

Hedging macroeconomic and financial uncertainty and volatility*

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Abstract

This paper studies the pricing of shocks to uncertainty and realized volatility using options contracts directly related to the state of the macroeconomy and of financial markets. Contracts that provide protection against shocks to macroeconomic uncertainty have historically earned statistically and economically significantly positive excess returns. If uncertainty shocks were viewed as bad by investors – in the sense of being associated with high marginal utility – portfolios that hedge them should instead earn negative premia. Portfolios exposed to the realization (as opposed to the expectation) of large shocks to fundamentals, on the other hand, have historically earned large and negative risk premia. These results imply that it is large realizations of shocks to fundamentals, not forward-looking uncertainty shocks, that drive investors' marginal utility; in turn, these implications can be used to guide and discipline the role of volatility in macroeconomic models.

1 Introduction

It is well established that a wide range of measures of economic volatility and uncertainty vary over time and with the business cycle. Uncertainty about numerous aspects of the economy, including productivity, the level of the stock market, inflation, interest rates, and energy prices, varies substantially, and often as the direct result of policy choices. It is therefore important to understand how uncertainty affects the economy, both to reveal the basic drivers of economic fluctuations, and also to guide policymakers.

There are numerous theories that explore the relationship between uncertainty and real activity. Some models focus on contractionary effects, such as models with wait-and-see effects in investment (e.g. Caballero (1999), Bloom (2009)), while others argue that uncertainty can be high in periods of high growth (like the late 1990's) due to learning effects (Pastor and Veronesi (2009)). Furthermore, even theoretical work that focuses on contractionary effects of uncertainty tends to find responses of the economy to uncertainty shocks whose sign is parameter-dependent. Gilchrist and

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Williams (2005) and Bloom et al. (2017) extensively discuss the potentially expansionary effects of uncertainty shocks.

The empirical literature studying uncertainty has focused almost entirely on analyzing raw correlations or using vector autoregressions with varying identifying assumptions. Empirical work thus far has not resolved the question of whether uncertainty is contractionary, with some arguing that uncertainty shocks are briefly contractionary followed by a large rebound (Bloom (2009)), others arguing that they are persistently contractionary (e.g. Alexopoulos and Cohen (2009); Leduc and Liu (2016), Caldara et al. (2016)), and a third set finding that they have little effect at all (Bachmann and Bayer (2013); Berger, Dew-Becker, and Giglio (2018)). A fourth set of papers argues the causation may run the opposite direction, with economic activity driving uncertainty (e.g. Ludvigson, Ma, and Ng (2015) and Creal and Wu (2017)).¹

This paper develops a novel empirical approach to evaluate the effects of uncertainty shocks. Instead of studying a VAR with all of the associated identification challenges, we argue that financial markets provide a direct window on how investors perceive uncertainty shocks. The basic idea is to construct portfolios that directly hedge uncertainty shocks and then measure their average returns. If investors are willing to accept negative average returns on those hedging portfolios (i.e., negative risk premia), that implies that they view uncertainty as being bad in the sense that it is high in high marginal utility – usually bad – states. On the other hand, if the hedging portfolios have positive average returns, then investors view uncertainty as typically being high in good states. The magnitude of the average return moreover measures the correlation between uncertainty and state prices. So rather than running sophisticated regressions of output on uncertainty, we let investors speak to the question.

While there is a large literature that estimates the risk premia for uncertainty about the S&P 500,² recent evidence shows that aggregate uncertainty has multiple dimensions (Ludvigson, Ma, and Ng (2015); Baker, Bloom, and Davis (2015)). S&P 500 uncertainty is related to conditions in the financial sector, but it is possible that the driving force in the economy is actually uncertainty about other features of the macroeconomy, such as interest rates, inflation, or the availability of inputs to production, like crude oil. This paper contributes to the literature by estimating risk premia associated with uncertainty in 19 different markets covering a range of different features of the economy, including financial conditions, inflation, and real assets. Using the range of contracts – which are exchange-traded and available to retail investors – we construct portfolios that allow investors to directly hedge different types of uncertainty shocks, including shocks to prominent recent uncertainty indexes from Jurado, Ludvigson, and Ng (JLN; 2015) and the economic policy uncertainty (EPU) index of Baker, Bloom, and Davis (2015).

The first step in the analysis is to document the strong relationship between the implied volatility in the 19 options markets and the JLN and EPU indexes. Implied volatility for the financial

¹For related theories, see Decker, D’erasmo and Boedo (2016), Berger and Vavra (2013), Ilut, Kehrig and Schneider (2015), Kozlowski, Veldkamp, and Venkateswaran (2016), and Cesa-Bianchi, Pesaran, and Rebucci (2018).

²See Egloff, Leippold, and Wu (2010), Dew-Becker et al. (2017), Van Binsbergen and Koijen (2017), Andries et al. (2015), and Ait-Sahalia, Karaman, and Mancini (2015).

underlyings – the S&P 500 and Treasury bonds in particular – is primarily associated with the JLN financial uncertainty and EPU indexes, while implied volatility for the nonfinancial underlyings is much more strongly associated with JLN uncertainty about the real economy and goods prices. The relationships are strong in the sense that the implied volatilities explain 60–80 percent of the variation in the JLN and EPU indexes. Together, these results confirm that hedging shocks to implied volatility in these markets represents a good way to hedge various types of aggregate uncertainty shocks, both macroeconomic and financial, and they show why it is important to study more than just S&P 500 options.

We next examine the pricing of shocks. The discussion so far has focused on economic uncertainty – some measure of the dispersion of agents’ conditional distribution for future outcomes. But much of the literature also studies *volatility* – the magnitude of realized shocks to fundamentals. Whereas uncertainty in theoretical models is a forward-looking conditional variance, volatility is a backward-looking sample variance. That is, for some shock ε , with $var_t(\varepsilon_{t+1}) = \sigma_t^2$, uncertainty is σ_t^2 , while volatility is ε_t^2 . The distinction is crucial from the theoretical point of view: models in which forward-looking uncertainty matters for the economy have predictions about σ_t^2 but not about ε_t^2 .

Our analysis of returns on options yields hedging portfolios for both. The basic technique takes advantage of the fact that as the maturity of an option varies, its exposure to volatility and uncertainty changes. Longer maturity options are relatively more exposed to uncertainty about the future than to current volatility, while short-maturity option returns are the opposite. That fact allows one to construct two portfolios from short- and long-maturity options, one of which yields pure exposure to changes in implied volatility or σ^2 , while the other yields exposure to squared returns in the underlying futures, or ε^2 .

The empirical analysis yields two key findings. First, across 19 individual option markets and also when hedging the JLN and EPU indexes, portfolios that directly hedge uncertainty shocks have historically earned returns that are in almost all cases statistically and economically significantly positive. The average returns are nearly as positive as those on the aggregate US stock market. That result implies that investors view periods of high uncertainty as being good on average, rather than bad, in the same way and to the same degree that stock returns are high in good times. The second result runs in the opposite direction: portfolios that hedge realized volatility – large realized futures returns, or ε^2 – earn statistically and economically significantly negative returns. That implies that investors on average view periods in which shocks to fundamentals themselves are large as being bad.

The returns on the uncertainty hedging portfolios are difficult to reconcile with the view that innovations in economic uncertainty are contractionary. If increases in uncertainty were viewed as bad in the sense of raising marginal utility, then we would find a negative premium on implied volatility – investors would be willing to accept negative average returns on assets that are hedges against high marginal utility states. Instead, the results imply that investors have historically viewed periods of high uncertainty and implied volatility as being good, in the sense that they are

associated with low marginal utility, consistent with models such as that of Pastor and Veronesi (2009).

What is associated with bad outcomes, from the perspective of investors, is instead realized volatility. That finding contributes to the growing literature studying skewness risk in the economy (e.g. Barro (2006), Bloom, Guvenen, and Salgado (2016), and Seo and Wachter (2018a,b)). If shocks to the economy are skewed to the left, then large shocks tend to be negative. That is, $E[\varepsilon^3] < 0$ implies $cov(\varepsilon, \varepsilon^2) < 0$. An explanation for the pricing of realized volatility, developed formally in Berger, Dew-Becker, and Giglio (2018), is simply that hedging realized volatility helps hedge downward jumps and disasters.

The paper is related to two main strands of literature. The first studies the relationship between uncertainty and the macroeconomy. There are numerous channels that have been proposed through which uncertainty about various aspects of the aggregate economy may have real effects.³ Importantly, these models do not generate a uniform prediction that uncertainty shocks are necessarily contractionary. While there are contractionary forces, such as wait-and see effects and Keynesian demand channels, there are also forces through which uncertainty can be expansionary, including precautionary saving and the Oi–Hartmann–Abel effect that is extensively discussed by Gilchrist and Williams (2005) and Bloom et al. (2017). Our results are therefore more consistent with the expansionary forces. There is also a related empirical literature that tries to measure whether uncertainty does in fact have contractionary effects.⁴ This paper builds on that work by providing measures of risk premia that indicate how investors perceive the effects of aggregate uncertainty shocks. Furthermore, while the past literature has often used S&P 500 implied volatility to measure uncertainty (e.g. Bloom (2009) and Basu and Bundick (2017)), this paper covers a much broader range of assets.

The second literature we build on estimates the pricing of volatility risk in financial markets. Again, that literature primarily studies the S&P 500. There are various papers that have studied specific markets, such as individual equities (e.g. Bakshi, Kapadia, and Madan (2003)) or Treasury bonds (Mueller, Vedolin, and Yen (2017)). Prokopczuk et al. (2017) examine the variance risk premium across many of the same markets that we study (see also Trolle and Schwartz (2010)). Our contribution involves using multiple maturities in each market to isolate the premium on implied volatility as opposed to just the realized variance risk premium – the distinction between the two is crucial because it is only implied volatility, not realized volatility, that captures the forward-looking concept of uncertainty on which the theoretical models are based.

The remainder of the paper is organized as follows. Section 2 describes the data and its basic characteristics. Section 3 discusses the construction of portfolios that hedge realized volatility and uncertainty. Section 4 reports the cost of hedging volatility and uncertainty in our data. Section 5

³These include a Keynesian demand channel (Basu and Bundick (2017)), real options effects on investment (Bloom (2009), Bloom et al. (2017)), effects on labor search (Leduc and Liu (2015)), or through financial frictions and credit spreads (Gourio (2013)).

⁴Recent examples include Berger, Dew-Becker, and Giglio (2017), Jurado, Ludvigson, and Ng (2015), Ludvigson, Ma, and Ng (2015), Baker, Bloom, and Davis (2015), and Alexopoulos and Cohen (2009), among many others.

presents robustness results. To provide more confidence in some of the results, section 6 examines the crude oil market in detail. Finally, section 7 concludes.

2 Measures of uncertainty and realized volatility

This section describes our main data sources and then examines various measures of uncertainty and realized volatility.

2.1 Data

2.1.1 Options and futures

We obtain data on prices of financial and commodity futures and options from the end-of-day database from the CME Group, which reports closing settlement prices, volume, and open interest for the period 1983–2015. The CME data is important for covering a broad array of features of the economy, including stock prices, interest rates, exchange rates, and prices of metals, petroleum products, and agricultural products.

Each market includes both futures and options, with the options written on the futures. The futures may be cash- or physically settled, while the options settle into futures. As an example, a crude oil call option gives its holder the right to buy a crude oil future at the strike price. The underlying crude oil future is itself physically settled – if held to maturity, the buyer must take delivery of oil.⁵

To be included in the analysis, contracts are required to have least 15 years of data and maturities for options extending to at least six months, which leaves 14 commodity and 5 financial underlyings. The final contracts included in the data set have 18 to 31 years of data.

A number of standard filters are applied to the data to reduce noise and eliminate outliers. Those filters are described in appendix A.1.

We calculate implied volatility for all of the options using the Black–Scholes (1973) model (technically, the Black (1976) model for the case of futures).⁶ Unless otherwise specified, implied volatility is calculated at the three-month maturity.

