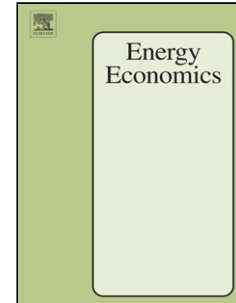


Journal Pre-proof

The effect of economic policy uncertainty on stock-commodity correlations and its implications on optimal hedging

Ihsan Badshah, Riza Demirer, Tahir Suleman



PII: S0140-9883(19)30348-2

DOI: <https://doi.org/10.1016/j.eneco.2019.104553>

Reference: ENEECO 104553

To appear in:

Received Date: 2 September 2018

Revised Date: 1 October 2019

Accepted Date: 16 October 2019

Please cite this article as: Badshah I, Demirer R, Suleman T, The effect of economic policy uncertainty on stock-commodity correlations and its implications on optimal hedging, *Energy Economics* (2019), doi: <https://doi.org/10.1016/j.eneco.2019.104553>

This is a PDF file of an article that has undergone enhancements after acceptance, such as the addition of a cover page and metadata, and formatting for readability, but it is not yet the definitive version of record. This version will undergo additional copyediting, typesetting and review before it is published in its final form, but we are providing this version to give early visibility of the article. Please note that, during the production process, errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

© 2019 Published by Elsevier.

The effect of economic policy uncertainty on stock-commodity correlations and its implications on optimal hedging

Ihsan Badshah^a ihsan.badshah@aut.ac.nz, Riza Demirel^{b*} rdemire@siue.edu, Tahir Suleman^c tahir.suleman@lincoln.ac.nz.

^aDepartment of Finance, Business School, Auckland University of Technology, Private Bag 92006, Auckland 1142, New Zealand

^bDepartment of Economics and Finance, Southern Illinois University Edwardsville, Edwardsville, IL 62026- 1102, USA

^cDepartment of Financial and Business Analysis, Lincoln University, Christchurch, New Zealand

*Corresponding author

Highlights

- EPU has a positive and significant effect on stock-commodity correlations
- The effect is particularly strong for energy and industrial metals commodity sectors
- The EPU effect is stronger during weak economic conditions
- The economic effect of EPU is implied by a significant effect on optimal hedge ratios

Abstract

Motivated by previous studies documenting significant return and volatility effects of economic policy uncertainty (EPU) on the stock market, this study examines whether EPU has an effect on the dynamic conditional correlations between stock and commodity returns. Our findings point to a positive and significant effect of EPU on stock-commodity correlations with particularly stronger effects in the case of energy and industrial metals. The EPU effect is stronger during weak economic conditions, while VIX as a proxy of market uncertainty is generally found to be insignificant. Finally, we show that the EPU effect on correlations has investment implications as well, implied by a significant effect on optimal hedge ratios in commodities in order to mitigate stock market risks. Our results underscore the importance of selective hedging strategies in which risk managers base the timing and size of their hedging programs on future price expectations, conditional on the level of policy uncertainty state and prevalent economic conditions.

Keywords: Commodity market; Policy uncertainty; Conditional correlation.

JEL Codes: C22, C32, G14, G15.

1. Introduction

There is now a well-established literature on the effect of economic policy uncertainty (EPU) on return and volatility dynamics in financial markets (e.g. Arouri et al., 2016; Brogaard and Detzel, 2015). In earlier works, Gomes et al. (2012) relate policy uncertainty to personal consumption, saving, labor supply, and portfolio choices, while Pastor and Veronesi (2012, 2013) lay out the theoretical framework on how uncertainty in governmental policies may influence asset prices and drive return dynamics in financial markets. From an economic perspective, it can be argued that the high level of uncertainty regarding potential policy changes contributes to a risk premium that firms require from investment projects, deterring them from taking on new investment ventures given the political uncertainty environment. A similar risk premium may also be embedded in interest rates, making loans more expensive for households, which in turn affects earnings projections, thus depressing stock prices and/or driving volatility in financial markets.

