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Co-movements Between Stock and Oil Markets

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ABSTRACT

Our study is an analysis of the characteristics of stock-oil hedges. We have used a comprehensive sample of international stock market indices both from developed as well as emerging countries and Brent oil as the key energy asset. Our results indicate that the hedge ratios of major stock market indices are time-varying and have significantly increased after the GFC. Apart from studying hedge ratios and effectiveness, this study has contributed to the literature by identifying those factors that actually drive hedge portfolio returns. Despite the hedge ratios differing among the various indices, we have identified two common drivers of hedge portfolio returns: the most important driver is the changes in the VIX, significant in all markets; the second major driver is changes in the USD/EUR spot rate. Hedge portfolio returns are related negatively to both of these variables. In addition, we find that since the GFC hedge effectiveness has increased and hedge portfolio returns are additionally influenced by gold returns and changes in the term structure. Our findings are important for portfolio managers, especially during periods of market stress, since they can use this information to further improve their hedging performance.

KEYWORDS

Beta-hedge; Brent oil; Commodities; Economic policy uncertainty (EPU); Hedge ratio; International asset pricing; Market risk; Systemic risk; WTI oil.

1. Introduction

Understanding the co-movements between stock and oil markets is important for at least two main reasons.1 First, portfolio managers can use the co-movement information to reduce the risk of unfavorable price fluctuations. For example, there is now an extensive empirical literature, which shows these risks can beoffset, i.e. "hedged", in the stock market by holding commodities, which include energy assets.[See for example: Chkili et al., 2014; Lin et al., 2014; Basher and Sadorsky, 2016; Batten et al., 2017. 3

COP21 and COP23 refer to the agreement from the 2015 United Nations Climate Change Conference in Paris for emissions targets for 2021 and 2023, respectively. The key result was an agreement to set a goal of limiting global warming to <2 degrees Celsius (°C) compared to pre-industrial levels. The agreement calls for zero net anthropogenic greenhouse gas emissions to be reached during the second half of the 21st century. 4 See for example. Vandyck et al., 2016; Panagiotis et al., 2017.] The use of an energy hedge is motivated by its time-varying correlation, (due to the complex interaction effects of both demand and supply shocks), that offers both diversification as well as hedging properties. Second, recent developments in energy policy will impact future energy prices and thereby affect stock portfolio outcomes. For example, one key impact arising from the COP21 and COP233 agreements is the expected ongoing decline in the future demand for fossil fuels such as coal, oil and gas4 and, at the same time, an increasing demand for alternate energy sources. Consequently, portfolio investors will need to adjust the weighting and hedge the associated risks of those stocks affected by fossil fuel demand in their domestic and international portfolios.

In this paper, we address these issues by studying the feasibility of hedging stock indices with oil. For this purpose, we study stockoil hedging in a comprehensive set of international stock markets. Moreover, not only hedge effectiveness but also the drivers of hedge portfolio returns are analyzed, which provides a clearer understanding of the benefits of stock-oil hedging for investors. Importantly, while we show that there are economic benefits derived from hedging, an important feature of this paper is that we also identify those financial and macroeconomic factors that drive uncertainty in the hedging process. Since stock-energy hedging can be used to address the energy policy challenges caused by climate change, this study also relates to broader concerns of stock-oil market integration. Thus, this study extends earlier work in this area, including the earlier study by Batten et al. (2018) that considers the time-varying degree of integration between stock and oil markets and its implications for COP21 (and now COP23). In this paper the time-varying hedge ratios are more precisely derived using Engle's (2002) Dynamic Conditional Correlation (DCC), Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. Since constant correlations are not supported empirically (e.g. Lin et al., 2014), this improved approach allows better estimation and more accurate reporting of the hedge ratios and portfolio returns, thereby allowing better determination of hedge effectiveness.

The paper is organized as follows: Next a brief overview of the hedging literature with a focus on the use of stock-oil hedging is provided to highlight the context of the paper. Then, we discuss the theoretical motivation and empirical modelling of the hedge portfolio returns. The data used in the study are described in Section 4. Section 5 outlines the results from DCC-GARCH(1,1) estimation and analyzes the estimated hedge ratios and portfolio returns. In addition, drivers of hedge portfolio returns are analyzed. The final section allows for concluding remarks.