A key distinction in the analysis is between uncertainty and realized volatility. Realized volatility measures how much some factor actually varies over some period, while uncertainty represents variation in the conditional distribution of the factor. Option implied volatility theoretically measures investors’ conditional standard deviation for futures returns going forward, so we measure realized volatility analogously as the sample standard deviation of futures returns. Specifically, in

⁵The underlying futures general expire in the same month as the option. Crude oil options, for example, currently expire three business days before the underlying future.

⁶The majority of the options that we study have American exercise, while the Black model technically refers to European options. We examine IVs calculated assuming both exercise styles (we calculate American IVs using a binomial tree) and obtain nearly identical results. Since there are no dividends on futures contracts, early exercise is only rarely optimal for the options studied here.

the various futures markets, realized volatility is defined in month t as

$$RV_{i,t} = \left(\frac{365}{\#days \in t} \sum_{days \in t} f_i^2 \right)^{1/2}, \quad (1)$$

where f_i here is a daily return on the near-month futures return in market i . Realized volatility in month t is the annualized sample standard deviation during that month.

2.1.2 Alternative uncertainty measures

The implied volatilities of the CME options give direct measures of investor uncertainty, similar to the VIX. We also examine two other measures of uncertainty.

The first uncertainty index is developed in a pair of papers by Jurado, Ludvigson, and Ng (JLN; 2015) and Ludvigson, Ma, and Ng (2017). The construction involves two basic steps. First, realized squared forecast errors are constructed for 280 macroeconomic and financial time series. Denoting the error for series i as $\varepsilon_{i,t}$, the basic assumption is that there is a variance process, $\sigma_{i,t}^2$, such that $E[\varepsilon_{i,t}^2] = \sigma_{i,t}^2$. So $\varepsilon_{i,t}^2$ constitutes a noisy signal about $\sigma_{i,t}^2$. JLN then estimate $\sigma_{i,t}^2$ from the history of $\varepsilon_{i,t}^2$ using a two-sided smoother and create an uncertainty index as the first principal component of the estimated $\sigma_{i,t}^2$. We divide the 280 series among those that pertain financial markets, real activity, and goods prices, with the latter two also being combined into an overall macroeconomy group, and take the first principal component from each group to get different subindexes.

The goal of the JLN framework is to estimate uncertainty on each date, σ_t^2 . The method can also be extended to create a realized volatility index by taking the first principal component from the cross-section of the $\varepsilon_{i,t}^2$. We therefore construct both uncertainty and realized volatility under the JLN framework.

The second uncertainty index is the Economic Policy Uncertainty (EPU) index of Baker, Bloom, and Davis (2015). The EPU index is constructed based on media discussion of uncertainty, the number of federal tax provisions changing in the near future, and forecaster disagreement. Unlike the JLN framework, there is no distinction in this case between volatility and uncertainty, so we treat the EPU index as measuring only uncertainty.

2.2 The time series of uncertainty

Figure 1 plots option implied volatility for three major futures: the S&P 500, crude oil, and US Treasury bonds. The implied volatilities clearly share common variation; for example, all rise around 1991, 2001, and 2008. On the other hand, they also have substantial independent variation. The period around the 1991 Gulf War was a period of extremely high implied volatility for crude oil, but much lower uncertainty for stocks and bonds. Conversely, the Financial Crisis was associated with larger relative increases in stock and bond than crude oil implied volatility. So while they move together, their overall correlations (also reported in the figure) are only in the range 0.5–0.6.

Table 1 reports pairwise correlations of implied volatility across the 19 underlyings, and also gives the first introduction to the full list of 19 markets. The various markets are sorted in this table into related categories, with the result that the largest correlations are generally along the main diagonal. Shading denotes the degree of correlation, with darker cells representing greater correlation. The largest correlations in implied volatility are among similar underlyings – crude and heating oil, the agricultural products, gold and silver, and the British Pound and Swiss Franc. Correlations outside those groups are notably smaller, in many cases close to zero.

The eigenvalues of the correlation matrix quantify the degree of common variation. The largest eigenvalue explains 43 percent of the total variation. The remaining eigenvalues are much smaller, though – even the second largest is only 0.15. Eight eigenvalues are required to explain 90 percent of the total variation in the IVs, which is perhaps a reasonable estimate of the number of independent components in the data.

To understand the behavior of the implied volatilities in more detail, table 2 reports results from regressions of the 19 implied volatilities on various combinations of the EPU and JLN indexes. The left and middle panels of the table report results from the two regressions

$$\frac{IV_{i,t}}{SD(IV_{i,t})} = a_{1,i} + b_{1,i}JLNU_t^{\text{Financial}} + b_{2,i}JLNU_t^{\text{Macro}} + \varepsilon_{1,i,t}, \quad (2)$$

$$\frac{IV_{i,t}}{SD(IV_{i,t})} = a_{2,i} + b_{3,i}JLNU_t^{\text{Financial}} + b_{4,i}JLNU_t^{\text{Real}} + b_{5,i}JLNU_t^{\text{Price}} + \varepsilon_{2,i,t}, \quad (3)$$

where $IV_{i,t}$ denotes at-the-money implied volatility for underlying i averaged over month t , $SD(IV_{i,t})$ is the sample standard deviation of $IV_{i,t}$, and the various $JLNU_t^{\cdot}$ are the JLN uncertainty series. The uncertainty series all have unit standard deviations by construction, and the implied volatilities are also normalized for the regressions. The regressions help understand how the individual implied volatility series relate to other measures of uncertainty. The table reports the five financial underlyings in our data at the top of each panel, and the nonfinancial underlyings at the bottom.

For the S&P 500 and US Treasury bonds, implied volatilities are strongly related to financial uncertainty, which is natural since measures of aggregate stock prices and interest rates are included in JLN’s set of financial indicators. Among the nonfinancial underlyings, the loadings almost entirely favor macro uncertainty – in 12 of 14 cases, the coefficient on macro uncertainty is larger than that on financial uncertainty. The coefficients are generally economically large: the average coefficient on macro uncertainty among the nonfinancial underlyings is 0.32. The coefficients are larger for industrial products like energies and metals – all above 0.4 except natural gas; they are somewhat smaller for the agricultural products, averaging 0.23.

To further decompose those results, the middle panel in table 2 reports results from the regression (3) that replaces the macro uncertainty time series with its real and price subcomponents. The nonfinancial underlyings are nearly evenly split, with six having larger loadings on the price component and eight having larger loadings on the real component. The energies, perhaps naturally, are more associated with price uncertainty, with coefficients near 0.5. Metals and agricultural

products, on the other hand, are more associated with macro uncertainty, with coefficients near 0.4. Looking down the columns, the R^2 s range from 0.09 to 0.74. The bottom row of each panel reports results from a regression of the *average* of the 19 IVs on the JLN indexes. In that case, the coefficients on financial and macro uncertainty are similar, with values around 0.4, and the macro loading is split equally between real and price uncertainty. The R^2 in both cases is approximately 0.55.

The right panel in table 2 report results of regressions of the IVs on the EPU index. In almost every case, the coefficients and R^2 s are smaller than for the JLN regressions. The R^2 for the average across the IVs is only 0.14. That suggests that the EPU index, in measuring policy uncertainty, captures somewhat different features of the economy from what is in the JLN indexes and our IVs. The S&P 500, Treasury bonds, currencies, and gold and silver uncertainty have the strongest relationships with EPU, suggesting that EPU more closely related to financial than nonfinancial uncertainty in our data.

Overall, table 2 shows that there is a statistically and economically strong relationship between implied volatility measured in futures markets and the JLN uncertainty measure constructed from aggregate time series. Past work has focused on S&P 500 implied and realized volatility, which the evidence here shows primarily measures financial uncertainty. The wide range of markets used here is therefore valuable for giving direct measures of investor uncertainty about broader features of the macroeconomy than simply the financial sector.

2.3 Projecting the uncertainty indexes onto the 19 IVs

Figure 2 examines how well the 19 IVs can fit the JLN and EPU indexes. These regressions are then used to construct hedging portfolios for the indexes.

Figure 2 plots the time series of the JLN and EPU indexes in the bottom row against the fitted values from their projection onto the 19 implied volatilities and a constant. The R^2 s are reported in the left-hand panels. The highest R^2 , at 80 percent, is for financial uncertainty. The top-right panel plots the pairwise correlations of the implied volatilities in the individual markets with the fitted uncertainty. For financials, the correlation with S&P 500 implied volatility (which is nearly identical to the VIX) is 95 percent. The next highest correlation is only 69 percent, for Treasury bonds. So figure 2 reinforces the result from table 2 that fitted financial uncertainty is very nearly equivalent to S&P 500 implied volatility.

The second best fit for the JLN uncertainty projections is for price uncertainty in the third row, where the implied volatilities generate an R^2 of 73 percent. In this case, the highest correlations are for heating oil, crude oil, natural gas, gold, and copper. These results show the value of the alternative markets in helping provide a better fit to inflation uncertainty than the S&P 500.

Last, the second row plots fitted uncertainty for real variables. The same implied volatilities – gold, copper, crude oil, and heating oil – appear with the highest pairwise correlations as for price uncertainty. The R^2 is lower in this case, at 59 percent. The commodity options therefore

appear to be slightly better at hedging financial and inflation uncertainty than in uncertainty about variables like GDP or industrial production. But the R^2 for real uncertainty is still substantial, and the implied volatilities seem to capture well the lower-frequency variation, missing some of the more high-frequency variation; overall, these investments still provide a hedge against a substantial fraction of real (GDP, IP, etc.) risk.

The bottom panels plot results for the EPU index. The overall R^2 is similar to what is obtained for JLN real uncertainty. Consistent with the results in table 2, the highest pairwise correlations are with financial IVs, Treasuries, gold, the S&P 500, and currencies. So the fit of the IVs to the EPU index comes mostly from the financial rather than the nonfinancial options, but note that Treasury and gold uncertainty have gotten relatively little attention in past work.

Ideally, we would like the R^2 s in this exercise to be as high as possible, because the hedging portfolios will use option returns. When we examine the cost to hedge the JLN indexes, we ultimately can only measure the cost to hedge the part spanned by the implied volatilities. Our results will be potentially biased if the unexplained residual is priced differentially – or differentially correlated with marginal utility – from the part that is spanned by the options. For financial and price uncertainty, in particular, that fact seems unlikely given how high the R^2 is. For EPU and macro uncertainty, it is more of a risk, but inspection of the figures shows that the residuals appear primarily at high frequency. The options span the lower frequency variation in the series well, so when we obtain returns on hedging portfolios, it is that lower frequency component that will be hedged best.

A potential concern about the results is that these regressions might be overfit due to the fact that we have 19 explanatory variables. We experimented with various methods of reducing the degrees of freedom, including lasso and variable selection based on information criteria. The results were highly similar in all cases. One might also worry that it would be difficult for investors to know the correct hedging weights contemporaneously. There are two factors that make that concern unlikely to affect the results. First, one could choose the hedging portfolios based on economic considerations and end up with a similar outcome to what we have in the figure. In particular, the natural way to hedge financial uncertainty would be to use S&P 500 options, while the natural way to hedge price uncertainty would be to focus on the underlyings related to particularly volatile components of price indexes, like energy, metals, and food prices. Second, in the hedging results that we report below, the average returns are highly consistent across the various underlyings, especially within financials and nonfinancials, so changing the relative weights on the different underlyings has only small quantitative effects on the cost of hedging.

2.4 Realized volatility

Table 3 reports the correlation of implied and realized volatility for the 19 underlyings, along with their standard deviations. Realized volatility tends to be substantially more volatile than implied volatility, which is natural if implied volatility represents (approximately) an expectation

of future realized volatility. Implied and realized volatility are also strongly correlated with each other, which is again natural given that implied volatility represents expected future volatility. The key difference between the two is that realized volatility isolates realizations of extreme events – price jumps – whereas implied volatility measures expectations of the probability or size of future extreme events.

Table 4 reports the correlation matrix for realized volatility across the 19 markets. As in the IV correlation matrix, the correlations are relatively strong near the main diagonal, but they are all smaller in the RV case. The largest eigenvalue is only 0.32, compared to 0.43 for IV, implying there is less common and more idiosyncratic variation in realized than implied volatility.