Subsequently, numerous studies provide ample evidence for a policy uncertainty effect on the stock market (Kang and Ratti, 2013; Liu and Zhang, 2015; Dakhlaoui and Aloui, 2016; Arouri et al., 2016; Bekiros et al., 2016), bond market (Wisniewski and Lambe, 2015) and commodities including crude oil (Antonakakis et al., 2014; Watugala, 2014; Yin and Han, 2014; Wang et al., 2015). Extending the literature to the stock returns of energy related corporations, Kang et al. (2017a) document evidence of a significant negative policy uncertainty effect on stock returns, while the effect of policy related shocks is found to interact with oil shocks. More recent studies extend the literature to correlations among various financial asset classes, documenting a negative effect of EPU on U.S. stock and bond market correlations (Fang et al., 2017) and a positive effect on the long-run oil-stock market correlation (Fang et al., 2018). This

paper contributes to the literature by examining the effect of policy uncertainty and the state of the economy on the time-varying correlations between the stock and commodity markets using a large set of commodity sectors included in the Dow Jones commodity index and several alternative proxies for the state of the economy. We then examine whether the EPU effect on correlations has economic implications by studying how optimal hedge positions in various commodities relate to the level of EPU for an investor who uses these assets to mitigate stock market risks.

Undoubtedly, correlation plays a crucial role in asset allocation decisions, risk management as well as in the analysis of risk transmissions across financial markets. Consequently, numerous studies in the literature have examined the time-variation in correlations among various asset classes and possible determinants ranging from macroeconomic variables to uncertainty proxies (e.g., Ang and Chen, 2002; Baele, 2005; Baele et al., 2010; Creti et al., 2013; Alomari et al., 2017 among others).¹ There is also a vast literature examining the relationship between stock and commodity markets, with most studies focusing on how oil price dynamics relate to stock market movements (e.g. Hammoudeh and Aleisa, 2002; Sadorsky, 2004; Chiou and Lee, 2009; Chang et al., 2010; Choi and Hammoudeh, 2010; Creti et al., 2013; among others).

Recently, several studies specifically focus on the role of economic policy uncertainty as a driver of the time-variation in asset correlations. Fang et al. (2017) show that EPU has a negative effect on U.S. stock and bond market correlations, consistent with the flight to quality phenomenon. Later, Fang et al. (2018) document a positive policy uncertainty effect on the long-

¹ See Twala et al. (2018) for a detailed review of the literature on time-varying correlations and related models.

run oil-stock correlation with the positive impact of EPU mostly prevalent during the post 2008 sub-sample. Focusing on the market sensitivities of industrial returns to the aggregate stock market fluctuations, Yu et al. (2017) examine daily returns for ten U.S. industries and show that EPU significantly drives industry betas, arguing that industry betas driven by EPU may serve as a leading indicator of market stress conditions.

This study takes a more comprehensive approach and examines the correlations between stock and commodity returns using a large set of commodities included in the Dow Jones index. By doing so, the paper (i) contributes to the emerging literature on the role of economic policy uncertainty on financial market correlations; (ii) provides further insight to the diversification benefits of commodities for stock market investors, particularly during periods of weak economic conditions (see for example Jensen et al., 2000; Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006); and (iii) explores the economic implications of a possible “EPU effect” on hedging strategies.

Our findings suggest that economic policy uncertainty is a major driver of dynamic conditional correlations between stock and commodities, particularly in the case of energy and industrial metals sectors of the commodity market, while mostly insignificant results are observed when VIX is used as a proxy for financial market uncertainty. The analysis of the joint effect of uncertainty and economic conditions on time-varying correlations suggests that policy uncertainty drives stock-commodity correlations higher, more so during weak economic conditions, consistent with the argument by Pástor and Veronesi (2013) that policy uncertainty would bear a greater risk premium during weaker economic conditions. Finally, we show that the policy uncertainty effect on correlations has also economic implications, implied by a significant effect on the optimal hedge ratios. The results overall underscore the importance of selective

hedging strategies in which risk managers base the timing and size of their hedging programs on future price expectations, conditional on the level of policy uncertainty state and prevalent economic conditions. The rest of the paper is structured as follows. Section 2 discusses the data and methodology. Section 3 presents the empirical results and Section 4 concludes.

