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Hedging pressure and oil volatility: Insurance versus liquidity demands

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Abstract

This study evaluates the dual role of hedging pressure (HP) in oil futures markets and analyses its effects on weekly oil volatility. We find that HP driven by hedgers' insurance demands is negatively related to volatility, while HP driven by speculators' short-term liquidity demands is positively related to volatility. Oil volatility tends to be more responsive to speculators' short-term liquidity demands than variations induced by hedgers' insurance demands. These channels are also significant determinants of volatility in inverted and normal markets, with the effects being more pronounced in inverted markets. Under low financial and business-cycle risk environments, the two HP channels typically have a measurable impact on volatility. These opposing effects of HP on weekly volatility provide empirical support on the significance of the dual role of hedgers in oil markets, as price insurance seekers and as short-term liquidity providers.

KEYWORDS

hedgers, hedging pressure, liquidity provision, oil volatility, speculators

JEL CLASSIFICATION

C58, G10, Q40

1 | INTRODUCTION

It is widely acceptable in industry and academia that hedging pressure (HP) is a key determinant of oil volatility and risk premia.[1] The notion of two risk premiums (associated with the traditional hedgers' insurance demands and the short-term liquidity demands from speculators) captured by two distinct measures of HP as established by Kang, Rouwenhorst et al. (2020), mandates the re-examination of the relationship between HP and volatility. These findings also revive discussions on controversial debates on how hedgers and speculators are classified,[2] and who is responsible for the volatility in oil markets: the (perceived) speculation or hedging?

[1]A representative list of related works includes Symeonidis et al. (2012), Basu and Miffre (2013), Szymanowska et al. (2014), and Kang, Nikitopoulos et al. (2020).

[2]Following the customary classification in the literature (e.g., Gorton et al., 2013), commercial traders are hereafter defined as hedgers, while noncommercial traders represent speculators.

This study provides empirical evidence to support the distinct and differential impact of two HP channels in determining oil volatility. Using the weekly reports on hedgers' positions, published by the Commodity Futures Trading Commission (CFTC), we disentangle the impact of these two HP measures and assess the effect of these two channels on determining weekly oil volatility. We control for the impact of important determinants of weekly volatility, including past volatility, returns, and weekly information on inventory (Bianchi, 2021; Gorton et al., 2013; Kilian & Murphy, 2014). We find that a 1% increase in the long-term component of HP driven by hedgers' insurance demands reduces volatility by 16%, while a 1% increase in the short-term component of HP driven by speculators' liquidity demands increases volatility by 68%. Further, oil volatility tends to be more responsive to speculators' liquidity demands (thus the hedgers' short-term liquidity provision) than to variations induced by speculators' liquidity provisions enforced by hedgers' insurance demands.

Motivated by the findings of Büyükşahin and Harris (2011) and Kang, Rouwenhorst et al. (2020), we also investigate the interaction between asymmetric volatility effects and the impact of HP channels on oil volatility. We find that the two HP measures exert opposite effects on weekly oil volatility, independent of the asymmetric effects in the oil market and the interaction of positive and negative return shocks. Furthermore, speculators tend to provide liquidity in both rising and falling oil markets for hedgers to insure their positions, whereas hedgers engage in short-term liquidity provision to fulfill speculators' liquidity demands only in bull oil markets.

Crude oil markets have experienced substantial variation in recent years linked to supply inelasticity and the global economic slowdown, which has been reflected in 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; Symeonidis et al., 2012). Since normal and inverted markets respond differently to volatility shocks, we assess the impact of the HP channels on volatility under these market 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; Nikitopoulos et al., 2017). The aggregate effects on volatility are negative for HP by hedgers' insurance demands and positive for HP by speculators' liquidity demands, with the effects being more pronounced in inverted markets.

We also examine the responsiveness of the HP measures (in determining oil volatility) to macroeconomic conditions associated with financial market and business-cycle risks. Cheng et al. (2015) assert a *convective risk flow* from speculators to hedgers during periods of financial distress.[3] We find that independent of the level of market risk, the aggregate effect of HP by hedgers' insurance demands on volatility is negative. However, the reduction in volatility is greater 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 HP by speculators' short-term liquidity demands on volatility is positive in both high- and low-market-risk environments. However, HP by speculators' short-term liquidity demands tends to increase volatility substantially 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 liquidity provision by speculators (Baumeister & Kilian, 2016; Lang & Auer, 2020), while business cycles have a profound effect on the relation of HP with commodity risk premiums (Bianchi, 2021). We demonstrate that the aggregate effects of the two HP channels on oil volatility remain the same, irrespective of economic boom or downturn signals.

This study offers novel insights into the role of speculators and, for the 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 and opposite effects on oil price volatility. The hedgers' dual role as insurance seekers and short-term liquidity providers may provide a justification for references regarding hedgers' excessive trading, addressed by Cheng and Wei (2014) and Kang, Rouwenhorst et al. (2020). Indeed, Kang, Rouwenhorst et al. (2020) observe that hedgers, acting as liquidity providers for momentum speculators in the short term, earn comparatively higher returns (premiums). Their findings show that a considerable portion of speculators' trading is orthogonal to momentum and that the benefits to hedgers of 'immediate' liquidity provision are higher than losses from facilitating momentum trading.[4] Although many studies, including those of De Roon et al. (2000), Basu and Miffre (2013), and Bosch and Smimou (2022), acknowledge that hedgers' insurance demand is highly influenced by the

[3]As a result, increased trading activity from speculators, which is beyond the standard trading associated with responding to hedger's insurance needs (HP), may have adverse effects on commodity prices. An increase in speculators' trading positions in response to HP tends to decrease prices, while an increase in speculators' trading positions in high volatility index (VIX) conditions, may increase prices.

[4]Kang, Rouwenhorst et al. (2020) assess the profit/loss potential of three components of hedger's activities, namely, insurance demand, liquidity provision, and momentum trading. They find that the speculator's losses generated by their short-term momentum trading partly offset the insurance premium earned, while hedgers benefit more from liquidity provision than momentum trading.

theory of normal backwardation, they fail to account for the contemporaneous effect of hedgers' short-term liquidity provision. These findings also extend the notion of the HP hypothesis asserting that net short (long) hedging relates only to backwardation (contango).[5]

Furthermore, 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.[6] We find that speculators can indeed affect price volatility, particularly through their 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 long-term insurance demands from hedgers and short-term liquidity demands from speculators exert opposite effects on volatility, thus providing an explanation for the contradictory evidence in terms of the influence of speculation on volatility.

This study also offers insight into practical relevance to the debate regarding the distinction between the CFTC classification of the trading positions associated with hedgers and speculators, as certain aspects of their activities do not align with CFTC classifications (Kang, Rouwenhorst, et al., 2020). Differences between trading activities of hedgers/speculators for short-term and long-term horizons can be justified by the purpose of the two premiums and the corresponding HP measures. Grossman and Miller (1988) and Campbell et al. (1993) argue that market makers would trade against price trends while subsequent price reversals reward them for their liquidity provision.[7] Additionally, even though trend-following is a common trading practice in futures markets, only 40% of the commodity position changes from speculators can be explained by trend and momentum signals, while hedgers act as contrarians following the behavior of momentum traders (Boos & Grob, 2022). This further supports the dual role of hedgers as insurance seekers and liquidity providers and the dual role of speculators as liquidity providers and momentum traders.

The remainder of the paper is structured as follows. Section 2 delves into the hypothesis development, and Section 3 introduces the data used in the study. In Section 4, we present the effects of the two HP channels on determining volatility. We further investigate the sensitivity of these effects in normal and inverted markets, and in low/high market and business-cycle risk environments, in Sections 5 and 6, respectively. Section 7 summarizes robustness tests, and Section 8 concludes.

2 | LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Hedgers' trading motives are traditionally driven by demand for price insurance (namely, insurance demand), 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 have the effect of inducing speculators to provide liquidity and receive an *insurance premium* for bearing the risk of oil price changes.[8] However, insurance demand is not the only driver of hedgers' trading activity in oil futures markets. Kang, Rouwenhorst et al. (2020) present empirical evidence of two premiums; the traditional insurance premium paid from hedgers to speculators (e.g., institutional investors and large hedge funds) to fulfill long-term insurance demand, and the *liquidity premium* paid from speculators to hedgers for providing short-term liquidity, with these short- and long-term trading activities having opposite effects on future commodity returns. Indeed, the insurance premium paid by hedgers to speculators is partially offset by the liquidity premium paid by momentum speculators to hedgers to satisfy their

[5]Representative literature on HP hypothesis includes works, such as Keynes (1930), Hirshleifer (1989), Hirshleifer (1990), Bessembinder (1992), De Roon et al. (2000), Rouwenhorst and Tang (2012), and Basu and Miffre (2013).

[6]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.

[7]Rouwenhorst and Tang (2012) show that money managers are generally momentum (positive feedback) traders, while producers are net short and contrarian (negative feedback) traders. There is less evidence that index traders and swap dealers trade based on past futures returns. Fishe and Smith (2019) demonstrate that speculators (more specifically) managed money traders are trend-followers (change position in the same directions as prices) while hedgers are contrarian.

[8]The normal backwardation 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. Thus, the futures price trades below (at a discount to) the expected future spot price, which implies an increasing trend in futures prices over time. As a result, on average, hedgers incur losses and speculators make gains, which reflects their compensation for the risk. This discount reflects the oil futures risk premium, namely, the insurance premium.

short-term liquidity demands.[9] Furthermore, based on a dynamic self-fulfilling rational expectations equilibrium model, Soares and Borocco (2022) provide supporting evidence on the validity of two risk premiums in commodity markets, one for speculators (who tend to be technical traders) and one for hedgers (who tend to be contrarians), while both serve as counterparts to each other's risk-taking demands. Evidence also supports a *convective risk flow* away from commodity speculators to hedgers during periods of distress in the financial markets (Cheng et al., 2015).

Practical implications of the theory of normal backwardation establish a relation between risk premiums and HP (measuring the relative size of hedgers trading positions) which is closely linked to liquidity provisions. Indeed, De Roon et al. (2000) and Basu and Miffre (2013) demonstrate that HP is a systemic determining factor of risk premium in commodity futures markets. Further, Kang, Rouwenhorst et al. (2020) use the direction of returns following positions changes to conjecture the liquidity providers in oil futures markets. They also argue that the traditional HP consists of two components. The short-term HP that is driven by the liquidity demands of speculators and the long-term HP that is driven by the hedgers' insurance demands. These two measures of HP are associated with two different risk premia. One premium is the insurance premium for the risk transfer from hedgers to speculators, as hedgers demand risk protection and speculators provide liquidity. The other premium is the liquidity premium to account for the liquidity hedgers provide to momentum speculators, as speculators demand short-term liquidity and hedgers are willing to provide it (Cho et al., 2019). Zhang (2022) confirms the presence of these liquidity channels in commodity option markets as well, while Maréchal (2023) verifies financialization effects. Accordingly, these two risk premia, stemmed by the two measures of HP, establish two channels of liquidity provision; the traditional liquidity provision from speculators and the short-term liquidity provision from hedgers to momentum speculators.