Table A.1 in the appendix reports results from regressions analogous to (2)–(3), but replacing *IV* with *RV* and the *JLNU* series with *JLNRV*, which is the JLN-type realized volatility index described above. The results are similar in the sense that S&P 500 and Treasury bond RV load more on the financial *JLNRV* index, whereas the nonfinancials load more on the macro indexes. The R^2 s in this case are smaller than for IV, which is consistent with the result from the correlation matrices that there is more common variation in IV than RV.

Figure 3 replicates figure 2, but using realized instead of implied volatility. That is, it examines the ability of the RV series for the 19 futures markets to fit the three JLN RV indexes. As before, the R^2 s are lower in this case. Interestingly, S&P 500 realized volatility appears to fit better to the JLN RV indexes than in the IV case. Nevertheless, it remains the case that for fitting real and price RV, the nonfinancial markets, including in particular the energies and copper, are especially useful.

3 Using option portfolios to hedge uncertainty

Implied volatility and the uncertainty indexes are not directly tradable – only the options themselves are. This section shows how to construct option portfolios that hedge shocks to implied and realized volatility in each of the 19 markets and also the JLN and EPU indexes.

3.1 Straddle portfolios

We study two-week returns on straddles with maturities between one and six months.⁷ A straddle is a portfolio holding a put and a call with the same maturity and strike, with the strike set to the

⁷Past work on option returns and volatility risk premia has examined returns at frequencies of a day (e.g. Andries et al. (2017)), a week (Coval and Shumway (2001)), a month (Constantinides, Jackwerth, and Savov (2013); Dew-Becker et al. (2017)), and holding the options to maturity (Bakshi and Kapadia (2003)). The precision of estimates of the riskiness of the straddles is, all else equal, expected to be higher with shorter windows. On the other hand, shorter windows cause any measurement error in option prices to have larger effects. We choose two-week windows because they are within the typical range used and they are short enough to allow us to still calculate returns on relatively short-maturity options. Some of the existing literature, beginning with Bakshi and Kapadia (2003), examines delta-hedged returns. Bakshi and Kapadia (2003) study returns to maturity, but only on options with maturities shorter than 60 days. Even with delta hedging, the higher-order risk exposures of the straddles change substantially as the spot changes. Higher-frequency returns avoid that problem. Section 5 describes alternative specifications that we have examined to check the robustness of the main results.

current futures price. The final payoff of a straddle depends on the absolute value of the return on the underlying, meaning that they have symmetrical exposures to positive and negative returns.

Straddles give investors exposure both to realized and implied volatility. They are exposed to realized volatility because the final payoff of the portfolio is a function of the absolute value of the underlying futures return. But when a straddle is sold before maturity, the sale price will also depend on expected future volatility, meaning that straddles can give exposure to uncertainty shocks.

The exposures of straddles can be approximated theoretically using the Black–Scholes model, as in Coval and Shumway (2001), Bakshi and Kapadia (2003), and Cremers, Halling, and Weinbaum (2015). Appendix A.2 shows that the partial derivatives of the straddle return with respect to the underlying futures return, f , its square, and the change in volatility, can be approximated as

$$\frac{\partial r_{n,t}}{\partial f_t} \approx 0, \tag{4}$$

$$\frac{\partial^2 r_{n,t}}{\partial (f_t/\sigma_{t-1})^2} \approx n^{-1}, \tag{5}$$

$$\frac{\partial r_{n,t}}{\partial (\Delta\sigma_t/\sigma_{t-1})} \approx 1, \tag{6}$$

where $r_{n,t}$ is the return on date t of a straddle with maturity n , f_t is the return on the underlying future, σ_t is the implied volatility of the underlying, and Δ is the first-difference operator.⁸

The first partial derivative says that the straddles all have close to zero local exposure to the futures return, which is natural since their payoff is a symmetrical function of the underlying return. The second line says that the exposure of straddles to squared returns on the underlying – scaled by volatility – is approximately inversely proportional to time to maturity. Throughout the paper, we interpret exposures to squared returns as representing exposure to realized volatility, since realized volatility is calculated based on squared returns over some period. The third line shows that straddles are also exposed to changes in expected future volatility, through $\frac{\Delta\sigma_t}{\sigma_{t-1}}$, and that exposure is approximately constant across maturities.

Overall, then, all straddles have approximately equal exposure to proportional shifts in implied volatility, while the exposure to realized volatility decreases with maturity. Long-maturity straddle returns, for which the term n^{-1} is sufficiently small, therefore reveal the premium associated with uncertainty shocks.

3.2 Hedging RV and IV in each market

The implied sensitivities in (4)–(6) give a method for constructing portfolios that the Black–Scholes model says should give exposures *only* to realized volatility – squared returns, measured by

⁸We ignore here the fact that options at different maturities have different underlying futures contracts. If that elision is important, it can be expected to appear as a deviation of the estimated factor loadings from the predictions of the approximations (4)–(6).

$(f_{n,t}/\sigma_{t-1})^2$ – and *only* implied volatility, measured by $\Delta\sigma_t/\sigma_{t-1}$ (Cremers, Halling, and Weinbaum (2015)). Specifically, we construct, for each market, two portfolios,

$$rv_{i,t} = \frac{5}{24}(r_{i,1,t} - r_{i,5,t}), \quad (7)$$

$$iv_{i,t} = \frac{5}{4}r_{i,5,t} - \frac{1}{4}r_{i,1,t}. \quad (8)$$

Throughout the paper, capitalized RV and IV refer to the levels of realized and implied volatility, while lower-case rv and iv refer to the associated portfolio returns.

Given equations (4)–(6), the rv and iv portfolios will both have zero local sensitivity to f_t . The rv portfolio will have a unit sensitivity to $(f_t/\sigma_t)^2$ and zero sensitivity to $\Delta\sigma_t/\sigma_{t-1}$ in each market, while the iv portfolio will have a unit sensitivity to $\Delta\sigma_t/\sigma_{t-1}$ and zero sensitivity to the squared returns in each market. We use the one- and five-month straddles to construct the portfolios as those are the shortest and longest maturities that we consistently observe in the data.

The purpose of constructing these portfolios is to give a simple and direct method of measuring the premia associated with realized and implied volatility that does not require any complicated estimation or data transformation. One might worry, though, that they do not obtain the desired exposures in practice. Figure A.2 in the appendix shows that the loadings of the straddles fit the Black–Scholes predictions well. Furthermore table A.2 in the appendix reports results of regressions, for each underlying, of the returns of the two portfolios on the underlying futures return, the squared futures return, and the change in implied volatility. The table shows that while the Black–Scholes predictions do not hold perfectly, the rv portfolio is nevertheless much more strongly exposed to realized than implied volatility, and the opposite holds for the iv portfolio. The coefficients on $(f_t/\sigma_{t-1})^2$ average 0.76 for the rv portfolio and 0.10 for the iv portfolio. Conversely, the coefficients on $\Delta\sigma_t/\sigma_{t-1}$ average 0.03 for the rv portfolio and 0.79 for the iv portfolio. Furthermore, the R^2 s are large, averaging 72 percent across the various portfolios, implying that their returns are well described by the approximation (4). Appendix A.2 also examines the accuracy of the Black–Scholes approximation for returns in a simulated setting. Finally, section 5 reports results on the cost of hedging volatility and uncertainty that do not rely on the Black–Scholes assumptions at all, rather using exposures to IV and RV in the data without imposing any model-based assumptions. The results of that robustness exercise are highly similar to those in the baseline case based on Black–Scholes.

It is important to note that we would not necessarily expect the returns of the rv and iv portfolios to be uncorrelated. It is well known from the GARCH literature (e.g. Engle (1982) and Bollerslev (1986)) that in many markets, innovations to realized volatility are correlated with innovations to implied volatility. Table A.2 reports the correlations between the rv and iv returns in the 19 markets (note that this differs from table 3 in looking at returns instead of the levels of RV and IV). GARCH effects appear most strongly for the financial underlyings and precious metals. In those cases, the average correlation is 0.46. While that shows that GARCH effects are

present, only a minority of the variation in the rv and iv returns is driven by a common component. For the nonfinancial underlyings, the effects are much smaller, and the correlation between the rv and iv returns is only 0.03. So for the nonfinancials, innovations to realized and implied volatility returns are essentially independent on average.

3.3 Hedging the JLN and EPU indexes

Finally, using the results in figure 2 showing that the 19 IVs span most of the variation in the JLN and EPU uncertainty indexes, we construct portfolios that optimally hedge those indexes. For each index, we obtain the weights for the hedging portfolio from the regression coefficients in sections 2.3 and 2.4. For each uncertainty index j , we estimate the regression

$$JLNU_t^j = a + \sum_i b_i^j IV_{i,t} + \varepsilon_{j,t} \quad (9)$$

and then construct a hedging portfolio as

$$iv_t^{hedge,j} \equiv \sum_i b_i^j iv_{i,t} \quad (10)$$

the coefficients b_i^j therefore tell us the weight of the iv portfolio of market i in the hedging portfolio for index j . We create such portfolios for each of the JLN uncertainty indexes and the EPU index. We also construct similarly a hedge portfolio for the JLN realized volatility series ($JLNRV$) from the regression

$$JLNRV_t^j = a + \sum_i b_i^{RV,j} RV_{i,t} + \varepsilon_{RV,j,t} \quad (11)$$

$$rv_t^{hedge,j} \equiv \sum_i b_i^j rv_{i,t} \quad (12)$$

4 The cost of hedging

This section reports our main results on the price of hedging shocks to volatility and uncertainty. Given a hedging portfolio, the cost of hedging is the negative of the average excess return (risk premium) on the portfolio. For example, holding an iv portfolio represents holding insurance against increases in implied volatility, so if the iv portfolio earns, say, a -10 percent excess return on average, the cost of that insurance is 10 percent on average. A mean excess return cannot be interpreted without reference to the associated volatility – leveraging a portfolio up or down will shift the mean excess return but also the volatility – so we report all risk premia in terms of Sharpe ratios: the mean excess return divided by the standard deviation. The Sharpe ratio reveals the compensation for bearing a risk (or the cost of hedging it) per unit of risk, and is therefore more easily comparable across markets. For reference, the historical Sharpe ratio of US equities in our

sample is 0.52.

The cost of hedging a risk has a simple but important economic interpretation: it measures the extent to which the risk is “bad” with respect to state prices or marginal utility. To formalize that intuition, consider a factor X and an asset with returns R_X that hedges it, in the sense that R_X varies one-for-one (and is perfectly correlated) with X . Then if M represents the stochastic discount factor (i.e. the Arrow–Debreu state prices divided by state probabilities), then

$$E[R_X - R_f] = -cov(M, X) R_f, \tag{13}$$

where R_f is the gross risk-free rate. The equation says that the negative of the risk premium on a portfolio that hedges the risk X captures the covariance of that risk with state prices.⁹ More generally, when the correlation between R_X and X is less than 1, $E[R_X - R_f]$ measures the covariance of state prices with the part of the factor X that is spanned by R_X . So if the premium $E[R_X - R_f]$ is negative, times when R_X , and hence X , is high are bad times, in which state prices are high (in consumption-based models, these are the times when consumption is low and the marginal utility of consumption is high).

4.1 Hedging uncertainty shocks

The solid series in figure 4 plots sample Sharpe ratios and confidence bands for the various rv and iv portfolios, which hedge realized and implied volatility in the individual markets. The top panel plots results for iv and the bottom panel rv . The boxes are point estimates while the bars represent 95-percent confidence bands based on a block bootstrap.

Across the top panel, the iv portfolios clearly tend to earn zero or even positive returns on average. For financials, the average Sharpe ratios tend to be near zero, while for the nonfinancials, all 14 sample Sharpe ratios are actually positive. To formally estimate the average Sharpe ratios, we use a random effects model, which yields an estimate of the population mean Sharpe ratio while simultaneously accounting for the fact that each of the sample Sharpe ratios is estimated with error, and that the errors are potentially correlated across contracts. The procedure is described in detail in appendix A.3. The estimated mean Sharpe ratios for just the financial and nonfinancial groups are reported in their respective sections, and the estimated population mean across both groups is in the right-hand section (“overall mean”).