2. Data and Methodology

2.1 Data

Our sample contains daily data for the S&P500 index and nearby futures prices for the commodities included in the Dow Jones Commodity index over the period January 20, 1999-September 30, 2016.² The commodities in the sample are listed in Table 1. Although the descriptive statistics are not reported due to space considerations, we observe that energy commodities are generally more volatile relative to other commodity groups, with natural gas exhibiting the highest return volatility, followed by gasoline and crude oil. Most commodities as well as the stock market index exhibit negative skewness, suggesting the presence of large negative returns more likely than in the other direction. Excess kurtosis is also observed in all return series, suggesting that these assets experience extreme returns, more frequently than predicted by a normal distribution, overall, indicating non-normality in all time series.

As the goal of our analysis is to examine the interaction between commodity and stock markets during various economic and uncertainty states, we employ several alternative measures of uncertainty and economic conditions. In the case of uncertainty measures, the first is the U.S. economic policy uncertainty index (**PU**) of Baker et al. (2016). This index is constructed as a

² For details how this index is constructed, please refer to;
<https://us.spindices.com/documents/methodologies/methodology-dj-commodity-index.pdf>

weighted average of three components capturing (i) the news coverage related to policy-related uncertainty; (ii) the number of federal tax code provisions set to expire in future years; and (iii) disagreement among economic forecasters. The second uncertainty variable is **VIX**, i.e. the implied volatility for the S&P 500 index, which is also termed the fear index as it serves as a proxy for aggregate market volatility. The choice of VIX as a measure of financial stress in the commodity context follows Cheng et al. (2015) who establish a link between changes in this index and commodity prices as well as traders' positions.

Following Pastor and Veronesi (2013), we use five alternative measures of economic conditions in our empirical tests. The first three are macroeconomic measures of economic conditions, namely (i) the Chicago Fed National Activity Index (CFI), constructed by the Federal Reserve from 85 monthly indicators of economic activity; (ii) month-to-month industrial production growth (IPG) obtained from the Board of Governors, and (iii) NBER recession dummy (REC), equal to one during recession months and zero otherwise. The last two measures include stock market measures of economic conditions, i.e. (iv) the cyclically adjusted price-to-earnings ratio for the aggregate stock market (P/E), sourced from Robert Shiller's website; and (v) the credit default spread (DEF), which is computed as the difference between the yields on BBB and AAA corporate bonds, obtained from FED Saint Louis database. These five proxies together capture wide range of information regarding economic conditions from both macro and financial perspectives, while the former group captures information regarding real economic activity and the latter group relates more to financial market sentiment as well as discount rate related shocks. These proxies for economic conditions are also utilized by Pastor and Veronesi (2013) to study the effect of policy uncertainty on stock market correlations, allowing us to

compare our findings for commodities to those obtained for stock market correlations. Further detail for these indexes are provided in the Appendix.

2.2 Methodology

The first step in our empirical analysis is to estimate the dynamic conditional correlations between the stock market index and each commodity via the ADCC-GARCH model of Cappiello et al. (2006). This specification is a generalization of the DCC-GARCH model of Engle (2002) which considers the conditional asymmetries in correlations while it allows correlations to vary over time. It includes a two-step procedure to isolate the dynamic conditional correlation process. We first fit a univariate asymmetric GARCH model for each commodity residual series (residuals received from VAR (2) specification) and use the time-varying estimated standard deviations to obtain standardized residual series for each commodity. Next, standardized residuals (standardized return shocks) are used to estimate the time-varying DCCs. More specifically, let u_t denote a $n \times 1$ vector of commodity residuals at time t , which is assumed to be conditional normally distributed with mean zero and covariance matrix V_t as