2. Literature

The hedging literature in finance consists of three main strands. The first considers the positive effects of hedging on firm value (e.g. Gilje and Taillard, 2017) or takes a broader macroeconomic perspective. The second addresses the modelling of hedge ratios and determines hedging effectiveness (e.g. Sadorsky, 2014). The third identifies key features of risk management products used by economic agents as part of a broader discussion on financial market design (e.g. Tsetsekos and Varangis, 2000; Carr et al., 2001). This last group of papers also includes a rich literature that shows how financial market participants can hedge macroeconomic news (e.g. Beber and Brandt, 2009).

Those papers in the first group that take a macroeconomic perspective, also consider the positive effects of hedging certain types of assets from the viewpoint of economic stability. For example, Narayan et al. (2010) investigate whether gold is an effective hedge against inflation, while the more recent study by Raza et al. (2018) determines if certain commodities can hedge risk in real estate. The recent stock-oil hedge literature takes this perspective and typically considers the relationships between broad classes of financial and non-financial assets. For example, Yang et al. (2009) and Ciner et al. (2013) examine the complex interaction between assets including stocks, bonds, gold, oil and exchange rates. While there are clear portfolio management benefits from articulating the best strategy to hedge one asset portfolio with another asset, there are also important lessons for policymakers with respect to maintaining macroeconomic stability. For example, it is important to ensure that there is enough liquidity in financial markets to facilitate trading and arbitrage.

The second group of papers typically takes more technical perspectives and address statistical concerns associated with the modelling of hedge ratios and hedging effectiveness. When determining how best to hedge a bought, or long, position in one asset with a sold, or short, position in another asset, the standard approach is to identify a hedge ratio by regressing historical price data from the physical market against the equivalent price data from the futures market. Early studies that estimate the hedge ratio as the regression beta, estimated from the asset and its hedge, includes Figlewski (1984) and Cecchetti et al. (1988). Due to liquidity and timing considerations, futures products seldom match actual positions held in the cash market. Thus, the estimation of optimal hedge strategies is usually undertaken using mismatched futures contracts, which introduces basis risk.

Myers (1991), among others, argues that the fundamental problem with this approach is the assumption that these optimal hedge ratios and therefore basis risk - is constant over time. New econometric procedures, discussed in the next section, are better able to tackle the estimation problems associated with time-variation in the hedge ratio. The preferred approach for modelling time-varying hedge ratios in the literature utilizes bivariate GARCH models. There is an extensive literature in this area that includes an extensive set of papers. For example, see Chang et al. (2011), Arouri et al. (2011), Arouri et al. (2012), Chkili et al. (2014), Lin et al. (2014), Basher and Sadorsky (2016), Maghyereh et al. (2017), Junttila et al. (2018), and Mensi et al. (2019).

3. Data and Preliminary Analysis

We collect monthly closing prices of ICE-Brent near month futures contracts and stock market indices from January 1990 to December 2017. There are two key measures of the oil price, the ICE-Brent and NYMEX West Texas Intermediate (WTI) contract. Note that henceforth, for convenience, these contracts are simply referred to as Brent and WTI oil. Both contracts have an underlying value of 1000 barrels and are deliverable at maturity or settled against cash. We use Brent oil instead of WTI oil for three reasons. First, WTI contains a local price spread due to the transport logistics associated with the movement of oil at the Cushing, Oklahoma oil storage and transport hub. Second, Table 1a reports that the volatility of WTI oil futures returns (9.30) is slightly higher than the volatility of Brent oil futures returns (9.28). Third, our results in Section 5 reveal that Brent oil is more appropriate for hedging as the hedge effectiveness is higher than the one of WTI oil. All data are measured in U.S. dollars. The stock portfolios comprise the following indices[Basically, investors have two opportunities to invest in these stock market indices. First, they can buy an exchange traded fund that replicates the index. Second, they can replicate the index on their own by buying the respective stocks of the index.]: MSCI Emerging Markets (EM); MSCI MXWO (Developed Markets); MSCI ACWI (Emerging and Developed Markets); MSCI Europe; MSCI G7 (Canada, France, Germany, Italy, Japan, United Kingdom, U.S.); MSCI Far East (Japan, Hong Kong, Singapore); MSCI North America (NA; Canada, U.S.); and the S&P 500 (U.S. only).