For both nonfinancials and all markets overall, the estimated population mean Sharpe ratio is statistically and economically significantly positive, while for financials it is close to zero. The group-level means have the advantage of being much more precisely estimated than the Sharpe ratios for the markets individually. They show that on average, instead of there being a cost, in the form of a negative return, to hedging uncertainty shocks, *uncertainty-hedging portfolios actually earn positive returns*. In particular, for nonfinancials, the average Sharpe ratio is 0.48, and the

⁹The last term on the right, R_f , is close to 1, and is the same for all assets and all risk factors, so it plays no significant role in interpreting this equation.

lower end of the 95-percent confidence interval is 0.25. For the overall mean, the corresponding numbers are 0.39 and 0.17. These are not just statistically but economically significant – the return to portfolios hedging uncertainty shocks has earned average returns nearly as high as the overall stock market. But whereas the stock market is risky, in the sense that it rises in good times and falls in bad, the *iv* portfolios are actually *hedges*, by construction giving positive returns when uncertainty rises. Even for financials, the point estimate for the average Sharpe ratio is positive, though the confidence band runs below zero.

The right-hand section of figure 4 reports the Sharpe ratios for the portfolios hedging the EPU and JLN indexes. Since those hedging portfolios are constructed combining the individual *iv* portfolios (weighting them across the 19 markets to obtain the best hedge for the JLN and EPU indexes), it is not surprising that they are all near zero or positive. The hedging portfolios for JLN financial uncertainty and the EPU index both place relatively more weight on the financials, which have Sharpe ratios close to zero or even slightly negative, so they have overall lower Sharpe ratios. The portfolios hedging macro and price uncertainty, though, since they have larger weights on markets like crude oil, heating oil, and copper, have statistically and economically significantly positive Sharpe ratios, with point estimates both near 0.50, similar to the overall mean for the *iv* portfolios.

As discussed above, even if an investor did not know precisely what weight to put on the various financial or nonfinancial underlyings, it is clear from the figure that almost any set of weights would yield similar results, in the sense that the Sharpe ratios within the nonfinancial and financial categories are all similar, and 18 of the 19 are positive. That fact makes uncertainty about the coefficients in the hedging portfolios unlikely to have important quantitative effects.

The top panel of figure 4 contains all of our key results on the cost of hedging different types of uncertainty shocks. It shows that in our sample spanning almost 30 years, the cost of hedging shocks to uncertainty, whether it is uncertainty in a specific commodity or financial market or a more general macro uncertainty index, has been zero or even negative (the risk premium has been zero or positive).

If uncertainty was perceived to be bad by investors, hedging uncertainty shocks would be costly, and the point estimates in the top panel of figure 4 would be negative – the graph would be the opposite of what we actually see. But at most, some of the *iv* portfolios and hedging portfolios for JLN and EPU have very slightly negative Sharpe ratios. In the majority of the cases – and in particular for uncertainty about the nonfinancial macroeconomy – the Sharpe ratios are statistically and economically significantly positive. In other words, investors have been able to purchase portfolios that directly hedge them against uncertainty shocks and simultaneously earn returns as large as those on the overall stock market.

4.2 Hedging realized volatility shocks

The bottom panel of figure 4 reports analogous results for the cost of hedging realized volatility shocks. The numbers are drastically different. Whereas the *iv* portfolios have historically earned positive returns, the *rv* portfolios have almost all historically earned negative returns. For the S&P 500, this result is well known and is often referred to as the variance risk premium. The S&P 500 *rv* portfolio has the most negative Sharpe ratio, at -0.99 – the return to selling insurance against shocks to realized volatility is *twice* as large as the average return on the stock market over the same period. Treasuries also have a significantly negative return, but the other financials in our sample – all currencies – have Sharpe ratios slightly above zero. For the nonfinancials, 12 of 14 estimated Sharpe ratios are negative. So whereas the cost of hedging uncertainty shocks with the *iv* portfolios is consistently negative in the top panel, the cost of hedging realized volatility shocks using the *rv* portfolios is positive in the bottom panel.

As with the *iv* portfolios, we use a random effects model to calculate the population mean Sharpe ratios and report them in the three sections of the figure. In this case, all three estimates – financials, nonfinancials, and all assets – are negative. The values are again statistically and economically significant. The point estimate for the overall mean Sharpe ratio is -0.33 and the upper end of the 95-percent confidence interval is -0.08. Those values are almost the same as what we obtain for the *iv* portfolios, but with the opposite sign.

Finally, the right-hand section of the bottom panel of figure 4 reports the returns from the JLN *rv* hedging portfolios – those that hedge the realized volatility of the JLN macro series. Again, consistent with the fact that the *rv* portfolios themselves consistently earn negative returns, hedging the JLN indexes for realized volatility – as opposed to uncertainty – historically has a positive cost. For all three subindexes, the hedging portfolios earn extremely negative returns, with the Sharpe ratios for financial, real, and price volatility at -1.02, -0.84, and -0.82.

So in stark contrast to the results for hedging uncertainty, the bottom panel of figure 4 shows that there has historically been an extremely large cost to hedge realized volatility. That is, contracts that, rather than loading on changes in implied volatility, load on actual realized squared returns – which the analysis above shows directly hedge extreme events in the macroeconomy – earn negative Sharpe ratios with magnitudes up to twice as large as the return on the overall stock market.

One potential concern with the results for the pricing of uncertainty shocks is that they might be driven by outliers. The returns on the *iv* portfolios are positively skewed, so it is possible that the sample we have just contains more positive jumps than the population. There are a number of factors that make that story unlikely. First, since we have 19 different markets, which we showed above are far from perfectly correlated with each other, there would have to be outliers in every market. Second, the *rv* portfolios examined in this section in fact have even higher skewness than the *iv* portfolios – the median skewness for the *rv* portfolios is 2.23, compared to 2.09 for the *iv* portfolios. So if outliers were systematically creating an upward bias, we would expect to also

find positive returns for the rv portfolios. Third, since we use bootstrap standard errors, we are not relying on normality in constructing confidence bands. Fourth, and finally, section 6 looks at returns on the rv and iv portfolios for crude oil in rolling five-year windows and finds that the results are stable over time, which is inconsistent with the idea that they are driven by a small number of positive outliers.

In summary, across both individual markets and also the hedging portfolios for the JLN and EPU indexes, exposure to realized volatility has consistently earned a negative premium, while exposure to implied volatility has earned a zero or positive premium. Investors have therefore historically paid money – by accepting negative returns – to hedge surprise realizations of large shocks, while hedging surprises in uncertainty has had a zero or even negative cost. Those results hold across a wide range of markets that provide hedges against uncertainty in both real activity and aggregate prices.

The results here are inconsistent with the view that uncertainty shocks are major drivers of economic declines. If they were – that is, if they were associated with periods of high marginal utility – the equilibrium return on assets hedging those shocks would be negative. If anything is associated with high marginal utility here, it is not periods when investors are particularly uncertain about the future, but periods of high realized volatility, when large movements occur in stock, bond, and commodity markets.

4.3 Hedging average rv and iv

An alternative way to hedge aggregate uncertainty is simply to buy all the iv or rv portfolios simultaneously. Since tables 1 and 4 show that realized and implied volatility are imperfectly correlated across markets, even larger returns can be earned by holding portfolios that diversify across the various underlyings. Table 5 reports results of various implementations of such a strategy. The first row reports results for portfolios that put equal weight on every available underlying in each period, the second row uses only nonfinancial underlyings, and the third row only financial underlyings. The columns report Sharpe ratios for various combinations of the rv and iv portfolios. The first two columns report Sharpe ratios for strategies that hold only the rv or only the iv portfolios, the third column uses a strategy that is short rv and long iv portfolios in equal weights, while the final column is short rv and long iv , but with weights inversely proportional to their variances (i.e. a simple risk parity strategy).

The Sharpe ratios reported in table 5 are generally larger than those in figure 4. The portfolios that are short rv and long iv are able to attain Sharpe ratios well above 1. The largest Sharpe ratios come in the portfolios that combine rv and iv , which follows from the fact that they are positively correlated, so going short rv and long iv leads to internal hedging. All of that said, these Sharpe ratios remain generally plausible. Values near 1 are observed in other contexts (e.g. Broadie, Chernov, and Johannes (2009) for put option returns, Asness and Moskowitz (2013) for global value and momentum strategies, and Dew-Becker et al. (2017) for variance swaps).

The portfolios that take advantage of all underlyings simultaneously seem to perform best, presumably because they are the most diversified. While holding exposure to implied volatility among the financials earns a relatively small premium, it is still generally worthwhile to include financials for the sake of hedging.

Finally, it is important to note that the combined portfolios have returns that are much less skewed than those on the market-specific rv and iv portfolios. The bottom panel of table 5 reports the skewness of the various strategies from above, and, for the portfolios that include both rv and iv , they range between -0.77 and 3.27. So while there may be some skewness, it does not run consistently in either direction – it is negative with equal weighting of the rv and iv portfolios, and positive for the variance weighting. That suggests that the premia from these factors can be earned without necessarily holding a portfolio that is substantially negatively skewed (as with writing puts or straddles). In fact, the risk-parity strategy that holds both financials and nonfinancials has earned a historical Sharpe ratio of 1.26 with *positive* skewness of 0.94.

Overall, these results show that the economic magnitudes related to hedging realized volatility and uncertainty across the 19 markets are very large, and can be obtained with portfolios that do not expose investors to particular additional risks like skewness. The results confirm that the cost of hedging realized volatility (large movements in the underlyings) in the last 30 years has been extremely high, whereas hedging uncertainty has actually yielded a large and positive risk premium.

5 Robustness

This section examines some potential concerns about the robustness of the results.

5.1 One-week holding period returns

Our main analysis is based two-week holding period returns for straddles, which strike a balance between having more precise estimates of risk premia and reducing the impact of measurement error in prices. We have repeated all of our analysis using one-week holding period returns, and find very similar results. Appendix figure A.3 is the analog of figure 4, but constructed using one-week returns. The results are qualitatively and quantitatively very similar, confirming the robustness of our analysis to the period considered.

5.2 Linear factor models

The evidence presented on the pricing of implied and realized volatility risk relies on the Black–Scholes model to give an approximation for the risk exposures of the portfolios. Appendix A.2 provides evidence that those predictions are an accurate description of the data, but our findings are not actually dependent on Black–Scholes holding with perfect accuracy. To estimate the price of risk for realized and implied volatility purely empirically, with no appeal to exposures from a

theoretical model, we now estimate standard factor specifications which estimate risk exposures freely from the data.

Typical factor models use a small number of aggregate factors. Here, though, we are interested in the price of risk for shocks to all 19 types of uncertainty. We therefore estimate market-specific factor models. This is similar to the common practice of pricing equities with equity-specific factors, bonds with bond factors, currencies with currency factors, etc.¹⁰

5.2.1 Specification

For each market we estimate a time-series model of the form

$$r_{i,n,t} = a_{i,n} + \beta_{i,n}^f \frac{f_{i,t}}{IV_{i,t-1}} + \beta_{i,n}^{f^2} \frac{1}{2} \left(\frac{f_{i,t}}{IV_{i,t-1}} \right)^2 + \beta_{i,n}^{\Delta IV} \frac{\Delta IV_{i,t}}{IV_{i,t-1}} + \varepsilon_{i,n,t}, \quad (14)$$

where $f_{i,t}$ is the futures return for underlying i and $\Delta IV_{i,t}$ is the change in the five-month at-the-money implied volatility for underlying i . The underlying futures return controls for any exposure of the straddles to the underlying, though the Black–Scholes model predicts that effect to be small.