The importance of the distinction between short- and long-term components of the HP has been further supported by Yu et al. (2023) using a measure of HP momentum.[10] Bianchi (2021) also gauges the effects of HP on commodity risk premiums confirming a more positive yet short-lived relationship between them, while time-series momentum has a persistent effect on risk premiums. Furthermore, commodity risk premiums are time varying mainly affected by the trading decisions of hedgers and speculators, and are negatively correlated to volatility. While Kang, Rouwenhorst et al. (2020) provide empirical evidence of higher liquidity premiums paid to hedgers to satisfy short-term momentum trading of speculators, Cho et al. (2019) show higher insurance premiums to be paid to speculators for hedgers to manage price risks in illiquid commodity markets. Furthermore, in illiquid bear commodity markets, hedgers would require a higher liquidity premium to satisfy speculators' momentum trading needs. We conclude that the HP in oil futures markets is not only guided exclusively by trading driven by speculators liquidity provision but also in the short term by hedgers' liquidity provision.

Market liquidity is typically negatively related to its volatility.[11] Chang et al. (1997) argue that a higher trading position/volume, particularly for trading driven by investors' speculative motives, is associated with higher price volatility. However, liquidity providers engage in contrarian strategies, and their positive returns are associated with an expected decrease in trading positions, resulting in a decrease in volatility (Kahraman & Tookes, 2017). In line with Grossman and Miller (1988) and Amihud and Mendelson (1989), Brunnermeier and Pedersen (2008) demonstrate that low liquidity conditions driven by tight funding make speculators reluctant to take positions that may cause an increase in volatility. They also argue that in high volatility conditions, market liquidity tends to decline, while liquidity premiums increase (Vayanos, 2004).

Another potential explanatory factor of volatility is related to information asymmetry between hedgers and speculators. With strong empirical evidence in equity markets, the perceived notion is that speculators are informed traders, while hedgers are uninformed traders (Spiegel & Subrahmanyam, 1992). Accordingly, trading from informed speculators (uniformed hedgers) would increase (decrease) volatility. However, while speculators may be better informed, their trading ability and consequent profits are affected by the liquidity of the market (Brunnermeier & Pedersen, 2009). Furthermore, hedgers in commodity markets (and some FX markets, Wang, 2002) tend to have better knowledge regarding production and demand changes and the extend at which macroeconomic conditions may affect

[9]Kang, Rouwenhorst et al. (2020) demonstrate that in the short term, long hedgers earn higher returns than long speculators, implying that hedgers receive a premium as they become liquidity providers to satisfy the short-term trading demand of momentum speculators.

[10]Yu et al. (2023) assess the impact on oil futures returns (not volatility).

[11]Market microstructure literature also addresses the effects of liquidity provision on asset returns. In equity markets, market makers are rewarded with higher returns for providing liquidity to "noninformational" traders (Campbell et al., 1993; Grossman & Miller, 1988). Further, liquidity providers act as contrarians and decrease their trading positions after a positive return or premium (Anand et al., 2013; Kahraman & Tookes, 2017). Thus, liquidity providers are awarded with higher returns while they engage in contrarians strategies.

their perspective commodity markets, thus they can be more informed than speculators (Frino et al., 2016). Although it is well documented that information-based trading increases volatility (Kacperczyk & Pagnotta, 2022), the effects of inside information on volatility depend on liquidity and who is the most informed, hedgers or speculators. Thus, we base our hypothesis development solely on the liquidity arguments.

Recall that typically, speculators liquidity provision is driven by short hedgers' insurance demands, while hedgers' liquidity provision fulfills the speculators' short-term momentum trading demands. Accordingly, as hedgers demand risk protection and speculators provide liquidity, two effects take place from the two parties involved. The first effect is an increase in the net short positions of hedgers which is reflected in an increase in HP. The second effect relates to the speculators' behavior. Long speculators receive the insurance premium and as liquidity providers, they behave as contrarians, and their positive returns instigate a decrease in trading positions and, consequently, a decrease in volatility (Kahraman & Tookes, 2017). Thus, an increase in the HP, driven by hedgers' insurance demand, is stipulated by speculators contrarian trading that reduces volatility. In other words, when liquidity provision is driven by speculators, an increase in HP is associated with a reduction in oil volatility. The long-term component of the HP shares the same attributes as the HP since it solely captures the effects of the long-term hedgers' insurance demands (Kang, Rouwenhorst, et al., 2020). These justifications support the two following hypotheses:

Hypothesis 1. Hedging pressure driven by the hedgers' insurance demands is negatively related to oil price volatility.

Hypothesis 2. The long-term component of hedging pressure driven by hedgers' insurance demands is negatively related to oil price volatility.

In contrast, the liquidity provision argument put forward by Kang, Rouwenhorst et al. (2020) stipulates that in the short run, as speculators demand liquidity to fulfill their momentum trading and hedgers provide this liquidity, two counterpart effects take place. On the one hand, when hedgers serve as liquidity providers, their net short positions decrease because they take long positions in futures contracts thus HP decreases. On the other hand, hedgers as liquidity providers earn a liquidity premium, they would consecutively execute contrarian trading strategies, and their positive returns would be associated with a decrease in trading positions thus a decrease in volatility (Kahraman & Tookes, 2017; Rouwenhorst & Tang, 2012). Thus, when liquidity provision is driven by hedgers, a decrease in HP is associated with a reduction in oil volatility. Therefore, a decrease in the HP, driven by speculators' liquidity demand, is stipulated by hedgers' contrarian trading which reduces volatility. These arguments establish the following hypothesis:

Hypothesis 3. The short-term component of hedging pressure driven by the liquidity demands of speculators is positively related to oil price volatility.

3 | DATA AND PRELIMINARY ANALYSIS

This section presents the data utilized to gauge the impact of the HP channels on weekly oil volatility. The study covers the period between January 2009 and December 2019.

3.1 | Oil realized variance (RV)

We use high-frequency prices of the front-month continuous futures contracts of crude oil traded on the New York Mercantile Exchange, collected from Refinitiv Tick History (RTH), to construct the daily RV. This serves as a measure of ex post volatility, and it is computed using midquotations prices (the average of bid and ask prices) sampled at 5-min intervals.[12] Daily RV, estimated as the sum of squared intraday returns over a day, is given by $\mathrm{RV}_{t,d} = \sum_{i=1}^{m} r_{i,t}^2$, where m is the number of intraday observations. Similarly, the weekly volatility is measured using the sum of the squared 5-min

[12]In the literature, the consensus is to aggregate returns into 5-min intervals as they usually provide the best RV approximation (Liu et al., 2015).

returns over a week, $RV_{t,w} = \sum_{i=1}^{s} r_{i,t}^2$, where s is the number of 5-min 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.[13]

The time series for crude oil's RV is depicted in Figure 1. Oil price volatility tended to exhibit periods of relatively low and high variation. For instance, despite the volatility spike during the Global Finance Crisis of 2008, volatility remained relatively high between 2015 and 2017. In this period, there was an oversupply of oil (referred to as the oil glut) in the Organization for Economic Cooperation and Development (OECD) countries, which reduced their economic growth. The expansion of the shale industry among US oil producers also contributed to the global oil oversupply.

3.2 | Short-term and long-term HP measures

The CFTC, via their weekly Commitment of Traders reports, provides information on the long and short positions of different trader' types (commercial, noncommercial, and nonreportable).[14] In this study, we focus on HP from the commercial traders' perspective that we termed as *hedgers*, while the noncommercial traders as termed as *speculators*. 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.[15] Open interest is the total number of short and long contracts jointly held by hedgers, speculators, and nonreportable traders.[16] Thus, HP is computed as

$$\begin{aligned} HP_{t,w} &= \frac{\text{Hedgers' short positions}_{t,w} - \text{Hedgers' long positions}_{t,w}}{\text{Open interest}_{t,w}} \\ &= -\frac{\text{Hedgers' net long positions}_{t,w}}{\text{Open interest}_{t,w}}. \end{aligned} \tag{1}$$

Kang, Rouwenhorst et al. (2020) demonstrate empirically that variation in HP is driven by two components: the traditional liquidity provision by speculators to meet hedgers' insurance demand and the liquidity provision by hedgers to satisfy the demand for short-term momentum trading of speculators.[17] Following the concept and terminology used in Kang, Rouwenhorst et al. (2020), we introduce net trading (NT) as the component of the HP that captures the behavior of hedgers with no palpable hedging motives who earn the liquidity premium and provide liquidity for short-term speculative trading. This is computed 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

$$NT_{t,w} = \frac{\text{Hedgers' net long positions}_{t,w} - \text{Hedgers' net long positions}_{t-1,w}}{\text{Open interest}_{t-1,w}}. \tag{2}$$

To separate the impact of the HP induced by the liquidity demands of speculators from the impact of HP driven by hedgers' insurance demands, we introduce smoothed hedging pressure (SHP). SHP captures the long-term component of HP that is driven by the need of hedgers for price insurance and relates to the liquidity provision by speculators. SHP

[13]Even though crude oil futures trade over a 24-h window (with a 1-h trading break), there are numerous periods of inactive trading. Hence, we follow a filter process that helps reduce this thin trading bias (Bollerslev et al., 2018). Days that 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 than or equal to the bid price. In each 5-min interval, we delete observations for which the spread is negative and more than 50 times the median spread on that day. For each 5-min return, we estimate the standard deviation of the returns on the respective days (excluding the current observation) and remove returns that exceed eight standard deviations from zero (Barndorff-Nielsen et al., 2009). This represents 0.065% of the data. We further test the sensitivity of our results to a less stringent filtering on the trading days discarded. The results are presented in Supporting Information Appendix E.

[14]Nonreportable 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 3 days later, after the market close on Friday.

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

[16]Open interest can also be estimated as the sum of hedgers' short and long positions. We have used both measures of open interest and give qualitatively similar results.

[17]The impact of these two HP channels is essentially disentangled from HP. Note that HP has been commonly studied in the literature (see, Basu & Miffre, 2013; Bosch & Smimou, 2022; De Roon et al., 2000).

