Refining Crude Oil Uncertainty Using Corridor Variance Premia

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Abstract

The economic importance of oil price uncertainty varies over time and may be stronger when oil prices rise or decline. We capture this using corridor variance risk premia, which reflect the cost of insurance against oil return variation accrued while the price of oil is within a pre-specified range. Corridor variance risk premia associated with oil price declines reflect economic agents' concerns about the state of the economy and are strong predictors of macroeconomic growth, more so than standard proxies of oil uncertainty. Corridor variance risk premia associated with oil price increases are mostly related to financial market conditions and can significantly predict expected equity returns and the tightening of funding constraints faced by financial intermediaries.

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1 Introduction

It has been well-established that oil uncertainty, typically measured as the conditional variance of crude oil returns, has a negative impact on macroeconomic outcomes by suppressing investment and reducing consumption (Bernanke, 1983; Pindyck, 1991; Edelstein and Kilian, 2009; Elder and Serletis, 2010; Kellogg, 2014; Jo, 2014; Gao, Hitzemann, Shaliastovich, and Xu, 2022). Recent evidence also suggests a tighter link with financial markets than previously thought, as it appears to be an important state variable (Chiang, Hughen, and Sagi, 2015; Christoffersen and Pan, 2018). However, the related literature has largely overlooked that the aversion of economic agents towards oil uncertainty will generally vary over time and may be stronger when the price of oil is above or below certain price thresholds.

In this paper, we attempt to capture these effects by studying the premia that economic agents are willing to pay to insure against future oil price variation. Our work builds on the *variance risk premium* measure of Carr and Wu (2009), which is tantamount to the expected payoff from investing in a security that pays off future realized oil variance and reveals the premium that economic agents are willing to pay to insure against oil uncertainty.[1] Expanding on this, we explore the concept of corridor variance (Andersen, Bondarenko, and Gonzalez-Perez, 2015), defined as the return variation accrued only when the price of oil is within a pre-specified range (i.e., the "corridor"), to capture oil uncertainty associated with different oil price thresholds. This allows us to examine *corridor variance risk premia*, which reveal the premium that economic agents are willing to pay to insure against future oil corridor realized variance.

We estimate corridor variance risk premia using expected corridor variances, generated by time-series models, and corridor variance swaps (Carr and Lewis, 2004), obtained through the market prices of crude oil options. We consider various corridor ranges, estimated *ex ante* using fixed percentiles of the conditional crude oil monthly return distribution.[2] Among other things, our results reveal that corridor variance risk premia associated with oil price declines ("downside oil uncertainty risk premia") are linked to both macroeconomic and financial conditions, while corridor variance risk premia associated with oil price increases

[1]Commencing with Bollerslev, Tauchen, and Zhou (2009) the variance risk premium has been found to predict the expected returns of equities (Drechsler and Yaron, 2011; Bekaert, Hoerova, and Duca, 2013; Bollerslev, Marrone, Xu, and Zhou, 2014) and currencies (Della Corte, Ramadorai, and Sarno, 2016; Londono and Zhou, 2017). In other applications, the equity variance risk premium has emerged as a prominent predictor of credit spreads (Wang, Zhou, and Zhou, 2013) and future bank lending conditions (Wu and Suardi, 2021).

[2]Special corridor ranges correspond to the full variance risk premium as well as the downside and upside variance risk premia measures. The latter two capture the cost of insurance against downside and upside corridor realized variances, defined as return variation accrued when the price of oil is below and above the expected futures oil price at the beginning of the month, respectively.

("upside oil uncertainty risk premia") appear mostly related to financial markets. Notably, we show that oil variance risk premia ("oil uncertainty risk premia"), especially those related to downside measures, are better predictors of macroeconomic growth than expected oil price variance ("oil uncertainty"). One the other hand, upside oil uncertainty risk premia are significant predictors of future equity returns, unlike their full or downside counterparts.

The reason that oil variance risk premia can better track the economic relevance of oil uncertainty is that the latter has a rather complicated relationship with the macroeconomy and financial markets. First, oil price uncertainty encapsulates uncertainty about both demand and supply shocks, with each component varying across time and having a disparate impact on macroeconomic outcomes (Kilian, 2009; Baumeister and Hamilton, 2019) and financial markets (Kilian and Park, 2009; Ready, 2018).[3] Second, as shown in Basak and Pavlova (2016) and Cheng, Kirilenko, and Xiong (2015), financial market flows have emerged as an additional source of variation, altering the dynamics of oil prices and affecting both their variance and correlation with financial markets. Third, as noted in Jurado, Ludvigson, and Ng (2015), the effect of uncertainty can propagate simultaneously via multiple channels ("real options", "precautionary savings", or "financial frictions"), so oil uncertainty may manifest in different ways to the various sectors of the economy and corners of financial markets. All in all, it can be challenging to capture the economy's sensitivity to oil price uncertainty, whether using a complex structural model or by simply relying on expected oil variance as a proxy. On the contrary, times of heightened aversion towards oil uncertainty will manifest in elevated variance risk premia, regardless of the potential source of shock or transmission channel that economic agents are particularly concerned about.

Our analysis takes note of some limitations of symmetric oil volatility measures. Alquist, Kilian, and Vigfusson (2013) highlight that, because economic agents' loss functions are generally asymmetric and vary across different users (e.g., oil consumers versus oil producers, durable versus non-durable industries), oil volatility may not fully reflect the economic importance of oil uncertainty, as it fails to capture different levels of aversion to upside and downside oil price risks. Mork (1989), Hamilton (1996) and Hamilton (2003) argue that an oil price shock might need to exceed a certain threshold to generate a significant economic response, so distinguishing between variances above or below certain price levels might also be necessary. Segal, Shaliastovich, and Yaron (2015) decompose macroeconomic uncertainty into "bad" and "good" volatility components, defined as the variance of negative and positive

[3] Baumeister and Peersman (2013a) empirically investigate how the evolution of crude oil price volatility can be attributed to changes in the individual variances of supply and demand shocks as well as their corresponding price elasticities, while Baumeister and Peersman (2013b) show that as the composition between structural oil supply and demand shocks evolves, so does their dynamic correlation with the price of oil and the economy.

innovations of macroeconomic growth respectively, and find that "bad" volatility predicts a decline in economic growth and asset prices, while the opposite is true for "good" volatility. Along the same lines, high oil variance will not always directly translate to a pessimistic economic outlook. Christoffersen, Jacobs, and Pan (2022) show that while investors dislike both large positive and large negative oil price shocks, their respective risk premia appear to be driven by different factors. Such an effect could generate asymmetric oil volatility preferences across time.[4] Similarly, the results of Ready (2018) imply that economic agents might have a stronger aversion to volatility associated with negative oil demand shocks compared to that generated by positive oil demand shocks, while the converse should be true for volatility driven by oil supply shocks.[5] The empirical importance of asymmetric oil volatility measures for the economy and financial markets can be revealed by examining corridor variance risk premia.

Our first contribution is documenting the empirical properties of corridor oil uncertainty measures, captured by expected corridor variances and associated corridor variance risk premia. To the best of our knowledge, this is the first paper that provides a comprehensive analysis of these measures for either crude oil or other assets. Expected corridor variances for equities have been defined and discussed, but not empirically explored, in Andersen et al. (2015). With respect to corridor variance risk-premia, the papers closest to ours are those of Feunou, Jahan-Parvar, and Okou (2018), Kilic and Shaliastovich (2019) and Londono and Xu (2019), who decompose variance risk-premia into upside and downside components. However, these authors base their calculations on expected semi-variances rather than expected corridor variances as theory instructs.[6] Moreover, our analysis goes beyond upside and downside variance risk premia, as we also look at variance premia associated with more extreme price shocks. It is also worth noting that the aforementioned papers focus on the case of equity indices rather than crude oil. Regarding the latter, variance risk premia are examined by Trolle and Schwartz (2010) and Prokopczuk, Symeonidis, and Simen (2017), but are not decomposed into separate components.

Along these lines, we empirically investigate the interactions of the various oil corridor

[4] Asymmetric volatility preferences have been explored for the case of equities, where downside risk measures are needed to capture investors' stronger aversion to volatility associated with negative, rather than positive, returns. Such measures, including semi-variances, semi-betas and semi-covariances, have been empirically successful in practice, see Bollerslev (2022) for a recent review.

[5] For instance, Alquist et al. (2013) note that "in 1986 oil price volatility increased as OPEC collapsed and the price of oil dropped sharply, whereas by all accounts consumers were pleased with lower oil prices and the diminished risk of an OPEC-induced supply disruption."

[6] Feunou et al. (2018), Kilic and Shaliastovich (2019) and Londono and Xu (2019) estimate downside (upside) variance risk premia as the difference between expected risk-neutral downside (upside) corridor variances and expected real-world negative (positive) semi-variances. The latter is defined as the expected variance on negative (positive) returns. We elaborate further on this point in Section 2.4.

measures with the general economic environment. Our analysis provides a number of novel insights. For example, we report that downside corridor variance risk premia are strongly counter-cyclical and significantly related to both macroeconomic and financial uncertainty, while upside measures appear to be predominantly driven by financial market fluctuations. We also examine the influence of speculators' and hedgers' trading flows on oil variance risk premia, extending the related literature that has until now exclusively focused on the impact of trading pressure on oil futures price risk premia (Acharya, Lochstoer, and Ramadorai, 2013; Li, 2018; Kang, Rouwenhorst, and Tang, 2020).[7] Interestingly, we document that speculative trading pressure increases full and downside (but not upside) corridor variance risk premia, while hedging pressure from commodity producers reduces upside (but not full or downside) corridor variance risk premia.

Second, this paper adds to the literature that investigates the relationship between oil uncertainty and macroeconomic growth, explored in the prominent studies of Bernanke (1983), Pindyck (1991), Elder and Serletis (2010), Jo (2014), and Gao et al. (2022), among others. However, we deviate from these studies by comparing the predictive power of oil uncertainty with that of oil uncertainty risk premia, as proxied by expected variances and variance risk premia, respectively. Additionally, we consider corridor variance risk premia measures to capture any potential asymmetries in the economy's sensitivity to oil uncertainty.

Our empirical design closely mirrors the study of Gao et al. (2022) who found that oil uncertainty, proxied by option-implied variance, has a strong predictive power over various macroeconomic growth aggregates.[8] Our study reveals that this result is driven by variation in risk premia associated with oil uncertainty, as captured by the oil variance risk premium, rather than oil uncertainty itself.[9] We also show that downside uncertainty risk premia are significantly better in forecasting macroeconomic growth compared to their full or upside counterparts. These results hold despite including proxies of financial and macroeconomic uncertainty as controls, indicating that oil variance risk premia do not merely reflect general levels of risk aversion in the economy. We explore the role that the precautionary oil inventories channel, suggested by Gao et al. (2022), might play in explaining our findings. While we confirm the presence of this channel, it appears to operate through oil uncertainty rather than uncertainty risk premia. Instead we argue that variation in uncertainty risk premia reflects concerns about oil price shocks originating from the aggregate oil demand channel

[7]One exception is the recent paper of Jacobs and Li (2023) who study, *inter alia*, the effect of trading activity on expected call option returns but do not find a significant relationship.

[8]The option-implied measure of Gao et al. (2022), which is akin to the "oil VIX" index (OVX) published by the CBOE, encapsulates both expected oil variance as well as the oil variance risk premium.

[9]It is plausible that the same mechanism explains why Kellogg (2014) finds that option-implied variance can predict future investment decisions while expected oil variance, captured by a GARCH model, cannot.

discussed in Kilian (2009).

Third, our paper contributes to the literature that investigates the relationship between oil variance risk and asset prices. Empirical evidence that oil variance risk is priced in financial markets has been provided by Doran and Ronn (2008), Trolle and Schwartz (2010), Prokopczuk and Simen (2014) and Prokopczuk et al. (2017), amongst others, who reported that the oil variance risk premium is significantly negative. Christoffersen and Pan (2018) use changes in option-implied variance as a proxy for variance risk, and show that their factor predicts excess aggregate market returns and explains variation in expected equity returns. They argue that this is because their factor contains information about shocks to the oil variance risk premium rather than oil variance itself. We also add to the literature that examines the relationship between upside and downside variance risk premia and expected returns, which has thus far exclusively focused on the case of equities (Feunou et al., 2018; Kilic and Shaliastovich, 2019; Londono and Xu, 2019).

Along these lines, this paper is the first to investigate the links between oil corridor variance risk premia and expected equity returns. Looking at the CRSP value-weighted index, as well as the 30 Fama-French industry portfolios as a robustness check, we find that the predictive power of the overall oil variance risk premium is weak. On the contrary, upside corridor variance risk premia significantly predict near term (monthly) excess equity returns. This result is particularly strong during the post financialization period of the oil market, appears consistent for both the aggregate US equity market and industry portfolios, and remains robust when we control for other popular expected return predictors, including the equity variance risk premium. We explore whether a financial frictions channel, which has emerged as an important determinant of equity returns (He and Krishnamurthy, 2013; Adrian, Etula, and Muir, 2014; He, Kelly, and Manela, 2017), can explain the source of this predictability. Indeed, we find that upside corridor variance risk premia are significant predictors of financial intermediaries' future funding constraints, more so than their downside counterparts. In other words, upside corridor variance risk premia can predict expected equity returns because they can forecast the tightening of funding conditions in financial markets.

The structure of the paper is as follows. Section 2 presents the definitions of our oil uncertainty and oil uncertainty risk premia measures. Section 3 discusses the estimation methodology we adopt. Section 4 describes the dataset. Section 5 contains our main empirical results on the interaction of our measures with the general economic environment, aggregate macroeconomic growth, and expected stock returns. Section 6 examines the robustness of our results. Section 7 concludes.

2 Uncertainty measures

In this section we provide an overview of the theoretical underpinnings behind our measures of oil price uncertainty and associated uncertainty risk premia. Many of the concepts discussed are well-known in the literature, but we present them here for the reader's convenience.

2.1 Oil price uncertainty

Our measure of *oil price uncertainty* is the expected variance of crude oil futures returns. While different notions of uncertainty exist, using return variance as a proxy is standard practice in literature (Bloom, 2009; Elder and Serletis, 2010; Kellogg, 2014; Jo, 2014; Gao et al., 2022). More precisely, we assume that the log futures price for a contract maturing at time T, $0 < t < T < T'$, is generated by the following stochastic process defined on the probability space $(\Omega, \mathcal{F}_t, \mathbb{P})$,

$$\frac{dF_t}{F_t} = \mu_t dt + \sigma_t dW_t \quad ,$$

where W_t is a Wiener process. The drift μ_t and volatility σ_t can change across time according to the filtration $\mathcal{F}_t$. There are very few restrictions on the stochastic process governing the volatility dynamics other than that σ_t must be strictly positive and càdlàg. The total variation of log futures price changes from $t = 0$ to T is then given by the quadratic variation (QV), defined as,

$$QV_{0,T} = \int_0^T \sigma_t^2 dt.$$

The quadratic variation is unobservable but can be estimated with a high degree of precision using realized variance (RV),

$$RV_{0,T} = \sum_{i=1}^{M} r_{t_i}^2,$$

where the interval $[0, T]$ is partitioned into $M+1$ equally spaced times t_i, $i = 0, 1, \ldots, M$, and r_{t_i} is the log futures return from time t_{i-1} to t_i. Formally, Barndorff-Nielsen and Shephard (2002) show that the probability limit of RV as M goes to infinity is equal to QV. This means that, theoretically, as the grid over which prices are observed becomes increasingly finer, $RV_{0,T}$ can be used to estimate $QV_{0,T}$ with an arbitrary degree of accuracy.

Our measure of oil price uncertainty is then the conditional expected value of $RV_{0,T}$,

$$E_0^{\mathbb{P}}\Big[RV_{0,T}\Big] = E_0^{\mathbb{P}}\Big[QV_{0,T}\Big] = E_0^{\mathbb{P}}\Big[\int_0^T \sigma_t^2 dt\Big], \tag{1}$$

where we have emphasized that expectations are taken with respect to the real-world probability measure $\mathbb{P}$. Expectations formed under the risk-neutral probability measure $\mathbb{Q}$ will be important later when we define our measures of oil price uncertainty risk premia. In practice, we use forecasts from a time-series model of $RV_{0,T}$ as our measure of oil price uncertainty. We elaborate on our preferred model in Section 3.

2.2 Corridor oil price uncertainty

As noted in Alquist et al. (2013), although volatility plays a prominent role in understanding the impact of oil uncertainty on the economy, it fails to capture that economic agents may have different preferences over price variation above or below certain price thresholds. To this end, we explore the concept of corridor realized variance which is discussed, but not examined empirically, by Andersen et al. (2015).

Unlike quadratic variation, where return variation is accumulated irrespective of the futures price path, corridor quadratic variation only accrues return variation when the futures price is between two pre-specified price barriers. Let B_1 and B_2 denote the barriers and define the indicator function $I_t(B_1, B_2)$ such that it takes the value of one if $B_1 \leq F_t \leq B_2$ and zero otherwise. *Corridor Quadratic Variation (CQV)* is then defined as,

$$CQV_{0,T}^{B_1,B_2} = \int_0^T \sigma_t^2 I_t(B_1, B_2)dt. \tag{2}$$

We use corridor realized variance (CRV) to estimate CQV,

$$CRV_{0,T}^{B_1,B_2} = \sum_{i=1}^{M} r_{t_i}^2 I_{t_i}(B_1, B_2),$$

where $I_{t_i}(B_1, B_2)$ takes a value of one if $B_1 \leq F_{t_i} < B_2$, i.e., if the futures price at time t_i falls within the price barriers. Note that, if F_{t_i} enters the corridor, then $I_{t_i}(B_1, B_2)$ will be equal to one and r_{t_i} will be included in the calculation of $CRV_{0,T}^{B_1,B_2}$. As shown in Carr and Lewis (2004) this ensures that the sum of $CRV_{0,T}^{B_1,B_2}$ across disjoint corridors equates to $RV_{0,T}$.

Similar to Equation (1), our measure of *corridor oil price uncertainty* is the expected corridor realized variance, which is equal to the expected corridor quadratic variation under the real-world probability measure $\mathbb{P}$,

$$E_0^{\mathbb{P}}\left[CRV_{0,T}^{B_1,B_2}\right] = E_0^{\mathbb{P}}\left[CQV_{0,T}^{B_1,B_2}\right] = E_0^{\mathbb{P}}\left[\int_0^T \sigma_t^2 I_t(B_1,B_2)dt\right]. \tag{3}$$

In analogy to expected RV, we generate expected CRV using forecasts from a time-series model described in Section 3. We note that while risk-neutral expected corridor variances have been studied in the literature by Carr and Lewis (2004), Andersen and Bondarenko (2007) and Andersen et al. (2015), amongst others, to the best of the authors' knowledge, no other paper has constructed and empirically examined real-world expected corridor variances.

2.3 Oil price uncertainty under the risk-neutral measure

Carr and Madan (1998), Britten-Jones and Neuberger (2000) and Carr and Wu (2009) show that the payoff from a security, consisting of a static portfolio in European options and a zero-cost delta-hedging strategy in futures, is equal to the realized variance of the underlying asset accumulated over the life of the options. This means investors can use this security to hedge their exposure to variance risk. It also follows that the forward price of the option portfolio is equal to risk-neutral expected variance.

More formally, suppose European options written on an underlying futures contract F_t and expiring at time $t = T$ trade for a continuum of strike prices K. The expected realized variance from time $t = 0$ to time T under the risk-neutral measure $\mathbb{Q}$ can then be obtained by,

$$IV_{0,T} = E^{\mathbb{Q}}\left[RV_{0,T}\right] = E^{\mathbb{Q}}\left[\int_0^T \sigma_t^2 dt\right] = 2e^{r_f T}\int_0^\infty \frac{M_{0,T}(K)}{K^2}dK\ , \tag{4}$$

where $M_{0,T}(K)$ is the price of a European out-of-the-money option (i.e., either a put or a call), with strike price K and maturity T, and r_f is the risk-free rate. Since this expectation does not depend on a particular option pricing model, such as the Black-Scholes model for example, it is referred to as the model-free *implied variance* (IV).

Similarly, as shown in Carr and Madan (1998), Carr and Lewis (2004), Andersen and Bondarenko (2007), and Andersen et al. (2015), *corridor implied variance* (CIV), i.e., the risk-neutral expectation of corridor quadratic variation, can be obtained by calculating the value of a static position in European options with strikes ranging from B_1 to B_2,

$$CIV_{0,T}^{B_1,B_2} = E^{\mathbb{Q}}\left[CRV_{0,T}^{B_1,B_2}\right] = E^{\mathbb{Q}}\left[\int_0^T \sigma_t^2 I_t(B_1,B_2)dt\right] = 2e^{r_f T}\int_{B_1}^{B_2} \frac{M_{0,T}(K)}{K^2}dK. \tag{5}$$

In analogy to IV, the CIV represents the price of a European option portfolio whose deltahedged payoff is equal to the corridor realized variance pertaining to the life of the options.

2.4 Oil price uncertainty risk premium

Since option-implied variance represents a risk-neutral expectation, it reflects both expected realized variance as well as the risk premium investors are willing to pay to insure against future price variation. The latter is referred to as the *variance risk premium* and is our proxy for the oil price uncertainty premium. Specifically, following Carr and Wu (2009), Bollerslev et al. (2009), Trolle and Schwartz (2010), and Bekaert and Hoerova (2014), this measure is defined as the difference between the expected realized variance under the risk-neutral and real-world probability measures, i.e., the difference between IV and the expected realized variance (ERV),

$$VRP_{0,T} = E^{\mathbb{Q}}\Big[RV_{0,T}\Big] - E^{\mathbb{P}}\Big[RV_{0,T}\Big] = IV_{0,T} - ERV_{0,T}. \tag{6}$$

Intuitively, the VRP corresponds to the negated expected payoff from a variance swap; at maturity, an investor who is long in a variance swap pays a fixed swap rate, $E^{\mathbb{Q}}\left[RV_{0,T}\right]$, and receives $RV_{0,T}$. Therefore, a long position in a variance swap can be used to hedge against increases in volatility. Investors will accept a low expected payoff when they highly value this hedging opportunity. In other words, increased aversion to future oil price volatility will be manifested through a higher VRP.

In a similar fashion, corridor implied variance (CIV) will reflect both the (real-world) expected corridor realized variance and the risk premium investors are willing to pay for insurance against future price variation that accrues within the price thresholds B_1 and B_2. We refer to the latter as the *corridor variance risk premium* (CVRP) and use it as our proxy for the *corridor oil price uncertainty risk premium*. In particular, this measure is defined as the difference between the expected corridor realized variance under the risk-neutral and real-world probability measures, i.e., the difference between CIV and expected corridor realized variance (ECRV),

$$CVRP_{0,T}^{B_1,B_2} = E^{\mathbb{Q}}\Big[CRV_{0,T}^{B_1,B_2}\Big] - E^{\mathbb{P}}\Big[CRV_{0,T}^{B_1,B_2}\Big] = CIV_{0,T}^{B_1,B_2} - ECRV_{0,T}^{B_1,B_2}. \tag{7}$$

The CVRP measure can be interpreted as the negated expected payoff from a corridor variance swap; an investor with a long position in corridor variance swap pays $E^{\mathbb{Q}}\big[CRV_{0,T}^{B_1,B_2}\big]$ and receives $CRV_{0,T}^{B_1,B_2}$, i.e., the corridor variance swap can be used to hedge against price variation accumulated between the barriers B_1 and B_2. Mirroring the VRP, the CVRP provides a measure of investors' aversion towards future price variation that occurs within the specified corridor.

It should be noted that Feunou et al. (2018), Kilic and Shaliastovich (2019) and Londono and Xu (2019) have examined a similar measure to the CVRP for the equity market, namely the "upside" and "downside" VRPs. However, their calculation of upside and downside VRP differs to ours. Specifically, while they obtain their risk-neutral expectations of upside and downside variances using the corridor variance definition in Equation (5), their real-world expectations correspond to realized semi-variances instead of corridor realized variances.[10] Since the definitions of their variance measures under the risk-neutral and real-world measures are not identical, the resulting VRPs are not internally consistent. To the best of the authors' knowledge, we are the first to estimate corridor VRPs using expectations of *corridor* variance under *both* the risk-neutral and real-world measures.

3 Estimation methodology

Our oil price uncertainty and oil price uncertainty risk premia measures require the estimation *expected* realized variances under both the real-world and risk-neutral probability measures. Below we first explain how we calculate (corridor) realized variance and (corridor) option-implied variance. We then describe the density forecasting model we use to determine the price barriers used in the estimation of our corridor measures. We conclude by presenting the forecasting model we use to generate *expected* (corridor) realized variances and how they are used in conjunction with (corridor) option-implied variances to construct (corridor) variance risk premia.

3.1 Realized variance measures

To balance the requirement to mitigate microstructure noise with the desire to obtain accurate estimates, we use subsampled (C)RVs based on 5-min intraday returns (Andersen, Bollerslev, Diebold, and Labys, 2000). Since we are interested in realized volatility across multiple days, we add squared overnight returns to the intraday subsampled (C)RVs. The Supplementary Appendix provides a precise description of our subsampled measures. For ease of notation, henceforth, corridor realized variance and (C)RV refer to the subsampled measures.

[10]Realized semi-variances, defined by Barndorff-Nielsen, Kinnebrouk, and Shephard (2010), are constructed by summing either positive or negative squared intraday returns. As such, semi-variances are not measures of corridor variance as defined in Equation (2).

We define RV_t and $CRV_t^{B_1,B_2}$ to be the RV and CRV on day t, respectively. In addition, we use define the following measures,

$$RV_{D,t} = RV_t, \qquad RV_{W,t} = \sum_{u=t-4}^{t} RV_u, \qquad RV_{M,t} = \sum_{u=t-21}^{t} RV_u,$$

which refer to the daily, weekly and monthly RV, respectively, while

$$CRV_{M,t}^{B_1,B_2} = \sum_{u=t-21}^{t} CRV_u^{B_1,B_2},$$

refers to the monthly CRV.

