a very difficult task. The first study proposes two new EDR measures and shows their superior performance compared to existing measures, particularly when used as benchmark to mitigate portfolio risk. Market participants are highly conscious of the negative effect of daily energy volatility. By identifying a new transmission channel of macro-economic information in energy volatility via daily volatility persistence and accommodating this information in a volatility model, the second study demonstrates that this channel offers significant utility benefits to investors. The crude oil market is the most liquid commodity market, and the role of hedgers and speculators in driving the liquidity provision in this market are factors of critical importance for determining oil volatility. The third study gauges the (opposing) effects of liquidity provision induced by speculators and hedgers on oil market volatility.

5.1. Forecasting with New Measures of Extreme Downside Risk

Optimal forecasting of the EDR requires comprehensive metrics and modeling capabilities. The first study, presented in Chapter 2, devises two new and more effective EDR measures. We compare the forecasting abilities of the new measures against four well-known measures in the literature. This study also adopts a shorter (more realistic) forecasting horizon, which is in line with common portfolio rebalancing practices, to predict EDR. As opposed to existing research that focuses exclusively on looking at the in-sample performance of EDR measures, this study also generates out-of-sample forecasts. The sensitivity of the measures to predict EDR out of sample is also assessed under different market conditions. Moreover, we use the EDR measures as a benchmark to create an investment strategy that shorts stocks with a high probability of crashing.

The results in this study reveal that large market capitalization and high-return stocks are more likely to crash one month and six months in the future. The new measures have better out-of-sample predictive power over both shorter and longer forecasting horizons. We find the new measures outperform existing measures even under different market conditions. Our investment strategy, which avoids stocks with the most extreme downside risk, gives the highest risk-adjusted returns across most portfolios, particularly when the new measures are used as a benchmark.

The strategy devised in this study can be used a diversification tool by investors to preserve their wealth in times of crisis. This can help practitioners better manage their portfolio risk. Future work in this area might include replicating this study using individual stocks quoted on non-U.S. exchanges (Habib et al. (2018)). Since markets are known to price risk differently, diverging factors might affect the EDR differently as well. A utility-based valuation approach could be used to capture EDR, assuming that financial markets are often incomplete (Gârleanu and Pedersen (2013), Gârleanu and Pedersen (2016), and Bollerslev et al. (2018)).

5.2. The Economic Impact of Daily Volatility Persistence on Energy Markets

Existing literature provides little economic understanding as to what drives daily volatility persistence, particularly in energy markets. The second study, discussed in Chapter 3, identifies a range of macro-economic variables that are likely to influence volatility persistence in two key energy markets: the crude oil and natural gas markets. By adding these macro-economic variables to a heterogeneous autoregressive model, this study evaluates the ability of this enhanced model to forecast daily volatility and derives the economic value of volatility forecasts.

We find evidence that returns and volatility, traditional determinants of volatility persistence, have a significant impact on future volatility in the two energy markets. The main contribution of this study is that different macro-economic drivers of volatility persistence are formally identified. While the credit spreads, Baltic Index, and VIX impact volatility persistence in the crude oil market, Treasury bills affect volatility persistence in the natural gas market. Thus, there is significant statistical evidence that volatility persistence transmits macro-economic information to the volatility of energy markets, especially the crude oil markets. For the volatility models accommodating information from macro-economic variables, the latter tend to outperform the classical volatility models and provide utility benefit to investors in oil markets that can reach up to 160 basis points, again in the crude oil markets. On a risk management level, this represents a significant benefit that is marginally below the institutional fees typically required for active asset management.

By introducing a new volatility model that provides superior forecasting performance and economic gains compared to competing models, this study offers a robust approach for assessing and managing daily risk exposure relevant for momentum trading strategies as well as dynamic hedging applications. At present, there is ample evidence that energy markets are highly sensitive to almost all global events from the COVID-19 pandemic to the ongoing Ukraine crisis. Consequently, effective modeling and accurate forecasting of volatility are extremely important. These findings also open new directions for research, including assessing the impact of a wider range of macro-economic variables such as inventory on daily volatility persistence (Brennan (1976), Williams and Wright (1991), and Peterson and Tomek (2005)). This can be achieved by using other model specifications, such as the mixed-data sampling regression, that allow variables with varying frequencies (Ghysels and Sohn (2009) and Ma et al. (2021)). Another extension of this study would be to test whether volatility jumps influence daily volatility persistence (Wang and Yang (2018)).

5.3. Liquidity Provision Channels and Oil Price Volatility

The classical theory of backwardation postulates that liquidity is inherently driven by speculators in oil futures markets. However, an alternative (newer) argument is that hedgers in the short term take the role of liquidity providers. The third study, covered in Chapter 4, analyzes the impact of liquidity provision on oil futures volatility induced by speculators and, for the first time in the literature, by hedgers. This is achieved by using two measures of hedging pressure, instead of its traditional definition, to disentangle the effect of the two liquidity provision channels. We also assess the impact of liquidity provision by speculators and hedgers on volatility conditioned on observable oil market conditions, such as normal and inverted states. This study also examines whether macro-economic shocks and business cycle risk, when conditioned on liquidity provision channels, impact volatility.

An increase in hedging pressure induced by speculators' liquidity provision is likely to decrease volatility. However, as hedgers become the liquidity providers, hedging pressure instead increases volatility. This is in line with microstructure theory, which stipulates that liquidity providers act as contrarians and influence volatility. We also observe that volatility is more responsive to hedgers' short-term liquidity provision in comparison to variations induced by speculators' long-term liquidity provision. Furthermore, this study provides evidence that liquidity provision channels are built on the assumption that oil markets are inverted. As oil markets shift into a normal state, the liquidity provision channels determine volatility in opposite directions. Macro-economic factors, via the liquidity provision channels, influence oil price volatility. Low market volatility environments rather than high volatility environments encourage both speculators and hedgers to provide liquidity. Economic upturns (downturns) from the U.S. incentivize commercials to hedge less (more) aggressively, which influences predominantly the liquidity provision by speculators.

This study establishes the dual role of hedgers in oil markets, as insurance seekers and short-term liquidity providers, justifying hedgers' excessive trading. The demand for 'hedging' is driven by two liquidity provision channels that generate opposite volatility predictions. Thus, this study provides an explanation for the contradictory evidence on the influence of speculation on volatility. These findings also pave the way for future research that might explore the impact of the liquidity provision channels on volatility in other commodity futures markets, grouped in order of importance by trading volume (Kang, Rouwenhorst and Tang (2020)). Moreover, the two measures capturing the impact of speculators' and hedgers' liquidity provision channels can be estimated using data from the Disaggregated Commitment of Trader (DCOT) published by the CFTC. The latter is known to provide finer classifications of hedgers and speculators in the commodity futures markets (Kang, Rouwenhorst and Tang (2020)).

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