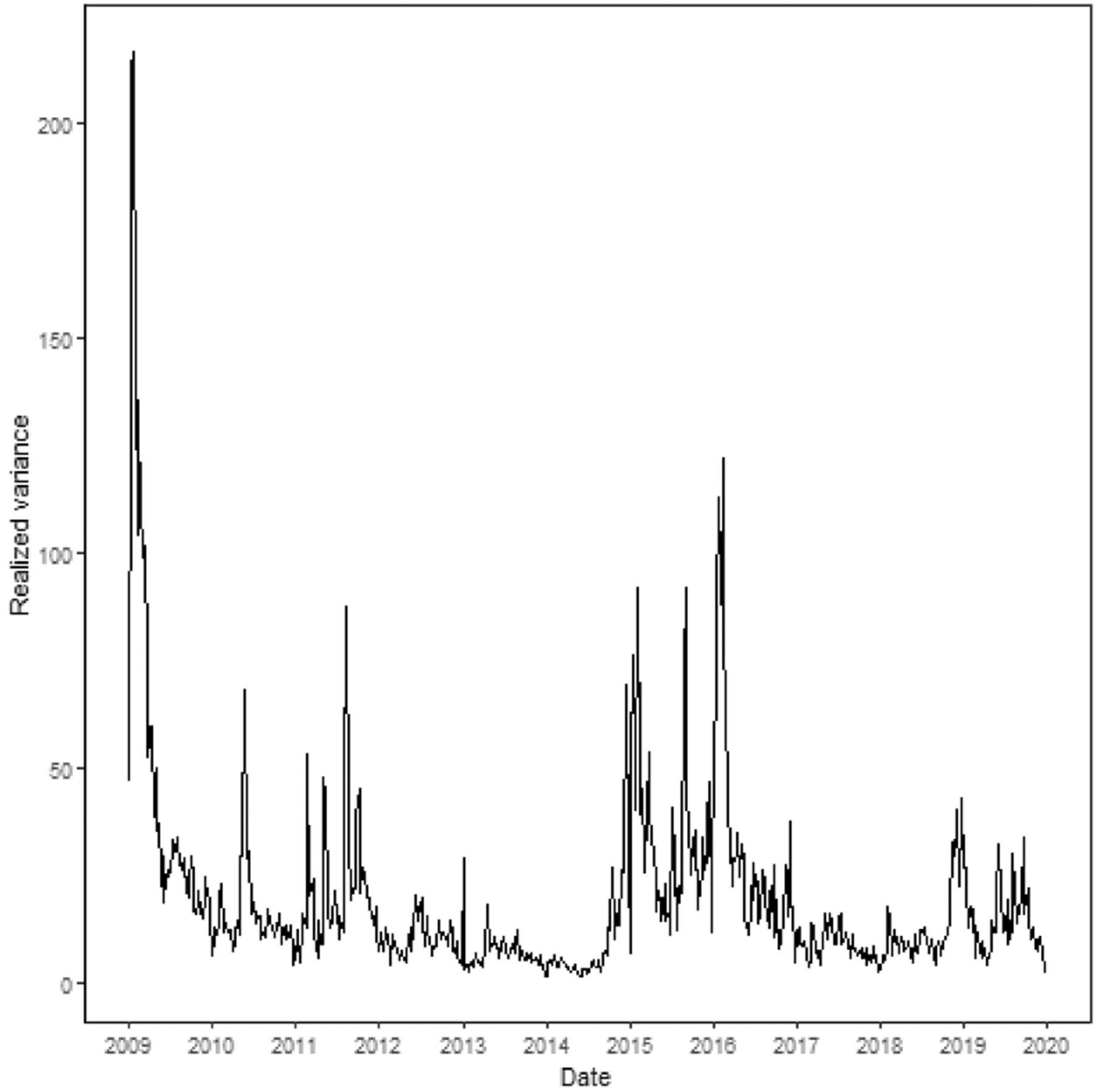

FIGURE 1 Crude oil weekly realized variance (RV). The figure plots the time series of the weekly RV of crude oil front-month futures contracts between January 2009 and December 2019. RV is scaled by 10^4.

is computed as 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 by[18]

$$\mathrm{SHP}_{t,w} = \frac{n\text{-weeks moving average of hedgers' net short positions}_{t,w}}{\text{Open interest}_{t,w}}. \tag{3}$$

Figure 2 shows the time series of HP, SHP (over 52, 26, and 13 weeks), and NT from 2009 to 2019. The top panel, which represents HP, shows that hedgers were predominantly net short (i.e., HP was mainly positive). For example, in the last week of December 2011, HP was at 12%. This means that 12% of hedgers' positions were more short than long. The middle panel captures the component of HP driven by speculators' liquidity provision, namely, the SHP, which it is

[18]Since we are looking at the behavior of hedgers over the past 10 years (not 30 years as reported in Kang, Rouwenhorst, et al., 2020), we report a shorter moving average (26 weeks) of the net short positions of hedgers in the main paper. Alternative measures of SHP, which use 52- and 13-week moving averages of the net short positions of hedgers, are also examined. n represents the 52, 26, and 13 weeks.

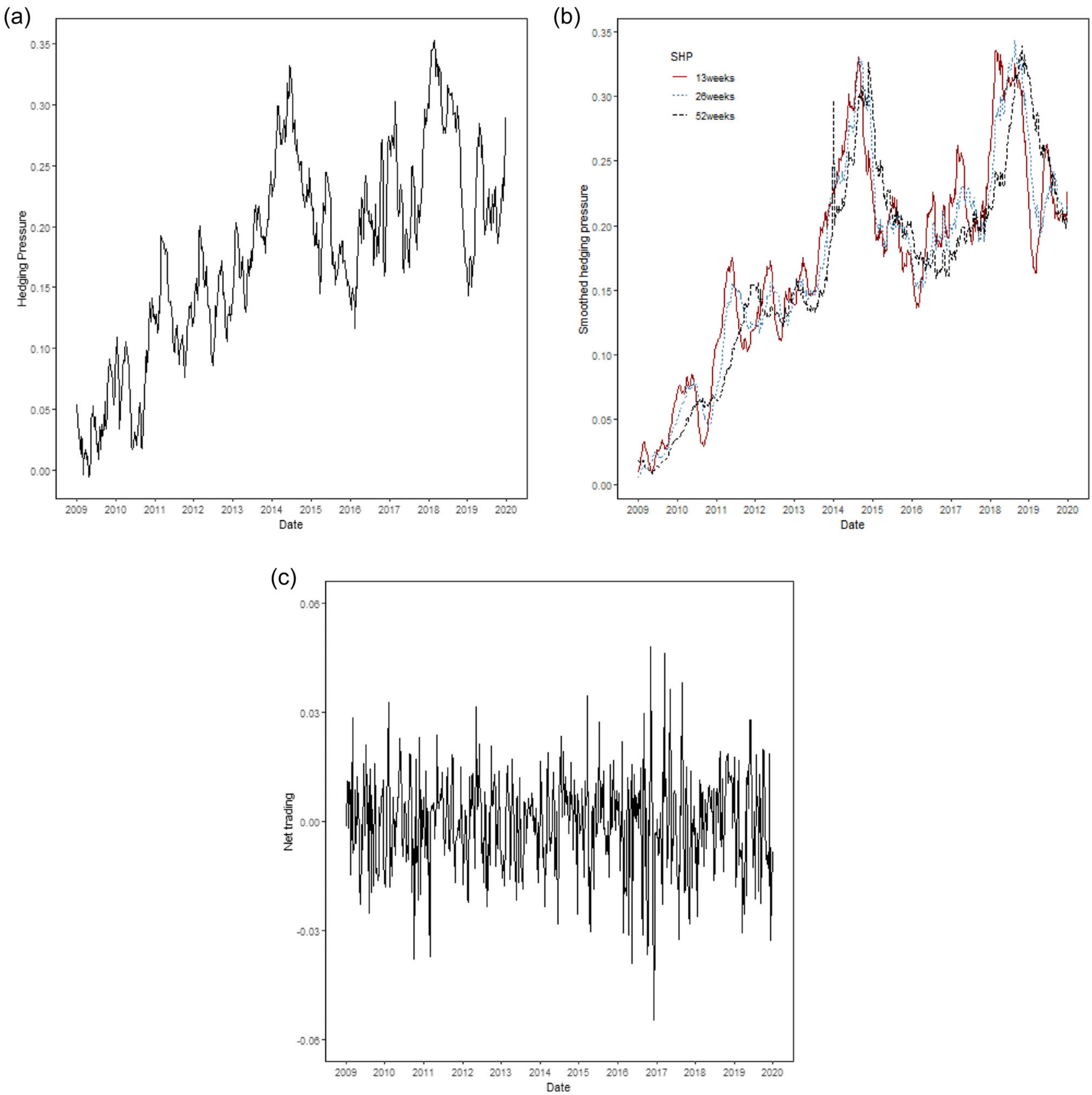

FIGURE 2 Crude oil: (a) Hedging pressure (HP), (b) smoothed hedging pressure (SHP), and (c) net trading (NT). The figure plots the time series of the weekly HP and its two components (SHP and NT) of crude oil between January 2009 and December 2019. SHP is estimated using 13-, 26-, and 52-week moving averages of hedgers' net short positions.

evident emulates the dynamics of HP. The bottom panel depicts the NT, which is the component of HP driven by the short-term liquidity provision of hedgers.

3.3 | Crude oil and petroleum inventory

Inventory is known to influence oil volatility and is proxied by the Energy Information Administration (EIA) weekly series on primary stocks of US crude oil and petroleum inventory.[19] Nikitopoulos et al. (2017) demonstrate that the EIA's

[19]The weekly US ending stocks of crude oil and petroleum products (in thousand barrels). EIA stands for the US EIA.