$$u_t | \Psi_{t-1} \sim N(0, V_t) \quad (1)$$

where Ψ_{t-1} is the information set available at time $t - 1$ and the conditional covariance matrix V_t is

$$V_t = D_t C_t D_t \quad (2)$$

where, D_t is the diagonal matrix of time-varying standard deviations obtained from the fitted univariate asymmetric GJR-GARCH models in step 1. The time-varying conditional correlation matrix given by C_t formulated as

$$C_t = \text{diag}(Q_t)^{-1/2} \text{diag}(Q_t)^{-1/2} \quad (3)$$

where $diag(Q_t)$ is the diagonal matrix that is formed from the diagonal elements of Q_t . In this specification, Q_t is a positive definite matrix that follows the ADCC structure,

$$Q_t = \Omega + \theta_1 u_{t-1} u_{t-1}' + \theta_2 Q_{t-1} + g \eta_{t-1} \eta_{t-1}' \quad (4)$$

where $\eta_t = \min[u_t, 0]$ with the product of $\eta_{i,t} \eta_{j,t}$ being nonzero if and only if both shocks are negative (see e.g., Cappiello et al. 2006; Alexander 2008; Engle 2009).

From an economic point of view, as portfolio adjustment/hedging decisions are neither practical nor meaningful at daily frequency, we focus on monthly frequency in our empirical tests. For this purpose, following Pastor and Veronesi (2013), we use the estimated correlation values and compute monthly correlations from daily data in terms of their means within the month. It must, however, be noted that we do not observe a great deal of variation in the daily correlation estimates within the month, which further supports the Pastor and Veronesi (2013) approach that we adopt in our analysis. Having established the correlation series between the stock and commodity returns on a monthly basis, we next examine whether market uncertainty has any effect on the association between these two asset classes. As mentioned earlier, this is an important consideration for investors as the pattern of correlations during periods of uncertainty can have significant effects on the effectiveness of diversification strategies. Following Pastor and Veronesi (2013), one can argue that high level of uncertainty in economic policies can (i) negatively affect investments and cash flows and also drive discount rates higher; and (ii) lower the demand by households and businesses as they hold back on spending. As these forces will commonly affect both stock and commodity markets in a similar direction, our first hypothesis is that higher level of policy uncertainty will generally increase the correlations across stock and commodities. In order to analyse the statistical significance of this relationship, we test the hypotheses as a null hypothesis of $\beta_2 = 0$ against $\beta_2 > 0$ in the following models:

$$\text{Model 1: } Cor_t = \beta_1 + \beta_2 U_t + \epsilon_t \quad (5a)$$

$$\text{Model 2: } Cor_t = \beta_1 + \beta_2 U_t + \beta_3 Cor_{t-1} + \epsilon_t \quad (5b)$$

where Cor_t is the correlation between the S&P 500 index and a given commodity in month t , computed as the average of the estimated daily correlations from the DCC model for a given month, and U is the uncertainty measure, either USA policy uncertainty index by Baker et al. (2016) or the CBOE VIX index as explained earlier. In our estimations, the policy uncertainty index is scaled down by 100 and monthly VIX index values are employed by computing the average daily levels of the VIX index within a month. Note that in Eq. (5b), we also include Cor_{t-1} in order to remove any serial correlation in Cor_t .

3. Empirical Findings

3.1 Uncertainty and time-varying correlations

Figure 1 displays the estimated dynamic conditional correlations between S&P500 index (SPX) and each commodity. We observe a great deal of time variation in the estimated DCCs throughout the sample period, consistent with the findings of Creti et al. (2013) and Choi and Hammoudeh (2010). Interestingly, there seems to be a general structural shift in the association of commodities with the stock market during the Global Financial Crisis period (2007-2008), indicated by a drop in the pairwise correlations during the crisis period and rising to a higher level subsequently. This structural shift towards higher correlations is indeed consistent with the observation by Bernanke (2016) that stock and oil markets have moved lockstep in recent years, reflecting concerns about global economic growth, particularly following the global financial crisis. Finally, gold seems to stand out, exhibiting negative correlation with the stock market

during much of the sample period, suggesting that this commodity might offer hedging and safe haven benefits to stock market investors.