3.2 Option-implied variance

As shown in Equations (4) and (5), the computation of risk-neutral variance expectations for a given maturity requires the prices of options trading at a continuum of strike prices. In practice, of course, options only trade for a discrete number of strikes. To guard against discretisation errors caused by directly applying the formula to observed option prices, it is customary to fit a risk-neutral density or, equivalently, an implied volatility function that can generate option prices for arbitrary strikes. Our preferred specification is the flexible Generalized Beta Distribution of the second kind (GB2) of Bookstaber and McDonald (1987). Specifically, for each month, we estimate a GB2 risk-neutral density fitted to the market prices of European crude oil options with (approximately) one-month to expiration. The estimated density parameters are then used to generate the desired option prices needed to numerically evaluate Equations (4) and (5).

3.3 Estimating the Corridors

The price barriers B_1 and B_2 are critical inputs for the calculation of CRV and CIV. To simplify notation, B_1 and B_2 correspond to fixed percentiles of the one-month-ahead return probability distribution. Specifically, at any given time, the barrier levels needed to estimate CRV and CIV relate to the 10, 25, 50, 75 and 90$^{\text{th}}$ out-of-sample percentile forecasts of the monthly oil return distribution. For example, $B_1 = 50$ means that the lower price barrier is set equal to the 50$^{\text{th}}$ percentile forecast, while $B_1 = 0$ and $B_2 = 100$ correspond to no lower and no upper barrier, respectively. Thus, $CRV_t^{0,10}$ represents the realized variance accumulated while the oil price was below the 10$^{\text{th}}$ percentile of the forecast distribution. In our empirical analysis, we use the following values of (B_1, B_2): $(0, 10)$, $(0, 25)$, $(0, 50)$, (50, 100), (75, 100) and (90, 100).

It should be noted that our calculation of CIV is similar to Andersen et al. (2015) who also estimate CIV using barriers that correspond to specific quantiles. However, our application differs in that we use barriers derived from the real-world return distribution, whereas Andersen et al. (2015) use quantiles from the risk-neutral return distribution.[11] Thus, we use identical price barriers for both $CIV_{0,T}^{0,10}$ and $CRV_{0,T}^{0,10}$.

We now explain how we generate out-of-sample barrier forecasts for a reference month m. Specifically, denoting r_m as the monthly futures price return, barrier forecasts are generated by the following density forecast model,

$$r_m = \mu_m + \sqrt{h_m} z_m \quad , \quad z_m \sim g\left(\eta_m, \lambda_m\right),$$

where μ_m and $\sqrt{h_m}$ are the conditional mean and conditional variance of r_m, respectively, and $g\left(z; \eta, \lambda\right)$ is the standardized skewed-t distribution of Hansen with degrees of freedom η and skewness parameter λ, defined as

$$g\left(z; \eta, \lambda\right) = \begin{cases} bc\left(1 + \frac{1}{\eta-2}\left(\frac{bz+a}{1-\lambda}\right)^2\right)^{-(\eta+1)/2} & \text{if} \quad z < -a/b, \\ bc\left(1 + \frac{1}{\eta-2}\left(\frac{bz+a}{1+\lambda}\right)^2\right)^{-(\eta+1)/2} & \text{if} \quad z \geq -a/b, \end{cases}$$

where $2 < \eta < \infty$, $-1 < \lambda < 1$, $a = 4\lambda c\left(\frac{\eta-2}{\eta-1}\right)$, $b^2 = 1 + 3\lambda^2 - a^2$ and $c = \frac{\Gamma\left(\frac{\eta+1}{2}\right)}{\sqrt{\pi(\eta-2)}\Gamma\left(\frac{\eta}{2}\right)}$.

Our forecast density for a given month m is completely defined by the parameters μ_m, $\sqrt{h_m}$, η_m, and λ_m which are all estimated using data up to month $m-1$. The conditional mean of the return distribution is estimated using an MA(1) model,

$$r_m = \mu + \theta\epsilon_{m-1} + \epsilon_m.$$

The conditional mean forecast is then obtained by $\mu_m = E_{m-1}\left[r_m\right] = \hat{\mu} + \hat{\theta}\epsilon_{m-1}$, where the parameters $\hat{\mu}$ and $\hat{\theta}$ are estimated using four years of non-overlapping monthly observations.

The conditional volatility forecast is generated using the HAR model of Corsi (2009),

$$\sqrt{RV_{M,m}} = \beta_0 + \beta_1\sqrt{RV_{D,m-1}} + \beta_2\sqrt{RV_{W,m-1}} + \beta_3\sqrt{RV_{M,m-1}} + \xi_m, \tag{8}$$

where distance between m and $m-1$ is exactly 22 trading days. The HAR model parameters are estimated via OLS using the four years of overlapping daily observations. The conditional

[11] Using the quantiles of the risk-neutral distribution would result in price barriers that are at least partially determined by risk premia.

volatility forecast is then obtained as follows,

$$\sqrt{h_m} = E_{m-1}\left[\sqrt{RV_{M,m}}\right] = b_0 + b_1\sqrt{RV_{D,m-1}} + b_2\sqrt{RV_{W,m-1}} + b_3\sqrt{RV_{M,m-1}},$$

where b_0, b_1, b_2, b_3 are estimated parameters.

Finally, the parameters $\hat{\eta}$, $\hat{\lambda}$ are estimated by fitting the standardized skewed-t distribution on an expanding window of non-overlapping monthly standardized residuals, defined as,

$$z_x = \frac{r_x - \mu_x}{\sqrt{h_x}},$$

where $x \leq m-1$, r_x is the realized futures return at time x, while μ_x and $\sqrt{h_x}$ are conditional mean and volatility forecasts generated sequentially using the procedure described earlier using data prior to time x.

The estimated parameters for μ_m, $\sqrt{h_m}$, η_m, and λ_m can be then used to generate out-of-sample quantile, and hence price barrier, forecasts corresponding to the one-month-ahead oil return distribution. We then move one month into the future and repeat the same steps to produce a time series of oil price barriers. We test the robustness of our model in Section 6.

3.4 Estimating oil price uncertainty and uncertainty risk premia

As mentioned earlier, our proxy for (corridor) oil price uncertainty is *expected* (corridor) realized variance, i.e., $E^{\mathbb{P}}[RV_{0,T}]$ and $E^{\mathbb{P}}[CRV_{0,T}^{B_1,B_2}]$. To form these expectations we use forecasts from the following HAR-type model which we term as HAR-CRV,

$$\sqrt{CRV_{M,m}^{B_1,B_2}} = \tilde{\beta}_0 + \tilde{\beta}_1\sqrt{RV_{D,m-1}} + \tilde{\beta}_2\sqrt{RV_{W,m-1}} + \tilde{\beta}_3\sqrt{RV_{M,m-1}} + \xi_m. \tag{9}$$

Note that when the barriers are set at $B_1 = 0$ and $B_2 = 100$, corridor realized variance is equal to realized variance, i.e., $CRV_m^{0,100} = RV_m$. We estimate the HAR-CRV model using OLS on a window of 1,000 daily observations of overlapping (C)RVs. It should be noted that realizations of $CRV_m^{B_1,B_2}$ depend on barriers estimated using information available up to time $m-1$. Since regressions are overlapping, these ex ante monthly barrier forecasts need to be updated every trading day using the procure described in Section 3.3.

Our (corridor) oil uncertainty measures are then set equal to the out-of-sample one-month-ahead forecasts of (C)RVs using information up until time $m-1$ according to,

$$ECRV_m^{B_1,B_2} = E_{m-1}^{\mathbb{P}}\left[CRV_{M,m}^{B_1,B_2}\right] = \left(\tilde{b}_0 + \tilde{b}_1\sqrt{RV_{D,m-1}} + \tilde{b}_2\sqrt{RV_{W,m-1}} + \tilde{b}_3\sqrt{RV_{M,m-1}}\right)^2,$$

where $\tilde{b}_i$, $i = 0, 1, 2, 3$, are the estimated parameters and $ERV_m = ECRV_m^{0,100}$.

We measure the (corridor) oil price uncertainty risk premium using the (corridor) VRP, as defined in Equations (6) and (7). Specifically, this is calculated as the difference between the estimates of (C)IV, discussed in Section 3.2, and E(C)RVs , described above, i.e.,

$$VRP_m = IV_m - ERV_m, \qquad and \qquad CVRP_m^{B_1,B_2} = CIV_m^{B_1,B_2} - ECRV_m^{B_1,B_2}.$$

To keep notation simple, for the lower-corridor measures we use the terms $ECRV10$, $ECRV25$ and $ECRVD$ to refer to lower-decile oil uncertainty ($ECRV_m^{0,10}$), lower-quartile oil uncertainty ($ECRV_m^{0,25}$) and downside oil uncertainty ($ECRV_m^{0,50}$), respectively. Similarly, for the upper-corridor measures we use the terms $ECRVU$, $ECRV75$ and $ECRV90$ to refer to upside oil uncertainty ($ECRV_m^{50,100}$), upper-quartile oil uncertainty ($ECRV_m^{75,100}$) and upper-decile uncertainty ($ECRV_m^{90,100}$). We use analogous terminology for CRV, CIV and CVRP.

4 Data

To construct our realized and option-implied variance measures we use high-frequency, intraday, transaction prices and daily option settlement prices on WTI Light Sweet Crude Oil futures for a sample period from January 1987 to April 2016. We prefer futures on WTI Light Sweet crude oil compared to other grades due to their liquidity and the availability of a long sample period.

4.1 Crude oil option data

We use options written on WTI Light Sweet Crude Oil futures trading on NYMEX. The delivery date of the underlying futures contract is approximately one-month and the options expire three business days earlier. We use daily settlement option prices which are recorded at 14:30 ET. All options are American. To find the corresponding prices for European style exercise contracts which, as shown in Equations (4) and (5), are required for the construction of our measures, we follow the literature and attempt to alleviate the effect of the early exercise premium in two ways. First, we exclude all in-the-money options, since the early-exercise premium for these contracts is relatively large. Second, we estimate the early-exercise premium using the Barone-Adesi and Whaley (1987) American option pricing formula and deduct it from our option prices. Finally, to prevent our option data being contaminated by noise, we also exclude all option contracts which have a price less than \$0.01 or violate standard no-arbitrage bounds.

4.2 High-frequency crude oil futures data

We use WTI Light Sweet Crude Oil futures transaction prices recorded at 30 sec intervals. In all our realized variance measure calculations we follow the standard practice in the literature and use the front contract, that is the futures contract with the shortest time to maturity. We roll over into the next futures contract when the trading volume in the contract with the next shortest maturity is higher.

Before June 2006, the futures were traded between 09:00 and 14:30 ET in a pit using an open outcry system. Since June 2006, the futures have been traded between 18:00 and 17:00 ET the following day on the electronic GLOBEX trading platform, i.e., the exchange is only closed for one hour on any given trading day. Therefore, pre-June 2006 our sample consists of 661 price observations each day and from June 2006 onwards our sample consists of 2,761 price observations each day.

5 Empirical analysis

Below we present our empirical results. Section 5.1 displays the descriptive statistics of the various uncertainty and uncertainty risk premia measures. Section 5.2 explores their interaction with the general economic environment. Section 5.3 examines their ability to forecast macroeconomic growth following the empirical design of Gao et al. (2022). Section 5.4 evaluates whether uncertainty risk-premia can predict equity returns in the spirit of Bollerslev et al. (2009).

5.1 Descriptive statistics

To gain a preliminary understanding of their behavior, we examine descriptive statistics and time series plots of our measures of oil uncertainty, uncertainty price risk premia, option-implied variances and raw corridor realized variances, denoted as E(C)RVs, (C)VRPs, (C)IVs and (C)RVs, respectively. Summary statistics are provided in Table 1, while Figures 1 and 2 display time series plots.

We begin by examining our (C)RVs. From summary statistics reported in Panel A of Table 1, our primary observation is that some degree of asymmetry exists between the statistical properties of the lower-corridor ($CRV10$, $CRV25$, and $CRVD$) and upper-corridor ($CRV90$, $CRV75$, and $CRVU$) realized variances. In particular, the mean, median, standard deviation, maximum and first-order autocorrelation are on the whole larger for our lower-corridor CRVs relative to their upper-corridor counterparts. In other words, compared to their upper-corridor counterparts, our lower-corridor CRVs are larger and more persistent.

Turning to our measures of oil price uncertainty (E(C)RVs), option-implied variance ((C)IVs) and oil price uncertainty risk premia ((C)VRPs), three features are worth highlighting. Firstly, as shown in Table 1, the mean value of the (risk-neutral) option-implied variance (IV) is considerably higher than the mean of oil price uncertainty, i.e., the (real-world) expected variance (ERV). This is consistent with the findings of Trolle and Schwartz (2010) and Prokopczuk et al. (2017). Furthermore, the uncertainty risk premium is a non-trivial component of the option-implied variance measure, representing around 20% of its value. Hence, the behavior of option-implied variance is heavily influenced by the uncertainty risk premium.

Secondly, the oil price uncertainty risk premium behaves quite differently to oil price uncertainty. This can be seen in Figure 1, which plots the time series of oil price uncertainty, option-implied variance and the uncertainty risk premium, while also highlighting important events, including NBER recessions, the Gulf War, the Asian currency crisis, the 9/11 terrorist attack, the start of the Iraq War, and the Global Financial Crisis (GFC). Notably, there are several episodes where a sudden increase in option-implied variance is not matched by a concomitant rise in the real-world uncertainty measure, which is reflected by large spikes in the uncertainty risk premium. Examples of these occasions include the spikes in the oil price uncertainty risk premium associated with the Asian Crisis, the 9/11 attacks and the Iraq War. In contrast, spikes of the oil price uncertainty risk premium during with the Gulf War and the GFC coincide with equally large shocks to oil price uncertainty. Consequently, the underlying factors driving the oil price uncertainty risk premium do not perfectly match those affecting oil price uncertainty.

Lastly, Table 1 shows that broadly the asymmetric behavior exhibited by the CRVs is also present in our oil price uncertainty (ECRVs), option-implied variance (CIVs) and uncertainty risk premia (CVRPs) measures. The distinct behavior of our upper- and lower-corridor uncertainty and uncertainty risk premia measures can also be seen in Figure 2, where we plot the time series of our ECRVs, CIVs and CVRPs. For example, comparing our downside and upside oil uncertainty measures in Figures 2a and 2b, clear differences in their behavior can be identified. First, there is a tendency for downside oil price uncertainty to be less volatile than the upside measure. Second, the difference between downside (upside) option-implied variance and downside (upside) real-world oil price uncertainty tends to be large (small). This translates into a higher (lower) downside (upside) oil price uncertainty risk premium. Analogous comments apply when comparing quartile and decile oil uncertainty and uncertainty risk premia measures in Figures 2c, 2d, 2e and 2f.

In summary, the descriptive statistics and time-series plots lead to the following key observations. Firstly, oil price uncertainty risk premia, (C)VRPs, behave differently to oil price uncertainty, E(C)RVs, and therefore are likely to reflect different information. This mirrors the equity market, where expected volatility and the variance risk premium incorporate disparate information about the real economy and financial markets (Bekaert et al., 2013; Corradi, Distaso, and Mele, 2013; Bekaert and Hoerova, 2014). Secondly, upper- and lower-corridor oil price uncertainty and uncertainty risk premia measures display different dynamics and therefore may also embed different information. This also resembles empirical evidence from the equity market, where upside and downside volatility and variance risk premia have been found to contain different predictive power over expected returns (Feunou et al., 2018; Kilic and Shaliastovich, 2019; Londono and Xu, 2019; Bollerslev, Li, and Zhao, 2020). Overall, this preliminary analysis supports our decision to examine oil price uncertainty and uncertainty risk premia separately, as well as to partition these measures into their upper- and lower-corridor components.

5.2 Oil uncertainty and the economic environment

To obtain insights about potential drivers of our uncertainty measures, we follow the literature and examine if macroeconomic and financial market variables contain significant predictive information about expected volatility (Engle and Rangel, 2008; Paye, 2012; Engle, Ghysels, and Sohn, 2013) or volatility risk premia (Bollerslev et al., 2009; Trolle and Schwartz, 2010; Bollerslev, Gibson, and Zhou, 2011; Konstantinidi and Skiadopoulos, 2016; Andreou and Ghysels, 2021). To this end, we explore if various economic and financial market variables (X) can explain variation in uncertainty or uncertainty risk premia measures (V) through this parsimonious predictive regression,

$$V_t = \beta_0 + \beta_1 V_{t-1} + \beta_x X_{t-1} + \xi_t.$$

Conversely, we also investigate if our measures can predict future economic and financial market conditions. This analysis can provide valuable insights on two fronts. Firstly, it can determine whether oil uncertainty and oil uncertainty risk premia can predict different aspects of the economic environment. For instance, Bekaert and Hoerova (2014) showed that, for the case of equities, uncertainty risk premia can predict equity returns, while equity market uncertainty, i.e., conditional variance, exhibits stronger predictive power over future economic activity and financial stability. Secondly, it is useful to explore any distinctions amongst the various corridor measures. In spirit, this is similar to the study of Segal et al. (2015) who documented that "good" and "bad" macroeconomic uncertainties, captured by positive and negative semi-variances of industrial production innovations, have different forecast performance over future economic activity and asset valuations. Along these lines, we run the following simple predictive regression,

$$X_t = \beta_0^* + \beta_1^* X_{t-1} + \beta_v^* V_{t-1} + \xi_t^*.$$

As discussed in Corradi et al. (2013) and Jurado et al. (2015), among others, uncertainty can interact with the economy via different channels. To this end, we consider four categories of indicators reflecting the prevailing economic environment: measures of economic activity, economic uncertainty, sentiment, as well as, trading activity in oil derivatives.

All regressions correspond to a monthly horizon. Since not all variables are recorded at the same frequency (i.e., some are observed monthly, others weekly or daily), the lagged dependent variable corresponds to the last known value at the time the lagged independent variable is observed. To facilitate comparisons, all variables are standardized to have a mean of zero and a variance equal to one.

5.2.1 Economic activity

We begin our analysis by looking at measures of economic activity. To capture domestic (US) economic conditions we use the National Activity Index (CFNAI) published by the Chicago FED, and the Arouba-Diebold-Scotti Economic Activity Index (ADS) of Aruoba, Diebold, and Scotti (2009) published by the Philadelphia FED. For the case of global economic activity we use the Real Global Economic Activity Index (KIRGEA) of Kilian (2009). Our empirical results are displayed in Panel A of Table 2.

Contemporaneous correlations between oil uncertainty measures and economic activity indicators are negative throughout and typically significant at the 5% level, indicating that bad states of the economy, i.e., times when economic activity is weak, tend to be associated with periods of high oil uncertainty. In line with finance theory, where risk premia are higher during bad times, uncertainty risk premia generally have a negative correlation with domestic and global economic conditions. This relationship appears particularly strong for lower-corridor uncertainty risk premia, although for the case of domestic economic conditions, the correlations are also significant for some upper-corridor measures.

Next, we examine if our measures have any predictive power over next-period economic conditions. In line with the studies of Bernanke (1983) and Edelstein and Kilian (2009), we document that oil uncertainty has a negative impact on future domestic economic activity. Comparing the different corridor measures, we find that the predictive ability of lower-corridor uncertainty measures appears to be stronger than their upper-corridor counterparts, although the upper-decile measure is also a significant predictor. Our parsimonious regressions also show that uncertainty risk premia have some predictive power over future domestic economic activity. Specifically, we find that periods of high premia tend to be followed by periods of low economic activity, i.e., bad states of the economy. This relationship appears to be driven by uncertainty risk premia associated with declining oil prices.

Finally, we examine if current economic activity can predict next-period oil uncertainty measures and associated risk premia. With respect to the former, our findings show that the relationship is negative throughout, indicating that bad economic conditions today are associated with higher oil price uncertainty in the future. However, this link appears to be significant mainly for the upper-corridor uncertainty measures. Domestic economic conditions also have significant predictive power over future uncertainty risk premia. Specifically, times when the US economy is relatively weak tend to be followed by periods of high uncertainty risk premia, i.e., periods when insurance against oil uncertainty is more costly. This relationship is significant for the full as well as lower-corridor uncertainty risk premia measures regardless of the domestic economic activity indicator considered. Notably, the same is true for uncertainty risk premia associated with extreme positive oil price shocks, i.e., the upper-decile uncertainty risk premium measure.

All in all, our measures appear to meaningfully interact with economic activity indicators. Not surprisingly, we document a negative relationship between economic activity and oil uncertainty. More intriguingly, the most interesting interactions appear to involve either uncertainty associated with declining oil prices or substantial oil price hikes, i.e., uncertainty related to modest oil price increases appears more loosely linked to economic conditions. Furthermore, while a negative relationship between uncertainty risk premia and economic activity was generally expected, there is clear evidence that their interplay is particularly strong for the case of downside measures.

5.2.2 Economic uncertainty

It is natural to assume that oil price uncertainty is linked to economic uncertainty. However, the latter encapsulates different types of uncertainty, such as that associated with macroeconomic or financial market outcomes, which, although conceptually distinct, often intersect. As these might be linked to oil price uncertainty via different channels, we attempt to disentangle their relationship using the macroeconomic uncertainty and financial uncertainty measures of Ludvigson, Ma, and Ng (2021). Our results are displayed in Panel B of Table 2.

Contemporaneous correlations reveal that oil price uncertainty goes hand in hand with both financial and macroeconomic uncertainty, i.e., periods of high oil price uncertainty generally overlap with periods of high financial and macroeconomic uncertainty. Similarly, oil price uncertainty risk premia are strongly related to both, indicating that high macroeconomic or financial market turbulence tend to coincide with times when insurance against oil uncertainty is expensive.

We now look whether our measures have any predictive power over the future financial and macroeconomic uncertainty.[12] We find that all uncertainty measures are significant predictors of both macroeconomic and financial market uncertainty at the 5% level. The same is true for the case of uncertainty risk premia, with the only exception being that of the upside uncertainty risk-premium, which is not a significant predictor of macroeconomic uncertainty.

On the other hand, we find that heightened financial or macroeconomic uncertainty will generally elevate future oil price uncertainty. Specifically, financial uncertainty has a significant impact on upper-corridor uncertainty measures, while the influence of macroeconomic uncertainty is widespread. Moreover, both financial and macroeconomic uncertainty are found to be positive drivers of future uncertainty risk premia, as a significantly positive relationship emerges across nearly all measures.

Since there is a natural intersection between macroeconomic and financial uncertainty, notably they are both high during bad economic times, we attempt to disentangle their incremental impacts by including both of them as explanatory variables in the following predictive regression,

$$V_t = b_0 + b_1 V_{t-1} + b_f FU_{t-1} + b_m MU_{t-1} + e_t.$$

As our results in Panel B of Table 2 show, three interesting patterns emerge. First, macroeconomic uncertainty is the only significant predictor of oil price uncertainty. This is in line with the intuition that oil price uncertainty is primarily driven by turmoil in macroeconomic conditions rather than financial market turbulence. Second, we find that, overall, uncertainty risk premia are driven by both macroeconomic and financial market conditions. This indicates that besides the state of macroeconomic fundamentals, fluctuations pertaining specifically to financial markets, such as shifts in risk-aversion, sentiment, or financial frictions, are necessary to explain variation in oil uncertainty risk premia. Third, while downside oil uncertainty premia are linked to both financial and macroeconomic uncertainty, upper-corridor risk premia are solely driven by financial market conditions. As shown later in the paper, this distinction appears empirically important when attempting to forecast economic growth and equity returns.

[12] Because of the methodology underpinning their estimation, the financial and macroeconomic uncertainty measures of Ludvigson et al. (2021) are highly autocorrelated by construction. For this reason, we do not use their lagged values as controls. This implies that we assess the overall, rather than the incremental, predictive power of our measures.

5.2.3 Economic sentiment

We examine three indicators reflecting economic agents' sentiment. The first one is the investor sentiment index (SI) of Baker and Wurgler (2007) that is designed to capture confidence in financial market prospects. As shown in Seo and Kim (2015), conditioning on investor sentiment is important in improving option-implied forecasts of equity volatility, which suggests an interesting interplay between sentiment, uncertainty, and uncertainty risk premia. The second is the University of Michigan Consumer Sentiment Index (UMCSI) which aims to measure consumers' expectations about business conditions and personal finances, overall level of optimism, and near-term attitude with respect to spending decisions. Interestingly, Corradi et al. (2013) find that while the majority of equity volatility is explained by business cycle factors, a persistent unobservable component that is highly correlated with the UMCSI is needed to match the empirical data. The third sentiment indicator is the media "attention to recession" index of Bybee, Kelly, Manela, and Xiu (2023), which quantifies the proportion of news allocated to the topic of recession. The results are presented in Panel C of Table 2.

Oil price uncertainty negatively correlates with both investor sentiment and consumer confidence but, in both cases, their association appears insignificant for upper-corridor uncertainty measures. On the other hand, extensive media coverage on the topic of recession coincides with times of high oil price uncertainty, with all correlations being significant at the 5% level. With respect to uncertainty risk premia, we find that investor sentiment does not significantly correlate with any of the measures. Consumer confidence, however, has a significantly negative relationship with overall, as well as several lower-corridor, uncertainty risk premia and a positive relationship with upper-corridor measures.[13] We also note that, albeit insignificant, the same sign pattern is observed for the case of the investor sentiment index. Finally, attention to recession has a positive and significant relationship with all uncertainty risk premia measures.

We now turn our discussion to whether our measures can predict future perceptions about the economy. While the coefficients corresponding to uncertainty risk premia are insignificant throughout, our results show that lower-corridor uncertainty measures have some predictive power over all three economic sentiment indicators. Specifically, for both investor sentiment and consumer confidence, the estimated regression coefficients are negative, implying that high downside uncertainty today predicts lower levels of optimism. Similarly, elevated lower-

[13] This might indicate the UMSCI correlates with a financial market variable, such as trading pressure, that affects equilibrium option prices. Alternatively, it might reflect that during times of strong consumer confidence, out-of-money call options, that determine the level of upside uncertainty risk premia through Equations (5) and (7), trade at a significant premium because they provide a valuable hedge against inflation.

corridor measures predict more extensive attention to the topic of recession. These results hint towards the presence of a channel through which oil price uncertainty, notably that associated with price declines, depresses economic optimism, potentially affecting the future behavior of consumers and the real economy.

Lastly, we examine if the three sentiment indicators have any predictive power over oil uncertainty and uncertainty risk premia. We find that investor sentiment and consumer confidence have no impact on any of the measures. On the contrary, there is widespread evidence that increased media attention to recessions tends to be accompanied by higher oil price uncertainty as well as higher oil uncertainty risk premia.