The MSCI EM captures large and mid-cap constituents from 24 emerging markets (Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Korea, Malaysia, Mexico, Pakistan, Peru, Philippines, Poland, Russia, Qatar, South Africa, Taiwan, Thailand, Turkey and the United Arab Emirates). The MSCI MXWO, sometimes called MSCI World, captures large and mid-cap stocks across 23 developed markets (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, United Kingdom and the U.S). The MSCI ACWI represents a combination of emerging and developed markets, which captures all large and mid-cap representations from the MSCI EM and MSCI MXWO.

The MSCI Europe index represents the performance of large and mid-cap equities across 15 developed countries in Europe (Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the U.K.). The index has a number of sub-indexes that cover various subregions, market segments/sizes and sectors, and covers approximately 85% of the free float-adjusted market capitalization in each country.

The MSCI Far East index captures large and mid-cap representation across three countries (Japan, Singapore, and Hong Kong) and has 392 constituents. The index covers approximately 85% of the free float adjusted market capitalization in each country.

Key descriptive statistics are reported in Table 1a. The statistics are for the full sample period from January 1990 to December 2017. We report statistics for monthly continuously compounded percentage returns: $R_{i,t} = (\ln P_{i,t} - \ln P_{i,t-1}) \cdot 100$, where $P_{i,t}$ ist the closing price of asset i. All asset returns (stock markets and oil) display negative skewness, which is a common finding especially for stock markets. This means that the right tail of all series is shorter than the left tail. In addition, we detect substantial kurtosis in all markets, with the highest and lowest values observed for the MSCI Emerging Markets (6.47) and MSCI Far East (4.19) indices, respectively. Oil returns show higher volatility than stock returns. Nevertheless, oil returns have a positive mean, which is smaller than the mean of the stock indices. However, this is not the case for the MSCI Far East as this index has a negative mean. Finally, as expected due to the presence of third and fourth moments, the Jarque-Bera test rejects the null hypothesis of normality at the 1% level for both oil and stock returns.

Table 1b reports Pearson pairwise correlations for all the variables to highlight the difficulty that many investors face when constructing diversified international stock portfolios. First, all unconditional pairwise stock portfolio correlations are positive and significant, with the highest correlations between developed country stock market portfolios (e.g. the correlation between the MSCI MXWO and the MSCI ACWI is 0.9978), and the lowest correlations between the MSCI Far East and the MSCI NA and S&P 500 indices (e.g. the correlation between the MSCI Far East and the S&P 500 is 0.5189). The correlation between oil and the stock indices is not significant at the 1% level for Brent oil and the MSCI NA and S&P 500.

Table 1a. Descriptive statistics of returns

	MSCI MXWO	MSCI ACWI	MSCI Europe	MSCI G7	MSCI Far East	MSCI NA	S&P 500	Brent Oil	WTI Oil
Mean	0.389993	0.387431	0.373763	0.383295	−0.017262	0.598390	0.602257	0.369065	0.302224
Median	1.037763	0.916619	0.836937	0.860256	0.271430	1.074099	1.043291	0.588023	0.731658
Std. dev.	4.294740	4.378431	4.999437	4.230733	5.619391	4.168421	4.129745	9.279001	9.298459
Skewness	−0.861708	−0.897674	−0.816177	−0.805854	−0.135577	−0.835864	−0.801277	−0.182283	−0.162851
Kurtosis	5.131678	5.403398	5.008401	4.889204	4.187888	5.065367	4.856276	5.433638	4.751331
Jarque-Bera	105.1990	125.9943	93.77552	86.33376	20.78444	98.84587	84.19516	84.77703	44.55758
p-Value	0.000000	0.000000	0.000000	0.000000	0.000031	0.000000	0.000000	0.000000	0.00000
Observations	336	336	336	336	336	336	336	336	336

4. Results

This section includes results from the empirical analysis that examines the hedge properties between eight stock market indices and Brent oil. First, we present the results of the DCC-GJR-GARCH(1,1). Second, we provide the optimal hedge ratio and examine the effectiveness of the hedges. Finally, we analyze the determinants of hedge portfolio return.