Much more important is the fact that straddles have a nonlinear exposure to the futures return. $(f_{i,t}/IV_{i,t-1})^2$ captures that nonlinearity. Consistent with the construction and interpretation of the rv portfolio, $\beta_{i,n}^{f^2}$ will be interpreted as the exposure of the straddles to realized volatility, since realized volatility is calculated based on squared returns of the underlying.¹¹ Finally, the third factor is the change in the at-the-money implied volatility for the specific market at the five-month maturity.¹²

We estimate a standard linear specification for the risk premia,

$$\begin{aligned} E[r_{i,n,t}] &= \gamma_i^f \beta_{i,n}^f Std \left(\frac{f_{i,t}}{IV_{i,t-1}} \right) + \gamma_i^{f^2} \beta_{i,n}^{f^2} Std \left(\left(\frac{f_{i,t}}{IV_{i,t-1}} \right)^2 \right) + \gamma_i^{\Delta IV} \beta_{i,n}^{\Delta IV} Std \left(\frac{\Delta IV_{i,t}}{IV_{i,t-1}} \right) + \alpha_{i,n}^{(15)} \\ E[f_{i,t}/IV_{i,t-1}] &= \gamma_i^f Std(f_{i,t}/IV_{i,t-1}). \end{aligned} \quad (16)$$

where $\alpha_{i,n}$ is a fitting error. The γ coefficients represent the risk premia that are earned by investments that provide direct exposure to the factors. That is, the γ 's are estimates of what the Sharpe ratios on the factors would be if it were possible to invest in them directly (neither $f_{i,t}^2$ nor $\Delta IV_{i,t}$ is an asset return that one can directly purchase in our data; $f_{i,t}$ itself is tradable, though, which is why we impose the second equality). The difference between the method here and the rv

¹⁰The analysis is similar to those of Jones (2006) and Constantinides, Jackwerth, and Savov (2013).

¹¹There are obviously numerous closely related specifications of that second term that could be substituted. We obtain similar results when the second factor is the absolute value of the futures return instead of its square, for example, or when it is measured as the sum of squared daily returns over the return period (recall that the straddle returns cover two weeks, so the factor in that case is the two-week daily realized volatility). We focus on the squared return because it can be interpreted as a second-order term in the pricing kernel and also because it allows a direct link to the gamma of the straddles.

¹²Since the IVs may be measured with error, we construct this factor by regressing available implied volatilities on maturity for each underlying and date and then taking the fitted value from that regression at the five-month maturity.

and *iv* portfolios discussed above is that the factor model does not require assumptions about the risk exposures of the straddles – instead estimating them from 14 – whereas the *rv* and *iv* portfolios rely on the Black–Scholes model. So the results using the factor models should be more robust, but also have more estimation error.

5.2.2 Results

The dashed series in figure 4 plots the estimated risk premia across the various markets along with 95-percent confidence bands. The top panel plots $\gamma_i^{\Delta IV}$, while the bottom panel plots $\gamma_i^{f^2}$. Simple inspection shows that the results are nearly identical to those for the *iv* and *rv* portfolios. The $\gamma_i^{\Delta IV}$ estimates are almost all positive, while the $\gamma_i^{f^2}$ are almost all negative. As before, we produce a random effects estimator of the mean of the risk premia in various groups. The random effects estimates of the means in the various groups are also similar, both in magnitude and statistical significance, to the main results in the solid series. The main difference between the two series is that the confidence bands are wider for the factor model estimates, which is consistent with the fact that the factor model estimates impose less structure and must estimate the factor loadings of the individual straddles.

5.3 Liquidity

If the options used here are highly illiquid, the analysis will be substantially complicated for three reasons. First, to the extent that illiquidity represents a real cost faced by investors – e.g. a bid/ask spread – then returns calculated from settlement prices do not represent returns earned by investors. Second, illiquidity itself could carry a risk premium that the options might be exposed to. Third, bid/ask spreads represent an added layer of noise in prices. The identification of the premia for realized volatility and uncertainty depends on differences in returns on options across maturities, so what is most important for our purposes is how liquidity varies across maturities. This section shows that the liquidity of the straddles studied here is generally highly similar to that of the widely studied S&P 500 contracts traded on the CBOE, and the liquidity does not appear to substantially deteriorate across maturities.

We measure liquidity using two methods. First, since our data set does not include posted bid/ask spreads, we estimate the standard Roll (1984) effective spread using the daily returns, which is a monotone transformation of negative autocorrelation in returns.¹³ The top panel of appendix figure A.4 plots the effective bid/ask spreads for straddles at maturities of 1, 3, and 5 months for the 19 contracts that we study. The average posted bid/ask spreads for CBOE S&P 500 straddles, for which we have data since 1996, are also reported in the figure. At the one-month maturity, the effective spreads are approximately 6 percent on average, which is similar to the

¹³The Roll model assumes that there is an unobservable mid-quote that follows a random walk in logs and that observed prices have equal probability of being from a buy or sell order. Bid-ask bounce then induces negative autocorrelation in returns, from which the spread can be inferred (when the autocorrelation is positive, we set the spread to zero).

6.6-percent average posted spreads for one-month CBOE S&P 500 straddles since 1996. More importantly, the spreads actually decline at longer maturities indicating that there is less observed negative autocovariance in returns for options at those maturities. For the three- and five-month options, the spreads are smaller by about half, averaging 2 to 3 percent. This is again consistent with posted spreads for CBOE S&P 500 contracts, which decline to 4.0 percent on average for 6-month options.

As a second measure of liquidity, we obtained posted bid/ask spreads for the options closest to the money on Friday, 8/4/2017 for our 19 contracts plus the CBOE S&P 500 options at maturities of 1, 4, and 7 months. Those spreads are plotted in the bottom panel of figure A.4. For the majority of the options, the spreads are less than 3 percent, consistent with the 4.1-percent bid/ask spread for one-month S&P 500 options at the CBOE. More importantly, though, across nearly all the contracts, the posted spreads again decline with maturity, consistent with the effective spreads. That said, for some of the contracts, there were no available bids or asks at the 4- and 7-month maturities on 8/4/2017. Note also, again similar to the effective spreads, for 10 of the 19 contracts, the one-month posted spreads are nearly indistinguishable from that for the S&P 500, which is typically viewed as a highly liquid market and where incorporating bid-ask spreads generally has minimal effects on return calculations (Bondarenko (2014)). For crude oil, which is studied in detail in the next section, the spreads at all three maturities are essentially identical to those for the S&P 500.

Figure A.4 yields two important results. First, it shows that the liquidity of the straddles is reasonably high, in the sense that effective and posted spreads are both relatively narrow in absolute terms for most of the contracts and that they compare favorably with spreads for the more widely studied S&P 500 options traded at the CBOE. Second, liquidity does not appear to deteriorate as the maturity of the options grows, and in fact in many cases there are improvements with increasing maturities, again consistent with CBOE data.

Finally, figure A.5 reports the average daily volume of all of the option contracts across maturities 1 to 6 months. For crude oil, which is the focus of the more in-depth study in the next section, the figure reports average daily volume in dollars; for all other contracts, it reports the average daily volume relative to crude oil. Empirically, crude oil options have volume numbers of the same order of magnitude as the S&P 500, while there is more heterogeneity across the other markets. Looking across maturities, the general pattern is that dollar volume declines by about a factor of three in almost all the markets between the 1- and 6-month maturities – so the 6-month maturity has less volume, but far from zero.

6 Case study: crude oil

It is worthwhile to briefly delve more deeply into one market to build confidence in the robustness of the paper’s results. We choose the crude oil market for this exercise because it has one of the longest time series available with the most maturities of any of the markets that we study, it is

highly liquid (e.g. Gibson and Schwartz (1990) and Trolle and Schwartz (2010)), and it has a strong link to the macroeconomy.

Figures 5 and 6 contain several plots that help illustrate the historical behavior of the crude oil market. Panel A of figure 5 plots the history of total volume for one- and five-month options (specifically, average daily dollar volume of all contracts with maturities between 15 and 45 or 135 and 165 days to maturity, respectively). The volume of contracts in both maturity bins has risen over time, peaking in 2008, with a subsequent decline. On average, there is about 3 times more volume in the one- than the five-month option, though the volume in the five-month option has been trending upward, reaching as high as 75 percent of the volume for the one-month option.

Panel B of figure 5 plots 5-year rolling sample Sharpe ratios for the *iv* and *rv* portfolios. The left-hand section plots results for crude oil, while, for reference, the right-hand panel plots results for the S&P 500. For crude oil, the *rv* portfolio had negative average returns in almost all five-year periods in our data, while the *iv* portfolio had positive returns in almost all five-year periods. The *rv* returns trend down over time, implying that the variance risk premium may have been growing. The *iv* returns are somewhat more consistent, though the returns were close to zero or even negative for short periods at the beginning and end of the sample.

The right-hand side of panel B gives further context to those results by plotting the *rv* and *iv* returns for the S&P 500 options. For the S&P, the *rv* portfolio has relatively more negative returns than for crude, while the *iv* portfolio has average returns that are generally centered on zero, rather than staying consistently positive as we observe for crude oil.

Panel C of figure 5 is similar to panel B, except instead of plotting returns on the *rv* and *iv* portfolios, it plots their constituents, the returns on the one- and five-month straddles. For crude oil, the five-month straddle has consistently *positive* returns, unlike the S&P 500, for which the five-month straddle tends to have negative returns. In both cases the one-month straddle has negative returns, though that effect is stronger for the S&P 500.

Overall, panels B and C have two uses. First, they show that the returns that we observe on the *iv* and *rv* portfolios are not driven by a small number of outliers; rather, they are consistent over time. Second, they provide further detail on the divergences between the behavior of straddle returns for the S&P 500 compared to crude oil.

Next, to help understand how crude oil volatility relates to macroeconomic uncertainty, the top panel of figure 6 plots one-month at-the-money implied volatility for crude oil along with the JLN financial and price uncertainty series. The correlation of oil price uncertainty with the two series is immediately apparent. The various spikes upward in crude oil volatility are all traceable to spikes in either price or financial uncertainty. This figure thus underscores the utility to an investor of buying five-month crude oil straddles: they provide good protection against increases in the JLN uncertainty indexes and at the same time earn positive average returns.

Because the crude oil market is so large, it has relatively more traded maturities than the other underlyings. At any given time, the CME currently has trading in the next 12 monthly expirations and also December expirations for a number of years into the future. Panel B of figure of figure

6 plots average returns for crude oil straddles with maturities between 1 and 11 months (not 12 because of how we interpolate to construct the monthly portfolios); panel C reports Sharpe ratios. The figure shows that the behavior at longer maturities remains similar, and returns continue to rise slightly beyond the five months examined in the main analysis, though they eventually flatten. When we calculate the *iv* portfolio using the 11- instead of the five-month maturity, we also obtain similar results.

Because crude oil prices are such a widely followed indicator, there are also exchange traded funds (ETFs) that track oil prices, and those ETFs have options traded on them. Appendix A.6 examines the returns on those options and shows that the results are consistent with those we obtain for the CME options, though with more noise because the ETF options were introduced in the 2000's.

7 Conclusion

This paper studies the pricing of uncertainty and realized volatility across a broad array of options on financial and commodity futures. Uncertainty is proxied by implied volatility – which theoretically measures investors' conditional variances for future returns – and a number of uncertainty indexes developed in the literature. Realized volatility, on the other hand, measures how large *realized* shocks have been. In modeling terms, if $\varepsilon \sim N(0, \sigma^2)$, uncertainty is σ^2 , while volatility is the realization of ε^2 .

A large literature in macroeconomics and finance has focused on the effects of uncertainty on the economy. In this paper we explore empirically how investors perceive uncertainty shocks. If uncertainty shocks have major contractionary effects so that they are associated with high marginal utility for the average investor, then assets that hedge uncertainty should earn negative average returns. Empirically, we find that such assets – constructed as portfolios of options – historically have earned *positive* returns. The contribution of this paper is to construct hedging portfolios for a range of types of macro uncertainty, including interest rates, energy prices, and uncertainty indexes. We show that using a wide range of options is important for capturing uncertainty about the real economy and inflation. The empirical results imply that uncertainty shocks, no matter what type of uncertainty we look at, are not viewed as being negative by investors, or at least not sufficiently negative that it is costly to hedge them.