5.2.4 Trading activity

Several papers have noted that trading activity can be an important determinant of equilibrium asset prices and risk premia, see Acharya et al. (2013), Li (2018) and Kang et al. (2020) among others for the case of the oil market. Furthermore, the literature has also demonstrated that trading activity of retail investors (Choy, 2015) and net demand pressure (Bollen and Whaley, 2004; Garleanu, Pedersen, and Poteshman, 2008) can affect option prices which, in turn, determine uncertainty risk premia through Equations (5) and (7). Indeed, for the case of the equities, Konstantinidi and Skiadopoulos (2016) find that trading activity is the most successful predictor of equity variance risk premia. Along the same lines, we examine the interplay of our measures with the intensity of speculative trading activity, as defined by Li (2018) and Christoffersen et al. (2022) among others, as well as the hedging pressure of oil producers using the smoothed hedging pressure index of Kang et al. (2020). A detailed description of the two measures is provided in the Supplementary Appendix. Our results are presented in Panel D of Table 2.

Contemporaneous correlations show that oil uncertainty tends to be higher when speculative pressure is strong. Uncertainty risk premia are also positively correlated with speculative pressure although this relationship appears significant only for the case of lower-corridor uncertainty measures. Interestingly, we also find that the speculative index can predict next-period oil price uncertainty and uncertainty risk premia, but this appears to be solely driven by successfully predicting lower-corridor measures.

On the contrary, hedging pressure only appears to meaningfully interact with upper-corridor measures. In particular, we find that hedging pressure is positively correlated with upper-decile corridor uncertainty and that low hedging pressure today predicts higher next-period upper-quartile and upper-decile corridor uncertainty. In addition, and most notable, there is a clear negative relationship between hedging pressure and upside, but not downside, oil uncertainty risk premia. Specifically, we find that: (i) contemporaneous correlations are negative and significant; (ii) high hedging pressure today predicts lower next-period upside and upper-quartile uncertainty risk premia; and (iii) upper-decile uncertainty risk premia today have some predictive power over next period hedging pressure.

Why does trading activity affect variance risk premia?

As our results show, speculative pressure appears to impact future lower-corridor uncertainty risk premia but not their upper-corridor counterparts, while the opposite is true for the case of hedging pressure. To the best of the authors' knowledge, this finding has not been reported previously in the literature, so it is worth elaborating further.

At first, it is important to note that, as shown in Equation (5) from which risk-neutral expectations are calculated, lower-corridor (upper-corridor) uncertainty risk premia are determined by out-of-the-money put (call) option prices. Hence, the finding that speculative pressure raises lower-corridor uncertainty risk premia translates to speculative pressure increasing the relative prices of out-of-the-money put options. In light of the empirical evidence reported by Büyükşahin and Robe (2014) and Basak and Pavlova (2016) that the correlation between equity and oil returns rises amid greater participation of speculators (notably institutional investors and hedge funds) in the crude oil derivatives market, we argue that when speculative pressure is strong, risk premia embedded in crude oil options mirror those of the equity market, where out-of-the-money put options trade at a significant premium leading to substantially large downside variance risk premia.

With respect to hedging pressure, our results indicate that stronger hedging pressure decreases the prices of out-of-the-money call options, which translates to a reduction of upper-corridor uncertainty risk premia. We first note that, as reported by Acharya et al. (2013) and Dionne, Gueyie, and Mnasri (2018), options are the most common instrument that oil producers use for hedging, while their most popular hedging strategy is setting up a costless collar. Since the latter is a combination of a long position in an out-of-the-money put option and a (price-equivalent) short position in an out-of-the-money call option, oil producers are simultaneously purchasing downside oil price insurance and providing upside oil price insurance. As oil producers retreat from hedging, they provide less insurance for upside oil risk to market participants, which then must be absorbed by financial intermediaries. Due to the capital constraints they face, financial intermediaries have limited capacity to bear additional upside oil risk, leading to higher call prices and, consequently, higher upside oil uncertainty risk premia. We also note that this retreat from hedging activities may be driven by conditions specific to the oil industry or can be due to systematic market factors, such as the tightening of capital constraints. For example, Dionne et al. (2018) document that oil producers prematurely close their costless collar positions when the spot price of oil increases to avoid margin calls. On the other hand, as shown in Acharya et al. (2013), oil producers experience limits to hedging due to elevated hedging costs leading to a reduction in their hedging activities.[14]

Overall, our findings highlight that trading activities in the crude oil market may have a role in determining oil uncertainty risk premia. Importantly, in line with the existing literature, our results also suggest that trading pressure may affect equilibrium option prices due to the presence of financial frictions manifested by the limited capacity of financial intermediaries to bear risk. However, while all previous studies have focused on the oil futures risk premium, our finding that trading pressure affects the oil variance risk premium is novel to the literature.

5.3 Oil uncertainty and macroeconomic growth

As shown by our parsimonious regressions in Section 5.2.1, both oil price uncertainty and uncertainty risk premia have some predictive power over future economic activity. We also reported some evidence of asymmetry. Most notably, while downside oil uncertainty risk premia are significantly related to future economic activity, the same is not true for their upside counterparts. Building on the literature that has documented that crude oil volatility is a significant predictor of economic growth, we now more rigorously examine the relationship of our measures with various macroeconomic growth aggregates.

In our empirical design, we very closely follow the recent study of Gao et al. (2022) who demonstrated that, even after controlling for macroeconomic and financial uncertainty, oil uncertainty, as proxied by option-implied variance, is a strong predictor of economic growth. It is important to note, however, that option-implied variance encapsulates both oil uncertainty and the oil uncertainty risk premium. To understand the true source of predictability, we study the performance of each component separately since, in light of our results in Section 5.2.1, both might be informative about future economic growth. Furthermore, we empirically examine various corridor measures in order to uncover any potential variation in their predictive performance.

In our analysis we use the predictive regression specification of Gao et al. (2022),

$$\sum_{k=1}^{h} y_{t+k} = \alpha + \beta_v' V_t + \beta_z' z_t + e_{t+h}, \tag{10}$$

[14] This could also explain why we do not observe a reduction in the prices of out-of-the-money put options when hedging pressure decreases. During periods of tighter capital constraints, the limited ability of financial intermediaries to absorb risk will tend to increase put prices, so the two effects will tend to offset each other.

where y_{t+k} is economic growth k-quarters ahead, V_t is a vector of uncertainty measures and z_t is a vector of control variables. We use identical economic growth measures to Gao et al. (2022): GDP growth (*GDP growth*), measured as the difference in the natural logarithm of quarterly GDP obtained from the Bureau of Economic Analysis (BEA); consumption growth (*Cons growth*), measured as the difference in the natural logarithm of quarterly nondurable consumption obtained from the BEA; private investment growth (*PI growth*), measured as the difference in the natural logarithm of quarterly private domestic investment obtained from the BEA; and non-farm payroll growth (*NFP growth*), measured as the difference in the natural logarithm of quarterly non-farm payrolls obtained from the St. Louis FED.

The uncertainty measures in V include one or more of the following measures: oil uncertainty, oil uncertainty risk premia, option-implied variance, financial market uncertainty (proxied by the *VIX*), and macroeconomic uncertainty. The latter is measured by the one-quarter-ahead forecast of volatility from an AR(1)-GARCH(1,1) model fitted to total factor productivity growth (TFP) growth. All the uncertainty measures in V are standardized to have a mean of zero and a variance equal to one. The control variables in z include the contemporaneous and lagged quarterly oil futures return and the contemporaneous quarterly oil supply growth and TFP growth.[15] It should be noted that *VIX* and *Macro Unc* are measured at the end of each quarter. For the oil uncertainty measures, we use values which are constructed as close to, but not beyond, the end of the quarter as possible. Moreover, excluding the case of *Macro Unc*, all uncertainty measures corresponds to a monthly horizon.

5.3.1 Empirical results

As highlighted in Gao et al. (2022) and confirmed by our results in Section 5.2.2, times of high oil uncertainty tend to coincide with high levels of financial and macroeconomic uncertainty. Their paper also emphasizes the negative relationship between economic growth and their measures of financial and macroeconomic uncertainty.[16] To this end, we assess the *incremental* predictive content of oil uncertainty and uncertainty risk premia measures after controlling for financial and macroeconomic uncertainty; i.e., V_t in Equation (10) includes

[15]Following Gao et al. (2022), all economic growth variables are seasonally adjusted. The proxies for financial and macroeconomic uncertainty, the standardization of the variables, and the definition of the controls are also identical. To conserve space, we are not presenting the results for predicting TFP growth since, similar to their paper, it appears largely unrelated to oil uncertainty. As an additional robustness check, we have used the conditional volatility from a AR(1)-GARCH(1,1) model fitted to GDP growth as a measure of macroeconomic uncertainty, but our main conclusions remained unaltered. All unreported results are available upon request.

[16]As shown in the Supplementary Appendix, we also confirm this result by estimating the regression Equation (10) where either *VIX* or *Macro Unc* is included as a single uncertainty measure. The signs of the parameters for both the *VIX* and *Macro Unc* are negative throughout. In terms of significance, the results are stronger for the *VIX* compared to *Macro Unc*.

an oil uncertainty or uncertainty risk premium measure, as well as the *VIX* and *Macro Unc*.[17] In Table 3 we report the estimated parameters for the oil uncertainty and uncertainty risk premia measures only. Those for the *VIX* and *Macro Unc* are presented in the Supplementary Appendix.

We begin by analysing the option-implied variance measure used in Gao et al. (2022). Mirroring their findings, our results in Panel A of Table 3 show that, with the exception of *Cons growth*, option-implied variance has a negative and broadly significant impact on economic growth at short (one- and two-quarter) horizons. Since option-implied variance contains information about both oil uncertainty and the uncertainty risk premium, we then examine their predictive content separately. As shown in Panel B of Table 3, oil uncertainty is insignificant throughout. In stark contrast, the oil uncertainty risk premium (Panel C) continues to be significant in most cases. Most notably, the oil price uncertainty risk premium is a significant predictor of all economic growth variables at the one-quarter horizon. This finding indicates that the strong predictive power of option-implied variance is driven by variation in the oil uncertainty risk premium rather than oil price uncertainty.

We next examine the performance of the various corridor measures. For option-implied corridor variances, we observe that lower-corridor measures are clearly stronger predictors of *GDP growth* and *Cons growth* than their upper-corridor counterparts, as the parameters of latter are insignificant throughout. On the other hand, there is no discernible evidence of asymmetry for the cases of *PI growth* and *NFP growth*, as both upper- and lower-corridor measures are often significant. For corridor uncertainty measures, we find that they are only significant predictors *NFP growth* across various quarters, as well as one-quarter *PI growth*. Moreover, we find no evidence of asymmetric performance between the various measures. Lastly, but perhaps most importantly, our results for the corridor uncertainty risk premia show that lower-corridor measures are strong predictors of future economic growth, especially at the one and two quarters. In particular, lower-corridor measures appear widely significant across all four economic growth variables. In contrast, upper-corridor measures are only significant for *NFP growth*, with the most pronounced case being that of the upper-decile tail measure. These results indicate that both the predictive power of corridor implied variance, as well as the asymmetric performance of the various option-implied measures, is driven by corridor uncertainty risk premia.

Another key observation from our empirical results is that the downside uncertainty risk premium ($CVRPD$) has a particularly strong forecasting performance. Most notably, at the

[17]Results for regressions where only a single oil uncertainty measure is included in Equation (10) are presented in the Supplementary Appendix. The interpretation of these results are in line with those we discuss here for multiple uncertainty measures. Also, consistent with the prior literature, we find that oil uncertainty, has a negative impact on economic growth, notably at short horizons.

one- and two-quarter horizons, this measure is a significant predictor of all four economic growth variables. The prominence of the $CVRPD$ as a strong predictor of economic growth is in line with the empirical evidence in Section 5.2.1 where, unlike its upside counterpart ($CVRPU$), it was able to significantly predict next-period domestic economic activity. Furthermore, as we reported in Section 5.2.3, in contrast to the $CVRPU$, it displayed a negative relationship with investor sentiment and consumer confidence, and appeared more closely linked to economic agents' recession concerns. In addition, the $CVRPD$ appears to reflect both macroeconomic and financial market concerns since, as the joint regressions results in Section 5.2.2 showed, both the macroeconomic and the financial uncertainty indices of Ludvigson et al. (2021) were required to predict its variation, whereas for the upper-corridor measures only the financial uncertainty index appeared relevant. Collectively, the above results suggest the downside uncertainty risk premium captures important information about the future economic environment. Further support for this conclusion is provided by robustness checks later in the paper, where we show that the downside uncertainty risk premium subsumes the predictive power of a wide collection of competing uncertainty measures.

5.3.2 Origins of predictability

In Kilian (2009) the fundamental shocks determining oil prices are decomposed into three types: oil supply shocks, which arise from unexpected reductions in the physical supply of oil, e.g., due to war or other exogenous events; aggregate demand shocks, i.e., shocks to global demand for commodities; and oil-specific demand shocks, which result from uncertainty over oil supplies. Each category of shock has different implications for the economy. In particular, oil supply shocks increase oil prices which negatively affect economic activity. Aggregate demand shocks coincide with stronger economic growth, but they also lead to higher oil prices that have a detrimental impact on the economy. Overall, as shown in Kilian (2009), aggregate demand shocks are more likely to have a growth-enhancing effect on the economy in the short-run. In contrast, as noted by Kilian and Park (2009), oil-specific demand shocks can be interpreted to result from shifts in the uncertainty over oil supply shortfalls and are likely to lead to growth-inhibiting oil price increases.

Gao et al. (2022) develop and provide empirical evidence in support of an equilibrium model which links oil uncertainty with the macroeconomy. In analogy to the oil-specific demand shocks outlined in Kilian (2009), their model predicts that precautionary oil inventories increase in response to high oil supply uncertainty. However, instead of focusing on the effect that elevated oil prices, ensuing from oil-specific demand shocks, have on the economy, Gao et al. (2022) directly relate the accumulation of oil inventories to economic growth. In particular, their model predicts that higher precautionary oil inventories, at least in part, result from an accompanying reduction in oil consumption due to oil uncertainty, which, in turn, causes lower economic output, consumption, investment, and employment.

We investigate whether our results are explained by the presence of a precautionary oil inventories channel. Closely following the set-up of Gao et al. (2022), we regress our oil uncertainty and uncertainty risk premia measures against quarterly log changes in oil consumption (*Oil cons growth*) and oil inventory (*Oil inventory growth*).[18] All oil market data was obtained from the Energy Information Administration. The theoretical prediction of their model is that oil uncertainty will increase inventory growth and decrease oil consumption growth.

Our results in Table 4 corroborate the presence of the precautionary oil inventories channel. In particular, mirroring the results of Gao et al. (2022), we find that option-implied variance is negatively related with *Oil cons growth* and positively related with *Oil inventory growth*, with the latter relationship being significant over one and two quarters. With respect to oil uncertainty, our results also show a negative relationship with *Oil cons growth* and a positive one with *Oil inventory growth*. We note that while these are not statistically significant for the full uncertainty measure, there is widespread significance across the corridors. In contrast, there is little significance amongst the corridor uncertainty risk premia measures. In summary, while our evidence supports the presence of a precautionary oil inventories channel, this appears to operate exclusively through oil uncertainty, and does not explain the ability of the downside uncertainty risk premium to predict future economic growth.

To confirm that the increase in oil inventories during times of high oil uncertainty, which is a key characteristic of the precautionary oil inventories channel, is not driven by changes in the production of oil, we repeat the regressions using quarterly log changes of oil production (*Oil prod growth*). Overall, there is limited evidence of a significant relationship between oil production growth and our uncertainty measures.[19]

Since a precautionary oil inventories channel, which is conceptually linked to oil-specific demand, appears unable to explain the ability of oil uncertainty risk premia to predict economic growth, a plausible alternative is that uncertainty risk premia reflect concerns related to aggregate oil demand shocks which, as explained in Kilian (2009), reflect global economic conditions. In this interpretation, when economic agents are particularly worried about shocks to aggregate demand, insurance against oil uncertainty will be particularly

[18]For brevity, we only discuss multiple uncertainty measure regressions, i.e., where *VIX* and *Macro Unc* are included in Equation (10). Results for single-measure regressions are in line with those we obtain for the multiple uncertainty measure regressions and are available upon request.

[19]Specifically, when looking at the full measures, they are significant predictors of oil production growth (at the 10% level) in just one out of nine regressions. Likewise, only a small fraction of corridor measures appears significant, mainly corresponding to oil uncertainty measures (i.e., E(C)RVs). We note that, apart for the four-quarter horizon, the latter appear insignificant in our (unreported) single measure regressions.

expensive, which is manifested by elevated uncertainty risk premia. As these economic concerns negatively affect concurrent investment, consumption and employment decisions, uncertainty risk premia, which are forward-looking by construction, will predict a slowdown in economic growth.[20]

The aggregate oil demand channel is also able to explain the asymmetric predictive power of the corridor uncertainty risk premia measures. Mirroring the equity case, where investors are averse to both high volatility and negative returns, economic agents dislike both oil price uncertainty and negative oil price shocks driven by aggregate demand. As a result, their aversion to uncertainty associated with negative demand shocks is particularly acute. This is manifested by a downside oil uncertainty risk premium measure that is unconditionally higher than its upside counterpart and, as shown in Section 5.2.2, responsive to both macroeconomic and financial market turbulence, rather than solely the latter. Hence, this adds further support to the argument that the uncertainty risk premia are strong predictors of macroeconomic growth because they reflect economic agents' concerns stemming from this aggregate demand channel.

5.4 Oil uncertainty and equity market returns

Commencing with the seminal paper of Bollerslev et al. (2009), the equity variance risk premium has been shown to predict aggregate stock market returns even after controlling for other popular predictor variables. More recently, Feunou et al. (2018), Kilic and Shaliastovich (2019) and Londono and Xu (2019) decomposed the equity variance risk premium into its upside and downside components and reported that only downside variance risk premia predict excess stock market returns. Building on these insights, we examine the relationship between aggregate equity market excess returns and our oil uncertainty risk premia measures. Our analysis is conducted using the standard regression specification proposed by Bollerslev et al. (2009) and used by Bekaert and Hoerova (2014) among others,

$$\sum_{k=1}^{h} r_{t+k} = \alpha + \beta_v VRP_t + \beta_z' z_t + e_{t+h}, \tag{11}$$

where r_{t+k} is the aggregate equity market excess return, as captured by the CRSP value-weighted index, for month $t+k$, VRP_t is a measure of the oil uncertainty risk premium,

[20]This is also in line with our evidence in Section 5.2 which showed that the oil uncertainty risk premium can predict future U.S. domestic economic activity indicators, as well as, the macroeconomic and financial uncertainty indices of Ludvigson et al. (2021). In addition, it is significantly positively correlated with recession concerns and negatively correlated with consumer confidence.

and z_t is a vector of control variables observed at time t. We consider four different horizons $h = 1, 3, 6, 12$ months.

As control variables we follow the related study of Christoffersen et al. (2022) and use the following: the consumption-wealth ratio (CAY) of Lettau and Ludvigson (2001); the log price-earnings ratio (PE); the log price-dividend ratio (PD); the term spread (TS), defined as the difference between the 10-year Treasury Bond yield and the 3-month U.S. Treasure Bill yield; and the default spread (DS) which is defined as the difference between BBB and AAA corporate bond yields. We also include the U.S. equity market VRP ($EqVRP$), computed as the difference between the (squared) VIX and monthly variance forecasts generated by the HAR model of Corsi (2009) applied to high-frequency return data of the SPDR ETF, and the oil state-price density slopes (SL) of Christoffersen et al. (2022).[21]

As argued by Singleton (2014) among others, the relationship between crude oil and financial markets has markedly changed since the mid-2000s. Therefore, similar to the studies of Christoffersen and Pan (2018) and Kang et al. (2020), we also split our full sample into two sub-periods, namely the pre-financialization (PreFin), 1991-2004, and the post-financialization (PostFin), 2005-2016, periods of the crude oil market.

Table 5 displays the results of univariate regressions, i.e., when a single expected return predictor is used in Equation (11). At the one-month horizon, the upside uncertainty risk premium ($CVRPU$) is highly significant in both the full (Panel A) and PostFin (Panel C) sample periods. In line with finance theory, the estimated parameter has a positive sign, indicating that times when insurance for upside oil uncertainty is expensive coincide with periods of high expected stock market returns. This important relationship between oil uncertainty risk premia and expected returns would be overshadowed if one relied on the full oil uncertainty risk premium measure, since the latter appears insignificant for all horizons and sub-samples considered.

With respect to other predictors that use option price data, the equity VRP is significant for medium term horizons, consistent with Bollerslev et al. (2009), but only during the PostFin sample. It is noteworthy that, in contrast to the equity VRP, our upside oil uncertainty risk premium predicts short-term (monthly) equity market returns. Our empirical results also confirm those of Christoffersen et al. (2022), as we find that the positive oil state-price density slope is a significant return predictor. With respect to the remaining popular predictors, all of them appear significant during either the PreFin or PostFin periods.

To investigate if the predictive power of upside uncertainty risk premia survives in the presence of other competing predictors, we include the latter as control variables as described

[21]We calculate the negative (positive) slope of the state-price density at the 10% (90%) percentile of the real-world oil return distribution.

in Equation (11). To conserve space, Table 6 only displays the t-statistics corresponding to our oil uncertainty risk premia variables. The full regression results are provided in the Supplementary Appendix. Our key finding is that, even after including all other control variables in the regression, upside oil uncertainty risk premia continue to be a significant predictor of short-term excess equity market returns. Resembling the univariate regression results, the parameter corresponding to the upside oil uncertainty risk premium measure has a positive sign and is highly significant at the one-month horizon for both the full (Panel A) and PostFin (Panel C) samples. Interestingly, including other predictors in Equation (11) results in various other upper-corridor oil uncertainty risk premia measures becoming significant during the PreFin sample period (Panel B). Again, similar to the univariate regression results, the full oil uncertainty risk premium measure appears insignificant throughout, so any relationship between oil price uncertainty risk premia and equity market returns would appear elusive if we had relied solely on this measure.

5.4.1 Origins of predictability

Recently, He and Krishnamurthy (2013), Adrian et al. (2014) and He et al. (2017) have highlighted that the health of financial intermediaries is an important driver of expected returns. These papers provide evidence that during poor financial conditions, intermediaries, who face capital constraints, have limited capacity to bear risk leading to frictions in financial markets and higher risk premia. Moreover, Brunnermeier and Pedersen (2009) show that volatility and financial intermediary capital constraints are interlinked, indicating a direct financial frictions channel through which volatility can affect equity market returns. Confirming this intuition, Christoffersen and Pan (2018) show that changes in oil volatility are able to predict changes in funding constraints.

To investigate whether this channel is able to explain our results, we follow the methodology of Christoffersen and Pan (2018) and examine if our oil uncertainty risk premia measures can predict future funding conditions. We explore different funding constraint proxies, namely the spread between BBB and 10-year constant maturity Treasury bonds (*Credit Spread*), the spread between 3-month LIBOR and 3-month Treasury bonds (*TED*), the Pástor and Stambaugh (2003) market liquidity factor (*LiqF*), the prime broker index (*PBI*), as well as the U.S. and global betting against beta factors (BAB_{US} and BAB_{GL}, respectively) of Frazzini and Pedersen (2014).

Panel A of Table 7 displays our results for the full sample. We find that all the funding constraint proxies are predicted by at least one of the measures. We also find evidence of asymmetry. Notably, while for *Credit Spread*, *TED* and *LiqF* both the upside and downside, as well as the full, oil uncertainty risk premia are significant, only upside measures are significant predictors of *PBI*, BAB_{US} and BAB_{GL}. We again split the sample into PreFin and PostFin periods to examine the robustness of our results. As a consequence of financialization, we expect the relationship between oil uncertainty risk premia and funding constraints to be stronger in the PostFin sample, similar to the finding of Christoffersen and Pan (2018).

Indeed, our results, displayed in Table 7, confirm this intuition. In the PreFin sample (Panel B) the ability of our oil uncertainty risk premia measures to predict future funding constraints is more sporadic. This is similar to Christoffersen and Pan (2018) who find that the relationship between oil volatility risk and future funding constraints is not significant during this period. Specifically, our measures only predict *PBI* and *LiqF*, with the former being driven by upside measures and the latter solely by the downside measure. On the contrary, in the PostFin sample (Panel C) the links between oil uncertainty risk premia and future funding constraints appear stronger. For example, the full oil uncertainty risk premium measure significantly predicts the majority of the funding constraint proxies. Furthermore, we find clear evidence of asymmetry. Besides the case of *CreditSpread*, where all measures are significant, the predictive ability of upside measures is stronger for the remaining proxies. In particular, while the downside oil uncertainty risk premium can only predict *LiqF*, the ability of the upside measures to predict funding constraints is extensive. This mirrors the full sample results in Panel A and corroborates the strong link between upside oil uncertainty risk premia and future funding constraints.

The above results provide support to the argument that upside oil uncertainty risk premia can predict expected returns because they reflect the presence of a financial frictions channel operating through the funding constraints faced by financial intermediaries. This finding is also consistent with the seminal work of Acharya et al. (2013) who show that increases in oil producers' hedging demand, or speculators' capital constraints, has an impact on oil derivative prices.[22] In line with their theoretical prediction, albeit for the case of options, our results in Section 5.2.4 suggest that variation in oil producers' hedging demand exposes the limited capacity of financial intermediaries to bear upside oil uncertainty risk. Specifically, by unwinding their hedges, oil producers reduce their short positions in out-of-money call options, decreasing the provision of upside price insurance to their market. In turn, this increases the risk burden that financial intermediaries have to absorb, leading to higher call option prices and, through the definition of corridor implied variance in Equation (5), higher upside uncertainty risk premia. Importantly, the same impact on upside variance risk premia would result through a "limits to hedging" effect (Acharya et al., 2013), where oil

[22] Acharya et al. (2013) focus on the effect on futures prices. The same argument could be extended to the case of options which, as their study shows, oil producers use more extensively for hedging. A similar demand-pressure effect on the prices of equity options is examined in Garleanu et al. (2008).

producers retreat from hedging activities due to higher hedging costs, manifested for example through margin requirements that become more stringent when financial intermediaries' capital constraints tighten.