Table 2 reports estimated coefficients from a bivariate DCC-GJRGARCH(1,1) model and associated p-values between the eight different monthly stock market returns and Brent oil. Interestingly, the conditional univariate mean equation has a highly significant AR (1) term at the 1% level only for the MSCI EM, whereas returns of MSCI Fareast, MSCI NA and S&P 500 show mild autocorrelation at the 10% percent level. A possible explanation is that the MSCI EM reacts to new information in a delayed manner due to illiquidity (see e.g. Bao et al., 2011). The lower significance of developed indicesunderpins this hypothesis, as developed markets basically provide higher levels of market liquidity.

Our results for the conditional univariate variance equation show that the GARCH coefficients (ω3) are highly significant, which suggests there is pronounced autocorrelation in the conditional volatility, a finding consistent with high persistence of volatility. Oil shows the lowest persistence followed by the MSCI NA and the S&P 500. The highest persistence is documented for the MSCI Far East. The latter also shows the highest significance of the asymmetric volatility parameter (ω2).

Overall, from the p-values we conclude that there is mild evidence of asymmetric volatility, except for the MSCI EM (p-value = 0.3899). The estimates for the first DCC parameter a show high, or almost medium, significance. Since the parameter b is highly significant for all index-oil combinations, except MSCI Fareast (p-value = 0.1069), the conditional correlation is time-varying rather than constant. The weaker significance of MSCI Far East's DCC parameters indicates that the respective hedge ratio, on average, is expected to fluctuate not as much as the ones of the other indices. Overall, the Bayesian Information Criterion(BIC) indicates the best model fit for the MSCI NA and the S&P 500, while the lowest one is achieved for the MSCI EM.

We also check whether the GARCH approach is specified correctly. For this purpose, we analyze whether standardized, as well as squared standardized, residuals show serial correlation. The Box-Ljung test is applied for low (i.e. lag 5) and high (i.e. lag 10) orders of serial correlation. Our results clearly show that the null hypothesis of no serial correlation cannot be rejected in any case. Therefore, we conclude that our GARCH setting is calibrated correctly.

Table 1b Pearson correlations of variables.

	MSCI EM	MSCI MXWO	MSCI ACWI	MSCI Europe	MSCI G7	MSCI Far East	S&P 500	Brent Oil
MSCI EM	1.000000							
p-Value	–							
MSCI MXWO	0.769324	1.000000						
p-Value	0.0000	–						
MSCI ACWI	0.804429	0.997809	1.000000					
p-Value	0.0000	0.0000	–					
MSCI Europe	0.722559	0.921759	0.922014	1.000000				
p-Value	0.0000	0.0000	0.0000	–				
MSCI G7	0.745116	0.996772	0.992349	0.896877	1.000000			
p-Value	0.0000	0.0000	0.0000	0.0000	–			
MSCI Far East	0.588430	0.755847	0.755483	0.598100	0.763566	1.000000		
p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	–		
MSCI NA	0.716476	0.917140	0.914326	0.810193	0.921160	0.524313		
p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000		
S&P 500	0.699329	0.912564	0.907763	0.805403	0.917456	0.518910	1.000000	
p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	–	
Brent oil	0.204103	0.153232	0.165824	0.163056	0.148326	0.157928	0.091852	1.000000
p-Value	0.0002	0.0049	0.0023	0.0027	0.0065	0.0037	0.0928	–

Table 2. Parameter estimates of bivariate DCC-GJR-GARCH(1,1).