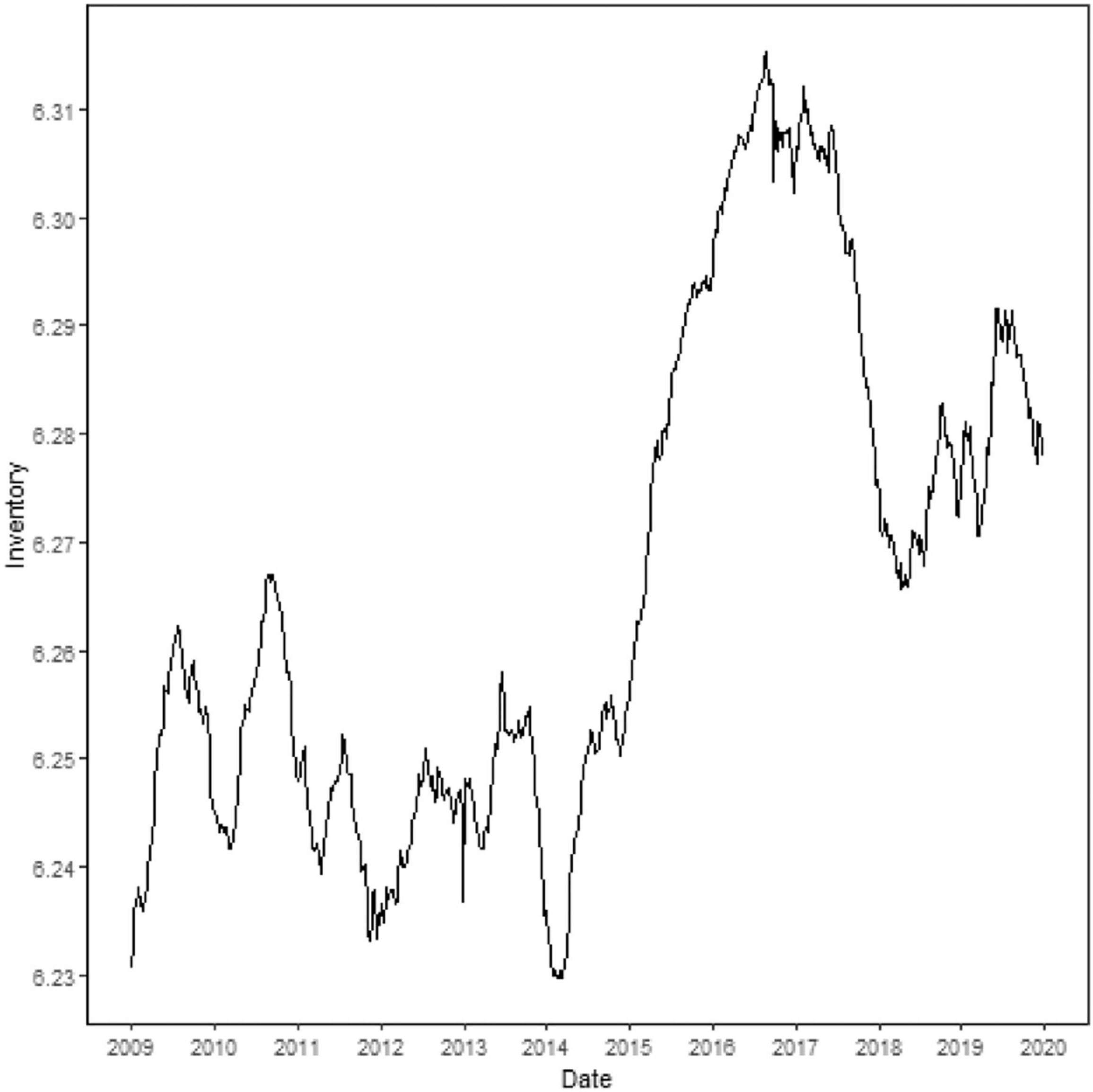

FIGURE 3 Crude oil and petroleum inventory. The figure plots the weekly US crude oil and petroleum inventory between January 2009 and December 2019.

definition of inventory (as opposed to the OECD's definition, which includes, petroleum inventory of non-US countries) is more likely to influence short-term oil prices/volatility. Figure 3 shows 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 of 2014–2016 is also evident. We use inventory as a control variable to eliminate exogeneity concerns.

3.4 | Futures interest-adjusted spreads (IASs)

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.[20] We use the daily prices of

[20]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.

CME light sweet crude oil (West Texas Intermediate) futures prices for the nearest (first), fourth, seventh, and 13th monthly contract expiry dates from RTH to build the weekly measure of futures spreads.[21] The London Interbank Offered Rate (LIBOR) rate is the US dollar (USD) LIBOR interest rate in n-month maturities.[22] The 12-month futures IAS is estimated as

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

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

Figure 4 graphs the 3-, 6-, and 12-month IASs between 2009 and 2019. From 2009 to 2018, the IASs were primarily positive, apart from between 2013 and 2015 (signaling that the crude oil futures market was normal). After 2018, the crude oil market oscillated between normal (positive spreads) and inverted states (negative spreads). Between 2009 and 2019, oil markets were more often normal (63%) than inverted (37%) (as measured by the weekly positive and negative 12-month interest-adjusted futures spread).[23]

3.5 | Financial market and business-cycle risk

The financial market risk is measured by the VIX index (CBOE VIX), which captures 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 *fear index* or *fear gauge*. We retrieve the daily VIX from the Federal Reserve Economic Data (FRED) database and calculate their weekly averages. 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 TS effectively captures the short-term business cycles (Fama & French, 1989).[24] The daily treasury bond constant maturity rates are collected from the FRED database, and the weekly 10-year and 3-month treasury bond constant maturity rates are computed by averaging their respective daily rates. For more details on these time series, see Supporting Information Appendix A.

3.6 | Summary statistics

Panel (A) of Table 1 reports the descriptive statistics of the associated variables. Weekly oil volatility is higher than the VIX and exhibits much more variation. A positive average HP means that oil hedgers were primarily net short in the last decade. SHP (for all trailing periods) and HP display similar statistical characteristics. NT has a negative mean, which may reflect an overall net long position by hedgers in the short term. While weekly inventory is relatively stable, the three measures of futures spreads are far more volatile. The longer the maturity of the futures spreads, the more variation is present in the IAS measures. The mean value of the TS reflects a bias toward positive spreads. We report the

[21]A crude oil futures contract represents 1000 bushels to be delivered to Cushing, Oklahoma. Each futures contract expires on the third business day before the 25th 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.

[22]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.

[23]For the 3- and 6-month interest-adjusted futures spread, most of the time, oil markets were again normal rather than inverted (72% vs. 28% and 69% vs. 31%, respectively).

[24]These business cycles are identified by the National Bureau of Economic Research.

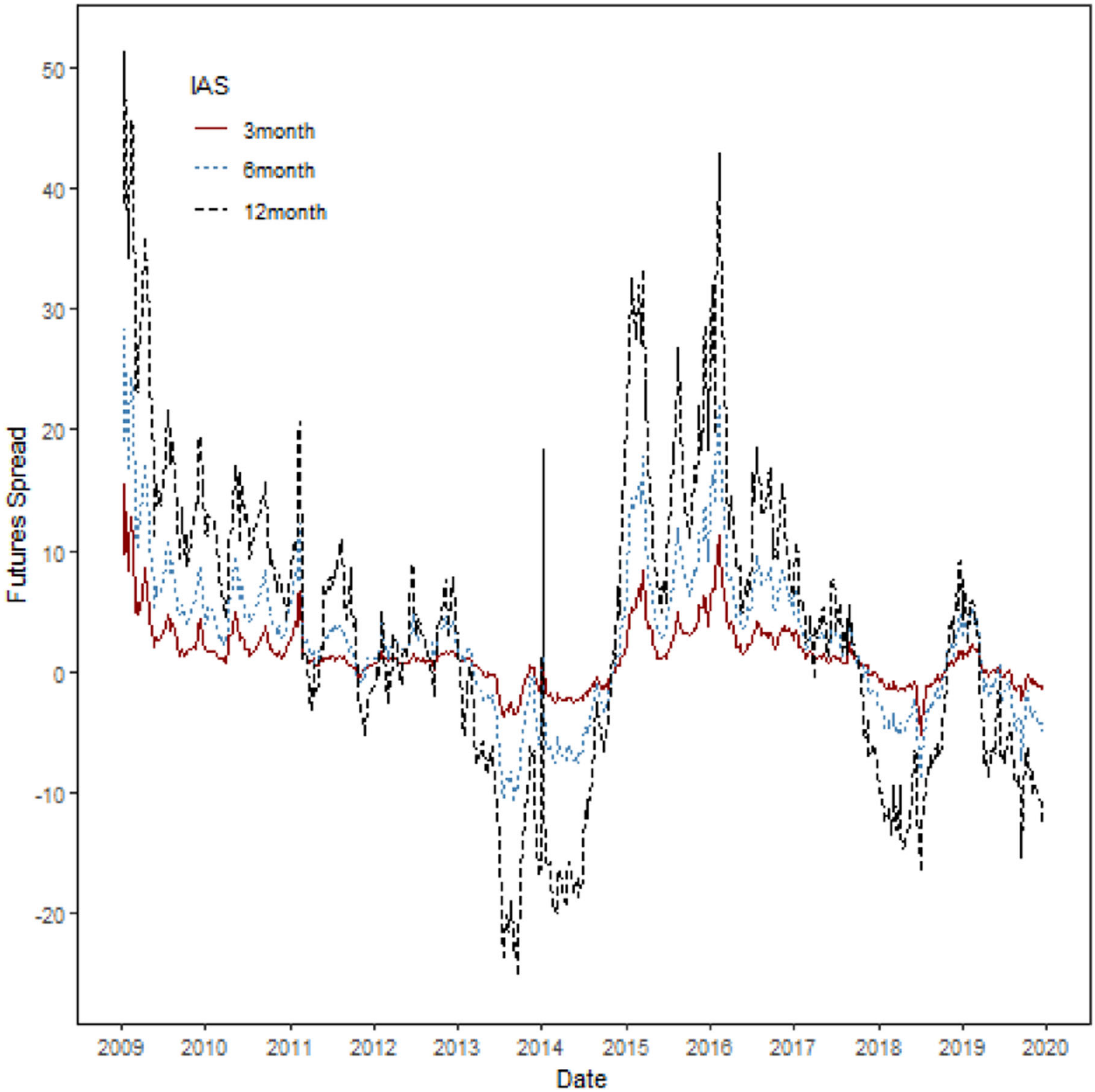

FIGURE 4 Futures interest-adjusted spreads (IASs). The figure plots the weekly average of daily 3-, 6-, and 12-month IASs the crude oil front-month futures contracts between January 2009 and December 2019.

correlation between the RV, variations of the SHP and NT in Panel (B) of Table 1. The results show that weekly RV is negatively correlated with HP and SHP but positively correlated with the NT. These correlations accord with the underlying effects of the HP channels of hedgers and speculators on volatility that are investigated in the study. HP and SHP are highly correlated, but NT (representing a proxy for liquidity provision by hedgers) displays a low correlation with HP or SHP.

4 | THE ROLE OF HP IN DETERMINING VOLATILITY

To assess the role of the HP measures in determining oil volatility, we first analyze the impact of NT and SHP on weekly volatility. Second, by acknowledging the importance of HP measures in determining oil returns (Kang, Rouwenhorst, et al., 2020), we assess the impact of NT and SHP on volatility while conditioning on falling or raising oil market conditions.