Table 1 presents the results for Equations (5a) and (5b) with policy uncertainty and VIX employed as the uncertainty proxy one at a time. Overall, we observe a significant positive effect of policy uncertainty on the time-varying correlations, with the largest positive effects observed in the case of energy commodities followed by industrial metals, implied by positive and highly significant estimates for β_2 . The positive effect of policy uncertainty on stock-commodity market correlations is in line with the recent evidence by Fang et al. (2018) who document that policy uncertainty has a significant positive influence on the long-run oil-stock market correlation as well as the finding by Yu et al. (2017) that policy uncertainty significantly drives industry betas. This finding is also in line with the observation by Bernanke (2016) of greater association between commodity and stock markets due to common fundamentals related to economic growth expectations driving return dynamics in both markets. In fact, the strong results observed particularly for energy and industrial metals sectors of commodities support the suggestion that the association between commodity and stock market returns may be driven by a fundamental source of uncertainty related to global growth expectations, partially captured by economic policy uncertainty.

Interestingly however, we observe the opposite results in the case of precious metals, indicated by negative β_2 estimates, suggesting that higher level political uncertainty is associated with lower correlations between precious metals and the stock markets. This is indeed good news for investors as it provides additional support to the suggestion that gold can serve as a safe haven during periods of uncertainty or economic downturns (e.g. Baur and Lucey, 2010). We

also observe that the significant and positive effect of policy uncertainty on commodity-stock market correlations remains robust even after including lagged correlation values in Model 2.³

On the other hand, we observe strikingly different results when VIX is used as the uncertainty proxy in our estimations. We see that VIX is not necessarily a significant determinant of stock-commodity market correlations, indicated by insignificant estimates for most commodities with a few exceptions. The insignificant effect of VIX on correlations also applies to precious metals, suggesting that economic policy uncertainty serves as a broader measure of market uncertainty and that the relation between the stock and commodity markets is affected by factors beyond market volatility only. In fact, considering the evidence by Liu and Zhang (2015) that higher economic policy uncertainty leads to a significant rise in stock market volatility, our findings underscore the role of policy uncertainty as a primary determinant of risk, driving both volatility and co-movement among asset returns.

Overall, our results are in line with the prediction of Pastor and Veronesi (2013) on the effect of policy uncertainty on stock market returns and consistent with the empirical evidence in Fang et al. (2018). From an investment perspective, an important implication of these findings is that policy uncertainty can be integrated into diversification models in order to identify optimal weights in a portfolio of stocks and commodities. If policy uncertainty has a significant effect on the correlations between these assets, as the results suggest, then one can formulate optimal portfolio weights as a function of policy uncertainty or perhaps devise an investment strategy that is conditional on the uncertainty state in the market.

3.2 Joint effect of policy uncertainty and economic conditions

³ For robustness checks, we have tested the significance of the estimates via Newey-West standard errors based on various lags and obtained similar results.

Having presented evidence of a significant policy uncertainty effect on stock-commodity market correlations, we next examine whether the uncertainty effect is exacerbated during particular economic states. For this reason, we use five alternative proxies for economic conditions (E_t): the AAA/BBB corporate bond default spread (**DEF**), industrial production growth (**IPG**), Shiller's price to earnings ratio for the aggregate stock market (**PE**), the Chicago Fed National Activity Index (**CFI**) and the NBER recession dummy (**REC**) which is equal to one during recession months and zero otherwise. We then examine the joint effect of policy uncertainty and economic conditions on the pairwise correlations between the stock market and each commodity by estimating

$$\text{Model 3: } Cor_t = \beta_1 + \beta_2 U_t E_t + \beta_3 U_t + \beta_4 E_t + \epsilon_t \quad (6a)$$