	MSCI EM	MSCI MXWO	MSCI ACWI	MSCI Europe	MSCI G7	MSCI Far East	S&P 500	Brent Oil
Mean equation μ	0.492116	0.495957**	0.500949**	0.525236**	0.525380**	0.143560	0.746079***	0.002115
p-Value	0.238689	0.026613	0.030876	0.044339	0.013494	0.625527	0.000010	0.683801
ϱ	0.154673***	−0.015708	−0.005653	−0.008022	−0.021915	0.098521*	−0.104200*	0.211395***
p-Value	0.005325	0.781742	0.919682	0.906867	0.704889	0.094447	0.084766	0.000873
Variance equation w_0	3.334564**	1.532206	1.664649	2.164136	1.292936	0.785842	0.870437*	0.000985**
p-Value	0.049513	0.161893	0.112212	0.346865	0.154903	0.473571	0.064882	0.035416
w_1	0.069289	0.002912	0.000000	0.000000	0.020125	0.065160	0.102502*	0.073852
p-Value	0.398194	0.961365	1.000000	0.999999	0.706355	0.500583	0.068234	0.117378
w_2	0.082864	0.222101*	0.225322*	0.165688	0.209685**	0.108119**	0.192938	0.171506
p-Value	0.389866	0.055759	0.051161	0.238272	0.040917	0.036111	0.105204	0.118710
w_3	0.803628***	0.775475***	0.772163***	0.806286***	0.777880***	0.850578***	0.744195***	0.688586***
p-Value	0.000000	0.000000	0.000000	0.000001	0.000000	0.000000	0.000000	0.000000
DCC equation a	0.039244	0.053439	0.048700	0.028480	0.062791	0.113628	0.072932	–
p-Value	0.000628***	0.025825**	0.013370**	0.004485***	0.038128**	0.057417*	0.005392***	–
b	0.951988***	0.933797***	0.940893***	0.963372***	0.922291***	0.559227	0.912883***	–
p-Value	0.000000	0.000000	0.000000	0.000000	0.000000	0.106860	0.000000	–
Diagnostics								
Log-likelihood	−2263.610	−2114.544	−2118.986	−2169.326	−2109.935	−2214.271	−2101.142	–
BIC	13.820	12.933	12.959	13.259	12.905	13.526	12.853	–
Q(5)	7.626	1.705	1.775	2.389	1.863	7.712	2.006	4.355
Q(10)	15.096	4.409	4.105	3.592	4.929	12.895	7.146	11.924
$Q^2(5)$	0.985	0.244	0.271	2.554	0.234	1.317	0.776	1.082
$Q^2(10)$	6.647	0.838	1.038	6.843	0.628	8.017	1.626	4.156

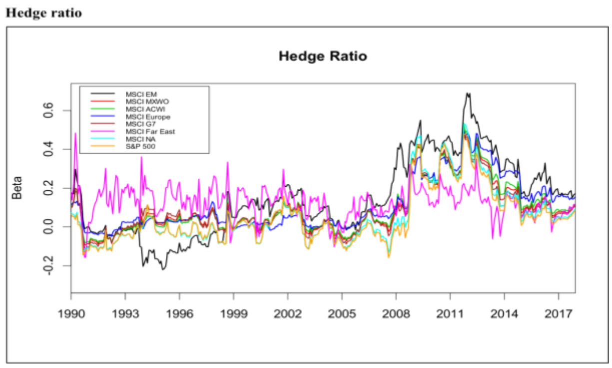

Figure 1. Hedge ratio. This figure plots the hedge ratio

5. Conclusion

First of all, our results show that for developed markets Brent oil provides better hedge effectiveness, although for emerging markets, WTI oil is more appropriate. Basically, hedge strategies can be applied, not only for a specific index, but also for other market indices, as hedge effectiveness is highly positively correlated across all stock markets. However, for MSCI Far East, we report a lower, but still significant, correlation. Moreover, in the entire sample, the lowest average hedge portfolio return is achieved for MSCI Far East. To further develop hedge strategies, it is of vital importance to be aware of hedge portfolio determinants. Among various determinants, the most important one is the VIX. Hedge portfolio returns across all markets are highly negatively related to jumps in the VIX, and its economic significance is quite high, i.e. coefficients are larger than 0.5 (except for MSCI Far East). Therefore, portfolio managers should take these factors into account when adjusting their hedge strategies.

Moreover, future research can use these outcomes to provide additional insights in other hedging strategies with other energy assets, such as natural gas. Note that to address COP21 and COP23 concerns, investors not only need a thorough understanding of stock energy market integration (see Batten et al. (2018)) but also of hedging techniques, which allow them to develop adequate risk management strategies to address the impacts on financial markets of climate change.

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