TABLE 1 Descriptive statistics.

Panel A: Descriptive statistics							
	Mean	**SD**	**Median**	**Minimum**	**Maximum**	**LB(1)**	**ADF**
RV	19.844	23.472	12.675	1.475	216.810	369	−6.158***
HP (%)	18.263	8.069	18.819	−0.548	35.248	495	−3.532**
SHP13 (%)	17.972	7.978	18.901	0.882	33.495	508	−3.112
SHP (%)	17.722	8.089	18.879	0.533	34.297	509	−2.666
SHP52 (%)	17.188	8.279	17.919	0.844	33.881	508	−1.577
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	−0.374***	0.931***				
SHP	−0.339***	0.865***	0.939***			
SHP13	−0.382***	0.924***	0.883***	0.963***		
NT	0.107***	−0.080*	0.008	0.097**	0.115***	

Note: 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 (volatility index [VIX]), and business-cycle risk (TS). LB(1) is the Ljung–Box test statistic at 1 lag and ADF is the augmented Dickey–Fuller (ADF) test. 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.

4.1 | HP channels

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

$$RV_{t+1,w} = \beta_0 + \beta_{HP_w} HP_{t,w} + \sum_{k=0}^{k=3} \beta_{RV_{k,w}} RV_{t-k,w} + \epsilon_{t+1,w}, \tag{4}$$

where $\sum_{k=0}^{k=3} RV_{t-k,d}$ represents an autoregressive process of order 4 for RV (the order selection criteria is based on Aikaike's information criterion [AIC]). This model acknowledges that the current and lagged values of volatility (in the past weeks) can also influence future volatility.[25] Equation (4) and all other equations defined hereafter are estimated using the weighted least

[25]The autoregressive process for RV can be rewritten as

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

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

squares (WLSs) estimation, with weights being the inverse of the fitted values of the error standard deviations, retrieved from the ordinary least square (OLS) estimation.[26] We use Equation (4) to test the empirical validity of Hypothesis 1.

To disentangle the effects of hedgers' insurance demands from speculators' liquidity demands on HP, we use two measures of HP: SHP and NT (Kang, Rouwenhorst, et al., 2020). SHP represents the long-term component of the HP driven by hedger's insurance demand and reflects speculators' liquidity provision. NT is the component of HP that is driven by speculators' liquidity demands to satisfy their short-term momentum trading that is fulfilled by hedgers' liquidity provision. The effects of these two drivers of variations in HP on weekly volatility are captured by the following regressions

$$\mathrm{RV}_{t+1,w} = \beta_0 + \beta_{\mathrm{SHP}_w}\mathrm{SHP}_{t,w} + \sum_{k=0}^{k=3}\beta_{\mathrm{RV}_{k,w}}\mathrm{RV}_{t-k,w} + \epsilon_{t+1,w}, \tag{5}$$

$$\mathrm{RV}_{t+1,w} = \beta_0 + \beta_{\mathrm{NT}_w}\mathrm{NT}_{t,w} + \sum_{k=0}^{k=3}\beta_{\mathrm{RV}_{k,w}}\mathrm{RV}_{t-k,w} + \epsilon_{t+1,w}, \tag{6}$$

where $\mathrm{SHP}_{t,w}$ and $\mathrm{NT}_{t,w}$ represent smoothed HP and net trading, respectively. Accordingly, these regressions are used to test empirically Hypotheses 2 and 3, respectively. To confirm that these two measures capture independent variations in HP, we assess the impact of both NT and SHP on weekly volatility by considering the following regression:

$$\mathrm{RV}_{t+1,w} = \beta_0 + \beta_{\mathrm{SHP}_w}\mathrm{SHP}_{t,w} + \beta_{\mathrm{NT}_w}\mathrm{NT}_{t,w} + \sum_{k=0}^{k=3}\beta_{\mathrm{RV}_{k,w}}\mathrm{RV}_{t-k,w} + \epsilon_{t+1,w}. \tag{7}$$

Table 2 presents the estimation results of these four models, and confirms the distinctive impact of the HP channels on determining weekly oil volatility. We find that HP is negatively associated with volatility (Model 1). An increase in the net short position of hedgers, who act as insurance seekers, means that more long speculators are earning more (positive returns), and they are likely to decrease their trading positions. This ultimately means a fall in oil volatility. A 1% increase in HP decreases future volatility by 18.5%. However, this change in HP 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 SHP (see Model 2) is related to a decrease in weekly volatility of only 15.9%. This implies that SHP can only capture a component of the (total) HP, and this component reflects the variation driven by hedgers seeking price protection and speculators offering liquidity provision. The other component of HP reflects the variations associated with hedgers becoming liquidity providers in the short run and requiring compensation (higher returns). They usually take on more long positions, which causes them to reduce their trading position (NT). Behaving as contrarian traders, this reduction in trading position from hedgers reduces oil volatility, as observed in Model (3) in Table 2. We see that a 1% increase in NT is likely to increase volatility by 67.5%. Thus, two key results emerge from this analysis. First, short-term and long-term components of HP have opposite effects on volatility. More specifically, the long-term component of HP driven by hedgers' insurance demands is negatively related to oil price volatility, while the short-term component of HP driven by speculators' liquidity demands is positively related to oil price volatility. Second, volatility is more sensitive to variations driven by speculators' liquidity demands than those induced by hedgers' insurance demands.

Further, we observe that the coefficients of SHP and NT remain the same among models assessing the individual impact of these measures and their combined impact when comparing Models (2)–(4). Thus, SHP and NT capture independent components of HP. In addition, the current and past 3-week volatility ($\mathrm{RV}_{t,w}$), as an additional control variable, significantly increases the next week's volatility.

Inventory is an important determinant of volatility in oil markets that 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

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

[26]Since the weekly RV time-series experiences numerous spikes which influence the estimated coefficients in the OLS estimation, 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 using OLS and carry out a residual analysis to 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 their 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.

TABLE 2 Impact of hedging pressure measures on weekly oil volatility.

	(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)
$\beta_{\mathrm{RV}^*_{0,w}}$	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)
Adjusted R^2	0.513	0.476	0.400	0.497	0.518	0.485	0.417	0.504
AIC	−1249	−1190	−1079	−1222	−1261	−1206	−1105	−1235

Note: This table reports the estimation results for eight model specifications of the following regressions:

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

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

where $\mathrm{RV}_{t+1,w}$ is the weekly realized variance (RV) of crude oil returns, $\mathrm{HP}_{t,w}$ represents the three measures of hedging pressure, namely, HP, smoothed hedging pressure (SHP), and net trading (NT), $\mathrm{Inv}_{t,w}$ represents inventory, $\sum_{k=0}^{k=3}\mathrm{RV}_{t-k,d}$ represents an autoregressive process of order 4 for RV, $\beta_{\mathrm{RV}^*_{0,w}}$ is the joint influence of current (week t) and past volatility (weeks $t-1$, $t-2$, and $t-3$) on next week's volatility (see footnote 17), and the order selection criteria is based on Aikaike's information criterion (AIC). 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.

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 (Haugom et al., 2014; Kogan et al., 2009; 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 liquidity provision in determining volatility while controlling for inventories (in the four above-mentioned models). Table 2 presents the estimation results of these regressions and confirms that growth in inventory levels increases oil price volatility (see Models 5–8). This is because inventory supply becomes inelastic when there is an inventory accumulation (Nikitopoulos et al., 2017). The statistical significance of the other predictors (including HP, SHP, and NT) of weekly volatility is not affected by the inclusion of inventory.

4.2 | Asymmetric effects and liquidity provision

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 effect.[27] In commodity

[27]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 an increase in volatility induces a decrease in returns. A behavioral explanation for the

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 investment commodities, such as gold.[28] However, recent empirical studies in oil markets have revealed an asymmetric volatility effect that could be attributed to risk and information sharing between commodity markets and other financial markets following the financialization of commodity markets (Baur & Dimpfl, 2018; Chiarella et al., 2016). Hence, we revisit the effects of oil price returns on volatility and investigate the role of the conditional impact of (positive or negative) returns in determining the effects of HP channels on volatility. We refer to rising (falling) futures markets when markets exhibit positive (negative) futures returns.

In rising markets, as short hedgers are not as concerned by oil price upturns, they may unwind some of their hedging positions (HP drops). Furthermore, short hedgers incur losses and long speculators generate gains. Speculators, as contrarian traders, would decrease their trading positions and volatility. Thus, in rising markets, liquidity provision by speculators and volatility would be positively associated. Conversely, in falling markets, hedgers make gains. Speculators, on the other hand, suffer losses, that would increase volatility as they increase their trading positions. Therefore, liquidity provision by speculators and volatility would be negatively related in falling markets. Hedgers may act as liquidity providers in the short run. In rising markets, oil hedgers are keen to provide liquidity (as they do not face any immediate price risk). By decreasing their net short positions, they earn comparatively lower returns. As they are now trading as contrarians, they increase their trading positions, consequently increasing volatility. Thus, in rising markets, liquidity provision by hedgers and volatility tend to be negatively related. In falling markets, hedgers are not eager to provide liquidity to speculators. Therefore, liquidity provision by hedgers should not have significant effects on volatility.

We investigate the validity of these arguments by considering the conditional impact of positive and negative returns on HP, SHP, and NT, and how this impact influences weekly volatility. We add positive and negative returns ($r_w^- = r_{t,w} I_{(r_{t,w}<0)}$ and $r_w^+ = r_{t,w} I_{(r_{t,w}>0)}$) to the model's specifications to account for their heterogeneous effect on volatility.[29] Table 3 summarizes these results.

We find that the asymmetric volatility effect is statistically significant in oil markets, where negative returns tend to increase weekly volatility, while positive returns tend to decrease it (see rows 25 and 27 in Table 3). This confirms the notion that following the financialization of commodity markets, volatility spillovers between financial markets and oil markets are strong, and thus, these markets share elements, such as the asymmetric volatility effect (Baur & Dimpfl, 2018; Chiarella et al., 2016; Kang, Nikitopoulos, et al., 2020). Furthermore we confirm that liquidity provision by speculators is linked to a statistically significant increase in volatility in rising markets (see row 13 of Model 2), but a statistically significant decrease in volatility in falling markets (see row 11 of Model 2). However, the aggregate effect of liquidity provision by speculators on weekly oil volatility is negative, as predicted in Section 4.1, with the reduction in volatility being more substantial in falling markets.[30] Even though, in rising market conditions, short-term liquidity provision by hedgers decreases volatility (see row 19 of Model 3), the aggregate effect of liquidity provision by hedgers on volatility is positive.[31] As expected, in falling markets, liquidity provision by hedgers does not have a significant effect on volatility (see row 17 of Model 3).