What is highly costly to hedge is instead realized volatility. Portfolios that hedge extreme returns in futures markets and large innovations in macroeconomic time series earn strongly negative returns, with premia that are in many cases 1–2 times as large as the premium on the aggregate stock market over the same period. So what is high in bad times is not uncertainty, but realized volatility. Periods in which futures markets and the macroeconomy are highly volatile and display large movements appear to be periods of high marginal utility, in the sense that their associated state prices are high. This is consistent with the findings in Berger, Dew-Becker, and Giglio (2018), who provide VAR evidence that shocks to volatility predict declines in real activity in the future,

while shocks to uncertainty do not.

Berger, Dew-Becker, and Giglio (2018) show that the VAR evidence and pricing results for realized volatility are consistent with the view that it is downward jumps in the economy that investors are most averse to. They show that a simple model in which fundamental shocks are both stochastically volatile and negatively skewed can quantitatively match the pricing of uncertainty and realized volatility, along with the VAR evidence. Similarly, Seo and Wachter (2018a,b) show that negative skewness can explain the pricing of credit default swaps and put options. This paper thus also contributes to the growing literature studying the effects of skewness. In a world where fundamental shocks are negatively skewed, the most extreme shocks – those that generate realized volatility – tend to be negative, which can explain why realized volatility would be so costly to hedge.

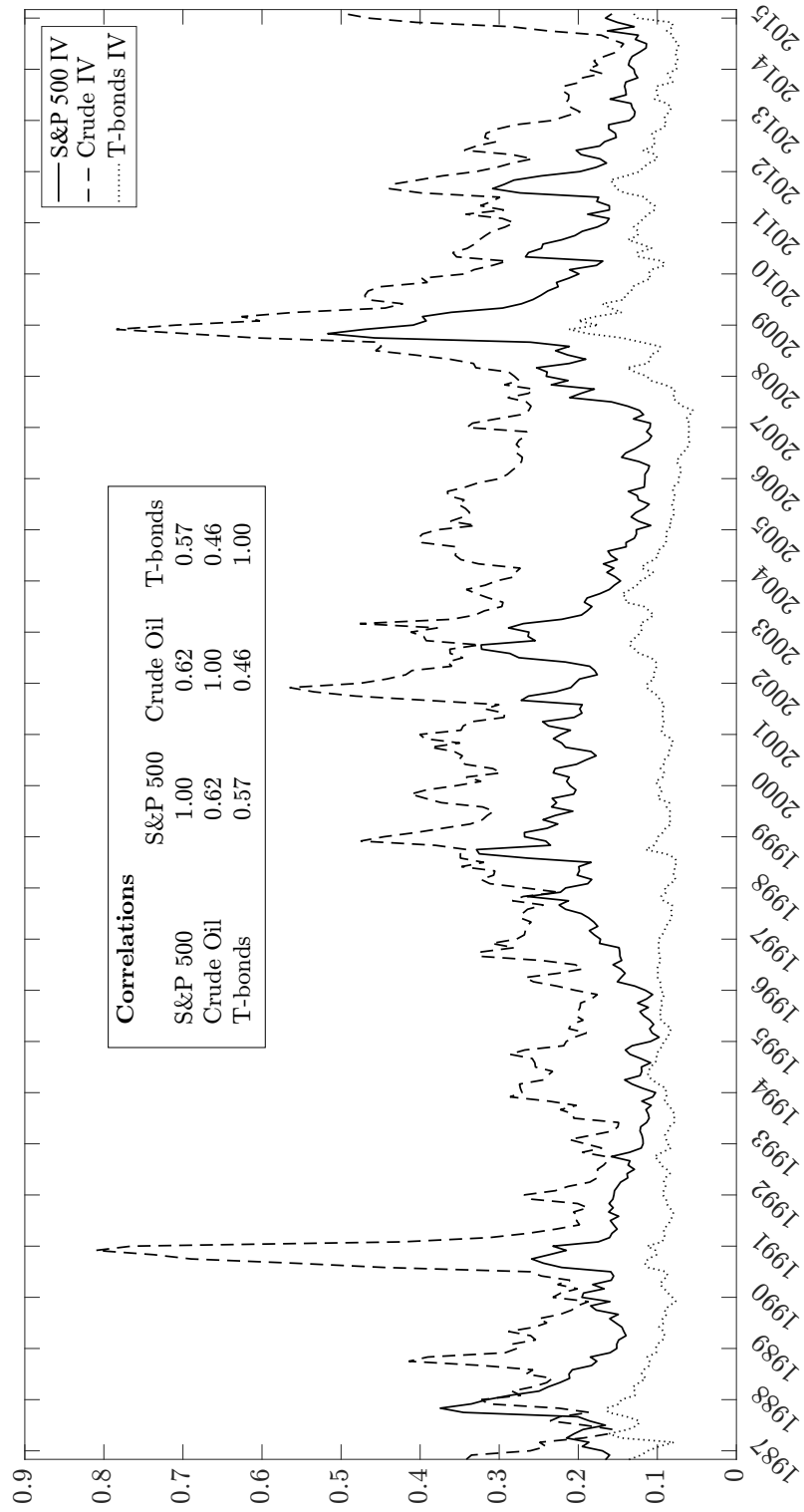
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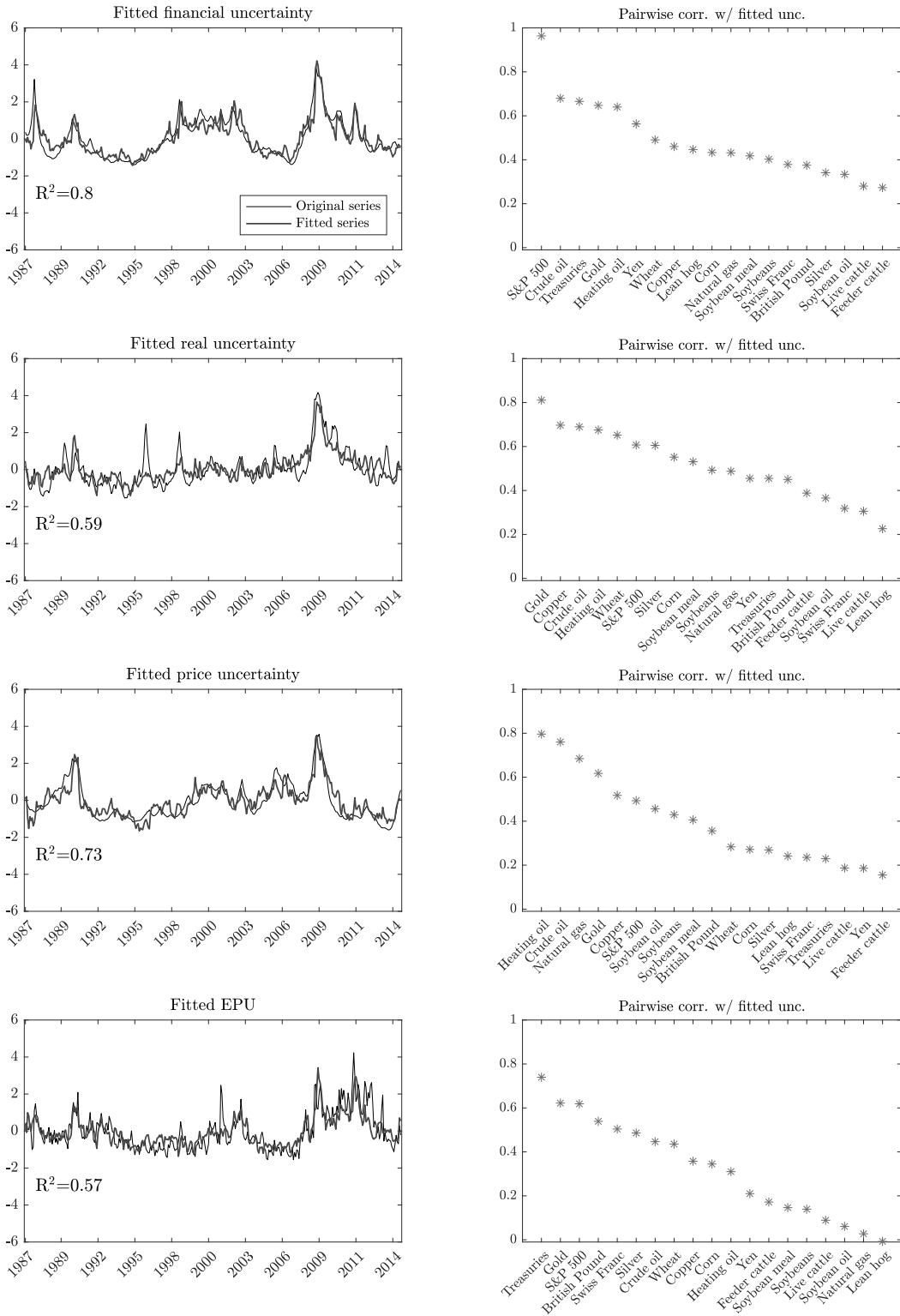
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Figure 1: Sample implied volatilities



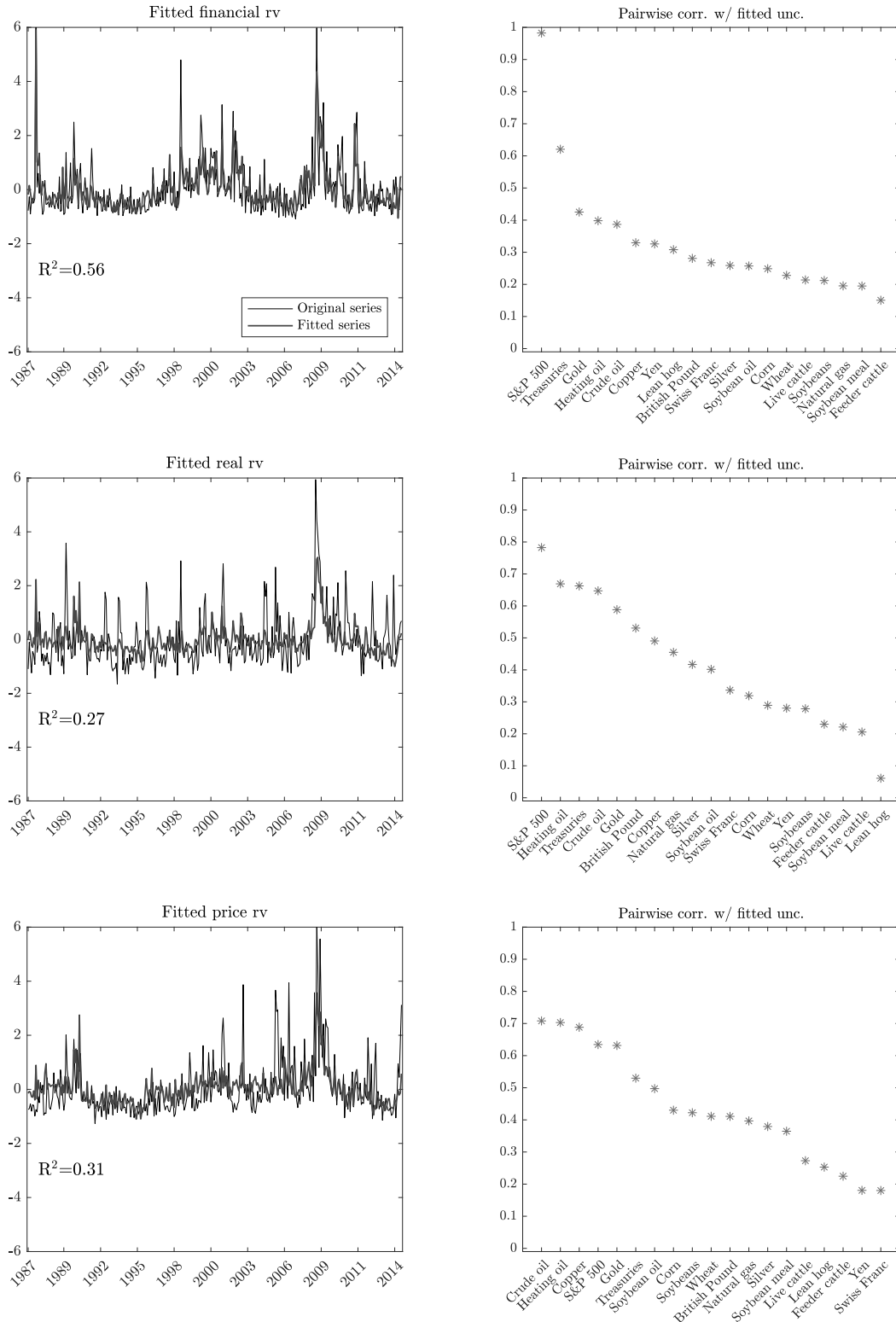
Note: Monthly implied volatilities calculated from three-month options using the Black-Scholes model.