$$\text{Model 4: } Cor_t = \beta_1 + \beta_2 U_t E_t + \beta_3 U_t + \beta_4 E_t + \beta_5 Cor_{t-1} + \epsilon_t \quad (6b)$$

where U is the uncertainty measure, either USA policy uncertainty index by Baker et al. (2016) or the VIX index, and E is the measure of economic conditions as described earlier. Once again, following Pastor and Veronesi (2013), we hypothesize that the uncertainty effect on correlations should be more pronounced during periods of unfavorable economic conditions as political shocks exert a larger influence on asset prices in a weaker economy. In order to empirically test this hypothesis, we test $\beta_2 = 0$ against $\beta_2 < 1$.

Table 2 reports the results for the joint effect of economic policy uncertainty and the state of the economy on the correlation between stock and commodity returns. We observe strong and consistent effects, particularly in the case of NBER recession dummy (REC) and the Chicago Fed National Activity Index (CFI), with largely insignificant effects for industrial production growth (IPG), Shiller's price to earnings ratio for the aggregate stock market (PE). As expected,

the results suggest that policy uncertainty drives the correlations between the stock and commodity markets, more so during recessionary periods indicated by higher values of REC and lower values for CFI. Once again, the joint effect of uncertainty and economic conditions is observed to be stronger in the case of energy commodities, followed by industrial metals. Consistent with the earlier findings in Table 1, the negative β_2 estimates observed for precious metals provide further support to the safe haven properties of precious metals during weak economic conditions and periods of high uncertainty.⁴

On the other hand, the findings for VIX reported in Table 3 suggest that stock market volatility could also be a determinant of stock-commodity market correlations, however, only depending on the state of the economy. Unlike the results in Table 2, we observe in Table 3 significant joint effects of VIX with several proxies for economic conditions, particularly the credit default spread (DEF) and the aggregate stock market price to earnings ratio (PE). Based on the signs of the estimated coefficients, we see that higher stock market volatility drives stock-commodity correlations higher during periods of high credit risk and at lower price multiples, indicating unfavourable economic conditions. Overall, the findings in Tables 2 and 3 suggest that both policy uncertainty and VIX could serve as determinants of stock-commodity correlations, while the effect of VIX is conditional on the state of the economy. This contrast could be an important consideration in the implementation of selective hedging strategies in which risk managers base the timing and size of their hedging programs on future price expectations, depending on the interaction of the uncertainty state and prevalent economic conditions.

⁴ Recently, Kang et al. (2017b) note the presence of interactions between U.S. EPU and various uncertainty variables, which may give rise to a possible endogeneity issue. While such causality is not warranted in the case of correlations, the use of lagged correlation term in the model should, to some extent, help to mitigate any biases that may occur.

3.3. Economic policy uncertainty and optimal hedge ratios

Having presented evidence of a significant policy uncertainty effect on the co-movement between commodity and stock market returns, we next explore the economic impact of the results by examining whether the observed effect of policy uncertainty on correlations has hedging implications. Consider a passive investor who is currently invested in the stock market. The investor takes a position in a given commodity in order to manage the market risk in the passive index portfolio by forming a hedge portfolio (hp) with the portfolio's return formulated as $R_{hp} = R_s - hR_c$ where $R_s(R_c)$ is the return on the stock market (commodity) and h is the hedge ratio. Having defined the hedge portfolio as a combination of the passive market index portfolio and the commodity futures position, the optimal hedge position (h_t^*) for each commodity is then estimated each month as the minimum-variance hedge ratio formulated as $h_t^* = \rho_{if,t}\sigma_{i,t}/\sigma_{f,t}$ where $\rho_{if,t}$ and $\sigma_{i,t}$ are the commodity-stock market correlation and standard deviations for month t , respectively.