Model (4) further confirms these effects. We also verify (again) that inventory (as a key control variable) is positively related to oil volatility. Finally, we consider the impact of HP on weekly oil volatility, conditioned on rising and

positive relationship between return shocks and volatility is that individuals (investors) perceive positive returns and low-risk investments as good investments (particularly for safe-haven commodities, such as gold) (Hibbert et al., 2008).

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

[29]For example, the impact of the HP on weekly volatility, conditioned on positive and negative returns, is assessed by the regression

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

Similar regressions apply for SHP and NT.

[30]For example, by conditioning the SHP on a rising state of oil markets, its effect on future volatility is estimated as $\beta_{\mathrm{SHP}_w} + \beta_{\mathrm{SHP}_w r_w^+} \times r_{t,d}^+$ $(-0.690 + 0.142 = -0.548)$ (for an increase of 1% in positive returns). Conditioned on a falling state of oil markets, the reduction in volatility would be more substantial $(-0.690 - 0.184 = -0.874)$.

[31]The effect of NT on future volatility is estimated as $\beta_{\mathrm{NT}_w} + \beta_{\mathrm{NT}_w r_w^-} \times r_{t,d}^+$ $(0.660 + (-0.166))$ for a 1% increase in positive returns.

TABLE 3 Impact of hedging pressure measures on weekly oil volatility and asymmetric effects.

	(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)			
$\beta_{\mathrm{HP}_w r_w^-}$	−0.138***			
	(−4.393)			
$\beta_{\mathrm{HP}_w r_w^+}$	0.143***			
	(7.815)			
β_{SHP_w}		−0.690***		−0.657***
		(−8.276)		(−8.137)
$\beta_{\mathrm{SHP}_w r_w^-}$		−0.184***		−0.161***
		(−5.780)		(−5.472)
$\beta_{\mathrm{SHP}_w r_w^+}$		0.142***		0.132***
		(6.543)		(6.452)
β_{NT_w}			0.660**	0.665**
			(2.380)	(2.103)
$\beta_{\mathrm{NT}_w r_w^-}$			−0.119	−0.322*
			(−1.299)	(−1.889)
$\beta_{\mathrm{NT}_w r_w^+}$			−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)
$\beta_{\mathrm{RV}^*_{0,w}}$	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)
Adjusted R^2	0.445	0.407	0.249	0.418
AIC	−1058	−988	−843	−1019

Note: This table reports the estimation results of the following regressions:

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

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

where $\mathrm{RV}_{t+1,w}$ is the weekly realized variance (RV) of crude oil returns, $\mathrm{HP}_{t,w}$ represents the three measures of hedging pressure, namely, HP, smoothed hedging pressure (SHP), and net trading (NT), $\mathrm{Inv}_{t,w}$ represents inventory, $\sum_{k=0}^{k=3}\mathrm{RV}_{t-k,d}$ represents an autoregressive process of order 4 for RV, $\beta_{\mathrm{RV}^*_{0,w}}$ is the joint influence of current (week t) and past volatility (weeks $t-1$, $t-2$, and $t-3$) on next week's volatility (see footnote 17), r_w^- represents the negative returns, r_w^+ represents the positive returns, and the order selection criteria is based on Aikaike's information criterion (AIC). 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.

declining market states (see Model 1 in Table 3). We find that HP increases volatility by 14.3% in rising markets, however decreases volatility by 13.8% in falling markets. Yet, the aggregate impact of HP on volatility is negative, confirming again the predictions in Section 4.1.

Overall, we conclude that the long-term and the short-term components of HP have opposite effects on weekly oil volatility, independent of the asymmetric effects of the oil market and its corresponding states (rising or falling). Speculators tend to provide liquidity in both rising and falling oil markets. However, hedgers tend to engage in short-term liquidity provision trading only in rising oil markets, potentially because they are not as concerned about managing price risks in bull markets.

5 | HP AND THE SHAPE OF THE FUTURES CURVE

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

The HP hypothesis by Hirshleifer (1990) underscores the importance of the shape of the futures curve in determining the demand for hedging. A downward-sloping futures curve, known as backwardation, represents inverted markets and is associated with an increase in HP, while an upward-sloping futures curve, known as contango, represents normal markets and is associated with a decrease in HP.[32] 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 oil market conditions on the relationship between HP channels and volatility, we incorporate positive and negative futures IASs in the regressions.[33] Tables 4 and 5 present the results in inverted markets and normal markets, respectively. Our findings suggest 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 Nikitopoulos et al. (2017), which demonstrate that positive and negative futures spreads induce higher oil volatility. A 1% increase in the negative and positive futures spreads could increase volatility by up to 50% (see row 15 in Tables 4 and 5). This effect is more pronounced in inverted oil markets, while in normal oil markets, it is statistically significant only when the liquidity provision of hedgers is incorporated into the model (see Model 3 of Table 5). This underscores the importance of the liquidity provision channel of hedgers and sheds further light on the V-shaped relationship between volatility and futures spreads, in particular in normal oil markets. The relationship between HP channels and volatility in inverted and normal oil markets is discussed next.

5.1 | Inverted markets

Inverted markets are associated with an expectation of price appreciation.[34] Hedgers, behaving as insurance seekers in the long run, increase their short positions (increasing HP) and earn negative returns reflecting the insurance premium for price protection. 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, in inverted markets,

[32]In inverted markets, net short oil producers seek price insurance, which subsequently increases HP and induces net long speculators to provide liquidity. Note that inverted markets are a bullish sign in oil markets. Conversely, in normal markets, net long oil consumers seek price insurance, which subsequently decreases HP 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.

[33]The positive and negative futures spreads ($IAS12_w^+$ 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 spreads interact with HP channels to measure their joint effect on future volatility. Liquidity provision by speculators conditioned on negative and positive futures spreads is given by $SHP_wIAS12_w^-$ and $SHP_wIAS12_w^+$. Liquidity provision by hedgers conditioned on negative and positive futures spreads is given by $NT_wIAS12_w^-$ and $NT_wIAS12_w^+$.

[34]Short position holders are expected to generate negative returns while long position holders are likely to earn positive returns.

TABLE 4 Impact of hedging pressure measures on weekly oil volatility 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)			
$\beta_{\mathrm{HP}_w \mathrm{IAS12}_w^-}$	−0.205***			
	(−3.513)			
β_{SHP_w}		−0.287***		−0.284***
		(−4.843)		(−5.267)
$\beta_{\mathrm{SHP}_w \mathrm{IAS12}_w^-}$		−0.188**		−0.175**
		(−2.687)		(−2.764)
β_{NT_w}			0.839***	0.846***
			(3.454)	(4.051)
$\beta_{\mathrm{NT}_w \mathrm{IAS12}_w^-}$			0.062**	0.046**
			(2.578)	(2.345)
$\beta_{\mathrm{IAS12}_w^-}$	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)
$\beta_{\mathrm{RV}_{0,w}^*}$	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)
Adjusted R^2	0.506	0.464	0.344	0.477
AIC	−1236	−1156	−956	−1184

Note: This table reports the estimation results of the following regressions:

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

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

where $\mathrm{RV}_{t+1,w}$ is the weekly realized variance (RV) of crude oil returns, $\mathrm{HP}_{t,w}$ represents the three measures of hedging pressure, namely, HP, smoothed hedging pressure (SHP), and net trading (NT), $\mathrm{Inv}_{t,w}$ represents inventory, $\sum_{k=0}^{k=3}\mathrm{RV}_{t-k,d}$ represents an autoregressive process of order 4 for RV, $\beta_{\mathrm{RV}_{0,w}^*}$ is the joint influence of current (week t) and past volatility (weeks $t-1$, $t-2$, and $t-3$) on next week's volatility (see footnote 17), r_w^- represents the negative returns, r_w^+ represents the positive returns, $\mathrm{IAS12}_{t,w}^-$ is the negative interest-adjusted spread which represents an inverted market, and the order selection criteria is based on Aikaike's information criterion (AIC). 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 5 Impact of hedging pressure measures on weekly oil volatility 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)			
$\beta_{\text{HP}_w\text{IAS12}_w^+}$	0.128**			
	(2.089)			
β_{SHP_w}		−0.306***		−0.298***
		(−5.241)		(−5.632)
$\beta_{\text{SHP}_w\text{IAS12}_w^+}$		0.193**		0.169**
		(2.416)		(2.206)
β_{NT_w}			0.523**	0.542***
			(2.406)	(3.187)
$\beta_{\text{NT}_w\text{IAS12}_w^+}$			0.049	0.053
			(1.388)	(1.585)
$\beta_{\text{IAS12}_w^+}$	−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)
$\beta_{\text{RV}_{0,w}^*}$	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)
Adjusted R^2	0.491	0.425	0.266	0.443
AIC	−1212	−1098	−868	−1128

Note: This table reports the estimation results of the following regressions:

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

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

where $\text{RV}_{t+1,w}$ is the weekly realized variance (RV) of crude oil returns, $\text{HP}_{t,w}$ represents the three measures of hedging pressure, namely, HP, smoothed hedging pressure (SHP), and net trading (NT), $\text{Inv}_{t,w}$ represents inventory, $\sum_{k=0}^{k=3}\text{RV}_{t-k,d}$ represents an autoregressive process of order 4 for RV, $\beta_{\text{RV}_{0,w}^*}$ is the joint influence of current (week t) and past volatility (weeks $t-1$, $t-2$, and $t-3$) on next week's volatility (see footnote 17), r_w^- represents the negative returns, r_w^+ represents the positive returns, $\text{IAS12}_{t,w}^+$ is the positive interest-adjusted spread which represents a normal market, and the order selection criteria is based on Aikaike's information criterion (AIC). 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.

speculators' liquidity provision negatively impacts oil volatility (an increase in HP decreases volatility). The prospect of rising oil prices impacts hedgers differently in the short term. As they increase their long positions (decreasing HP) to provide liquidity to speculators, they earn higher (positive) returns. Because they are now the contrarian traders, they are more likely to decrease their trading positions, which lowers volatility. Thus, hedgers' short-term liquidity provision positively impacts oil volatility (a decrease in HP lowers oil volatility).

We find that when oil markets are inverted, an increase in SHP leads to a decrease in volatility, while an increase in NT increases volatility (see Table 4). 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 SHP by 1% decreases future volatility by 47.5%.[35] From Model (3), we conclude that an increase in NT would increase volatility by 90.1%.[36] Accordingly, short-term liquidity provision by hedgers has a three-fold stronger effect on future volatility, which further underlines the importance of the liquidity channel of hedgers in determining weekly volatility in inverted markets.