6 Robustness

6.1 Model mis-specification

We examine the robustness of our modelling choices across two different dimensions. First, as shown in Equations (3) and (5), a critical input for the calculation of the corridor-based uncertainty measures are the price barriers corresponding to fixed percentiles of the next-period oil return distribution. We examine if our percentile forecasts, generated by our density forecast model described in Section 3.3, are well-behaved by conducting a variety of mis-specification tests. These include testing whether our model generates correctly specified forecasts for the entire support as well as for the different percentiles of the target distribution. The results, which are presented and explained in the Supplementary Appendix, show that our model comfortably passes all mis-specification tests.

Second, we check the accuracy of our corridor variance forecasts, generated by the HAR-CRV model in Equation (9), by comparing them to forecasts generated by a collection of plausible alternative models. These include a GARCH(1,1)-t model based on daily returns, an exponential weighted moving average (EWMA) specification that relies on past realized corridor variances, and a HAR-type model that uses past realized semi-variances. Forecast comparisons are made using Mincer-Zarnowitz and encompassing regressions. The results of these tests, which are displayed and discussed in the Supplementary Appendix, show that the HAR-CRV model delivers the most reliable corridor variance forecasts, confirming the robustness of our modelling choice.

6.2 Competing forecasts of macroeconomic growth

Our results in Section 5.3.1 suggest two key findings concerning the relationship between economic growth and oil uncertainty. Firstly, the predictive content of option-implied variance stems from the oil uncertainty risk premium rather than oil uncertainty *per se*. To examine the robustness of this finding, we include both measures in the predictive regression described in Equation (10). Note that testing for the significance of the option-implied variance parameter in this setting is akin to testing if oil price uncertainty (as proxied by expected variance) is significant, as the latter is simply the difference between the two regressors. The estimation results are displayed in Panel A of Table 8. While for the case of

PI growth both parameters become insignificant, for *GDP growth*, *Cons growth*, and *NFP growth* the parameter corresponding to the oil uncertainty risk premium has the correct sign and is statistically significant. On the contrary, the option-implied variance parameter is insignificant throughout. Therefore, option-implied variance (or, equivalently in this setup, oil price uncertainty) does not appear to contain any incremental predictive information about future economic growth beyond that captured by the uncertainty risk premium, supporting our earlier argument.

Our second key finding from Section 5.3.1 is that the strong predictive power of the uncertainty risk premium, that subsumes that of option-implied variance, appears to be driven by the downside uncertainty risk premium measure ($CVRPD$). However, since several option-implied variances are significant predictors of economic growth, we investigate the robustness of this result by comparing the information content of $CVRPD$ against the various option-implied variance measures. Panel B of Table 8 summarizes the results. For *GDP growth* and *Cons growth*, the superiority of the downside uncertainty risk premium over all other competing alternative measures is comprehensive. More precisely, the downside uncertainty risk premium measure is significant in the vast majority of the encompassing regressions, while the parameters for the competing measures are never significant. Compared to option-implied variances, the $CVRPD$ measure is also more often a significant predictor of *PI growth*. Only for the case of *NFP growth* are the results mixed, indicating that for employment growth there is relevant information beyond that captured by the $CVRPD$. Overall, the above results confirm that option-implied variances contain little relevant information about future economic growth besides that captured by the downside uncertainty risk premium measure.

6.3 Expected returns of industry portfolios

In Section 5.4, we reported that the upside oil uncertainty risk premium is a significant predictor of aggregate equity market returns, while the downside and full variance risk premia appeared insignificant. However, Chiang et al. (2015), Christoffersen and Pan (2018) and Ready (2018) have shown that oil interacts differently with disparate sectors of the economy. To examine the robustness of our findings, and potentially uncover variation in the results across industries, we replace the aggregate equity market returns in Equation (11) with the returns of each of the Fama-French 30 industry portfolios. All regressions include other known predictors of expected returns, described in Section 5.4, as controls.

Our results are displayed in Table 9. For each uncertainty risk premia measure, we report the number of industries for which the parameter is significant at the 5% level. Overall, the industry-level analysis supports our main finding for the aggregate equity market. Specifically, the upside oil uncertainty risk premium is significantly related to the one-month returns of half (15) the industry portfolios in the PostFin sample. This shows that the result for the aggregate market is not driven by a small subset of industries, as our main empirical finding appears consistent for a wide range of industry portfolios.

The regression results for the industry portfolio returns also unmask some noteworthy relationships with oil uncertainty risk premia that were not visible when examining the aggregate equity market. Firstly, in the Full and PreFin samples, the lower-decile corridor measure stands out as being significant for several industries at the one-month horizon. Secondly, the full VRP and lower-corridor oil uncertainty risk premia measures appear significant for several industries across multiple horizons in the PreFin sample. Lastly, in the PostFin sample, the upper-decile corridor measure is significant for almost half of the industries at the 12-month horizon. Therefore, there is some evidence that oil price uncertainty risk premia other than the upside measure may contain important information about expected returns at the industry level. This is consistent with the notion that the exposure to oil uncertainty varies across different industries.

7 Conclusion

In this paper we examine the importance of oil uncertainty for the macroeconomy and financial markets. Motivated by the observation that the aversion of economic agents to oil uncertainty should vary over time, we attempt to capture its economic relevance by studying the relative cost of insurance against future crude oil price variance, as reflected by the variance risk premium. Furthermore, we study corridor variance risk premia that reflect economic agents' aversion to oil price variation accrued within specific oil price ranges (i.e., "corridors").

First, we investigate the interaction of corridor variance risk premia with the general economic environment and provide several new insights. For example, lower-corridor risk premia appear more closely linked to macroeconomic and financial market conditions, while only the latter appear relevant for their upside counterparts. Bringing new evidence to the literature that examines the impact of trading flows on the prices of oil derivatives, but has exclusively focused on crude oil futures contracts (Acharya et al., 2013; Li, 2018; Kang et al., 2020), we find that speculators' trading pressure increases lower-corridor, but not upper-corridor variance risk premia, while the opposite is true for hedging pressure induced by oil producers.

Second, we revisit the study of Gao et al. (2022) who reported that option-implied variance is a strong predictor of macroeconomic growth. We find that this result is driven by variation in oil uncertainty risk premia, rather than oil uncertainty *per se*. Moreover, we report that lower corridor oil uncertainty risk premia are particularly strong predictors of future economic growth. We argue that this is because they reflect concerns about the state of both the macroeconomy and financial markets. This is also consistent with our interpretation that they reveal economic agents' apprehension towards future aggregate oil demand shocks.

Third, we explore the predictive power of oil corridor variance risk premia on future excess equity returns. We find that the upside corridor variance risk premium emerges as a strong predictor, even after controlling for other popular alternatives such as the equity variance risk premium. This predictability would remain concealed if one relied on the full oil variance risk premium measure. To explain this finding, we explore and find support for a channel related to the funding constraints of financial intermediaries. In particular, we argue that the upside corridor variance risk premium is able to predict expected equity returns because it can forecast the tightening of future funding constraints in financial markets.

Figures and Tables

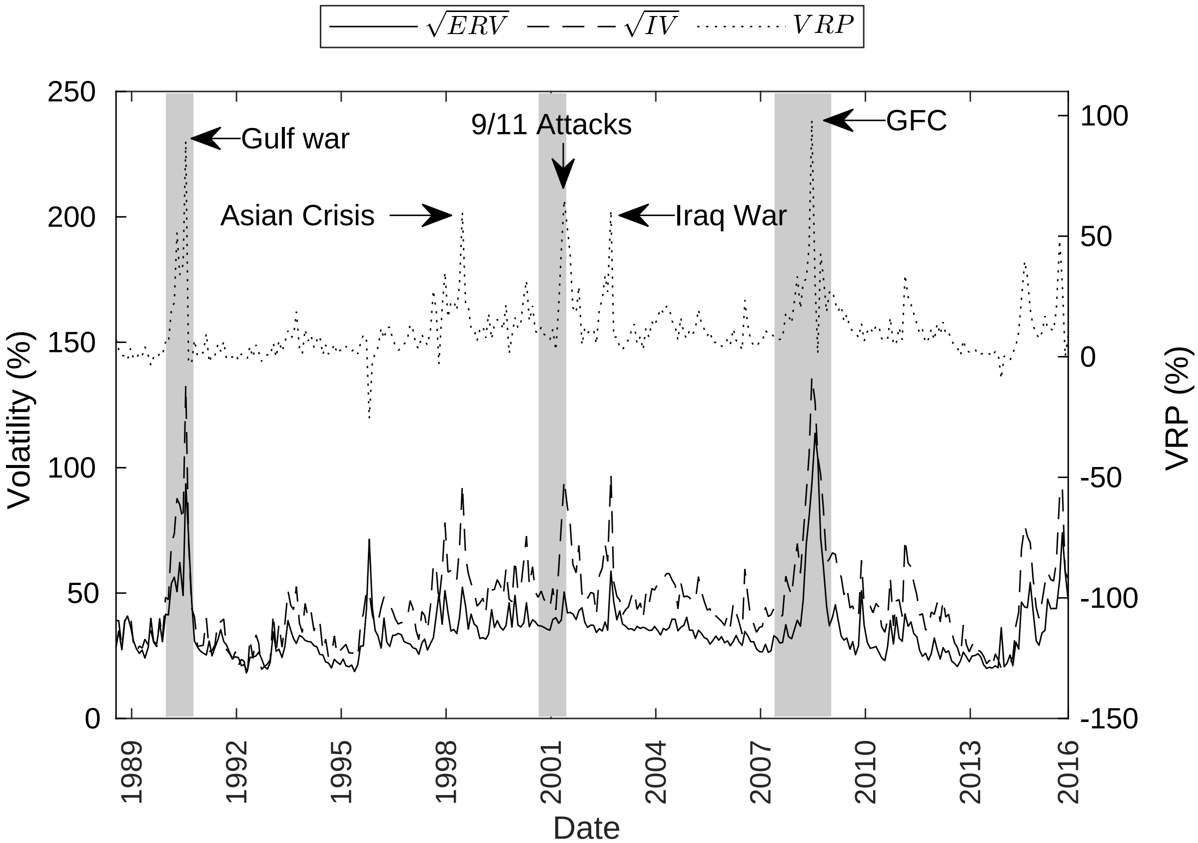
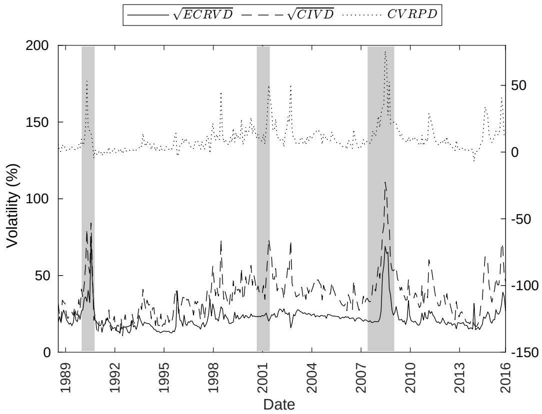
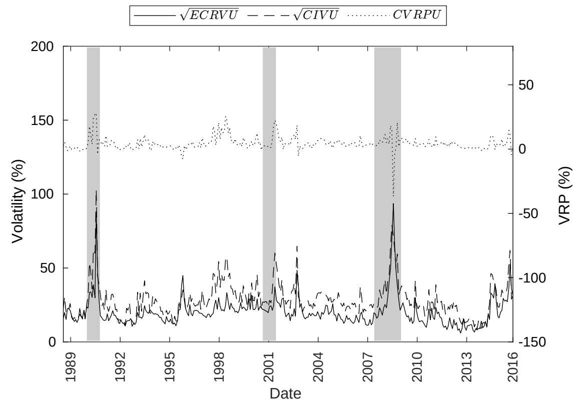


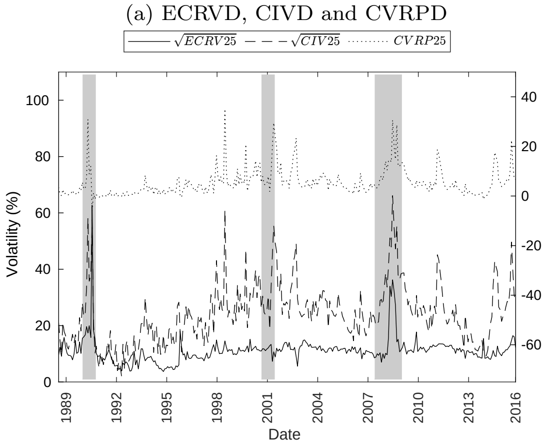
Figure 1: Time series of oil uncertainty (ERV), option-implied volatility (IV) and oil uncertainty risk premia (VRP). The values of ERV and IV are given by the left y-axis, while the values of VRP are given by the right y-axis. The three shaded grey areas correspond to NBER recessions spanning July 1990-March 1991, March 2001-November 2001 and December 2007-June 2009. To aid presentation, the values of ERV and IV are annualized *volatilities*, while the values of VRP are annualized *variance* risk premia. The coincidence between elevated values of the VRP and important exogenous shocks are annotated in the figure and include: the first Gulf War, the Asian Crisis, the 9/11 attacks on the world trade centre, the Iraq War and the Global Financial Crisis (GFC).



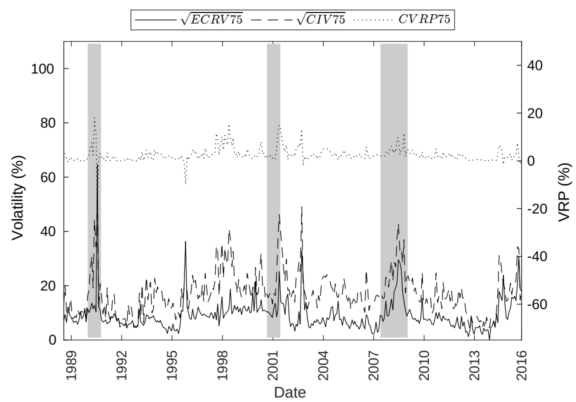
(a) ECRVD, CIVD and CVRPD



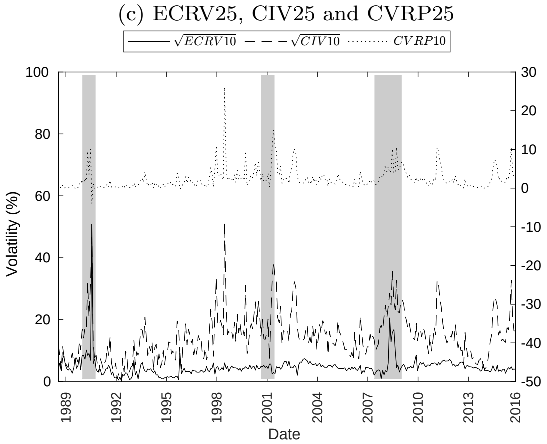
(b) ECRVU, CIVU and CVRPU



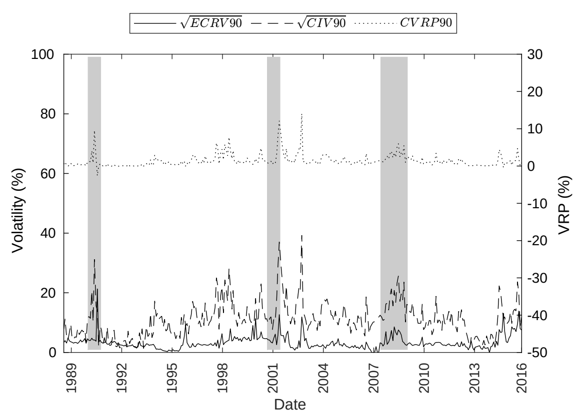
(c) ECRV25, CIV25 and CVRP25



(d) ECRV75, CIV75 and CVRP75



(e) ECRV10, CIV10 and CVRP10



(f) ECRV90, CIV90 and CVRP90

Figure 2: Time series of ECRVs, CIVs and CVRPs for different corridor values. The three shaded grey areas in each graph correspond to NBER recessions spanning July 1990-March 1991, March 2001-November 2001 and December 2007-June 2009. To aid presentation, the values of the ECRVs and CIVs are annualized *volatilities*, while the values of CVRPs are annualized *variance* risk premia.

Table 1: Descriptive statistics for (C)RVs, E(C)RVs, (C)IVs and (C)VRPs.
The first column lists the oil uncertainty measure; the second column the mean value; the third column the median; the fourth column the standard deviation; the fifth column the minimum value; the sixth column the maximum value; and the seventh column the first order autocorrelation. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

	Mean	Median	Std	Min	Max	AC(1)
RV	33.43	30.39	14.87	11.08	146.59	0.74***
CRV10	3.50	0	9.02	0	61.07	0.05
CRV25	10.54	0.97	15.26	0	108.93	0.11**
CRVD	23.16	21.63	15.47	0	113.83	0.35***
CRVU	18.40	16.83	15.00	0	92.36	0.21***
CRV75	8.26	0	11.99	0	70.61	-0.01
CRV90	2.48	0	7.45	0	70.21	0.05
ERV	34.87	32.90	12.19	18.69	113.72	0.82***
ECRV10	4.65	4.32	3.35	0.25	50.90	0.33***
ECRV25	11.11	10.95	4.79	3.70	62.71	0.60***
ECRVD	22.46	21.47	7.65	12.49	75.42	0.78***
ECRVU	20.39	18.65	9.99	5.95	93.63	0.76***
ECRV75	9.22	8.04	5.86	0.19	64.60	0.50***
ECRV90	3.34	2.76	2.34	0.12	21.30	0.54***
IV	46.80	44.28	17.94	16.48	136.17	0.83***
CIV10	14.53	13.61	7.51	0.82	51.38	0.67***
CIV25	23.98	23.10	10.63	1.87	66.16	0.76***
CIVD	36.66	35.12	14.58	10.66	111.00	0.83***
CIVU	28.54	26.48	11.90	8.60	102.93	0.73***
CIV75	17.47	16.46	7.97	4.29	49.10	0.68***
CIV90	11.14	10.61	5.95	1.34	39.31	0.67***
VRP	11.48	8.33	13.11	-25.61	98.11	0.58***
CVRP10	2.35	1.63	2.76	-4.02	26.03	0.49***
CVRP25	5.42	3.99	5.62	-6.17	35.08	0.63***
CVRPD	9.93	7.68	10.42	-6.99	75.59	0.71***
CVRPU	4.41	3.40	5.54	-36.83	28.10	0.43***
CVRP75	2.49	1.86	3.13	-20.03	18.04	0.43***
CVRP90	1.43	0.98	1.74	-2.60	14.04	0.54***

Table 2: Oil uncertainty and the economic environment.

This table reports interactions between economic variables X and oil uncertainty measures V (oil uncertainty, i.e., E(C)RVs, or oil uncertainty risk premia, i.e., (C)VRPs). Panel A reports parameter estimates for the economic activity indicators CFNAI, ADS and KIRGEA; Panel B for the economic uncertainty indicators Macro Uncertainty (MU) and Financial Uncertainty (FU); Panel C for the Investor Sentiment (Inv Sent), Consumer Confidence (Cons Conf) and Recession Attention (Rec Att) sentiment indicators; and Panel D for the trading activity indicators Speculative Index (Spec Index) and Hedging Pressure (Hedge Pres). The table displays the contemporaneous correlation coefficient ρ_{xv} for each pair of variables as well as the estimated β_v and β_x coefficients of the predictive regressions $X_t = \beta_0^* + \beta_1^* X_{t-1} + \beta_v V_{t-1} + \epsilon_t^*$ and $V_t = \beta_0 + \beta_1 V_{t-1} + \beta_x X_{t-1} + \epsilon_t$, respectively. For the economic uncertainty indicators (Panel B) the estimated parameters are for the predictive regressions $X_t = \beta_0^* + \beta_v V_{t-1} + \epsilon_t^*$ and $V_t = \beta_0 + \beta_1 V_{t-1} + \beta_x X_{t-1} + \epsilon_t$ as well as the joint (Joint) regression $V_t = \tilde{\beta}_0 + \tilde{\beta}_1 V_{t-1} + \beta_{FU}\, FU_{t-1} + \beta_{MU}\, MU_{t-1} + \tilde{\epsilon}_t$. Parameters significant at the 5% level, based on Newey-West standard errors with six lags, are in bold.

		ERV	*ECRV10*	*ECRV25*	*ECRVD*	*ECRVU*	*ECRV75*	*ECRV90*	*VRP*	*CVRP10*	*CVRP25*	*CVRPD*	*CVRPU*	*CVRP75*	*CVRP90*
Panel A: Economic activity															
CFNAI	ρ_{xv}	**-0.56**	**-0.49**	**-0.54**	**-0.57**	**-0.52**	**-0.35**	**-0.21**	**-0.34**	**-0.26**	**-0.39**	**-0.48**	0.03	**-0.18**	**-0.23**
	β_v	**-0.32**	**-0.19**	**-0.29**	**-0.31**	**-0.32**	-0.17	**-0.12**	**-0.22**	**-0.13**	**-0.22**	**-0.32**	0.02	-0.08	-0.10
	β_x	-0.17	-0.30	-0.19	-0.18	-0.18	**-0.19**	**-0.11**	**-0.12**	**-0.14**	**-0.15**	**-0.15**	0.02	-0.09	**-0.11**
ADS	ρ_{xv}	**-0.56**	**-0.43**	**-0.54**	**-0.57**	**-0.54**	**-0.37**	**-0.27**	**-0.41**	**-0.28**	**-0.44**	**-0.55**	0.03	**-0.20**	**-0.26**
	β_v	**-0.12**	**-0.16**	**-0.19**	**-0.17**	-0.07	-0.05	**-0.06**	**-0.08**	-0.03	-0.06	**-0.09**	-0.06	-0.06	-0.06
	β_x	**-0.17**	-0.21	-0.13	-0.14	-0.23	**-0.21**	**-0.15**	**-0.20**	**-0.16**	**-0.21**	**-0.25**	0.04	-0.08	**-0.12**
KIRGEA	ρ_{xv}	**-0.16**	-0.07	-0.09	**-0.10**	**-0.18**	**-0.22**	**-0.29**	-0.09	**-0.12**	-0.09	-0.09	-0.06	-0.06	-0.05
	β_v	0.02	-0.02	<0.01	0.02	0.04	<0.01	-0.03	-0.01	-0.01	-0.01	<0.01	-0.03	<0.01	<0.01
	β_x	-0.05	-0.02	-0.02	-0.04	-0.08	**-0.11**	-0.16	-0.03	-0.06	-0.03	-0.03	-0.02	-0.02	-0.02
Panel B: Economic uncertainty															
FU	ρ_{xv}	**0.54**	**0.42**	**0.52**	**0.54**	**0.47**	**0.37**	**0.30**	**0.55**	**0.50**	**0.59**	**0.61**	**0.25**	**0.43**	**0.42**
	β_v	**0.54**	**0.43**	**0.53**	**0.53**	**0.46**	**0.37**	**0.30**	**0.54**	**0.48**	**0.58**	**0.60**	0.24	**0.42**	**0.41**
	β_x	**0.13**	0.21	0.14	0.13	0.15	**0.19**	**0.17**	**0.31**	**0.32**	**0.31**	**0.27**	**0.17**	**0.23**	**0.22**
MU	ρ_{xv}	**0.68**	**0.54**	**0.67**	**0.70**	**0.61**	**0.44**	**0.28**	**0.55**	**0.40**	**0.58**	**0.68**	**0.10**	**0.33**	**0.37**
	β_v	**0.66**	**0.55**	**0.66**	**0.68**	**0.59**	0.43	**0.29**	**0.55**	**0.40**	**0.58**	**0.68**	0.11	**0.33**	**0.37**
	β_x	**0.24**	0.32	**0.24**	**0.24**	**0.25**	**0.26**	**0.16**	**0.30**	**0.23**	**0.30**	**0.36**	0.06	**0.16**	**0.18**
Joint	β_{FU}	0.03	0.06	0.04	0.02	0.03	0.07	0.12	**0.20**	**0.27**	**0.21**	**0.16**	**0.23**	**0.21**	**0.17**
	β_{MU}	**0.22**	0.28	0.22	**0.23**	**0.24**	**0.21**	0.08	**0.19**	0.08	**0.19**	**0.28**	-0.09	0.03	0.08
Panel C: Sentiment															
Inv Sent	ρ_{xv}	**-0.15**	**-0.21**	**-0.22**	**-0.21**	**-0.12**	-0.05	0.04	-0.06	<0.01	-0.04	-0.09	0.03	0.03	0.04
	β_v	**-0.03**	**-0.02**	**-0.03**	**-0.03**	-0.02	-0.03	-0.03	-0.03	-0.02	-0.02	-0.02	-0.03	-0.03	-0.04
	β_x	-0.01	-0.09	-0.03	-0.02	-0.02	-0.01	0.03	-0.01	0.01	<0.01	-0.01	0.03	0.03	0.04
Cons Conf	ρ_{xv}	**-0.15**	**-0.26**	**-0.26**	**-0.22**	**-0.14**	-0.03	0.08	**-0.10**	-0.04	**-0.10**	**-0.16**	**0.12**	0.08	0.03
	β_v	-0.02	**-0.05**	**-0.04**	**-0.03**	<0.01	<0.01	<0.01	<0.01	-0.01	-0.01	-0.01	0.02	0.02	0.01
	β_x	-0.02	-0.10	-0.03	-0.02	-0.04	-0.01	0.05	-0.04	-0.02	-0.03	-0.05	0.07	0.03	0.01
Rec Att	ρ_{xv}	**0.61**	**0.52**	**0.60**	**0.62**	**0.56**	**0.41**	**0.30**	**0.52**	**0.40**	**0.52**	**0.61**	**0.14**	**0.33**	**0.36**
	β_v	-0.01	**0.05**	**0.05**	0.02	-0.01	-0.01	-0.01	0.02	<0.01	0.02	0.03	-0.02	-0.01	<0.01
	β_x	**0.24**	0.31	0.22	**0.22**	**0.26**	**0.26**	**0.20**	**0.29**	**0.25**	**0.27**	**0.30**	0.10	**0.18**	**0.20**
Panel D: Trading activity															
Spec Index	ρ_{xv}	**0.29**	**0.26**	**0.34**	**0.33**	**0.22**	**0.19**	**0.25**	**0.28**	**0.20**	**0.30**	**0.37**	0.02	0.04	0.07
	β_v	<0.01	**0.03**	0.02	0.01	0.01	-0.01	-0.01	0.02	0.01	0.01	0.02	-0.01	<0.01	-0.01
	β_x	**0.07**	0.11	**0.08**	**0.07**	0.06	0.10	0.16	**0.11**	0.10	**0.11**	**0.12**	0.02	0.02	0.03
Hedge Pres	ρ_{xv}	-0.06	<0.01	<0.01	-0.07	-0.05	0.02	**0.14**	-0.09	-0.06	-0.04	-0.01	**-0.21**	**-0.26**	**-0.20**
	β_v	-0.01	<0.01	<0.01	<0.01	-0.02	**-0.03**	**-0.03**	-0.01	-0.01	-0.02	-0.02	-0.01	-0.01	**-0.02**
	β_x	<0.01	<0.01	<0.01	-0.01	<0.01	0.03	0.09	-0.03	-0.03	<0.01	0.01	**-0.13**	**-0.12**	-0.08