Figure 2: Fit to uncertainty indexes



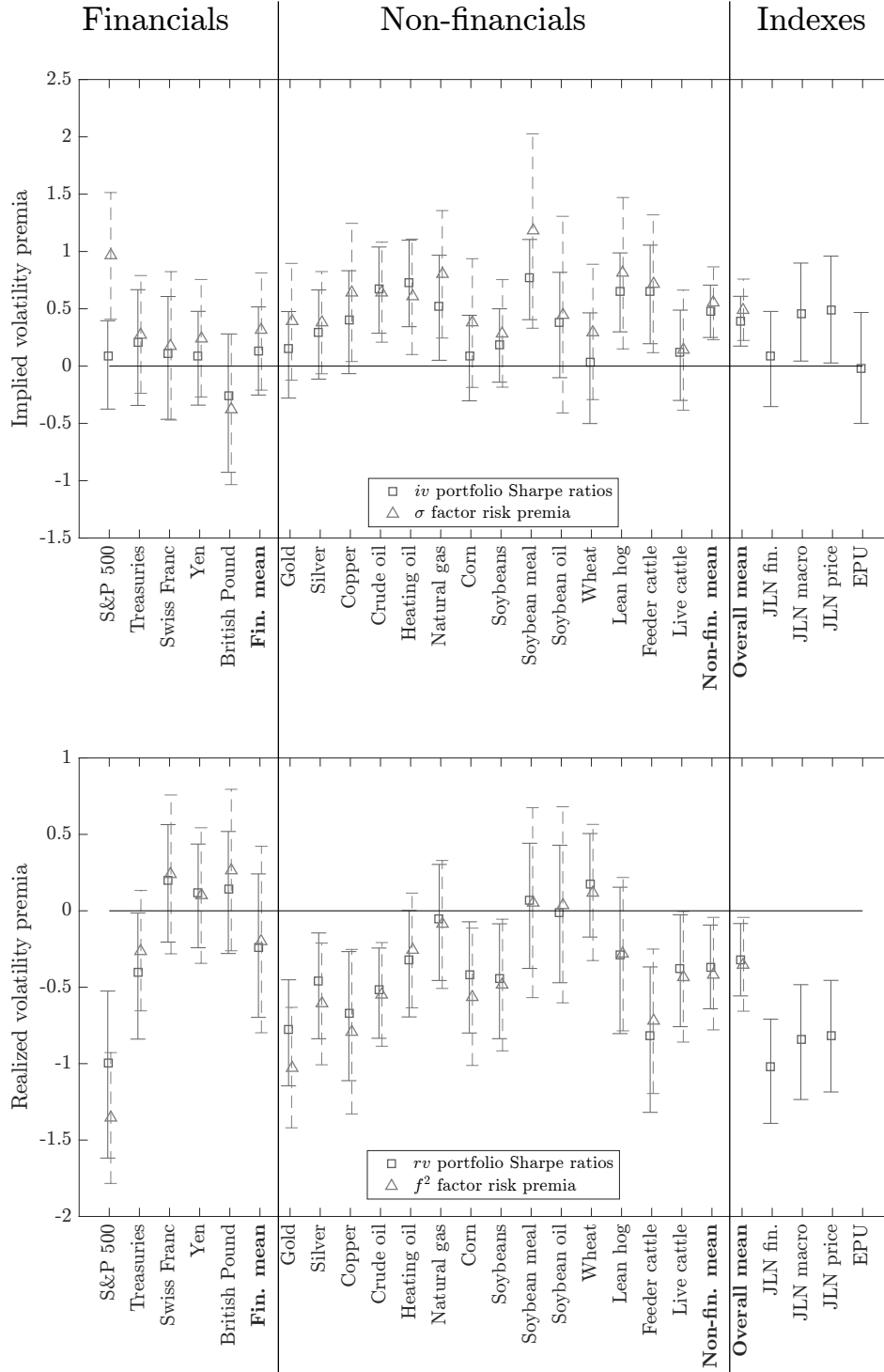
Note: The left-hand panels plot the fitted values from the regressions of the EPU and JLN indexes on three-month implied volatility in the 19 markets. The right-hand panels plot pairwise correlations between the individual implied volatility series and the fitted values from the regressions.

Figure 3: Fit to realized volatility indexes



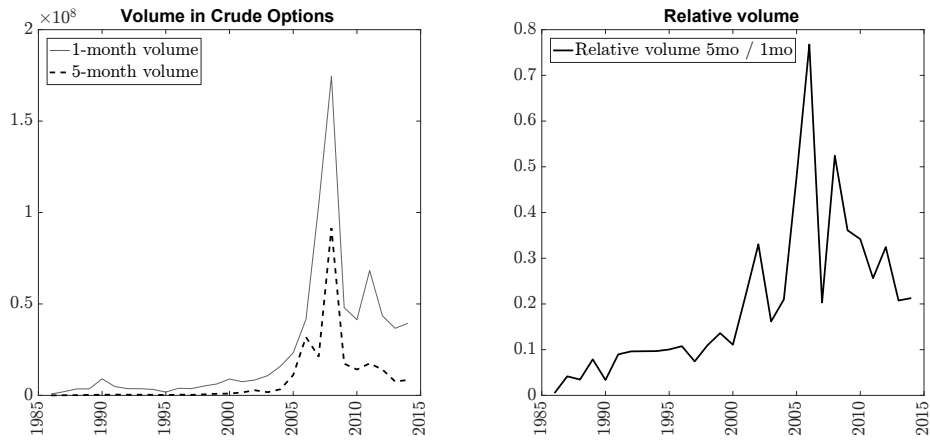
Note: See figure 2. This figure uses the JLN realized volatility series instead of uncertainty.

Figure 4: RV and IV portfolio Sharpe ratios and factor risk premia

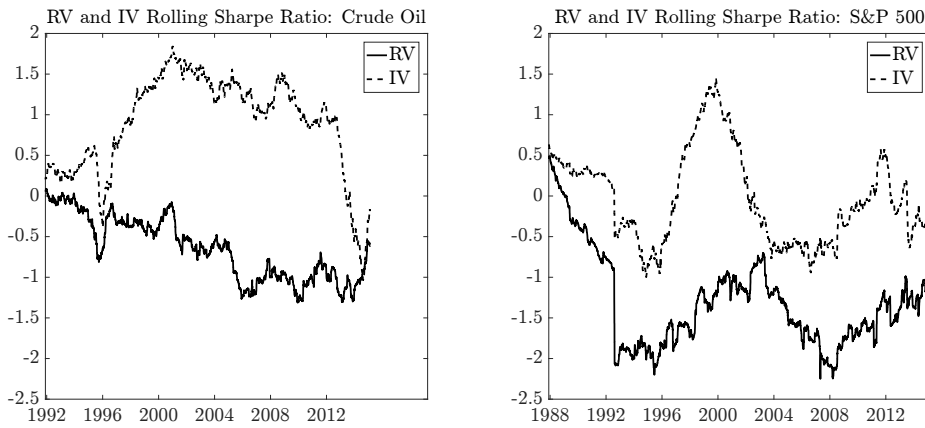


Note: Squares are point estimates and vertical lines represent 95-percent confidence intervals. The solid series plots the Sharpe ratios for the *rv* and *iv* portfolios. The dotted series plots the estimated risk premia from the factor model. The confidence bands for the *rv* and *iv* Sharpe ratios are calculated through a 50-day block bootstrap, while those for the factor model use GMM standard errors with the Hansen–Hodrick (1980) method used to calculate the long-run variance. The “Fin. mean”, “Non-fin. mean”, and “Overall mean” points represent random effects estimates of group-level and overall means. The “JLN” and “EPU” points are for the portfolios that hedge those indexes.

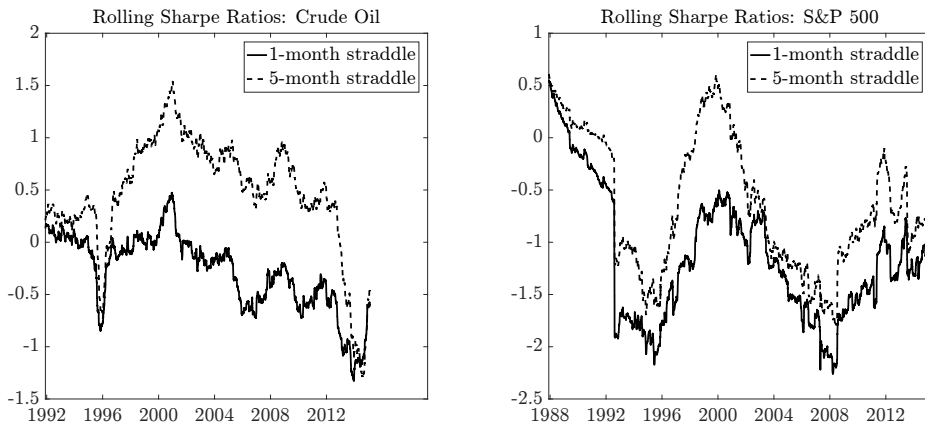
Figure 5: Case study: crude oil (I)



(a) Volume



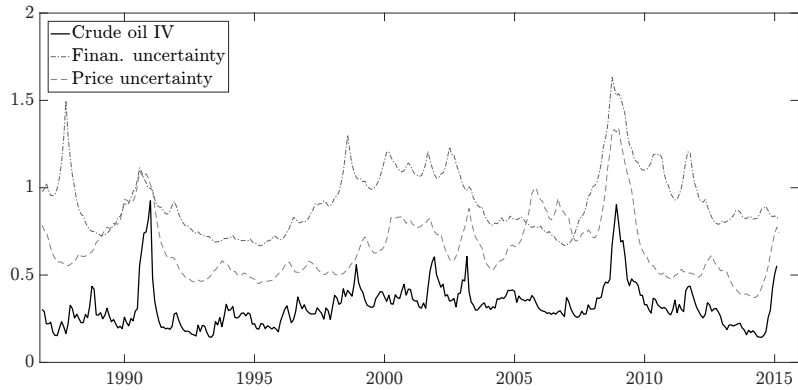
(b) Five-year rolling Sharpe ratios, RV and IV



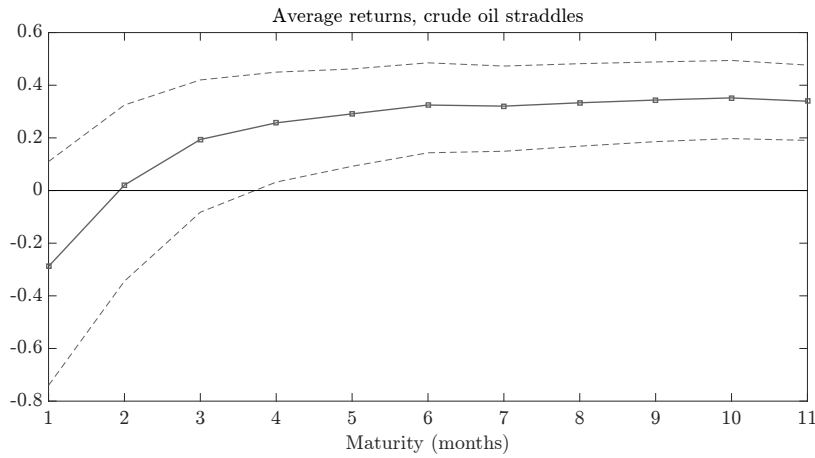
(c) Five-year rolling Sharpe ratios, 1mo and 5mo straddles

Note: The top row reports dollar volume for crude oil options. The middle row reports rolling sharpe ratios for the rv and iv portfolios for crude oil on the left and the S&P 500 on the right. The bottom panel reports rolling Sharpe ratios for the 1-month and 5-month straddles.