Model (1) reports the combined effect that HP has on determining volatility. The overall effect of HP on future volatility is negative in inverted markets and decreases weekly oil 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 with Models (2) and (3), we confirm that these two effects are distinct and capture the different components of the HP. Other predictors of volatility, including past volatility, returns, and inventory, behave as expected in the four models reported in Table 4.

These results highlight the importance of the HP channels in determining future volatility. In inverted markets, the long-term component of HP tends to dominate and to negatively impact weekly oil volatility. However, the short-term component of HP has a statistically significant and positive effect on volatility, which has been previously neglected by the literature.

5.2 | Normal markets

Normal markets are linked to a bearish market view.[37] 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. Accordingly, in normal markets, speculators' liquidity provision positively impacts oil volatility (a decrease in HP decreases volatility). In the short run, hedgers become the liquidity providers, increase their short positions (increasing HP), and earn positive returns. While they provide liquidity to speculators, they reduce their trading position (trading as contrarians). This reduces volatility. Therefore, in normal markets, hedgers' liquidity provision should negatively affect oil volatility (an increase in HP decreases volatility).

Model (2) in Table 5 confirms that in normal markets, even though SHP is positively associated with volatility, when conditioned on positive futures spreads (see line 9 of Table 5), the net effect of liquidity provision by speculators on oil volatility is negative.[38] Conditioned on positive futures spreads, the NT has no significant influence on volatility (line 13 of Model 3), however, the net effect of liquidity provision by hedgers is positively associated with oil volatility, as predicted in Section 4.1.[39] Thus, liquidity provision by hedgers also plays an important role in determining volatility, although the impact on volatility is less pronounced in normal markets than in inverted ones.

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

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

[37]In a bearish market, short position holders are expected to earn positive returns while long position holders generate negative returns.

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

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

Consistent with the baseline analysis in Section 4.1, the combined HP is negatively associated with oil volatility in normal markets (see Model 1 in Table 5). Model (4) further validates the measurable impact of the two HP channels on oil volatility.[40]

Depending on the shape of the oil futures curve, the two HP components affects weekly oil volatility differently. In inverted markets, long-term HP reduces weekly volatility, while short-term HP is related to a significant increase in volatility. In normal markets, the two HP channels make a moderate contribution in determining weekly volatility.

6 | THE IMPACT OF MACROECONOMIC CONDITIONS

In this section, we determine whether the HP channels are affected by macroeconomic conditions. We specifically gauge the sensitivity of the impact of the HP channels on weekly oil volatility under different environments of financial market and business-cycle risks.

Nagel (2012) and Kang, Rouwenhorst et al. (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 HP channels under high and low financial market risk environments. External (macroeconomic) shocks to the market can be perceived as either negative or positive news, and they are likely to influence the risk appetite of hedgers and speculators. We argue that these conditions incentivize them either to hold back or to provide liquidity in the market, while business-cycle shocks are likely to influence the demand for hedging via liquidity provision by speculators. Negative business-cycle changes indicate weakening macroeconomic conditions, and positive changes signal stable to growing macroeconomic conditions.

6.1 | 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) and Kang, Nikitopoulos et al. (2020) demonstrate that financial risks (measured by the VIX) significantly impact oil markets and, specifically, financial risk is positively associated with volatility in oil markets. The financialization of the commodity market was found to be a contributing factor affecting 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. To gauge such effects, we represent a *high* financial market risk environment by a positive change in the VIX that is above its sample median, and a *low* financial market risk environment by a negative shock in the VIX that is below its sample median (in a given week), denoted as VIX_w^+ and VIX_w^-, respectively.

The results presented in Table 6 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) and Kang, Nikitopoulos et al. (2020) (see row 15 in Models 5–8). However, in high financial risk environments, this relationship breaks down, potentially due to the idiosyncratic nature of the shocks driving this extreme risk (or volatility) (see row 15 in Models 1–4). We thus find evidence that the integration between equity and oil markets is stronger in low financial risk environments.

Long-term liquidity provision by speculators may be affected by financial market risk conditions in the following ways. High financial risk conditions make speculators reluctant to provide liquidity, while low financial risk conditions make speculators more eager to act as liquidity providers. In a high-market-risk environment, speculators, as liquidity providers, are not very keen to provide liquidity so may earn comparatively lower returns. However as contrarians, would increase their trading positions, inducing an increase in volatility. This (conditional on high market risk) positive relationship between SHP and weekly oil volatility is statistically significant, as shown in row 9 of Model (2) in Table 7. Otherwise, in a 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. The statistically

[40]We also consider the regressions, including both inverted and normal markets specifications. These investigations give similar results and they are available upon request.

TABLE 6 Impact of hedging pressure measures on oil weekly volatility and financial market risk.

	***High* financial market risk**					***Low* financial market 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)			
$\beta_{\mathrm{HP}_w\mathrm{VIX}_w^+}$	0.048				$\beta_{\mathrm{HP}_w\mathrm{VIX}_w^-}$	−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)
$\beta_{\mathrm{SHP}_w\mathrm{VIX}_w^+}$		0.077*		0.083*	$\beta_{\mathrm{SHP}_w\mathrm{VIX}_w^-}$		−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)
$\beta_{\mathrm{NT}_w\mathrm{VIX}_w^+}$			0.032	0.026	$\beta_{\mathrm{NT}_w\mathrm{VIX}_w^-}$			0.019**	0.024**
			(1.478)	(1.226)				(2.505)	(2.090)
$\beta_{\mathrm{VIX}_w^+}$	−0.050	−0.103	0.032	−0.103	$\beta_{\mathrm{VIX}_w^-}$	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)
$\beta_{\mathrm{RV}^*_{0,w}}$	0.684***	0.710***	0.670***	0.711***	$\beta_{\mathrm{RV}^*_{0,w}}$	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)
Adjusted R^2	0.502	0.449	0.239	0.475	Adjusted R^2	0.544	0.513	0.342	0.531
AIC	−1223	−1138	−819	−1173	AIC	−1309	−1258	−983	−1286

Note: This table reports the impact of the hedging pressure measures on oil weekly volatility in a high financial market risk environment (left panel) and in a low financial market risk environment (right panel). VIX_w^+ represents a negative shock in the VIX that is below its sample median, VIX_w^- represents a positive shock in the VIX that is above its sample median (in that week). The other parameters represent the coefficients of same type of variables as discussed in Tables 3–6. The order selection criteria is based on Aikaike's information criterion (AIC). 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.

Abbreviations: HP, hedging pressure; Inv, inventory; NT, net trading; SHP, smoothed hedging pressure; VIX, volatility index.

significant negative coefficient of row 9 of Model (6) in Table 7 provides evidence of this negative association between SHP and weekly oil volatility in low-market-risk conditions. Therefore, HP channels may impact volatility differently under different levels of financial risk.[41]

[41] This justifies the model specifications including additional explanatory variables that capture the impact of liquidity provision by speculators on volatility, conditioned on negative and positive financial shocks ($\mathrm{SHP}_{t,w}\mathrm{VIX}_w^+$ and $\mathrm{SHP}_{t,w}\mathrm{VIX}_w^-$).

TABLE 7 Impact of hedging pressure measures on oil weekly volatility and business-cycle risk.

	Low **business-cycle risk**					***High*** **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)			
$\beta_{\mathrm{HP}_w\mathrm{TS}_w^+}$	0.049**				$\beta_{\mathrm{HP}_w\mathrm{TS}_w^-}$	−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)
$\beta_{\mathrm{SHP}_w\mathrm{TS}_w^+}$		0.039**		0.040**	$\beta_{\mathrm{SHP}_w\mathrm{TS}_w^-}$		−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)
$\beta_{\mathrm{NT}_w\mathrm{TS}_w^+}$			−0.131	−0.147*	$\beta_{\mathrm{NT}_w\mathrm{TS}_w^-}$			0.086	0.051
			(−1.467)	(−1.714)				(0.717)	(0.457)
$\beta_{\mathrm{TS}_w^+}$	−0.117***	−0.094***	−0.036***	−0.097***	$\beta_{\mathrm{TS}_w^-}$	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)
$\beta_{\mathrm{RV}_{0,w}^*}$	0.746***	0.772***	0.733***	0.770***	$\beta_{\mathrm{RV}_{0,w}^*}$	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)
Adjusted R^2	0.547	0.517	0.342	0.538	Adjusted R^2	0.515	0.482	0.260	0.512
AIC	−1318	−1271	−986	−1303	AIC	−1253	−1203	−854	−1241

Note: This table reports the impact of the hedging pressure measures on oil weekly volatility in a low business-cycle risk environment (left panel) and in a high business-cycle risk environment (right panel). TS_w^+ represents a positive shock in term spreads (between 10-year and 3-month Treasury bond constant maturity rates) that is above its sample median, and TS_w^- represents a negative shock in term spread that is below its sample median (in that week). The other parameters represent the coefficients of the same type of variables as discussed in Tables 3–6. The order selection criteria are based on Aikaike's information criterion (AIC). 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.

Abbreviations: HP, hedging pressure; Inv, inventory; NT, net trading; RV, realized variance; SHP, smoothed hedging pressure.

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, while low financial risk may present an incentive for hedgers to provide liquidity. We argue that in low-market-risk conditions, hedgers increase their long positions (i.e., HP drops). They are likely to earn comparatively higher returns for providing liquidity. Since they are trading as contrarians, they will decrease their trade positions and thus, volatility. In low financial risk environments, the positive relationship between NT and weekly oil volatility is statistically significant, as shown in row

13 of Model (7) in Table 7. 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 (see row 13 of Table 7). Hedgers are risk-averse, after all. Therefore, we find empirical evidence that short-term liquidity provision by hedgers typically emerges in low financial risk conditions.[42]

However, when assessing the aggregate effect of liquidity provision, independent of the level of market risk (high or low financial risk conditions), liquidity provision by speculators is negatively associated with volatility (see Models 2 and 6 in Table 6, respectively). In high-market-risk conditions, SHP reduces volatility by 19.5%,[43] while in low-market-risk conditions, it reduces volatility by 26.7%.[44] 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 rather than high-risk environments.