Table 3: Regressions of economic growth against multiple uncertainty measures.
This table summarizes the parameter estimates from regressions described in Equation (10). In each regression an economic growth variable is regressed against an oil price uncertainty measure, the *VIX* and *Macro Unc* as well as a set of control variables. The economic growth measures used are *GDP growth*, *Cons growth*, *PI growth* and *NFP growth*, which are measured over either the one (1Q), two (2Q) or four (4Q) quarters that follow the quarter in which the uncertainty measures and control variables are constructed. The control variables include the contemporaneous and lagged quarterly oil futures return, contemporaneous quarterly oil supply growth and contemporaneous quarterly TFP growth. The first column lists the economic growth variable used in the regressions; the second column indicates the horizon over which the economic growth variable was measured; columns three to nine contain the parameter estimates for the oil price uncertainty measure (*Oil Unc*) listed at the head of each column. Panel A summarizes results for (C)IVs, i.e., option-implied oil variance measures; Panel B for E(C)RVs, i.e., oil uncertainty measures; and Panel C for (C)VRPs, i.e., oil uncertainty risk premia. Parameter estimates for the control variables are not reported to conserve space. Newey-West standard errors based on 4 lags were used. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Panel A: Option-implied oil variance								
		IV	*CIV10*	*CIV25*	*CIVD*	*CIVU*	*CIV75*	*CIV90*
GDP growth	1Q	-0.48**	-0.48***	-0.77***	-0.84***	-0.10	-0.15	-0.23
	2Q	-0.36	-0.49	-1.02**	-1.01	0.18	-0.14	-0.58
	4Q	-0.33	-0.90	-1.61	-1.29	0.43	-0.38	-1.40
Cons growth	1Q	-0.18	-0.27	-0.46**	-0.47*	0.08	0.03	-0.09
	2Q	-0.40	-0.63	-1.19**	-1.20*	0.26	-0.04	-0.52
	4Q	-0.37	-1.18	-1.89*	-1.46	0.49	-0.20	-1.14
PI growth	1Q	-3.12***	-1.38	-2.71**	-3.84***	-1.96**	-1.94**	-1.54*
	2Q	-3.77**	-1.37	-4.06**	-5.66***	-1.67	-2.24	-2.56
	4Q	-2.94	-1.91	-5.83	-6.35	0.08	-2.90	-5.95
NFP growth	1Q	-0.55***	-0.51***	-0.62***	-0.67***	-0.35***	-0.43***	-0.45***
	2Q	-0.99***	-0.98***	-1.30***	-1.34***	-0.55***	-0.78***	-0.92***
	4Q	-1.54***	-1.68**	-2.24**	-2.16***	-0.80**	-1.41**	-1.88***
Panel B: Oil uncertainty								
		ERV	*ECRV10*	*ECRV25*	*ECRVD*	*ECRVU*	*ECRV75*	*ECRV90*
GDP growth	1Q	0.01	-0.10	-0.13	-0.07	-0.03	0.02	-0.06
	2Q	0.45	0.08	0.01	0.23	0.55	0.26	0.00
	4Q	1.35	0.13	0.10	0.83	1.22	0.34	-0.19
Cons growth	1Q	0.20	-0.03	-0.05	0.05	0.16	0.04	0.03
	2Q	0.43	0.13	0.07	0.29	0.52	0.24	0.12
	4Q	1.40	0.05	0.03	0.74	1.28	0.26	0.00
PI growth	1Q	-3.04	-1.04**	-1.27**	-2.18*	-2.66*	-0.83	-1.08
	2Q	-3.35	-1.04	-1.57	-2.44	-2.29	-0.56	-1.44
	4Q	0.22	0.20	-0.21	0.59	1.13	0.35	-2.01
NFP growth	1Q	-0.21	-0.24***	-0.26***	-0.28**	-0.22	-0.21**	-0.28***
	2Q	-0.32	-0.43***	-0.49***	-0.46	-0.27	-0.38**	-0.58***
	4Q	-0.18	-0.64***	-0.71**	-0.53	-0.15	-0.56	-1.02**
Panel C: Oil uncertainty risk premia								
		VRP	*CVRP10*	*CVRP25*	*CVRPD*	*CVRPU*	*CVRP75*	*CVRP90*
GDP growth	1Q	-0.55***	-0.45**	-0.67***	-0.87***	-0.12	-0.14	-0.21
	2Q	-0.69	-0.74*	-1.10**	-1.34***	-0.29	-0.43	-0.57
	4Q	-1.16	-1.33	-1.81*	-2.12*	-0.61	-0.71	-1.29
Cons growth	1Q	-0.31*	-0.28	-0.42**	-0.55**	-0.04	-0.02	-0.10
	2Q	-0.72	-0.98**	-1.33***	-1.60***	-0.14	-0.32	-0.54
	4Q	-1.25	-1.61*	-2.04**	-2.26**	-0.59	-0.48	-1.11
PI growth	1Q	-1.88**	-0.48	-1.71	-2.77**	-0.26	-0.58	-1.18
	2Q	-2.44*	-0.49	-2.93	-4.73**	-0.19	-1.12	-2.01
	4Q	-3.55	-2.74	-6.06	-7.81	-1.06	-2.75	-5.11
NFP growth	1Q	-0.51***	-0.33*	-0.41*	-0.55***	-0.31*	-0.11	-0.36**
	2Q	-0.97***	-0.73**	-0.96**	-1.21***	-0.57*	-0.17	-0.70**
	4Q	-1.68**	-1.38*	-1.77*	-2.10**	-1.09	-0.45	-1.48**

Table 4: Regressions of crude oil market variables against multiple uncertainty measures.
This table summarizes the parameter estimates from regressions described in Equation (10). In each regression an oil market variable is regressed against an oil price uncertainty measure, the *VIX* and *Macro Unc*, as well as a set of control variables. The oil market variables used are *Oil cons growth*, *Oil prod growth* and *Oil inventory growth*, which are measured over either the one (1Q), two (2Q) or four (4Q) quarters that follow the quarter in which the uncertainty measures and control variables are constructed. The control variables include the contemporaneous and lagged quarterly oil futures return, contemporaneous quarterly oil supply growth and contemporaneous quarterly TFP growth. The first column lists the oil market variable used in the regressions; the second column indicates the horizon over which the oil market variable was measured; columns three to nine contain the parameter estimates for the oil price uncertainty measure listed at the head of each column. Panel A summarizes results for (C)IVs, i.e., option-implied variance measures; Panel B for E(C)RVs, i.e., oil uncertainty measures; and Panel C for (C)VRPs, i.e., oil uncertainty risk premia. Parameter estimates for the control variables are not reported to conserve space. Newey-West standard errors based on 4 lags were used. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Panel A: Option-implied oil variance								
		IV	*CIV10*	*CIV25*	*CIVD*	*CIVU*	*CIV75*	*CIV90*
Oil cons growth	1Q	-0.27	-0.33**	-0.35	-0.30	-0.19	-0.16	-0.13
	2Q	-0.19	-0.41	-0.34	-0.19	-0.15	-0.04	0.01
	4Q	-0.13	-0.56	-0.43	-0.15	-0.07	0.13	0.19
Oil prod growth	1Q	0.09	0.06	0.07	0.10	0.06	0.02	-0.01
	2Q	-0.04	-0.06	-0.09	-0.08	0.02	-0.06	-0.12
	4Q	-0.07	-0.08	-0.12	-0.11	0.00	-0.19	-0.31
Oil inventory growth	1Q	0.19**	0.18**	0.22**	0.24**	0.12	0.12	0.10
	2Q	0.23**	0.24**	0.28***	0.26**	0.15	0.14	0.14
	4Q	0.21	0.21	0.27	0.25	0.11	0.02	0.01
Panel B: Oil uncertainty								
		ERV	*ECRV10*	*ECRV25*	*ECRVD*	*ECRVU*	*ECRV75*	*ECRV90*
Oil cons growth	1Q	-0.21	-0.30***	-0.32***	-0.30	-0.21	-0.35***	-0.29***
	2Q	-0.19	-0.57***	-0.59***	-0.42	-0.20	-0.56***	-0.51***
	4Q	-0.17	-0.93***	-0.97***	-0.61	-0.17	-0.91***	-0.84**
Oil prod growth	1Q	0.22**	0.06**	0.08*	0.16	0.13*	0.08	0.04
	2Q	0.06	0.08*	0.07	0.07	0.06	0.11	0.06
	4Q	0.11	0.21***	0.19*	0.15	0.13	0.24***	0.17
Oil inventory growth	1Q	0.17	0.14***	0.14***	0.14**	0.18**	0.15***	0.15***
	2Q	0.19	0.17***	0.19***	0.19**	0.21**	0.19***	0.19***
	4Q	0.32	0.29***	0.33***	0.32*	0.31	0.41**	0.37***
Panel C: Oil uncertainty risk premia								
		VRP	*CVRP10*	*CVRP25*	*CVRPD*	*CVRPU*	*CVRP75*	*CVRP90*
Oil cons growth	1Q	-0.19	-0.06	-0.09	-0.14	-0.07	0.28	-0.04
	2Q	-0.14	0.07	-0.01	-0.02	0.03	0.63*	0.17
	4Q	-0.05	0.23	0.12	0.14	0.12	1.17*	0.44
Oil prod growth	1Q	-0.02	0.00	0.01	0.01	-0.04	-0.07	-0.02
	2Q	-0.12	-0.16	-0.16	-0.15	-0.05	-0.19**	-0.14
	4Q	-0.22	-0.30	-0.26	-0.24	-0.20	-0.46***	-0.36*
Oil inventory growth	1Q	0.13	0.06	0.11	0.17	-0.01	-0.09	0.06
	2Q	0.20	0.12	0.20**	0.24**	-0.05	-0.09	0.08
	4Q	0.04	-0.03	0.12	0.16	-0.27	-0.45**	-0.10

Table 5: Predictive regressions for expected equity market returns.
This table reports regression results corresponding to Equation (11) where only a single predictor is included. We consider four horizons, $h = 1, 3, 6, 12$, which correspond to monthly, quarterly, semi-annual and annual market returns. Each row reports the t-statistic for the predictor listed at the head of each column. Panel A reports results for the Full sample (1991-2016); Panel B for the PreFin sample (1991-2004); and Panel C for the PostFin sample (2005-2016). All standard errors are Newey-West computed using lags equal to $\max(3, 2 \times h)$, as in Bekaert and Hoerova (2014). Bold numbers indicate significance at the 5% level.

Panel A: Full sample															
h	*VRP*	*CVRP10*	*CVRP25*	*CVRPD*	*CVRPU*	*CVRP75*	*CVRP90*	*CAY*	*PE*	*PD*	*TS*	*DS*	*EqVRP*	*SL(-)*	*SL(+)*
1	-0.43	0.11	-0.67	-1.10	**2.17**	0.43	0.04	0.91	-0.49	**-1.98**	0.20	-0.49	-0.41	0.12	**-3.06**
3	-0.83	-0.52	-0.76	-0.91	-0.16	-0.23	-0.13	1.02	-0.29	**-2.25**	0.18	-0.29	1.56	0.06	**-1.81**
6	-0.92	-0.37	-0.56	-0.65	-1.20	-0.82	-0.64	0.93	-0.22	**-2.75**	0.52	0.19	1.61	-0.40	-1.25
12	-0.49	-0.41	-0.41	-0.25	-1.07	-0.36	-0.44	0.80	-0.25	**-3.51**	**1.79**	1.15	1.65	-0.87	-1.21
Panel B: PreFin sample															
h	*VRP*	*CVRP10*	*CVRP25*	*CVRPD*	*CVRPU*	*CVRP75*	*CVRP90*	*CAY*	*PE*	*PD*	*TS*	*DS*	*EqVRP*	*SL(-)*	*SL(+)*
1	-0.58	-0.21	-0.89	-1.25	0.94	0.41	0.46	**2.35**	**-2.65**	**-2.17**	-0.14	-0.58	-0.48	-0.16	**-2.52**
3	-0.66	-1.02	-1.14	-0.94	0.02	0.33	0.52	**2.58**	**-2.98**	**-2.39**	-0.13	-0.67	0.16	-0.26	-1.09
6	-1.16	-1.02	-1.26	-1.26	-0.92	-0.81	-0.34	**2.84**	**-3.29**	**-2.22**	0.15	-0.85	-0.06	-0.45	-0.34
12	-1.40	-1.08	-1.46	-1.54	-0.80	-0.65	-0.54	**2.83**	**-3.48**	**-2.42**	0.60	-0.46	-0.09	-1.34	-0.58
Panel C: PostFin sample															
h	*VRP*	*CVRP10*	*CVRP25*	*CVRPD*	*CVRPU*	*CVRP75*	*CVRP90*	*CAY*	*PE*	*PD*	*TS*	*DS*	*EqVRP*	*SL(-)*	*SL(+)*
1	-0.13	0.45	-0.11	-0.54	**3.03**	0.13	-0.43	-0.73	0.53	-0.86	0.52	-0.34	-0.13	0.58	**-1.90**
3	-0.62	0.26	-0.10	-0.44	-0.24	-0.53	-0.77	-0.52	0.92	-1.03	0.55	-0.06	**2.47**	0.26	**-1.95**
6	-0.11	0.71	0.46	0.32	-0.66	-0.30	-0.62	-0.23	1.31	**-2.73**	0.92	0.86	**5.07**	-0.15	**-1.82**
12	1.07	1.18	1.14	1.33	-1.02	0.34	0.01	-0.28	**1.66**	**-5.85**	**2.73**	**3.63**	**6.49**	0.00	-1.44

Table 6: Predictive regressions for expected equity market returns including control variables.
This table presents regression results corresponding to Equation (11) with all control variables included. We consider four horizons, $h = 1, 3, 6, 12$, which correspond to monthly, quarterly, semi-annual and annual market returns. To conserve space, we only report results for the oil uncertainty risk premia measures. Each row displays the t-statistic for the predictor listed at the head of each column. Panel A reports results for the full sample (1993-2016); Panel B for the PreFin sample (1993-2004); and Panel C for the PostFin sample (2005-2016). All standard errors are Newey-West computed using lags equal to $\max(3, 2 \times h)$, as in Bekaert and Hoerova (2014). Bold numbers indicate significance at the 5% level.

Panel A: Full sample							
h	*VRP*	*CVRP10*	*CVRP25*	*CVRPD*	*CVRPU*	*CVRP75*	*CVRP90*
1	0.05	1.39	0.22	-0.53	**1.89**	0.48	0.69
3	-0.63	-0.23	-0.58	-0.83	0.65	0.09	0.32
6	-0.92	0.33	-0.30	-0.91	-0.01	-0.59	-0.40
12	-0.65	0.09	-0.46	-0.78	0.40	0.21	-0.20
Panel B: PreFin sample							
h	*VRP*	*CVRP10*	*CVRP25*	*CVRPD*	*CVRPU*	*CVRP75*	*CVRP90*
1	1.22	1.58	0.99	0.89	**1.71**	1.30	**1.99**
3	1.13	-0.21	-0.02	0.38	**1.77**	**2.06**	**2.32**
6	0.22	-0.15	-0.45	-0.39	1.07	0.95	1.37
12	0.36	0.10	-0.32	-0.43	**1.88**	**1.69**	1.26
Panel C: PostFin sample							
h	*VRP*	*CVRP10*	*CVRP25*	*CVRPD*	*CVRPU*	*CVRP75*	*CVRP90*
1	-0.02	0.39	0.05	-0.38	**2.04**	0.38	-0.25
3	-1.19	-0.01	-0.44	-1.00	-0.06	-1.00	-1.21
6	-1.12	0.81	0.18	-0.68	-0.47	-1.24	-1.55
12	-0.34	0.33	0.16	-0.12	-0.09	-1.05	-1.61

Table 7: Regressions of financial constraint proxies against oil uncertainty risk premia.
This table presents results from univariate regressions in which one-month-ahead proxies for financial constraints are regressed against our monthly oil uncertainty risk premia measures. The financial constraint proxies include the spread between Baa and 10-year constant maturity Treasury bonds (*Credit Spread*), the spread between 3-month LIBOR and 3-month Treasury bonds (*TED*), the Pástor and Stambaugh (2003) market liquidity factor (*LiqF*), the prime broker index (*PBI*) as well as the U.S. and global betting against beta factors (BAB_{US} and BAB_{GL}, respectively) of Frazzini and Pedersen (2014). All the uncertainty risk premia measures are standardized to have a mean value of zero and a variance equal to one. Panel A reports results for the Full sample (1991-2016); Panel B for the PreFin sample (1991-2004); and Panel C for the PostFin sample (2005-2016). Newey-West standard errors were used with lags equal to $\max(3, 2 \times h)$. Values in bold indicate significance at the 5% level.

Panel A: Full sample						
	Credit Spread	*TED*	*LiqF*	*PBI*	BAB_{US}	BAB_{GL}
VRP	**2.12**	**-2.41**	**-2.18**	-0.43	-1.70	-1.55
CVRP10	1.48	-1.54	**-1.67**	-0.93	-1.15	-0.45
CVRP25	1.59	**-1.69**	**-2.11**	-0.62	-1.66	-0.98
CVRPD	**1.98**	-1.74	**-2.73**	-0.81	-1.38	-0.91
CVRPU	**2.54**	**-2.49**	**-2.05**	-1.26	**-2.14**	**-2.23**
CVRP75	1.44	**-1.98**	-0.64	**-3.28**	-1.21	-1.40
CVRP90	1.26	-1.65	-1.11	**-3.24**	-1.02	-0.85
Panel B: PreFin sample						
	Credit Spread	*TED*	*LiqF*	*PBI*	BAB_{US}	BAB_{GL}
VRP	0.65	-1.42	-1.55	**-2.06**	-0.87	-0.45
CVRP10	0.68	-1.21	-1.15	-0.72	-1.03	-0.19
CVRP25	0.44	-1.21	-1.34	-0.21	-1.50	-0.64
CVRPD	0.67	-0.97	**-2.05**	-0.82	-1.21	-0.48
CVRPU	0.77	**-2.39**	-0.96	**-3.29**	-0.38	-0.51
CVRP75	0.57	-1.47	-0.43	**-2.55**	-0.44	-0.71
CVRP90	0.62	-1.22	-1.36	**-2.37**	-0.48	-0.40
Panel C: PostFin sample						
	Credit Spread	*TED*	*LiqF*	*PBI*	BAB_{US}	BAB_{GL}
VRP	**3.32**	**-2.42**	**-2.42**	0.18	**-1.98**	**-2.85**
CVRP10	**2.74**	-1.30	-2.46	-0.51	-0.56	-0.88
CVRP25	**2.84**	-1.30	-2.49	-0.61	-0.67	-1.04
CVRPD	**2.67**	-1.66	**-2.22**	-0.49	-0.68	-1.04
CVRPU	**3.62**	-1.66	**-2.43**	-0.50	**-4.73**	**-4.29**
CVRP75	**1.96**	**-1.90**	-0.61	**-1.98**	**-1.84**	**-1.90**
CVRP90	**1.96**	**-1.70**	-0.43	**-2.73**	-1.63	**-1.76**

Table 8: Encompassing regressions of economic growth against competing oil uncertainty measures.
This table summarizes the parameter estimates from regressions described in Equation (10). In Panel A, an economic growth variable is regressed against *IV* and *VRP* as well as a set of control variables. In Panel B, an economic growth variable is regressed against *CVRPD* and a competing option-implied oil uncertainty measure, i.e., a (C)IV, as well as a set of control variables. The economic growth measures used are *GDP growth*, *Cons growth*, *PI growth* and *NFP growth*, which are measured over either the one (1Q), two (2Q) or four (4Q) quarters that follow the quarter in which the uncertainty measure and control variables are constructed. The control variables include the *VIX*, *Macro Unc*, the contemporaneous and lagged quarterly oil futures return, contemporaneous quarterly oil supply growth and contemporaneous quarterly TFP growth. The first column lists the economic growth variable used in the regressions; the second column indicates the horizon over which the economic growth variable was measured; the third column lists the uncertainty measures used in each regression, where *Unc* refers to the uncertainty measure listed at the head of columns four to twelve; columns four and five (Panel A) contain the parameter estimates for encompassing regressions involving *IV* and *VRP*; columns six to twelve (Panel B) contain the parameter estimates for encompassing regressions involving an the oil uncertainty measure (*Unc*) together with *CVRPD*; Parameter estimates for the *VIX*, *Macro Unc* and the control variables are not reported to conserve space. Newey-West standard errors based on 4 lags were used. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

			Panel A: *IV* vs *VRP*		Panel B: *CVRPD* vs (C)IVs						
		Unc:	*IV*	*VRP*	*IV*	*CIV10*	*CIV25*	*CIVD*	*CIVU*	*CIV75*	*CIV90*
GDP growth	Q1	*Unc*	0.44	-0.85**	0.17	0.01	-0.22	0.02	0.18	0.37	0.40
		CVRPD			-0.98***	-0.88***	-0.68**	-0.89***	-0.94***	-1.12***	-1.21***
	Q2	*Unc*	1.33	-1.60**	0.78	0.35	0.13	0.85	0.61	0.60	0.10
		CVRPD			-1.84***	-1.62***	-1.46*	-1.99***	-1.58***	-1.73***	-1.42**
	Q4	*Unc*	3.30	-3.41**	1.61	0.34	0.21	2.37	1.12	0.71	-0.63
		CVRPD			-3.16**	-2.39**	-2.31*	-3.94*	-2.56**	-2.58**	-1.60
Cons growth	Q1	*Unc*	0.60	-0.72*	0.32	0.06	-0.05	0.23	0.28	0.42	0.35
		CVRPD			-0.75***	-0.60**	-0.51	-0.73***	-0.66***	-0.83***	-0.84***
	Q2	*Unc*	1.31	-1.61*	0.98*	0.35	0.27	1.04	0.78	0.88*	0.42
		CVRPD			-2.24***	-1.88***	-1.85**	-2.40***	-1.91***	-2.18***	-1.95***
	Q4	*Unc*	3.47	-3.61*	1.67	-0.03	-0.40	2.21	1.23	1.05	-0.10
		CVRPD			-3.34**	-2.23*	-1.89	-3.96**	-2.74**	-2.94***	-2.18**
PI growth	Q1	*Unc*	-4.07	0.88	-2.21*	0.28	-1.69	-4.35	-1.28	-0.93	-0.18
		CVRPD			-1.37	-2.99*	-1.24	0.52	-2.27*	-2.15	-2.61
	Q2	*Unc*	-4.26	0.46	-1.40	1.83	-1.16	-4.42	-0.43	-0.31	-0.47
		CVRPD			-3.83	-6.20**	-3.67	-1.33	-4.56**	-4.53*	-4.35
	Q4	*Unc*	3.03	-5.61	3.06	3.64	1.10	3.15	2.45	0.55	-3.63
		CVRPD			-9.78	-10.76**	-8.82	-10.23	-8.78*	-8.17*	-4.84
NFP growth	Q1	*Unc*	0.01	-0.52**	-0.31*	-0.37***	-0.66***	-0.51	-0.21	-0.25	-0.29*
		CVRPD			-0.35	-0.26	0.04	-0.17	-0.47**	-0.39	-0.31
	Q2	*Unc*	0.14	-1.07**	-0.40	-0.60***	-1.26***	-0.76	-0.24	-0.37	-0.55*
		CVRPD			-0.95*	-0.73*	-0.05	-0.62	-1.11***	-0.97**	-0.76*
	Q4	*Unc*	0.93	-2.31*	-0.41	-1.01**	-2.13**	-0.72	-0.26	-0.72	-1.43
		CVRPD			-1.84	-1.28	-0.14	-1.55	-2.00*	-1.63	-0.93

Table 9: Predictive regressions for expected industry portfolio returns.
This table presents regression results corresponding to Equation (11) where equity market returns are substituted by returns of industry portfolios. All regressions include alternative equity return predictors as controls. We consider four horizons, $h = 1, 3, 6, 12$, which correspond to monthly, quarterly, semi-annual and annual industry portfolio returns. To conserve space, the table reports the number of industries for which the parameter fn the oil uncertainty measure listed at the head of each column is significant at the 5% level. The tests are conducted using Newey-West standard errors with lags equal to $\max(3, 2 \times h)$, as in Bekaert and Hoerova (2014) Panel A reports results for the Full sample (1991-2016); Panel B for the PreFin sample (1991-2004); and Panel C for the PostFin sample (2005-2016).

Panel A: Full sample							
h	*VRP*	*CVRP10*	*CVRP25*	*CVRPD*	*CVRPU*	*CVRP75*	*CVRP90*
1	0	8	1	0	1	0	0
3	0	0	0	0	0	0	2
6	0	2	2	1	2	0	2
12	1	2	3	2	1	4	2

Panel B: PreFin sample							
h	*VRP*	*CVRP10*	*CVRP25*	*CVRPD*	*CVRPU*	*CVRP75*	*CVRP90*
1	5	9	10	9	1	0	6
3	9	1	3	10	2	6	15
6	12	1	6	11	3	4	12
12	6	3	7	10	6	4	8

Panel C: PostFin sample							
h	*VRP*	*CVRP10*	*CVRP25*	*CVRPD*	*CVRPU*	*CVRP75*	*CVRP90*
1	1	1	0	0	15	1	0
3	5	0	2	6	0	0	0
6	5	3	2	4	0	1	2
12	1	2	2	0	0	4	13

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Supplementary Appendix for Online Publication

This Supplementary Appendix provides further details on methodological issues, model robustness tests, and empirical results.

Section A provides additional methodological notes. Section A.1 explains the calculation of corridor realized variances using a subsampling method, which is mentioned in Section 3.1 of the paper. Section A.2 explains how the speculative and hedging pressure indices, appearing in Section 5.2.4 of the paper, are constructed.