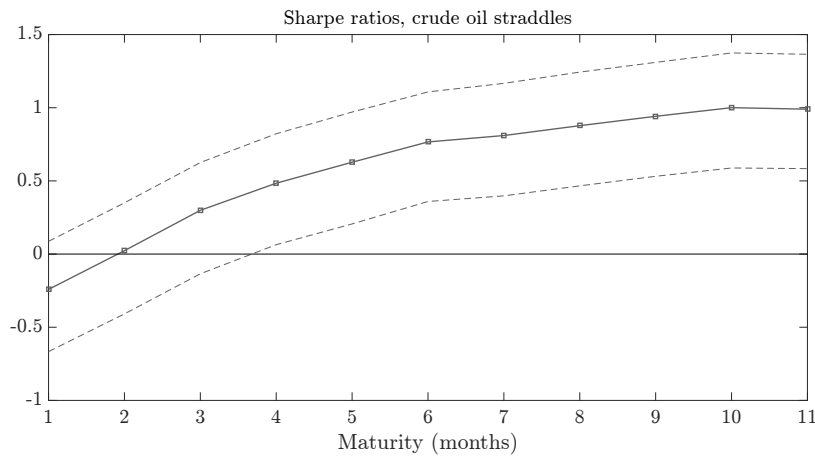
Figure 6: Case study: crude oil (II)



(a) Crude IV and Macro Uncertainty



(b) Straddle average returns



(c) Straddle Sharpe ratios

Note: The top panel reports the Jurado, Ludvigson, and Ng (2015) financial uncertainty series and the macroeconomic price uncertainty series together with the implied volatility for crude oil. The middle and bottom panels plot average returns and Sharpe ratios for straddles along with block-bootstrapped 95-percent confidence intervals.

Table 1: Pairwise correlations of implied volatility across markets

IV	Treasuries	S&P 500	Swiss Franc	Yen	British Pound	Gold	Silver	Copper	Crude oil	Heating oil	Natural gas	Corn	Soybeans	Soybean meal	Soybean oil	Wheat	Lean hog	Feeder cattle	
S&P 500	0.55																		
Swiss Franc	0.55	0.31																	
Yen	0.39	0.56	0.49																
British Pound	0.45	0.42	0.76	0.45															
Gold	0.51	0.57	0.24	0.27	0.37														
Silver	0.41	0.35	0.22	0.29	0.34	0.78													
Copper	0.38	0.50	0.12	0.35	0.33	0.79	0.82												
Crude oil	0.42	0.64	0.28	0.39	0.29	0.55	0.33	0.51											
Heating oil	0.41	0.65	0.23	0.36	0.23	0.54	0.30	0.51	0.96										
Natural gas	0.11	0.44	-0.03	0.03	0.04	0.33	0.07	0.47	0.49	0.62									
Corn	0.25	0.37	-0.09	0.14	0.12	0.51	0.57	0.61	0.23	0.20	0.13								
Soybeans	0.21	0.35	-0.03	0.16	0.17	0.47	0.48	0.62	0.30	0.29	0.22	0.85							
Soybean meal	0.29	0.35	-0.05	0.17	0.07	0.55	0.52	0.64	0.32	0.30	0.24	0.82	0.93						
Soybean oil	0.32	0.31	0.12	0.12	0.24	0.50	0.50	0.62	0.28	0.30	0.24	0.73	0.89	0.83					
Wheat	0.38	0.42	0.04	0.20	0.12	0.62	0.63	0.64	0.35	0.32	0.18	0.84	0.77	0.75	0.64				
Lean hog	0.28	0.41	-0.03	0.28	-0.09	0.27	0.16	0.37	0.41	0.46	0.41	0.29	0.37	0.40	0.39	0.36			
Feeder cattle	0.45	0.36	0.14	0.17	0.09	0.40	0.51	0.55	0.33	0.34	0.13	0.49	0.47	0.50	0.48	0.53	0.42		
Live cattle	0.50	0.28	0.25	0.18	0.08	0.37	0.40	0.46	0.33	0.38	0.27	0.31	0.33	0.43	0.49	0.43	0.47	0.84	

Note: Pairwise correlations of three-month option-implied volatility across markets. The darkness of the shading represents the degree of correlation.

Table 2: Regressions of IV onto macroeconomic uncertainty measures

	$\frac{IV_{i,t}}{SD(IV_{i,t})} = a_{1,i} + b_{1,i}LMNU_t^{\text{Financial}} + b_{2,i}LMNU_t^{\text{Macro}} + \varepsilon_{1,i,t}$		$\frac{IV_{i,t}}{SD(IV_{i,t})} = a_{2,i} + b_{3,i}LMNU_t^{\text{Financial}} + b_{4,i}LMNU_t^{\text{Real}} + b_{5,i}LMNU_t^{\text{Prices}} + \varepsilon_{2,i,t}$		$\frac{IV_{i,t}}{SD(IV_{i,t})} = a_{3,i} + b_{6,i}EPU_t + \varepsilon_{3,i,t}$	
IV	Financial Unc.	Macro Unc.	Macro Unc. (Real)	Macro Unc. (Prices)	EPU	R2
S&P 500	0.83	0.04	0.00	0.04	0.44	0.18
T-bonds	0.39	0.16	-0.06	0.11	0.54	0.31
GBP	-0.04	0.51	0.23	0.15	0.39	0.16
CHF	0.08	0.27	-0.07	0.16	0.45	0.20
JPY	0.41	0.11	0.09	-0.05	0.17	0.03
Copper	-0.15	0.67	0.41	0.35	0.25	0.04
Corn	0.26	0.20	0.37	-0.10	0.20	0.04
Crude oil	0.31	0.43	0.08	0.45	0.33	0.11
Feeder cattle	0.06	0.28	0.27	-0.06	0.13	0.02
Gold	0.26	0.46	0.34	0.23	0.47	0.22
Heating oil	0.34	0.40	0.01	0.47	0.27	0.07
Lean hog	0.43	-0.06	-0.13	0.08	0.00	0.00
Live cattle	0.06	0.25	-0.01	0.22	0.13	0.02
Natural gas	0.20	0.25	-0.15	0.61	-0.01	0.00
Silver	0.07	0.36	0.45	-0.04	0.35	0.13
Soybeans	0.14	0.34	0.28	0.06	0.05	0.00
Soybean meal	0.15	0.32	0.24	0.15	0.11	0.01
Soybean oil	0.03	0.40	0.03	0.31	0.04	0.00
Wheat	0.22	0.30	0.42	-0.10	0.32	0.10
Average of the IVs	0.37	0.44	0.20	0.23	0.38	0.14

Note: Regression equations are reported above the three sections. The left panel reports, in each row, the coefficients from regressions of each implied volatility onto the financial and macroeconomic uncertainty measures developed in Jurado, Ludvigson, and Ng (2015). The last row regresses the average of all 19 IVs on the JLN uncertainty measures. All variables are normalized to have unit standard deviations prior to the regressions. The middle panel repeats the exercise dividing the macro uncertainty measure in one constructed only real quantities and one constructed using prices. The right-hand panel uses just the EPU index. Cells with coefficients that are significant at the 5-percent level are shaded.

Table 3: Correlations between RV and IV in each market

	Std(RV)	Std(IV)	Corr(RV,IV)
S&P 500	0.09	0.06	0.64
T-bonds	0.04	0.03	0.73
GBP	0.04	0.03	0.77
CHF	0.05	0.02	0.43
JPY	0.04	0.03	0.64
Copper	0.11	0.10	0.68
Corn	0.10	0.08	0.75
Crude oil	0.16	0.11	0.60
Feeder cattle	0.04	0.03	0.66
Gold	0.07	0.06	0.70
Heating oil	0.15	0.10	0.54
Lean hog	0.07	0.05	0.74
Live cattle	0.05	0.04	0.76
Natural gas	0.19	0.12	0.48
Silver	0.14	0.09	0.68
Soybeans	0.09	0.07	0.73
Soybean meal	0.09	0.07	0.68
Soybean oil	0.08	0.06	0.71
Wheat	0.11	0.08	0.73

Note: The table reports, for each underlying, the standard deviation of the monthly RV and 3-month IV series, and their correlation.

Table 4: Pairwise correlations of realized volatility across markets

RV	Treasuries	S&P 500	Swiss Franc	Yen	British Pound	Gold	Silver	Copper	Crude oil	Heating oil	Natural gas	Corn	Soybeans	Soybean meal	Soybean oil	Wheat	Lean hog	Feeder cattle	
S&P 500	0.63																		
Swiss Franc	0.17	0.12																	
Yen	0.31	0.32	0.15																
British Pound	0.43	0.36	0.24	0.31															
Gold	0.44	0.47	0.15	0.24	0.31														
Silver	0.42	0.43	0.15	0.22	0.27	0.65													
Copper	0.51	0.51	0.11	0.24	0.43	0.50	0.52												
Crude oil	0.24	0.24	0.13	0.20	0.20	0.32	0.14	0.24											
Heating oil	0.20	0.22	0.04	0.14	0.15	0.30	0.11	0.15	0.91										
Natural gas	0.03	0.08	0.04	-0.04	0.00	0.05	-0.06	0.00	0.08	0.18									
Corn	0.33	0.35	0.04	0.09	0.27	0.37	0.40	0.49	0.12	0.03	-0.04								
Soybeans	0.33	0.30	0.03	0.16	0.30	0.33	0.35	0.40	0.11	0.05	-0.07	0.74							
Soybean meal	0.33	0.25	0.03	0.19	0.19	0.31	0.32	0.30	0.08	0.02	-0.06	0.68	0.94						
Soybean oil	0.48	0.43	0.11	0.21	0.41	0.40	0.41	0.51	0.17	0.12	-0.04	0.67	0.88	0.72					
Wheat	0.30	0.24	0.02	0.08	0.11	0.31	0.34	0.33	0.11	0.04	-0.08	0.63	0.51	0.47	0.47				
Lean hog	0.12	0.12	0.08	0.20	-0.03	0.00	0.00	0.05	0.10	0.09	0.11	0.06	0.11	0.12	0.11	0.12			
Feeder cattle	0.22	0.20	0.03	0.04	0.06	0.10	0.16	0.30	0.10	0.07	0.12	0.35	0.32	0.32	0.27	0.22	0.26		
Live cattle	0.41	0.24	0.13	0.11	0.11	0.17	0.24	0.28	0.07	0.07	0.09	0.22	0.22	0.27	0.30	0.23	0.28	0.63	

Note: Pairwise correlations of monthly realized volatility across markets. The darkness of the shading represents the degree of correlation.

Table 5: Portfolios of rv and iv across markets

Panel A: Sharpe ratios				rv+iv				
	rv		iv		Equal weight		Risk-parity	
All underlyings	-0.90	***	0.76	***	1.34	***	1.26	***
Nonfinancials	-0.82	***	0.75	***	1.16	***	1.12	***
Financials	-0.51	***	0.12		0.63	***	0.36	*

Panel B: Skewness				rv+iv				
	rv		iv		Equal weight		Risk-parity	
All underlyings	1.12	***	1.73	***	-0.69	***	0.94	***
Nonfinancials	1.26	***	1.49	***	-0.92	***	0.72	***
Financials	1.83	***	3.33	***	-0.77		3.27	***

Note: Sharpe ratios and skewness of portfolios combining rv and iv portfolios across markets. For each panel, the first row reports a portfolio constructed using straddles from all available markets on each date, the second row using only nonfinancial underlyings, the third row only financial underlyings. Each column corresponds to a different portfolio. The first column is an equal-weighted RV portfolio, the second is an equal-weighted IV portfolio, the third is an equal-weighted long-short IV minus RV portfolio, and the last is the same long/short portfolio but weighted by the inverse of the variance (risk-parity). *** indicates significance at the 1-percent level, ** the 5-percent level, and * the 10-percent level.