Having computed the optimal hedge ratios in each commodity each month, we then examine the effect of policy uncertainty on the hedge ratios by

$$\hat{h}_t = \theta_0 + \theta_1 U_t + \epsilon_t \quad (7)$$

where \hat{h}_t is the monthly optimal hedge ratio and U_t is the policy uncertainty for month t . Table 4 reports the effect of policy uncertainty on the optimal hedge ratios. We generally observe that higher levels of political uncertainty is associated with lower hedge positions that should be taken in a given commodity, implied by negative estimates for θ_1 . However, unlike the case for correlations where uncertainty plays a significant role for most commodities, we observe that the uncertainty effect on the hedge ratios is limited largely to industrial metals with the largest and

most significant results observed for these commodities. The negative effect of policy uncertainty on optimal hedge ratios is somewhat consistent with the finding by Yu et al. (2017) of a negative relation between policy uncertainty and industry betas during periods of market crisis. Yu et al. (2017) argue that during periods of market stress, industry level betas are less driven by policy uncertainty due to other simultaneous factors such as market liquidity or industry specific factors. Following this argument, the negative uncertainty effect on hedge ratios, particularly in the case of industrial metals, can be a manifestation of industrial returns decoupling from the aggregate stock market during periods of high policy uncertainty. Nevertheless, the results may be good news for a passive stock market investor as hedging strategies would require smaller hedge positions during such times and would be less costly. Overall, the findings further underscore the importance of selective hedging strategies conditional on the state of the economy as well as the level of policy uncertainty.

4. Conclusion

Motivated by previous studies documenting significant return and volatility effects of economic policy uncertainty on the stock market, this paper examines the effect of economic policy uncertainty and the state of the economy on the time-varying correlations between the stock and commodity market returns. Using two alternative proxies for market uncertainty and five alternative proxies for the state of the economy, we document a significant and positive effect of policy uncertainty on the dynamic correlations between stock and commodity returns, with particularly stronger effects in the case of energy and industrial metal sectors of the commodity market. VIX, however, is found to be mostly insignificant in our tests, suggesting that policy uncertainty serves as a broader measure of market uncertainty.

On the other hand, opposite effects are observed in the case of precious metals, with a negative policy uncertainty effect on these assets' correlations with stock market returns, underscoring the safe haven benefits of these commodities for stock market investors. The analysis of the joint effect of uncertainty and economic conditions on time-varying correlations suggests that policy uncertainty drives stock-commodity correlations higher, more so during recessionary periods, consistent with the argument by Pástor and Veronesi (2013) that policy uncertainty would bear a greater risk premium during weaker economic conditions.

Finally, we show that the policy uncertainty effect on correlations has also economic implications, implied by a significant and negative effect on the optimal hedge ratios. The negative effect of policy uncertainty on optimal hedge ratios, particularly in the case of industrial metals, may be good news for a passive stock market investor as hedging strategies would require smaller hedge positions in these commodities during periods of high uncertainty and would be less costly. The results overall underscore the importance of selective hedging strategies in which risk managers base the timing and size of their hedging programs on future price expectations, conditional on the level of policy uncertainty state and prevalent economic conditions.