Section B elaborates on our model robustness tests, as briefly summarized in Section 6.1 of the paper. This includes describing how the various tests are defined as well as presenting their results. Tests of the density forecast model, which determines the barriers used to construct our corridor realized variances are presented in Section B.1. Section B.2 compares our corridor variance forecasts with those obtained from alternative model specifications.

Section C presents additional empirical results which were not included in the main paper. Section C.1 relates to Section 5.3.1 of the paper, where we examined if our measures of oil uncertainty and uncertainty risk can predict macroeconomic growth aggregates while controlling for macroeconomic and financial uncertainty. In particular, Section C.1 presents and discusses the empirical results when only a single uncertainty measure is included in the predictive regressions. Finally, Section C.2 presents supplementary estimation results, notably relating to the significance of various control variables, linked to different parts of the paper.

A Methodological notes

A.1 Subsampled (corridor) realized variances

To calculate the realized variance from time 0 to time T (i.e., $RV_{0,T}$) we require $M+1$ equally spaced intraday price observations at times t_i, $i = 0, \ldots, M$, on day t. Letting p_{t_i} be the log price at time t_i, the intraday return between times t_{i-1} and t_i is $r_{t_i} = p_{t_i} - p_{t_{i-1}}$.

To minimize the amount of microstructure noise in our intraday returns, and therefore minimize any upward bias in our RV estimates, we use the common approach of calculating our intraday returns over 5-min intervals (Andersen et al., 2000). However, although microstructure noise is mitigated, using a coarse sampling interval leads to information being discarded and less precise RV estimates. To improve the precision of our RV estimates, we use the following sub-sampled RV estimator of Andersen, Bollerslev, and Meddahi (2011),

$$RV_t^{ss} = \frac{1}{\Delta}\left(\frac{M/\Delta}{(M/\Delta)-1}\sum_{j=2}^{\Delta-1}\sum_{i=1}^{M/\Delta-1}\bar{r}^2_{\Delta,t_{\Delta(i-1)+j}} + \sum_{k=1}^{M/\Delta}\bar{r}^2_{\Delta,t_{\Delta(k-1)+1}}\right) + r^2_{t_0}, \tag{A1}$$

where $\bar{r}_{\Delta,t_i} = \sum_{j=1}^{\Delta} r_{t_{i+(j-1)}} = p_{t_{i-1+\Delta}} - p_{t_{i-1}}$ is the Δ-period intraday return between times t_{i-1} and $t_{i-1+\Delta}$; M and Δ are chosen such that M/Δ is an integer; and r_{t_0} is the overnight return, i.e., the log of the opening price on day t minus the log of the closing price on day $t-1$. We use high-frequency prices sampled over 30-sec intervals and set Δ to be 5-min. Intuitively, our sub-sampled RV can be thought of as the average of RVs calculated over ten 5-min time grids that are separated by 30-sec intervals: the first grid is comprised of time points t_i starting at $i = 0$-min; the second of t_i starting at $i = 0.5$-min; the third of t_i starting at $i = 1$-min; and so on until the last grid of t_i which start at $i = 4.5$-min. Although we use RV_t^{ss} defined in Equation (A1), for ease of notation we continue to refer to it as RV_t in the text.

To estimate corridor realized variance we use a sub-sampled corridor realized variance (CRV). Our estimator of CRV for price barriers B_1 and B_2, $CRV_t^{B_1,B_2}$, is identical to Equation (A1) except we replace $\bar{r}_{\Delta,t_i}$ with its corridor-based counterpart $\tilde{r}^{B_1,B_2}_{\Delta,t_{\Delta(i-1)+j}} = (p_{t_{i-1+\Delta}} - p_{t_{i-1}})I_{t_{i-1+\Delta}}(B_1, B_2)$, where $I_{t_{i-1+\Delta}}(B_1, B_2)$ is equal to one if $B_1 \leq F_{t_{i-1+\Delta}} < B_2$. Therefore, the treatment of returns in which a price enters the corridor is asymmetric: if $F_{t_{i-1}}$ lies outside of the corridor but $F_{t_{i-1+\Delta}}$ lies within the corridor, then $F_{t_{i-1+\Delta}}$ is deemed to have entered the corridor and $\tilde{r}^{B_1,B_2}_{\Delta,t_{\Delta(i-1)+j}}$ is included in the calculation of $CRV_t^{B_1,B_2}$. This asymmetry ensures that the sum of $CRV_t^{B_1,B_2}$ across disjoint corridors equates to RV_t. Our realized variance estimates are plotted in Figure 3.

A.2 Definitions of the speculative index and hedging pressure

The Commodity Futures Trading Commission (CFTC) publishes weekly Commitment of Trader (COT) reports. These summarize the aggregate long and short positions of three types of commodity futures trader: commercials, noncommercials and nonreportables. A market participant is classified as being commercial if they engage in any form of hedging activity and noncommercial if they do not.[23] Therefore, as is common in the literature, commercial traders can be thought of as *hedgers* and noncommercial traders as *speculators*. We use the aggregate trading positions of hedgers and speculators in the COT reports to construct two measures of trading activity. The first is the speculative index of Working

[23] For nonreportable positions, it is unknown whether the traders involved are commercial or noncommercial.

(1960). This measures the position held by speculators which is in excess of what is required to meet the demand of hedgers. Specifically, if we define the number of contracts that a speculator is short (long) as SS (SL) and the number of contracts that a hedger is short (long) as HS (HL), then the speculative index is defined as,[24]

$$SI_t = \begin{cases} 1 + \frac{SS_t}{HL_t + HS_t}, & \text{if } HS_t \geq HL_t \\ 1 + \frac{SL_t}{HL_t + HS_t}, & \text{if } HS_t < HL_t. \end{cases}$$

Therefore, higher values for the speculative index coincide with speculators being more prominent in the futures market.

Our second trading activity measure is hedging pressure as defined in Kang et al. (2020). Hedging pressure is the net short position of hedgers standardized by open interest (OI),

$$HP_t = \frac{HS_t - HL_t}{OI_t}.$$

Therefore, high values of hedging pressure correspond to high levels of hedging demand by commercial traders.

Kang et al. (2020) point out that short-term fluctuations in hedging pressure may in fact be driven by the trading motives of speculators. More precisely, the liquidity required by speculators to execute their trading strategies is provided by hedgers, which manifests as short-term variation in hedging pressure. In contrast, hedging demand reacts to adjustments in the output decisions of producers, which occur over longer time frames. Thus, long-term changes in hedging pressure are more likely to reflect alterations in the true hedging demand of commercial traders. To isolate the long-term changes in hedging pressure, Kang et al. (2020) advocate using *smoothed hedging pressure*,

$$\overline{HP}_t = \frac{\frac{1}{52}\sum_{s=t-51}^{t}(HS_s - HL_s)}{OI_t}.$$

In other words, smoothed hedging pressure is the 52-week moving average of the net short position of hedgers divided by the current level of open interest. We use the speculative index and smoothed hedging pressure in Section 5.2.4.

[24] We use the same notation as Li (2018).

B Model robustness tests

In this section we present robustness tests for our density and corridor variance forecast models, both of which are fundamental in accurately determining our corridor-based uncertainty measures.

B.1 Density forecast model

As shown in Equations (3) and (5) of the main paper, the estimation of expected corridor variances relies on accurate price barrier forecasts which, in turn, correspond to fixed percentiles of the next-period oil return distribution. Since these are generated *ex ante* using our density forecasting model, any misspecification of our forecasts will lead to inaccurate estimates of price barriers and, in turn, unreliable corridor oil price uncertainty and uncertainty risk premia measures. To this end, we conduct a variety of commonly employed density forecasting misspecification tests.

B.1.1 Mis-specification tests: full density forecasts

The first set of tests we use examine whether the out-of-sample probability integral transforms (PITs) of our density forecasts are i.i.d. uniformly distributed. As highlighted in Diebold, Gunther, and Tay (1998), this property must hold for density forecasts to be well-specified. The PITs are equal to the value of the cumulative distribution function of the density forecasts evaluated at the point of the realized oil futures return. We test the i.i.d. uniform assumption in two ways. Firstly, we perform a joint test of the i.i.d. uniform assumption using the likelihood ratio statistic of Berkowitz (2001). Secondly, we analyse the i.i.d. and uniform distribution assumptions separately. We use the Kolmogorov-Smirnov test to examine the adequacy of the uniformity assumption, and the Lagrange-Multiplier test of Diebold et al. (1998) to check for serial correlation in the time series of the first four moments of the PITs. A detailed description of the moment independence and Berkowitz (2001) tests is provided at the end of this section.

As shown in Panel A of Table B1, our model passes all these tests at the 5% level. More precisely, in the moment independence tests, the p-values of the parameters for the lagged values of the first, second, third and fourth moments of $(z_t - \bar{z})$ are all substantially above conventional levels of significance; the Kolmogorov-Smirnov test statistic is insignificant; and the p-value on the $LR3$ statistic of the Berkowitz test is far above conventional levels of significance.

Test description: moment independence test

To apply the moment independence test of Diebold et al. (1998), we first transform the return series $\{r_t\}_{t=1}^{T}$ into $u_t = F_t(r_t|\mathcal{F}_{t-1})$, where $t = 1, \ldots, T$ and F_t is the cumulative distribution function derived from the density forecasts. Thus, $\{u_t\}_{t=1}^{T}$ represents a series of probability integral transforms (PITs). According to Diebold et al. (1998), a property of a correctly specified forecast density model is that it produces a series of PIT realizations that are i.i.d. Uniform (0,1). To evaluate the validity of the independence assumption, Diebold et al. (1998) suggest checking the autocorrelations of $(u_t - \bar{u})^q$, where $q = 1, 2, 3, 4$.

To operationalize this analysis, we perform the following transformation on the u_t: $z_t = \Phi^{-1}(u_t)$, where $\Phi^{-1}(\cdot)$ is the inverse of the standard normal distribution. We then test for independence in the first four moments of u_t by regressing $(z_t - \bar{z})^q$, $q = 1, 2, 3, 4$, on its first 6, 12, and 24 lags. If the u_t are independent then the z_t will be as well. Therefore, if the parameters on the lagged values of $(z_t - \bar{z})^q$, $q = 1, 2, 3, 4$, are all equal to zero, then we cannot reject the null hypothesis that the u_t are independent.

Test description: Berkowitz test

In the Berkowitz (2001) test, we jointly test whether the series z_t, as defined above, is i.i.d standard normal against the alternative that it follows a gaussian AR(1) process with mean μ and variance σ^2. To apply the test we fit the following AR(1) model,

$$z_t - \mu = \rho(z_{t-1} - \mu) + \epsilon_t.$$

Parameters are estimated by maximising the log-likelihood of the model,

$$\begin{aligned}\mathcal{L}(\mu, \sigma^2, \rho) = &-\frac{1}{2}\log(2\pi) - \frac{1}{2}\log\left(\frac{\sigma^2}{1-\rho^2}\right) - \frac{\left(z_t - \mu/(1-\rho)\right)^2}{2\sigma^2/(1-\rho^2)} \\ &- \frac{T-1}{2}\log(2\pi) - \frac{T-1}{2}\log(\sigma^2) - \sum_{t=2}^{T}\left(\frac{\left(z_t - \mu - \rho z_{t-1}\right)^2}{2\sigma^2}\right),\end{aligned}$$

where σ^2 is the variance of ϵ_t. The i.i.d standard normal null can then be jointly tested using the likelihood ratio statistic given by $LR3 = -2(\mathcal{L}(0, 1, 0) - \mathcal{L}(\hat{\mu}, \hat{\sigma}^2, \hat{\rho})) \sim \chi^2(3)$, where hats denote estimated parameters.

B.1.2 Mis-specification tests: Quantile forecasts

Our second category of tests examines whether our density model generates well-specified forecasts for various relevant percentiles of the target distribution. In particular, we use the "hit" regression test of Patton (2006) to test for any misspecification in our forecasts of the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentiles. Briefly, this test assesses whether the proportion of time the realized oil futures return falls within (i.e., "hits") each region, defined by the aforementioned percentiles of the forecasted densities, is in line with *a priori* expectations.[25] It also tests whether there is any serial dependence between the number of hits over the last one, six, and twelve months. A comprehensive explanation of the test is displayed at the end of this section. Our results, presented in Panel B of Table B1, confirm that our model delivers well-specified forecasts for all the regions of the density considered.

Test description: "hit" regression test

To implement the hit test of Patton (2006) we define r_t to be the monthly crude oil futures return and we divide the support of r_t into five regions, $\{R_j\}_{j=0}^{4}$. Let r^x be the x^{th} percentile of the return distribution inferred from our density forecasts. Then the first region is, $R_0 = (-\infty, r^{10}]$; the second is $R_1 = (-\infty, r^{25}]$; the third is $R_2 = (-\infty, r^{50}]$; the fourth is $R_3 = [r^{75}, \infty)$; and the fifth is $R_4 = [r^{90}, \infty)$. Let $\pi_{j,t}$ be the true probability that $r_t \in R_j$ and $s_{j,t}$ be the probability inferred from our density forecasts. Finally, let $Hit_t^j = \mathbf{1}(r_t \in R_j)$, where $\mathbf{1}(x)$ is equal to one if x is true and zero otherwise.

To test whether the regions of the distribution are correctly specified we allow $\pi_{j,t}$ to be a function of $s_{j,t}$ as well as other variables known at time $t-1$. We model $\pi_{j,t}$ as follows,

$$\pi_{j,t} = \pi_j\left(Z_{j,t}, \beta_j, s_{j,t}\right) = \Lambda\left(\lambda_j(Z_{j,t}, \beta_j) - \ln\left[\frac{1-s_{j,t}}{s_{j,t}}\right]\right),$$

where $\Lambda(x) = \frac{1}{1+e^{-x}}$, $Z_{j,t}$ is a matrix of explanatory variables which plausibly influence the probability of a hit, β_j is a $(k_j \times 1)$ vector of parameters, and λ_j is a function of regressors and parameters with the restriction that $\lambda_j(Z, 0) = 0$ for all Z. We follow Patton (2006) and use a linear function for λ_j, specifically $\lambda_j(Z_{j,t}, \beta_j) = Z_{j,t} \cdot \beta_j$. In $Z_{j,t}$ we include a constant, and the sum of the hits over the past one, six and twelve months. The specification for $Z_{j,t}$ enables us to test for any serial correlation, which should be absent, in the hits.

Our null hypothesis is that $\pi_{j,t} = s_{j,t}$, i.e., that the density forecasting model is specified correctly. Testing the null is tantamount to testing whether $\beta_j = 0$ against the alternative that $\beta_j \neq 0$. To estimate β_j we use maximum likelihood. The likelihood function to be

[25] Specifically, 10% of the realized futures returns should fall below the 10^{th} percentile forecasts, 25% should fall below the 25^{th} percentile, and so on.

maximized is,

$$\mathcal{L}(\pi_j(Z_j,\beta_j,s_{j,t})|Hit^j) = \sum_{t=1}^{T}\left[Hit_t^j \cdot \ln \pi_j\left(Z_{j,t},\beta_j,s_{j,t}\right) + \left(1 - Hit_t^j\right)\cdot \ln\left(1 - \pi_j\left(Z_{j,t},\beta_j,s_{j,t}\right)\right)\right].$$

The null hypothesis that $\beta_j = 0$ can then be tested using a likelihood ratio test, where $LR_j = -2 \cdot [\mathcal{L}(s_j|Hit^j) - \mathcal{L}(\pi_j(Z_j,\beta_j,s_{j,t})|Hit^j)] \sim \chi^2_{k_j}$.

B.2 Alternative models for corridor variance forecasts

Given their importance as a proxy for oil price uncertainty and their role in determining uncertainty risk premia, we check the accuracy of our corridor variance forecasts, generated using our HAR-CRV model in Equation (9), by comparing them to forecasts generated by a collection of plausible alternative models. The first alternative model we consider is the MA(1)- GARCH(1,1)-t model estimated using daily returns. For each month, we estimate the model using 4 years of past data and simulate 200,000 crude oil price paths corresponding to a monthly horizon. These paths provide the necessary information to compute expected corridor variances.[26] Note that, unlike our preferred HAR-CRV model, where *monthly* (corridor) realized variance measures are directly forecasted, this model generated forecasts based on the *daily* oil price dynamics.

The second model is a simple exponential weighted moving average (EWMA) specification, akin to the Riskmetrics model used in the industry. For this model, monthly corridor realized variance forecasts (ECRVs) are obtained by $ECRV_{m+1}^{B_1,B_2} = \alpha ECRV_m^{B_1,B_2} + (1-\alpha)CRV_m^{B_1,B_2}$. The parameter α is estimated once using the full dataset, while the initial forecast (i.e., $ECRV_0^{B_1,B_2}$) is set equal to the (in-sample) unconditional mean of the relevant monthly realized corridor variance series.

The third model is based on the realized semi-variance measures introduced by Barndorff-Nielsen et al. (2010). Several authors (Feunou et al., 2018; Kilic and Shaliastovich, 2019) have used negative and positive semi-variances to proxy for upside and downside corridor expected variances. These are defined as follows,

$$RV_t^- = \sum_{i=1}^{M} r_{t_i}^2 I(r_{t_i} < 0), \qquad RV_t^+ = \sum_{i=1}^{M} r_{t_i}^2 I(r_{t_i} \geq 0),$$

where RV_t^- and RV_t^+ are the negative and positive semi-variances, respectively, on day t. In other words, the negative (positive) realized semi-variance is the sum of the negative

[26] To keep the corridor forecasts internally consistent with the model, the barrier levels for each month are obtained by the corresponding simulated terminal price distribution.

(positive) squared intraday returns r_{t_i}. Following the related literature, we estimate HAR-based semi-variance models (HAR-SVR) that generate expected positive and negative semi-variances,

$$ERV^{+}_{M,m+1} = \beta^{p}_{0} + \beta^{p}_{1} RV^{+}_{D,m} + \beta^{p}_{2} RV^{+}_{W,m} + \beta^{p}_{3} RV^{+}_{M,m,},$$
$$ERV^{-}_{M,m+1} = \beta^{n}_{0} + \beta^{n}_{1} RV^{-}_{D,m} + \beta^{n}_{2} RV^{-}_{W,m} + \beta^{n}_{3} RV^{-}_{M,m},$$

where the definitions of $RV^{+(-)}_{D,t}$, $RV^{+(-)}_{W,t}$ and $RV^{+(-)}_{M,t,}$ are analogous to those for daily, weekly and monthly RVs defined in Section 3.1, the distance between m and $m-1$ is exactly 22 trading days, and model parameters are estimated by regressing these measures on realized (positive or negative) semi-variances. We use expected positive semi-variances ($ERV^{+}_{M,m+1}$) to forecast upper-corridor corridor realized variances (CRV10, CRV25, CRVD), and expected negative semi-variances ($ERV^{-}_{M,m+1}$) to forecast lower-corridor corridor realized variances (CRV75, CRVU, CRV90). For a forecast of the full realized variance, we use the sum of the negative and positive semi-variance forecasts.

We evaluate the forecasts produced by the models using Mincer-Zarnowitz and encompassing regressions. In the latter case, we combine our HAR-CRV forecasts with those of each of the above alternative specifications. Panel A of Table B2 shows the results of the Mincer-Zarnowitz regressions. While various models generate forecasts that significantly relate to some future corridor variances, only the forecasts from the HAR-CRV model are significant predictors in all cases. Furthermore, the encompassing regression results, displayed in Panel B of Table B2, show that the HAR-CRV forecasts nearly always remain statistically significant when combined with those of other models and often subsume the information content of the competing alternatives.

C Additional empirical results

C.1 Single uncertainty measures and macroeconomic growth

In Section 5.3.1 of the paper, we examined the ability of our oil uncertainty and uncertainty risk premia measures to predict macroeconomic growth using the financial and macroeconomic uncertainty measures of Gao et al. (2022) as controls. Here, we present and discuss the results when only a single measure of uncertainty is included in the predictive regression described by Equation (10).

We first note that, as shown in Table C1, both financial and macroeconomic uncertainty have a negative relationship with future economic growth. The forecast performance of the

VIX, used as a proxy of financial uncertainty, is particularly strong, as it is highly significant for all economic variables and forecast horizons. The results are weaker for the case of *Macro Unc*, although the corresponding parameters are also negative throughout and statistically significant at the one-quarter horizon for *Cons growth*, *PI growth* and *NFP growth*.

Next, we examine the performance of option-implied variance which is used as a proxy for oil uncertainty by Gao et al. (2022). Our results, summarized in Panel A of Table C2, clearly confirm their key finding, namely that there is a negative and broadly significant relationship between option-implied variance and the various economic growth variables. To understand which component of option-implied variance drives these results, we then examine oil price uncertainty and uncertainty risk premia separately. The results for oil price uncertainty are reported in Panel B of Table C2. For horizons up to two quarters, the parameter estimates are negative for all economic growth variables and significant for *GDP growth*, *PI growth* and *NFP growth*. The uncertainty risk premium, shown in Panel C of Table C2, also appears to be important in forecasting economic growth, perhaps even more so than oil uncertainty itself. In particular, for the one- and two-quarter horizons, the corresponding parameter estimates are negative and significant for all four economic growth variables.

We conclude by commenting on the notable differences between the various corridor measures. For option-implied corridor variances, displayed in Panel A of Table C2, we find stronger evidence that lower-corridor, rather than upper-corridor, measures are significant predictors of *GDP growth* and *Cons growth*. On the other hand, we find practically no evidence of asymmetry for the case of oil uncertainty (Panel B), with the only exception being the one-quarter-ahead *GDP growth* where upside corridor variance is the only significant measure. Finally, the results for corridor uncertainty risk premia (Panel C) reveal widespread evidence that lower-corridor, but not upper-corridor, measures are significant predictors of future economic growth. This empirical finding reconciles the differences between oil uncertainty estimates and option-implied corridor variances, indicating that the asymmetry observed in the latter is due to oil price uncertainty risk premia rather than uncertainty *per se*. This finding also hints that economic agents might have asymmetric volatility preferences. It is also noteworthy that none of the parameters corresponding to the upper-corridor uncertainty risk premia measures are significant, with the only exception being the extreme upside tail measure that is a significant predictor of *PI growth* and *NFP growth*.

C.2 Supplementary tables

The last part of the Supplementary Appendix provides extended versions of various key tables presented in the main paper. Specifically, these summarize the parameters of the control variables included in the various regression exercises. These results were omitted from the main paper to conserve space but are displayed here for completeness.

In Section 5.3 of the paper we examined if oil uncertainty and oil uncertainty risk premia measures are significant predictors of economic growth using regression models that included financial and macroeconomic uncertainty as control variables. Table C3 is an extended version of Table 3 of the main paper where the parameter estimates for these control variables are also displayed.

Similarly, Table C4 shows the estimation results related to the precautionary savings channel, discussed in Section 5.3.2 of the paper, but in addition to the parameter estimates for the oil uncertainty and oil uncertainty risk premia measures, displayed in Table 4 of the main paper, we also report the results for the parameters corresponding to financial and macroeconomic uncertainty measures which are included as controls.

Finally, in Section 5.4 we examined if oil uncertainty risk premia measures can predict aggregate equity market returns after controlling for other popular predictors. Table 6 in the main paper only presented the results for the parameters corresponding to oil uncertainty risk premia. The complete regression results for the Full, PreFin, and PostFin periods, are displayed in Table C5, Table C6, and Table C7, respectively.

Figures and Tables (Appendix)

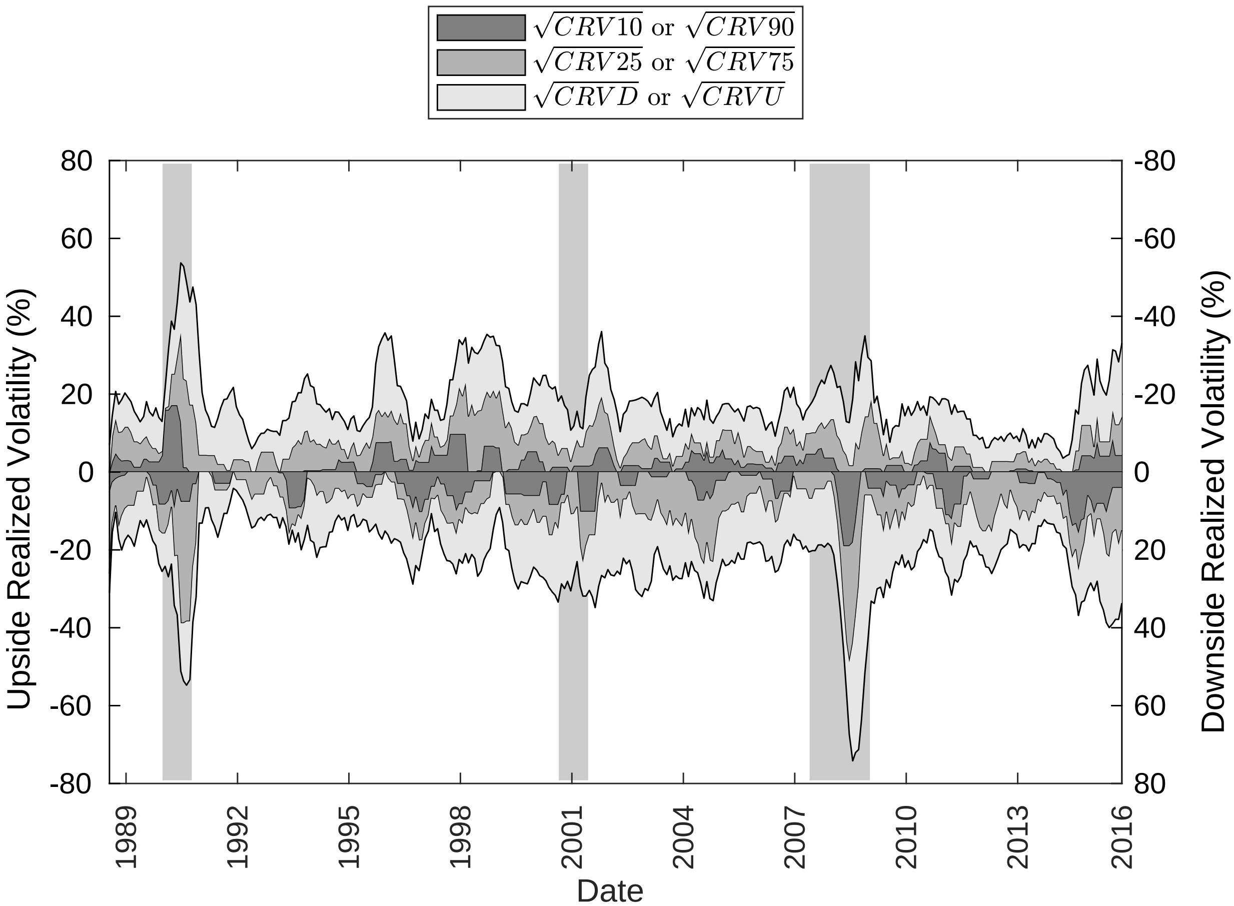

Figure 3: Time series of the six-month moving average of corridor realized volatilities.
To aid presentation, all values represent the six-month moving averages of the square roots of the CRVs. All values can be interpreted as annualized percentage *volatilities*. The left-hand-side y-axis pertains to the values of upper-corridor $\sqrt{\text{CRVs}}$: $\sqrt{CRVU}$ (light grey), $\sqrt{CRV75}$ (intermediate grey) and $\sqrt{CRV90}$ (dark grey). The right-hand-side y-axis pertains to the values of lower-corridor $\sqrt{\text{CRVs}}$: $\sqrt{CRVD}$ (light grey), $\sqrt{CRV25}$ (intermediate grey) and $\sqrt{CRV10}$ (dark grey). Note, to aid presentation, the right-hand-side y-axis is inverted so that the downside measures are plotted below the x-axis. The three shaded grey vertical blocks represent NBER recessions spanning July 1990-March 1991, March 2001-November 2001, and December 2007-June2009.