As predicted by theory, the short-term "'aggregate" liquidity provision by hedgers is positively associated with volatility in both high and low financial risk conditions (see Models 3 and 7 in Table 6, respectively). However, NT increases volatility substantially in low-market-risk conditions (83.7%)[45] compared with the increase induced in high-market-risk conditions. Hedgers tend to be willing to provide liquidity only in low-risk environments and are reluctant to do so in high-risk environments, 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 6 reveal that HP has a negative (overall) effect on volatility, in line with theoretical predictions, independent of the level of market risk. However, HP 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 (e.g., 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-market-risk conditions, while they are reluctant to do so in high-market-risk conditions.

6.2 | Business-cycle risk

Oil volatility may be affected by business-cycle risk (capturing short-term patterns in monetary policy) and financial uncertainty (Gao et al., 2022; Kang, Nikitopoulos, et al., 2020; Prokopczuk et al., 2019). Empirical evidence suggests that TS and oil volatility are negatively associated. Particularly since 2004, markets exhibit low TSs, which have been linked with high oil volatility. Furthermore, recessions can be explained and related to oil market shocks (Kilian & Vigfusson, 2017). A "normal" yield curve indicates a stronger future economy, and an inverted yield curve signals an impending recession (Bauer & Mertens, 2018; Estrella & Hardouvelis, 1991; Estrella & Mishkin, 1998; Wheelock & Wohar, 2009). Therefore, negative business-cycle shocks reflect weakening macroeconomic conditions as a negative slope of the TS implies that there is increasing investor' pessimism in the market. A positive business-cycle shock signifies stable/optimistic macroeconomic conditions and is likely to be interrelated with low volatility. To assess these effects, we represent a *low* business-cycle risk environment by a positive change in the TS that is above its sample median, and a *high* business-cycle risk environment by a negative shock in the TS that is below its sample median (in a given week), denoted as TS^{+}_{w} and TS^{-}_{w}, respectively. Recall that the business-cycle risk (represented by TS) is estimated as the difference between the 10-year and 3-month US Treasury bond constant maturity rates. Table 7 displays the impact of the HP measures on oil volatility in high- and low-business-cycle risk environments.

Models (1)–(4) in Table 7 reveal that positive business-cycle shocks significantly decrease oil volatility, in line with findings from the literature (e.g., see Kang, Nikitopoulos, et al., 2020). When the TS increases by 1%, future volatility

[42]The impact of liquidity provision by hedgers on volatility, conditioned on the negative and positive financial shocks, is given by $NT_{t,w}VIX^{+}_{w}$ and $NT_{t,w}VIX^{-}_{w}$.

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

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

[45]The net effect of NT 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.

decreases by approximately 9%–11% (see row 15). Negative business-cycle shocks, however, have no (statistically significant) impact on oil volatility.

We assert that business-cycle shocks impact liquidity provision by speculators differently. Negative business-cycle shocks signals recessions and high business-cycle risk. Short hedgers are not concerned about covering their positions in times of recession (typically falling market conditions), thus HP is expected to decrease under these circumstances. Speculators are not keen to provide liquidity in a high-risk environment, thus driving an increase in volatility.[46] Conversely, positive business shocks are indicative of a booming economy and low business-cycle risk, where speculators as willing contrarian liquidity providers would decrease their trading positions and volatility.[47] The results confirm that in a low business-cycle risk environment, SHP and oil volatility are positively associated (see row 9 of Model 2 in Table 7), while in a high business-cycle risk environment, SHP and volatility are negatively associated (see row 9 of Model 6). However, also as predicted in Section 4.1, the aggregate effect of SHP on oil's weekly volatility is a reduction in volatility, of 15% in a low business-cycle risk environment[48] and 26.2% in a high business-cycle risk environment.[49]

Business-cycle shocks also influence hedgers' willingness to provide liquidity in the short term. We argue that in a low business-cycle risk environment (boom cycle), hedgers would increase their HP (covering their physical positions), however, they would be keen to provide liquidity, and via contrarian trading, this would decrease their trading positions and volatility. Therefore, in a low business-cycle risk environment, NT and volatility would be negatively associated. In a high business-cycle risk environment (recession cycle), hedgers would be reluctant to engage in trading as liquidity providers in the short term, thus, the impact on volatility would be negligible.[50] Row 13 in Table 7 provides empirical evidence for these effects, which lack statistical significance. Most importantly, when we gauge the aggregate effect of NT on oil volatility, we find that NT increases oil's weekly volatility by 87.9% in a low business-cycle risk environment and by 60.9% in a high business-cycle risk environment (see Models 3 and 7, respectively).[51] Thus, even though a high business-cycle risk environment renders speculators and hedgers more reluctant to provide liquidity, independent of the business-cycle risk, HP driven by hedgers' insurance demands decrease oil volatility, while HP driven by speculators' short-term liquidity demands increases oil volatility.[52]

Overall, we find evidence that independent of the business-cycle risk, HP driven by hedgers' insurance demands and that of speculators' short-term liquidity demands have opposite effects on oil's weekly volatility, which empirically support our hypotheses. Further, the prospect of recessionary pressure renders speculators and hedgers reluctant to provide liquidity.

7 | ROBUSTNESS TESTS

We also consider several robustness tests to further confirm the validity of the results.

7.1 | Alternative short-term HP measures

For the main analysis we use an SHP defined as the trailing 26-week moving average of the net short positions of hedgers scaled by the weekly open interest. We also test longer (52-week) and shorter (13-week) trailing periods to

[46]Speculators would earn relatively lower returns, but their contrarian trading would increase trading positions and volatility.

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

[48]The net effect of SHP on oil volatility is estimated as $\beta_{\mathrm{SHP}_w} + \beta_{\mathrm{SHP}_w TS_w^+} \times \mathrm{SHP}_{t,w}\mathrm{TS}_{t,w}^+$ $(-0.189 + 0.039)$, assuming that there is a 1% rise in the positive business-cycle shocks.

[49]The net effect of SHP on oil volatility is estimated as $\beta_{\mathrm{SHP}_w} + \beta_{\mathrm{SHP}_w\mathrm{TS}_w^-} \times \mathrm{SHP}_{t,w}\mathrm{TS}_{t,w}^-$ $(-0.223 + (-0.039))$, assuming that there is a 1% rise in the negative business-cycle shocks.

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

[51]The net effect of NT on future volatility is estimated as $\beta_{\mathrm{NT}_w} + \beta_{\mathrm{NT}_w\mathrm{TS}_w^-} \times \mathrm{NT}_{t,w}\mathrm{TS}_{t,w}^-$ $(0.793 + 0.086)$, assuming that there is a 1% rise in the negative business-cycle shocks. Similarly, the net effect of NT on future volatility is estimated as $\beta_{\mathrm{NT}_w} + \beta_{\mathrm{NT}_w\mathrm{TS}_w^+} \times \mathrm{NT}_{t,w}\mathrm{TS}_{t,w}^+$ $(0.740 + (-0.131))$, assuming that there is a 1% rise in the positive business-cycle shocks.

[52]Models (1), (4), (5), and (8) in Table 7 further confirm the validity of these effects.

estimate the moving average of hedgers' net short positions (SHP). This allows us to determine whether alternative trailing periods affect the relationship between SHP and future volatility. These results are summarized in Supporting Information Appendix B. We find that longer and shorter trailing periods do not affect the statistical significance of SHP, NT, and their combined impact on volatility.

7.2 | Alternative measures for the shape of the futures curve

The extend of the backwardation in oil markets, determining the shape of the futures curve, is captured by the futures IASs, which we compute based on 3, 6, and 12 months maturities, see Section 3.4 for computational details. IASs with different maturities can have varying effects on volatility (Nikitopoulos et al., 2017). Using a 12-month futures IAS in this analysis, we find that the liquidity provision by hedgers and speculators impacts weekly oil volatility differently, in normal and inverted markets, with the effects being more pronounced in inverted markets, see Section 5. Thus we also test the sensitivity of these results using futures IASs of shorter maturities (3 and 6 months). The results are presented in Supporting Information Appendix C and we find quantitatively similar results.

7.3 | Alternative measure of weekly volatility

We also estimate a first order moving average (MA(1)) model of the 5-min return series and extract the model residuals for each day. This procedure removes the serial correlation induced by the uneven spacing of observed prices and bid–ask spread (Andersen et al., 2001; Thomakos & Wang, 2003; Wang et al., 2008). After re-estimating the models, we find quantitatively similar results that are presented in Supporting Information Appendix D.

8 | CONCLUSION

This study gauges the role of HP in determining weekly oil volatility and establishes that the short-term component of HP driven by the liquidity demands of speculators has an opposite effect on volatility compared with the long-term component of HP driven by hedgers' insurance demands. We show that HP induced by speculators' short-term liquidity demands tends to increase volatility, while HP driven by the hedgers' long-term insurance demands reduces volatility. We further assess the strength of the effects of these HP channels on oil weekly volatility, conditional on asymmetric effects and under normal/inverted oil market conditions. The responsiveness of the HP channels to oil volatility is also investigated under low and high financial market and business-cycle risk environments. We find that these effects still hold under the different influences of oil-sector and macroeconomic conditions.

Several other interesting results emerged from this analysis. Oil volatility tends to be more sensitive to hedgers' short-term liquidity provision to meet speculators' demand for momentum trading than variations induced by hedgers' insurance demands. Further, speculators may provide liquidity in both rising and falling oil markets, but hedgers tend to engage in short-term liquidity provision only when the oil markets experience positive shocks. Even though, in inverted markets, HP from hedgers' insurance demands decreases volatility while HP driven from speculators' short-term liquidity demands is likely to increase volatility, the effects are opposite and less pronounced in normal markets. In addition, speculators and hedgers are more motivated to provide liquidity in low markets risk conditions than in high-market-risk conditions, which is reflected in a more substantial impact on volatility. Moreover, signals of recession render hedgers and speculators reluctant to provide liquidity.

By offering a novel perspective on the role of hedgers as liquidity providers in oil markets (beyond the speculators), we identify a new channel through which hedgers can influence oil volatility dynamics. To satisfy the demands of short-term momentum trading by speculators, hedgers may employ *selective* hedging practises[53] and offer liquidity to speculators. We provide empirical evidence that these practises may have a significant opposite impact on volatility compared with speculators' liquidity provision. These findings ascribe distinctive potential motives to speculative

[53]According to Fernandez-Perez et al. (2022), selective hedging that would minimize price risk while earn a premium, is not a recommended practise compared with traditional minimum-variance hedges.

trading and its impact on oil volatility. Further, HP channels are sensitive to oil-sector and macroeconomic factors, and may influence volatility differently. These findings offer informative insights of practical relevance to financial market participants, such as oil producers, commodity momentum and derivatives traders, financial advisors, and financial market modelers, by providing a comprehensive account of the role of hedgers and speculators in determining oil volatility.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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