Table B1: Density forecasting mis-specification tests.

The table summarizes the results of four density mis-specification tests. Panel A reports results for the moment independence test of Diebold et al. (1998), the Kolmogorov-Smirnov test, and the LR3 test of Berkowitz (2001). For the moment independence test, the table shows the results of regressions where the first, second, third and fourth moment of $(z_t - \bar{z})$ is regressed against 6, 12 and 24 month lagged values, where z_t is the inverse of the cumulative standard normal distribution evaluated at the probability integral transform (PIT) realization corresponding to the density forecast and $\bar{z}$ is the mean of z_t. For the Kolmogorov-Smirnov test, the test statistic is provided along with its p-value. For the Berkowitz test, the estimated values of ρ, μ and σ are listed. The likelihood values of the restricted (LR_R) and unrestricted (LR_U) models are also provided along with the p-value for the $LR3$ likelihood ratio test. Panel B reports the results from hit tests, as described in Section B.1.2, for five regions of the density. Region Q10 refers to the region of the density below the 10th percentile; Region Q25 to the region of the density below the 25th percentile; Region Q50 to the region of the density below the 50th percentile; Region Q75 to the region of the density above the 75th percentile; Region Q90 to the region of the density above the 90th percentile. In each case, we report the likelihood values of the restricted and unrestricted models, the likelihood ratio statistic, and its corresponding p-value. The estimated parameters, t-statistics and p-values for the constant (b_c) and the number of hits during the last one (b_m), six (b_{6m}) and twelve months (b_{12m}), are also provided.

Panel A: Tests of i.i.d. uniform distribution assumption for PITs

Moment Independence Tests

	1st	2nd	3rd	4th
6 lags	0.19	0.60	0.92	>0.99
12 lags	0.07	0.83	>0.99	>0.99
24 lags	0.20	>0.99	>0.99	>0.99

Kolmogorov-Smirnov

K-S stat	p-val
0.04	0.54

Berkowitz LR3 test

ρ	μ	σ
-0.01	-0.05	0.99
LL_R	LL_U	$LR3$ p-val
463.80	463.33	0.82

Panel B: Hit tests

Region Q25

	param	t-stat	p-val
b_c	0.26	0.88	0.38
b_m	-0.13	-0.77	0.44
b_{6m}	0.14	1.16	0.25
b_{12m}	-0.12	-0.42	0.67
LL_U	LL_R	LR	p-val
-193.10	-195.14	4.09	0.39

Region Q50

	param	t-stat	p-val
b_c	-0.38	-1.55	0.12
b_m	-0.09	-0.63	0.53
b_{6m}	0.13	1.30	0.19
b_{12m}	-0.24	-0.63	0.53
LL_U	LL_R	LR	p-val
-224.60	-226.66	4.13	0.39

Region Q75

	param	t-stat	p-val
b_c	-0.17	-0.54	0.59
b_m	-0.19	-1.05	0.29
b_{6m}	0.06	0.45	0.65
b_{12m}	0.34	1.14	0.26
LL_U	LL_R	LR	p-val
-193.19	-195.14	3.91	0.42

Region Q10

	param	t-stat	p-val
b_c	0.39	0.61	0.54
b_m	-0.53	-1.40	0.16
b_{6m}	0.27	1.06	0.29
b_{12m}	0.01	0.02	0.98
LL_U	LL_R	LR	p-val
-108.07	-109.16	2.17	0.71

Region Q90

	param	t-stat	p-val
b_c	0.37	0.50	0.62
b_m	-0.71	-1.56	0.12
b_{6m}	0.48	1.66	0.10
b_{12m}	-0.33	-1.13	0.26
LL_U	LL_R	LR	p-val
-93.99	-95.98	3.96	0.41

Table B2: Comparisons of alternative ECRV forecast models.
Panel A reports the results from univariate Mincer-Zarnowitz regressions where forecasts generated by each of the models listed in each row are regressed against the realized values of ECRVs listed in each column. Only the parameter corresponding to the volatility forecast is reported. Panel B displays the results from encompassing regressions. In each encompassing regression, the forecasts from the HAR-CRV model are included as a benchmark along with competing forecasts from the model listed in each row. The table reports the estimated regression parameters for the HAR-CRV model (b_{har}) and the competing forecast model (b_x). All competing forecast models are described in Section B.2. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Panel A: Univariate Regressions								
		ERV	*ECRV10*	*ECRV25*	*ECRVD*	*ECRVU*	*ECRV75*	*ECRV90*
HAR-CRV		0.87***	0.49*	0.83**	1.07***	0.64***	0.56***	0.32**
EWMA		0.84***	-1.33	0.62	0.75***	0.63***	0.57**	-0.49
GARCH(1,1)		0.75***	-0.17	0.08	0.77***	0.64***	0.44***	0.03
HAR-SVR		1.11***	-0.03	0.08	0.76***	0.61***	0.18	0.01
Panel B: Encompassing Regressions								
		ERV	*ECRV10*	*ECRV25*	*ECRVD*	*ECRVU*	*ECRV75*	*ECRV90*
EWMA	b_{har}	0.56***	0.70**	0.93**	0.71***	0.61***	0.52***	0.36**
	b_x	0.32***	-2.95	-0.58	0.35**	0.14	0.23	-0.96
GARCH(1,1)	b_{har}	1.01***	0.74**	1.51***	0.99***	0.42	0.48**	0.46**
	b_x	-0.15	-0.41***	-0.75***	0.07	0.26	0.10	-0.15
HAR-SVR	b_{har}	1.00***	0.82**	1.42**	0.75***	0.93***	0.87***	0.48**
	b_x	-0.21	-0.14**	-0.34**	0.28**	-0.40	-0.27*	-0.08**

Table C1: Regressions of economic growth against *VIX* and *Macro Unc*.
This table summarizes the parameter estimates from regressions described in Equation (10) of the main paper. In each regression an economic growth variable is regressed against either *VIX* or *Macro Unc*, and a set of control variables. The economic growth measures used are *GDP growth*, *Cons growth*, *PI growth* and *NFP growth*, which are measured over either the one (1Q), two (2Q) or four (4Q) quarters that follow the quarter in which the uncertainty measure and control variables are constructed. The control variables include the contemporaneous and lagged quarterly oil futures return, contemporaneous quarterly oil supply growth and contemporaneous quarterly TFP growth. The first column lists the economic growth variable used in the regressions; the second column indicates the horizon over which the economic growth variable was measured; columns three and four contain the parameter estimates for the uncertainty measure listed at the head of each column. Parameter estimates for the control variables are not reported to conserve space. Newey-West standard errors based on 4 lags were used. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

		VIX	*Macro Unc*
GDP growth	1Q	-1.50***	-0.90
	2Q	-2.62***	-1.57
	4Q	-3.70***	-2.68
Cons growth	1Q	-1.13***	-0.61***
	2Q	-1.85***	-1.18
	4Q	-2.63**	-2.27
PI growth	1Q	-7.13***	-4.18***
	2Q	-13.64***	-6.73
	4Q	-16.93***	-8.57
NFP growth	1Q	-1.24***	-0.97***
	2Q	-2.45***	-1.83*
	4Q	-4.23***	-2.86

Table C2: Regressions of economic growth against a single uncertainty measure.

This table summarizes the parameter estimates from regressions described in Equation (10) of the main paper. In each regression an economic growth variable is regressed against either a single oil price uncertainty or uncertainty risk premium measure, and a set of control variables. The economic growth measures used are *GDP growth*, *Cons growth*, *PI growth* and *NFP growth*, which are measured over either the one (1Q), two (2Q) or four (4Q) quarters that follow the quarter in which the uncertainty measure and control variables are constructed. The control variables include the contemporaneous and lagged quarterly oil futures return, contemporaneous quarterly oil supply growth and contemporaneous quarterly TFP growth. The first column lists the economic growth variable used in the regressions; the second column indicates the horizon over which the economic growth variable was measured; columns three to nine contain the parameter estimates for the uncertainty measure listed at the head of each column. Panel A summarizes results for (C)IVs, i.e., option-implied variance measures; Panel B for E(C)RVs, i.e., oil uncertainty measures; and Panel C for (C)VRPs, i.e., oil uncertainty risk premia. Parameter estimates for the control variables are not reported to conserve space. Newey-West standard errors based on 4 lags were used. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Panel A: Option-implied oil variance								
		IV	*CIV10*	*CIV25*	*CIVD*	*CIVU*	*CIV75*	*CIV90*
GDP growth	1Q	-1.28***	-0.96***	-1.34***	-1.49***	-0.75	-0.72*	-0.64*
	2Q	-2.00*	-1.45*	-2.21**	-2.45***	-1.01	-1.21	-1.36
	4Q	-0.33	-0.90	-1.61	-1.29	0.43	-0.38	-1.40
Cons growth	1Q	-0.85*	-0.66**	-0.94***	-1.05***	-0.42	-0.41	-0.41
	2Q	-1.50	-1.25	-1.84**	-1.95***	-0.61	-0.81	-1.04
	4Q	-0.37	-1.18	-1.89*	-1.46	0.49	-0.20	-1.14
PI growth	1Q	-6.60***	-3.84***	-5.78***	-7.02***	-4.77*	-4.46***	-3.46**
	2Q	-11.39**	-6.60**	-10.79**	-12.88***	-7.27	-7.49**	-6.71*
	4Q	-2.94	-1.91	-5.83	-6.35	0.08	-2.90	-5.95
NFP growth	1Q	-1.17***	-0.88***	-1.09***	-1.22***	-0.86*	-0.86***	-0.75***
	2Q	-2.28***	-1.77***	-2.26***	-2.48***	-1.59*	-1.69***	-1.58**
	4Q	-1.54***	-1.68**	-2.24**	-2.16***	-0.80**	-1.41**	-1.88***
Panel B: Oil uncertainty								
		ERV	*ECRV10*	*ECRV25*	*ECRVD*	*ECRVU*	*ECRV75*	*ECRV90*
GDP growth	1Q	-1.15**	-0.33	-0.59	-0.98	-1.03*	-0.21	-0.20
	2Q	-1.77*	-0.32	-0.82	-1.46	-1.40	-0.13	-0.24
	4Q	1.35	0.13	0.10	0.83	1.22	0.34	-0.19
Cons growth	1Q	-0.75	-0.20	-0.40	-0.65	-0.64	-0.12	-0.07
	2Q	-1.20	-0.16	-0.53	-0.95	-0.90	-0.05	-0.05
	4Q	1.40	0.05	0.03	0.74	1.28	0.26	0.00
PI growth	1Q	-7.03***	-2.10**	-3.40	-5.86*	-6.53**	-1.86*	-1.72**
	2Q	-12.03***	-2.96	-5.60	-9.88	-10.45**	-2.44	-2.68
	4Q	0.22	0.20	-0.21	0.59	1.13	0.35	-2.01
NFP growth	1Q	-1.08***	-0.45**	-0.65*	-0.98**	-1.00***	-0.40**	-0.39***
	2Q	-2.08***	-0.83**	-1.25	-1.87**	-1.87***	-0.76**	-0.81***
	4Q	-0.18	-0.64***	-0.71**	-0.53	-0.15	-0.56	-1.02**
Panel C: Oil uncertainty risk premia								
		VRP	*CVRP10*	*CVRP25*	*CVRPD*	*CVRPU*	*CVRP75*	*CVRP90*
GDP growth	1Q	-1.03***	-0.82***	-1.16***	-1.42***	0.22	-0.41	-0.59
	2Q	-1.61*	-1.53*	-2.10**	-2.47***	0.31	-0.93	-1.27
	4Q	-1.16	-1.33	-1.81*	-2.12*	-0.61	-0.71	-1.29
Cons growth	1Q	-0.68**	-0.58**	-0.82**	-1.01***	0.21	-0.24	-0.40
	2Q	-1.33*	-1.44*	-1.85**	-2.09***	0.29	-0.67	-1.02
	4Q	-1.25	-1.61*	-2.04**	-2.26**	-0.59	-0.48	-1.11
PI growth	1Q	-4.24***	-2.53	-4.46**	-5.97***	1.34	-1.90	-2.97*
	2Q	-7.38**	-5.38	-9.16**	-11.71***	2.93	-3.87	-5.84
	4Q	-3.55	-2.74	-6.06	-7.81	-1.06	-2.75	-5.11
NFP growth	1Q	-0.89***	-0.61**	-0.83**	-1.06***	-0.02	-0.32	-0.64*
	2Q	-1.79***	-1.40**	-1.87**	-2.27***	0.01	-0.63	-1.32*
	4Q	-1.68**	-1.38*	-1.77*	-2.10**	-1.09	-0.45	-1.48**

Table C3: Regressions of economic growth against multiple uncertainty measures.
This table summarizes the parameter estimates from regressions described in Equation (10) of the main paper. In each regression an economic growth variable is regressed against an oil price uncertainty measure, the *VIX* and *Macro Unc* as well as a set of control variables. The economic growth measures used are *GDP growth*, *Cons growth*, *PI growth* and *NFP growth*, which are measured over either the one (1Q), two (2Q) or four (4Q) quarters that follow the quarter in which the uncertainty measures and control variables are constructed. The control variables include the contemporaneous and lagged quarterly oil futures return, contemporaneous quarterly oil supply growth and contemporaneous quarterly TFP growth. The first column lists the economic growth variable used in the regressions; the second column indicates the horizon over which the economic growth variable was measured; the third column lists the uncertainty measures used in each regression; columns four to ten contain the parameter estimates for the oil price uncertainty measure (*Oil Unc*) listed at the head of each column as well as for the *VIX* and *Macro Unc*. Panel A summarizes results for (C)IVs, i.e., option-implied oil variance measures; Panel B for E(C)RVs, i.e., oil uncertainty measures; and Panel C for (C)VRPs, i.e., oil uncertainty risk premia. Parameter estimates for the control variables are not reported to conserve space. Newey-West standard errors based on 4 lags were used. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Panel A: Option-implied oil variance

		Unc:	*IV*	*CIV10*	*CIV25*	*CIVD*	*CIVU*	*CIV75*	*CIV90*
GDP growth	1Q	*Oil Unc*	-0.48**	-0.48***	-0.77***	-0.84***	-0.10	-0.15	-0.23
		VIX	-1.06***	-1.14***	-0.85**	-0.73*	-1.31***	-1.28***	-1.26***
		Macro Unc	-0.51	-0.56*	-0.58**	-0.53*	-0.53	-0.54	-0.55*
	2Q	*Oil Unc*	-0.36	-0.49	-1.02**	-1.01	0.18	-0.14	-0.58
		VIX	-2.13***	-2.14***	-1.69***	-1.61**	-2.40***	-2.29***	-2.13***
		Macro Unc	-0.91	-0.95	-0.97	-0.91	-0.96	-0.93	-0.96
	4Q	*Oil Unc*	-0.33	-0.90	-1.61	-1.29	0.43	-0.38	-1.40
		VIX	-2.96***	-2.78***	-2.13**	-2.22*	-3.30***	-3.01***	-2.65***
		Macro Unc	-1.83	-1.89	-1.91	-1.82	-1.91	-1.84	-1.91
Cons growth	1Q	*Oil Unc*	-0.18	-0.27	-0.46**	-0.47*	0.08	0.03	-0.09
		VIX	-0.92***	-0.91***	-0.73**	-0.68*	-1.06***	-1.04***	-0.99***
		Macro Unc	-0.32	-0.34	-0.35	-0.33	-0.34	-0.33	-0.34
	2Q	*Oil Unc*	-0.40	-0.63	-1.19**	-1.20*	0.26	-0.04	-0.52
		VIX	-1.38*	-1.36**	-0.86	-0.76	-1.71***	-1.60***	-1.44***
		Macro Unc	-0.72	-0.77	-0.79	-0.72	-0.78	-0.75	-0.77
	4Q	*Oil Unc*	-0.37	-1.18	-1.89*	-1.46	0.49	-0.20	-1.14
		VIX	-1.91*	-1.64	-0.92	-1.07	-2.30***	-2.05**	-1.72*
		Macro Unc	-1.69	-1.76	-1.78	-1.67	-1.77	-1.71	-1.76
PI growth	1Q	*Oil Unc*	-3.12***	-1.38	-2.71**	-3.84***	-1.96**	-1.94**	-1.54*
		VIX	-4.55***	-5.81***	-4.65***	-3.61*	-5.72***	-5.65***	-5.83***
		Macro Unc	-2.29*	-2.53*	-2.60**	-2.42**	-2.26*	-2.42**	-2.55**
	2Q	*Oil Unc*	-3.77**	-1.37	-4.06**	-5.66***	-1.67	-2.24	-2.56
		VIX	-10.42***	-12.06***	-10.05***	-8.57***	-12.07***	-11.79***	-11.73***
		Macro Unc	-3.07	-3.36	-3.46	-3.18	-3.13	-3.24	-3.42
	4Q	*Oil Unc*	-2.94	-1.91	-5.83	-6.35	0.08	-2.90	-5.95
		VIX	-13.88***	-14.82***	-11.88***	-11.02**	-15.65***	-14.51***	-13.49***
		Macro Unc	-4.27	-4.54	-4.66	-4.30	-4.49	-4.37	-4.71
NFP growth	1Q	*Oil Unc*	-0.55***	-0.51***	-0.62***	-0.67***	-0.35***	-0.43***	-0.45***
		VIX	-0.71***	-0.82***	-0.63***	-0.55***	-0.91***	-0.86***	-0.87***
		Macro Unc	-0.66***	-0.72***	-0.72***	-0.68***	-0.65***	-0.68***	-0.72***
	2Q	*Oil Unc*	-0.99***	-0.98***	-1.30***	-1.34***	-0.55***	-0.78***	-0.92***
		VIX	-1.48***	-1.66***	-1.23***	-1.10***	-1.88***	-1.77***	-1.74***
		Macro Unc	-1.21**	-1.31***	-1.32***	-1.24***	-1.21**	-1.24***	-1.31***
	4Q	*Oil Unc*	-1.54***	-1.68**	-2.24**	-2.16***	-0.80**	-1.41**	-1.88***
		VIX	-2.76***	-2.97***	-2.24***	-2.11***	-3.40***	-3.14***	-3.00***
		Macro Unc	-1.79	-1.96	-1.97	-1.84	-1.81	-1.85	-1.97

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		Unc:	*ERV*	*ECRV10*	*ECRV25*	*ECRVD*	*ECRVU*	*ECRV75*	*ECRV90*
Panel B: Oil uncertainty									
GDP growth	1Q	*Oil Unc*	0.01	-0.10	-0.13	-0.07	-0.03	0.02	-0.06
		VIX	-1.34***	-1.33***	-1.31***	-1.30***	-1.32***	-1.34***	-1.34***
		Macro Unc	-0.54	-0.53	-0.53	-0.53	-0.54	-0.54	-0.54
	2Q	*Oil Unc*	0.45	0.08	0.01	0.23	0.55	0.26	0.00
		VIX	-2.62***	-2.35***	-2.34***	-2.46***	-2.61***	-2.37***	-2.34***
		Macro Unc	-0.98	-0.94	-0.94	-0.96	-0.99	-0.95	-0.94
	4Q	*Oil Unc*	1.35	0.13	0.10	0.83	1.22	0.34	-0.19
		VIX	-4.00***	-3.17***	-3.18***	-3.58***	-3.75***	-3.19***	-3.14***
		Macro Unc	-1.99	-1.87	-1.87	-1.95	-1.99	-1.88	-1.85
Cons growth	1Q	*Oil Unc*	0.20	-0.03	-0.05	0.05	0.16	0.04	0.03
		VIX	-1.15***	-1.02***	-1.01***	-1.05***	-1.11***	-1.03***	-1.03***
		Macro Unc	-0.35	-0.33	-0.33	-0.34	-0.35	-0.33	-0.33
	2Q	*Oil Unc*	0.43	0.13	0.07	0.29	0.52	0.24	0.12
		VIX	-1.89**	-1.63***	-1.64***	-1.77***	-1.87***	-1.64***	-1.63***
		Macro Unc	-0.79	-0.76	-0.75	-0.78	-0.80	-0.76	-0.75
	4Q	*Oil Unc*	1.40	0.05	0.03	0.74	1.28	0.26	0.00
		VIX	-3.00**	-2.14**	-2.14**	-2.51**	-2.76**	-2.16**	-2.13**
		Macro Unc	-1.85	-1.72	-1.72	-1.80	-1.86	-1.73	-1.72
PI growth	1Q	*Oil Unc*	-3.04	-1.04**	-1.27**	-2.18*	-2.66*	-0.83	-1.08
		VIX	-4.50**	-6.29***	-6.08***	-5.28***	-5.09***	-6.31***	-6.30***
		Macro Unc	-2.19	-2.37*	-2.35*	-2.23	-2.18	-2.41*	-2.46*
	2Q	*Oil Unc*	-3.35	-1.04	-1.57	-2.44	-2.29	-0.56	-1.44
		VIX	-10.56***	-12.54***	-12.25***	-11.39***	-11.52***	-12.58***	-12.52***
		Macro Unc	-3.01	-3.23	-3.18	-3.06	-3.07	-3.28	-3.30
	4Q	*Oil Unc*	0.22	0.20	-0.21	0.59	1.13	0.35	-2.01
		VIX	-15.76***	-15.64***	-15.57***	-15.92***	-16.18***	-15.66***	-15.45***
		Macro Unc	-4.50	-4.49	-4.46	-4.54	-4.60	-4.50	-4.45
NFP growth	1Q	*Oil Unc*	-0.21	-0.24***	-0.26***	-0.28**	-0.22	-0.21**	-0.28***
		VIX	-0.90***	-1.01***	-0.97***	-0.89***	-0.93***	-1.01***	-1.01***
		Macro Unc	-0.67***	-0.67***	-0.67***	-0.66***	-0.67***	-0.68***	-0.69***
	2Q	*Oil Unc*	-0.32	-0.43***	-0.49***	-0.46	-0.27	-0.38**	-0.58***
		VIX	-1.87***	-2.02***	-1.94***	-1.83***	-1.93***	-2.03***	-2.02***
		Macro Unc	-1.24**	-1.24**	-1.23**	-1.22**	-1.24**	-1.24**	-1.26**
	4Q	*Oil Unc*	-0.18	-0.64***	-0.71**	-0.53	-0.15	-0.56	-1.02**
		VIX	-3.56***	-3.61***	-3.50***	-3.40***	-3.60***	-3.62***	-3.59***
		Macro Unc	-1.88	-1.85	-1.84	-1.84	-1.88	-1.86	-1.88

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Panel C: Oil uncertainty risk premia

		Unc:	*VRP*	*CVRP10*	*CVRP25*	*CVRPD*	*CVRPU*	*CVRP75*	*CVRP90*
GDP growth	1Q	*Oil Unc*	-0.55***	-0.45**	-0.67***	-0.87***	-0.12	-0.14	-0.21
		VIX	-1.12***	-1.15***	-0.95***	-0.73**	-1.37***	-1.31***	-1.27***
		Macro Unc	-0.54*	-0.61**	-0.62**	-0.58**	-0.54	-0.55*	-0.55*
	2Q	*Oil Unc*	-0.69	-0.74*	-1.10**	-1.34***	-0.29	-0.43	-0.57
		VIX	-2.07***	-2.02***	-1.70***	-1.42***	-2.41***	-2.24***	-2.15***
		Macro Unc	-0.92	-1.03	-1.05	-0.98	-0.93	-0.96	-0.96
	4Q	*Oil Unc*	-1.16	-1.33	-1.81*	-2.12*	-0.61	-0.71	-1.29
		VIX	-2.70***	-2.58***	-2.08***	-1.68*	-3.30***	-2.98***	-2.72***
		Macro Unc	-1.83	-2.02	-2.03	-1.91	-1.85	-1.89	-1.91
Cons growth	1Q	*Oil Unc*	-0.31*	-0.28	-0.42**	-0.55**	-0.04	-0.02	-0.10
		VIX	-0.90***	-0.90***	-0.78**	-0.64*	-1.04***	-1.02***	-0.99***
		Macro Unc	-0.33	-0.37	-0.38	-0.36	-0.33	-0.33	-0.34
	2Q	*Oil Unc*	-0.72	-0.98**	-1.33***	-1.60***	-0.14	-0.32	-0.54
		VIX	-1.34**	-1.20**	-0.84	-0.51	-1.65***	-1.54***	-1.44***
		Macro Unc	-0.73	-0.87	-0.88	-0.80	-0.75	-0.76	-0.77
	4Q	*Oil Unc*	-1.25	-1.61*	-2.04**	-2.26**	-0.59	-0.48	-1.11
		VIX	-1.64*	-1.44	-0.92	-0.56	-2.27**	-2.01**	-1.76*
		Macro Unc	-1.69	-1.92	-1.91	-1.78	-1.71	-1.74	-1.77
PI growth	1Q	*Oil Unc*	-1.88**	-0.48	-1.71	-2.77**	-0.26	-0.58	-1.18
		VIX	-5.65***	-6.18***	-5.38***	-4.47***	-6.45***	-6.24***	-5.99***
		Macro Unc	-2.46*	-2.54*	-2.67**	-2.60**	-2.46*	-2.50*	-2.54**
	2Q	*Oil Unc*	-2.44*	-0.49	-2.93	-4.73**	-0.19	-1.12	-2.01
		VIX	-11.69***	-12.43***	-10.92***	-9.37***	-12.68***	-12.36***	-11.97***
		Macro Unc	-3.27	-3.38	-3.61	-3.47	-3.31	-3.37	-3.41
	4Q	*Oil Unc*	-3.55	-2.74	-6.06	-7.81	-1.06	-2.75	-5.11
		VIX	-14.23***	-14.44***	-12.04***	-10.19***	-15.87***	-14.94***	-13.91***
		Macro Unc	-4.40	-4.82	-5.05	-4.68	-4.46	-4.61	-4.70
NFP growth	1Q	*Oil Unc*	-0.51***	-0.33*	-0.41*	-0.55***	-0.31*	-0.11	-0.36**
		VIX	-0.83***	-0.89***	-0.78***	-0.65***	-1.10***	-1.00***	-0.91***
		Macro Unc	-0.69***	-0.74***	-0.74***	-0.72***	-0.69***	-0.70***	-0.71***
	2Q	*Oil Unc*	-0.97***	-0.73**	-0.96**	-1.21***	-0.57*	-0.17	-0.70**
		VIX	-1.69***	-1.75***	-1.50***	-1.23***	-2.20***	-2.02***	-1.83***
		Macro Unc	-1.25***	-1.36***	-1.37***	-1.31***	-1.26***	-1.28**	-1.30***
	4Q	*Oil Unc*	-1.68**	-1.38*	-1.77*	-2.10**	-1.09	-0.45	-1.48**
		VIX	-3.02***	-3.08***	-2.63***	-2.21**	-3.93***	-3.56***	-3.18***
		Macro Unc	-1.86	-2.07	-2.07	-1.95	-1.88	-1.92	-1.96

Table C4: Regressions of precautionary oil savings variables against multiple uncertainty measures.
This table summarizes the parameter estimates from regressions described in Equation (10) of the main paper. In each regression an oil market variable is regressed against an oil price uncertainty measure, the *VIX* and *Macro Unc*, as well as a set of control variables. The oil market variables used are *Oil cons growth*, *Oil prod growth* and *Oil inventory growth*, which are measured over either one (1Q), two (2Q) or four (4Q) quarters that follow the quarter in which the uncertainty measures and control variables are constructed. The control variables include the contemporaneous and lagged quarterly oil futures return, oil supply growth and TFP growth. The first column lists the oil market variable used in the regressions; the second column indicates the horizon over which the oil market variable was measured; the third column lists the uncertainty measures used in each regression; columns four to ten contain the parameter estimates for the oil price uncertainty measure listed at the head of each column as well as for the *VIX* and *Macro Unc*. Panel A summarizes results for (C)IVs, i.e., option-implied variance measures; Panel B for for E(C)RVs, i.e., oil uncertainty measures; and Panel C for (C)VRPs, i.e., oil uncertainty risk premia. Parameter estimates for the control variables are not reported to conserve space. Newey-West standard errors based on 4 lags were used. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Panel A: Option-implied oil variance

		Unc:	*IV*	*CIV10*	*CIV25*	*CIVD*	*CIVU*	*CIV75*	*CIV90*
Oil cons growth	1Q	*Oil Unc*	-0.27	-0.33**	-0.35	-0.30	-0.19	-0.16	-0.13
		VIX	-1.06***	-1.14***	-0.85**	-0.73*	-1.31***	-1.28***	-1.26***
		Macro Unc	-0.51	-0.56*	-0.58**	-0.53*	-0.53	-0.54	-0.55*
	2Q	*Oil Unc*	-0.19	-0.41	-0.34	-0.19	-0.15	-0.04	0.01
		VIX	-2.13***	-2.14***	-1.69***	-1.61**	-2.40***	-2.29***	-2.13***
		Macro Unc	-0.91	-0.95	-0.97	-0.91	-0.96	-0.93	-0.96
	4Q	*Oil Unc*	-0.13	-0.56	-0.43	-0.15	-0.07	0.13	0.19
		VIX	-2.96***	-2.78***	-2.13**	-2.22*	-3.30***	-3.01***	-2.65***
		Macro Unc	-1.83	-1.89	-1.91	-1.82	-1.91	-1.84	-1.91
Oil prod growth	1Q	*Oil Unc*	0.09	0.06	0.07	0.10	0.06	0.02	-0.01
		VIX	-0.92***	-0.91***	-0.73**	-0.68*	-1.06***	-1.04***	-0.99***
		Macro Unc	-0.32	-0.34	-0.35	-0.33	-0.34	-0.33	-0.34
	2Q	*Oil Unc*	-0.04	-0.06	-0.09	-0.08	0.02	-0.06	-0.12
		VIX	-1.38*	-1.36**	-0.86	-0.76	-1.71***	-1.60***	-1.44***
		Macro Unc	-0.72	-0.77	-0.79	-0.72	-0.78	-0.75	-0.77
	4Q	*Oil Unc*	-0.07	-0.08	-0.12	-0.11	0.00	-0.19	-0.31
		VIX	-1.91*	-1.64	-0.92	-1.07	-2.30***	-2.05**	-1.72*
		Macro Unc	-1.69	-1.76	-1.78	-1.67	-1.77	-1.71	-1.76
Oil inventory growth	1Q	*Oil Unc*	0.19**	0.18**	0.22**	0.24**	0.12	0.12	0.10
		VIX	-4.55***	-5.81***	-4.65***	-3.61*	-5.72***	-5.65***	-5.83***
		Macro Unc	-2.29*	-2.53*	-2.60**	-2.42**	-2.26*	-2.42**	-2.55**
	2Q	*Oil Unc*	0.23**	0.24**	0.28***	0.26**	0.15	0.14	0.14
		VIX	-10.42***	-12.06***	-10.05***	-8.57***	-12.07***	-11.79***	-11.73***
		Macro Unc	-3.07	-3.36	-3.46	-3.18	-3.13	-3.24	-3.42
	4Q	*Oil Unc*	0.21	0.21	0.27	0.25	0.11	0.02	0.01
		VIX	-13.88***	-14.82***	-11.88***	-11.02**	-15.65***	-14.51***	-13.49***
		Macro Unc	-4.27	-4.54	-4.66	-4.30	-4.49	-4.37	-4.71

Panel B: Oil uncertainty

		Unc:	*ERV*	*ECRV10*	*ECRV25*	*ECRVD*	*ECRVU*	*ECRV75*	*ECRV90*
Oil cons growth	1Q	*Oil Unc*	-0.21	-0.30***	-0.32***	-0.30	-0.21	-0.35***	-0.29***
		VIX	-1.34***	-1.33***	-1.31***	-1.30***	-1.32***	-1.34***	-1.34***
		Macro Unc	-0.54	-0.53	-0.53	-0.53	-0.54	-0.54	-0.54
	2Q	*Oil Unc*	-0.19	-0.57***	-0.59***	-0.42	-0.20	-0.56***	-0.51***
		VIX	-2.62***	-2.35***	-2.34***	-2.46***	-2.61***	-2.37***	-2.34***
		Macro Unc	-0.98	-0.94	-0.94	-0.96	-0.99	-0.95	-0.94
	4Q	*Oil Unc*	-0.17	-0.93***	-0.97***	-0.61	-0.17	-0.91***	-0.84**
		VIX	-4.00***	-3.17***	-3.18***	-3.58***	-3.75***	-3.19***	-3.14***
		Macro Unc	-1.99	-1.87	-1.87	-1.95	-1.99	-1.88	-1.85
Oil prod growth	1Q	*Oil Unc*	0.22**	0.06**	0.08*	0.16	0.13*	0.08	0.04
		VIX	-1.15***	-1.02***	-1.01***	-1.05***	-1.11***	-1.03***	-1.03***
		Macro Unc	-0.35	-0.33	-0.33	-0.34	-0.35	-0.33	-0.33
	2Q	*Oil Unc*	0.06	0.08*	0.07	0.07	0.06	0.11	0.06
		VIX	-1.89**	-1.63***	-1.64***	-1.77***	-1.87***	-1.64***	-1.63***
		Macro Unc	-0.79	-0.76	-0.75	-0.78	-0.80	-0.76	-0.75
	4Q	*Oil Unc*	0.11	0.21***	0.19*	0.15	0.13	0.24***	0.17
		VIX	-3.00**	-2.14**	-2.14**	-2.51**	-2.76**	-2.16**	-2.13**
		Macro Unc	-1.85	-1.72	-1.72	-1.80	-1.86	-1.73	-1.72
Oil inventory growth	1Q	*Oil Unc*	0.17	0.14***	0.14***	0.14**	0.18**	0.15***	0.15***
		VIX	-4.50**	-6.29***	-6.08***	-5.28***	-5.09***	-6.31***	-6.30***
		Macro Unc	-2.19	-2.37*	-2.35*	-2.23	-2.18	-2.41*	-2.46*
	2Q	*Oil Unc*	0.19	0.17***	0.19***	0.19**	0.21**	0.19***	0.19***
		VIX	-10.56***	-12.54***	-12.25***	-11.39***	-11.52***	-12.58***	-12.52***
		Macro Unc	-3.01	-3.23	-3.18	-3.06	-3.07	-3.28	-3.30
	4Q	*Oil Unc*	0.32	0.29***	0.33***	0.32*	0.31	0.41**	0.37***
		VIX	-15.76***	-15.64***	-15.57***	-15.92***	-16.18***	-15.66***	-15.45***
		Macro Unc	-4.50	-4.49	-4.46	-4.54	-4.60	-4.50	-4.45

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Panel C: Oil uncertainty risk premia									
		Unc:	*VRP*	*CVRP10*	*CVRP25*	*CVRPD*	*CVRPU*	*CVRP75*	*CVRP90*
Oil cons growth	1Q	*Oil Unc*	-0.19	-0.06	-0.09	-0.14	-0.07	0.28	-0.04
		VIX	-1.12***	-1.15***	-0.95***	-0.73**	-1.37***	-1.31***	-1.27***
		Macro Unc	-0.54*	-0.61**	-0.62**	-0.58**	-0.54	-0.55*	-0.55*
	2Q	*Oil Unc*	-0.14	0.07	-0.01	-0.02	0.03	0.63*	0.17
		VIX	-2.07***	-2.02***	-1.70***	-1.42***	-2.41***	-2.24***	-2.15***
		Macro Unc	-0.92	-1.03	-1.05	-0.98	-0.93	-0.96	-0.96
	4Q	*Oil Unc*	-0.05	0.23	0.12	0.14	0.12	1.17*	0.44
		VIX	-2.70***	-2.58***	-2.08***	-1.68*	-3.30***	-2.98***	-2.72***
		Macro Unc	-1.83	-2.02	-2.03	-1.91	-1.85	-1.89	-1.91
Oil prod growth	1Q	*Oil Unc*	-0.02	0.00	0.01	0.01	-0.04	-0.07	-0.02
		VIX	-0.90***	-0.90***	-0.78**	-0.64*	-1.04***	-1.02***	-0.99***
		Macro Unc	-0.33	-0.37	-0.38	-0.36	-0.33	-0.33	-0.34
	2Q	*Oil Unc*	-0.12	-0.16	-0.16	-0.15	-0.05	-0.19**	-0.14
		VIX	-1.34**	-1.20**	-0.84	-0.51	-1.65***	-1.54***	-1.44***
		Macro Unc	-0.73	-0.87	-0.88	-0.80	-0.75	-0.76	-0.77
	4Q	*Oil Unc*	-0.22	-0.30	-0.26	-0.24	-0.20	-0.46***	-0.36*
		VIX	-1.64*	-1.44	-0.92	-0.56	-2.27**	-2.01**	-1.76*
		Macro Unc	-1.69	-1.92	-1.91	-1.78	-1.71	-1.74	-1.77
Oil inventory growth	1Q	*Oil Unc*	0.13	0.06	0.11	0.17	-0.01	-0.09	0.06
		VIX	-5.65***	-6.18***	-5.38***	-4.47***	-6.45***	-6.24***	-5.99***
		Macro Unc	-2.46*	-2.54*	-2.67**	-2.60**	-2.46*	-2.50*	-2.54**
	2Q	*Oil Unc*	0.20	0.12	0.20**	0.24**	-0.05	-0.09	0.08
		VIX	-11.69***	-12.43***	-10.92***	-9.37***	-12.68***	-12.36***	-11.97***
		Macro Unc	-3.27	-3.38	-3.61	-3.47	-3.31	-3.37	-3.41
	4Q	*Oil Unc*	0.04	-0.03	0.12	0.16	-0.27	-0.45**	-0.10
		VIX	-14.23***	-14.44***	-12.04***	-10.19***	-15.87***	-14.94***	-13.91***
		Macro Unc	-4.40	-4.82	-5.05	-4.68	-4.46	-4.61	-4.70

Table C5: Predictive regressions for equity market returns, full sample period (1991-2016)

The table presents regression results corresponding to Equation (11) of the main paper with all control variables included. We consider four horizons, $h = 1, 3, 6, 12$, which correspond to monthly, quarterly, semi-annual and annual market returns. Results for the oil uncertainty risk premia and control variables are reported. Each row reports the t-statistic for the predictor listed at the head of each column. All standard errors are Newey-West computed using lags equal to $\max(3, 2 \times h)$, as in Bekaert and Hoerova (2014). Bold numbers indicate significance at the 5% level.

	h	*(C)VRP*	*CAY*	*PE*	*PD*	*TS*	*DS*	*EqVRP*	*Slope(-)*	*Slope(+)*
VRP	1	0.05	0.53	-0.26	-1.18	0.08	-0.39	-0.51	0.18	**-2.63**
VRP	3	-0.63	0.52	0.26	**-2.16**	-0.53	-0.80	1.63	0.61	-0.92
VRP	6	-0.92	0.80	0.21	**-2.46**	-0.36	-0.46	**1.70**	0.34	-0.31
VRP	12	-0.65	**1.76**	-0.55	**-2.76**	0.95	0.39	**2.04**	0.31	-0.44
CVRP10	1	1.39	0.61	-0.36	-1.28	0.05	-0.61	-0.61	-0.34	**-2.68**
CVRP10	3	-0.23	0.52	0.25	**-2.26**	-0.56	-0.96	**1.73**	0.32	-0.91
CVRP10	6	0.33	0.81	0.16	**-2.51**	-0.39	-0.76	**1.86**	-0.11	-0.29
CVRP10	12	0.09	**1.72**	-0.57	**-2.73**	0.91	0.16	**2.29**	-0.05	-0.43
CVRP10	1	0.22	0.54	-0.28	-1.20	0.08	-0.46	-0.51	0.11	-2.67
CVRP10	3	-0.58	0.51	0.30	**-2.24**	-0.56	-0.81	**1.82**	0.53	-0.85
CVRP10	6	-0.30	0.79	0.22	**-2.51**	-0.38	-0.57	**1.95**	0.15	-0.25
CVRP10	12	-0.46	**1.72**	-0.52	**-2.72**	0.92	0.33	**2.28**	0.26	-0.36
CVRPD	1	-0.53	0.52	-0.21	-1.13	0.07	-0.08	-0.40	0.38	**-2.57**
CVRPD	3	-0.83	0.53	0.32	**-2.23**	-0.57	-0.59	**1.99**	0.62	-0.81
CVRPD	6	-0.91	0.80	0.26	**-2.50**	-0.39	-0.33	**2.17**	0.28	-0.20
CVRPD	12	-0.78	**1.75**	-0.52	**-2.69**	0.90	0.49	**2.38**	0.34	-0.34
CVRPU	1	**1.89**	0.63	-0.28	-1.54	-0.09	-0.54	-0.11	-0.42	**-2.25**
CVRPU	3	0.65	0.57	0.22	**-2.25**	-0.59	-1.07	**1.73**	0.02	-0.65
CVRPU	6	-0.01	0.81	0.19	**-2.40**	-0.38	-0.75	**1.66**	0.04	-0.25
CVRPU	12	0.40	**1.77**	-0.54	**-2.85**	0.87	0.16	**1.93**	-0.18	-0.32
CVRP75	1	0.48	0.48	-0.28	-1.26	0.07	-0.42	-0.55	0.07	**-2.63**
CVRP75	3	0.09	0.53	0.22	**-2.25**	-0.56	-1.06	1.63	0.23	-0.84
CVRP75	6	-0.59	0.86	0.22	**-2.44**	-0.38	-0.69	**1.81**	0.20	-0.34
CVRP75	12	0.21	**1.79**	-0.55	**-2.85**	0.90	0.16	**2.19**	-0.09	-0.38
CVRP90	1	0.69	0.45	-0.29	-1.28	0.03	-0.45	-0.57	0.08	**-2.64**
CVRP90	3	0.32	0.50	0.20	**-2.29**	-0.59	-1.11	1.62	0.15	-0.89
CVRP90	6	-0.40	0.87	0.21	**-2.49**	-0.37	-0.72	**1.89**	0.15	-0.29
CVRP90	12	-0.20	**1.87**	-0.53	**-2.83**	0.92	0.25	**2.37**	0.09	-0.42

Table C6: Predictive regressions for equity market returns, PreFin sample period (1991-2004).
The table presents regression results corresponding to Equation (11) of the main paper with all control variables included. We consider four horizons, $h = 1, 3, 6, 12$, which correspond to monthly, quarterly, semi-annual and annual market returns. Results for the oil uncertainty risk premia and control variables are reported. Each row reports the t-statistic for the predictor listed at the head of each column. All standard errors are Newey-West computed using lags equal to $\max(3, 2 \times h)$, as in Bekaert and Hoerova (2014). Bold numbers indicate significance at the 5% level.

	h	*(C)VRP*	*CAY*	*PE*	*PD*	*TS*	*DS*	*EqVRP*	*Slope(-)*	*Slope(+)*
VRP	1	1.22	**2.01**	**-3.54**	**1.88**	0.77	**2.40**	-0.30	0.07	**-3.33**
VRP	3	1.13	1.63	**-3.26**	0.60	-0.22	**2.53**	0.81	-0.05	**-1.69**
VRP	6	0.22	1.34	**-3.01**	0.13	0.25	1.23	0.84	0.66	-0.43
VRP	12	0.36	1.18	**-3.36**	-0.96	-0.49	**3.39**	1.14	0.00	-0.82
CVRP10	1	1.58	**1.92**	**-3.61**	**1.95**	0.89	**2.36**	-0.27	0.00	**-3.36**
CVRP10	3	-0.21	1.60	**-3.15**	0.76	-0.08	**2.55**	1.16	0.71	-1.60
CVRP10	6	-0.15	1.34	**-2.93**	0.16	0.28	1.26	0.93	0.78	-0.43
CVRP10	12	0.10	1.19	**-3.27**	-0.86	-0.47	**3.54**	1.30	0.14	-0.83
CVRP25	1	0.99	**1.95**	**-3.53**	**1.92**	0.85	**2.38**	-0.21	0.20	**-3.32**
CVRP25	3	-0.02	1.59	**-3.17**	0.74	-0.09	**2.56**	1.16	0.54	**-1.80**
CVRP25	6	-0.45	1.36	**-2.91**	0.22	0.32	1.29	1.02	0.90	-0.34
CVRP25	12	-0.32	1.20	**-3.31**	-0.82	-0.42	**3.74**	1.45	0.35	-0.86
CVRPD	1	0.89	1.96	**-3.50**	**1.90**	0.81	**2.41**	-0.21	0.31	**-3.21**
CVRPD	3	0.38	1.56	**-3.23**	0.64	-0.16	**2.56**	1.05	0.37	-1.96
CVRPD	6	-0.39	1.36	**-2.97**	0.23	0.33	1.28	1.01	0.92	-0.36
CVRPD	12	-0.43	1.20	**-3.35**	-0.78	-0.39	**3.78**	1.52	0.41	-0.81
CVRPU	1	**1.71**	**2.14**	**-3.50**	**1.83**	0.88	**2.38**	-0.38	-0.09	**-3.30**
CVRPU	3	**1.77**	**1.76**	**-3.25**	0.62	-0.14	**2.51**	0.72	-0.17	-1.08
CVRPU	6	1.07	1.43	**-3.08**	0.08	0.26	1.20	0.67	0.48	-0.07
CVRPU	12	**1.88**	1.30	**-3.44**	-1.07	-0.51	**3.23**	0.75	-0.66	-0.28
CVRP75	1	1.30	**2.01**	**-3.50**	**1.89**	0.89	**2.39**	-0.31	0.20	**-3.36**
CVRP75	3	**2.06**	1.65	**-3.23**	0.63	-0.17	**2.50**	0.68	-0.06	-1.38
CVRP75	6	0.95	1.37	**-3.06**	0.10	0.25	1.21	0.70	0.63	-0.28
CVRP75	12	**1.69**	1.24	**-3.41**	-1.07	-0.52	**3.26**	0.76	-0.47	-0.59
CVRP90	1	**1.99**	**1.90**	**-3.56**	**1.88**	0.79	**2.46**	-0.36	0.24	**-3.43**
CVRP90	3	**2.32**	1.49	**-3.27**	0.63	-0.26	**2.55**	0.61	0.03	**-1.80**
CVRP90	6	1.37	1.31	**-3.01**	0.10	0.20	1.22	0.67	0.61	-0.47
CVRP90	12	1.26	1.20	**-3.41**	-1.01	-0.54	**3.29**	0.93	-0.15	-0.88

Table C7: Predictive regressions for equity market returns, PostFin sample period (2005-2016).
The table presents regression results corresponding toEquation (11) of the main paper with all control variables included. We consider four horizons, $h = 1, 3, 6, 12$, which correspond to monthly, quarterly, semi-annual and annual market returns. Results for the oil uncertainty risk premia and control variables are reported. Each row reports the t-statistic for the predictor listed at the head of each column. All standard errors are Newey-West computed using lags equal to $\max(3, 2 \times h)$, as in Bekaert and Hoerova (2014). Bold numbers indicate significance at the 5% level.

	h	*(C)VRP*	*CAY*	*PE*	*PD*	*TS*	*DS*	*EqVRP*	*Slope(-)*	*Slope(+)*
VRP	1	-0.02	**1.67**	-1.03	**-3.61**	-0.26	**-3.35**	-0.97	0.14	**-1.72**
VRP	3	-1.19	1.62	-0.37	**-4.62**	-0.81	**-3.67**	0.79	0.41	-1.50
VRP	6	-1.12	**1.88**	-0.83	**-4.80**	-0.65	**-3.43**	0.87	-0.38	**-1.93**
VRP	12	-0.34	1.28	-1.35	**-3.08**	1.61	**-3.07**	**1.72**	-1.00	**-2.67**
CVRP10	1	0.39	**1.75**	-1.09	**-3.78**	-0.20	**-3.44**	-0.94	-0.13	**-1.77**
CVRP10	3	-0.01	**1.73**	-0.47	**-5.25**	-0.84	**-4.60**	1.61	0.00	-1.45
CVRP10	6	0.81	**2.09**	-0.91	**-5.05**	-0.54	**-3.94**	1.47	-0.71	**-1.91**
CVRP10	12	0.33	1.39	-1.39	**-3.04**	1.58	**-3.88**	1.98	-0.92	**-2.64**
CVRP25	1	0.05	**1.69**	-1.07	**-3.62**	-0.26	**-3.01**	-0.88	0.10	**-1.79**
CVRP25	3	-0.44	1.61	-0.40	**-4.95**	-0.94	**-4.06**	1.71	0.15	-1.43
CVRP25	6	0.18	**1.89**	-0.88	**-4.98**	-0.64	**-3.45**	1.34	-0.56	**-1.90**
CVRP25	12	0.16	1.36	-1.41	**-3.13**	1.58	**-3.09**	**1.83**	-0.91	**-2.53**
CVRPD	1	-0.38	1.55	-1.00	**-3.45**	-0.34	**-2.55**	-0.74	0.27	**-1.77**
CVRPD	3	-1.00	1.41	-0.38	**-4.73**	-1.01	**-3.35**	**1.97**	0.21	-1.41
CVRPD	6	-0.68	**1.69**	-0.83	**-4.88**	-0.75	**-3.09**	1.62	-0.47	**-1.91**
CVRPD	12	-0.12	1.28	-1.37	**-3.11**	1.60	**-2.61**	**1.76**	-1.00	**-2.56**
CVRPU	1	**2.04**	1.40	-1.38	**-4.53**	-0.64	**-4.17**	0.47	-0.48	-1.14
CVRPU	3	-0.06	1.62	-0.45	**-4.77**	-0.71	**-5.41**	0.68	0.01	-1.17
CVRPU	6	-0.47	**2.06**	-0.81	**-4.86**	-0.56	**-4.74**	0.57	-0.54	**-1.70**
CVRPU	12	-0.09	1.35	-1.34	**-3.09**	1.58	**-4.06**	1.04	-1.38	**-2.08**
CVRP75	1	0.38	1.56	-1.06	**-3.79**	-0.28	**-3.55**	-0.91	0.05	-1.63
CVRP75	3	-1.00	**1.70**	-0.04	**-3.95**	-0.71	**-4.56**	1.06	0.32	-1.43
CVRP75	6	-1.24	**2.24**	-0.49	**-4.40**	-0.59	**-3.26**	0.78	-0.38	**-1.77**
CVRP75	12	-1.05	1.48	-1.21	**-3.01**	1.61	**-2.80**	1.38	-1.16	**-2.23**
CVRP90	1	-0.25	1.62	-0.87	**-3.43**	-0.25	**-3.19**	-0.92	0.22	**-1.72**
CVRP90	3	-1.21	**1.68**	0.04	**-3.54**	-0.71	**-3.40**	1.41	0.48	-1.50
CVRP90	6	-1.55	**1.98**	-0.37	**-3.87**	-0.61	**-2.06**	0.95	-0.24	**-1.87**
CVRP90	12	-1.61	1.35	-1.14	**-2.94**	**1.66**	**-1.76**	1.49	-0.99	**-2.39**