References

- Alexander, C., 2008. Market risk analysis: Practical financial econometrics (Vol. II). *Hoboken: Wiley*.
- Alomari, M., Power, D. M., & Tantisantiwong, N. 2018. Determinants of equity return correlations: a case study of the Amman Stock Exchange. *Review of Quantitative Finance and Accounting*, 50(1), 33-66.
- Ang, A., & Chen, J. 2002. Asymmetric correlations of equity portfolios. *Journal of financial Economics*, 63(3), 443-494.
- Antonakakis, N. , Chatziantoniou, I. , Filis, G. , 2014. Dynamic spillovers of oil price shocks and economic policy uncertainty. *Energy Econ.* 44, 433–447.
- Arouri, M. , Estay, C. , Rault, C. , Roubaud, D. , 2016. Economic policy uncertainty and stock markets: long-run evidence from the US. *Finance Res. Lett.* 18, 136–141.
- Baele, L. 2005. Volatility spillover effects in European equity markets. *Journal of Financial and Quantitative Analysis*, 40(2), 373-401.
- Baker, S. , Bloom, N. , Davis, S. , 2016. Measuring economic policy uncertainty. *Q. J. Econ.* 131 (4), 1593–1636 .
- Bekiros, S., Gupta, R. , Majumdar, A., 2016. Incorporating economic policy uncertainty in US equity premium models: a nonlinear predictability analysis. *Finance Res. Lett.* 18, 291–296.
- Bernanke, B. 2016. The relationship between stocks and oil prices. Brookings. <https://www.brookings.edu/blog/ben-bernanke/2016/02/19/the-relationship-between-stocks-and-oil-prices/>
- Brogaard, J. , Detzel, A. , 2015. The asset-pricing implications of government economic policy uncertainty. *Manag. Sci.* 61, 3–18.
- Cappiello, L., Engle, R. F., & Sheppard, K. 2006. Asymmetric dynamics in the correlations of global equity and bond returns. *Journal of Financial econometrics*, 4(4), 537-572.
- Chang, C.L., McAleer, M. and Tansuchat, R., 2013. Conditional correlations and volatility spillovers between crude oil and stock index returns. *The North American Journal of Economics and Finance*, 25, pp.116-138.
- Cheng, I. H., Kirilenko, A., & Xiong, W. 2015. Convective risk flows in commodity futures markets. *Review of Finance*, 19(5), 1733–1781.
- Chiou, J. S., & Lee, Y. H. 2009. Jump dynamics and volatility: Oil and the stock markets. *Energy*, 34(6), 788-796.
- Choi, K., & Hammoudeh, S. 2010. Volatility behavior of oil, industrial commodity and stock markets in a regime-switching environment. *Energy Policy*, 38(8), 4388-4399.

- Creti, A., Joëts, M., & Mignon, V. 2013. On the links between stock and commodity markets' volatility. *Energy Economics*, 37, 16-28.
- Dakhlaoui, I., Aloui, C., 2016. The interactive relationship between the US economic policy uncertainty and BRIC stock markets. *Int. Econ.* 146, 141–157.
- Engle, R. 2002. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics*, 20(3), 339-350.
- Engle, R. 2009. *Anticipating correlations: a new paradigm for risk management*. Princeton University Press.
- Erb, C. B., & Harvey, C. R. 2006. The strategic and tactical value of commodity futures. *Financial Analysts Journal*, 62(2), 69-97.
- Fang, L., Yu, H., Li, L. 2017. The effect of economic policy uncertainty on the long-term correlation between U.S. stock and bond markets. *Economic Modelling* 66, 139–145.
- Fang, L., Chen, B., Yu, H., Xiong, C. 2018. The effect of economic policy uncertainty on the long-run correlation between crude oil and the U.S. stock markets. *Finance Research Letters* 24, 56–63
- Gomes, F. J., Kotlikoff, L. J., & Viceira, L. M. 2012. The excess burden of government indecision. *Tax Policy and the Economy*, 26(1), 125-164.
- Gorton, G., & Rouwenhorst, K. G. 2006. Facts and fantasies about commodity futures. *Financial Analysts Journal*, 62(2), 47-68.
- Hammoudeh, S., & Aleisa, E. 2002. Relationship between spot/futures price of crude oil and equity indices for oil-producing economies and oil-related industries. *Arab Economic Journal*, 11(27), 37-62.
- Hammoudeh, S., Dibooglu, S., & Aleisa, E. 2004. Relationships among US oil prices and oil industry equity indices. *International Review of Economics & Finance*, 13(4), 427-453.
- Jensen, G. R., Johnson, R. R., & Mercer, J. M. 2000. Efficient use of commodity futures in diversified portfolios. *Journal of Futures Markets: Futures, Options, and Other Derivative Products*, 20(5), 489-506.
- Kang, W., Ratti, R.A., 2013. Oil shocks, policy uncertainty and stock market return. *J. Int. Financ. Mark. Inst. Money* 26, 305–318.
- Kang, W. & Perez de Gracia, F. & Ratti, R.A., 2017a. Oil price shocks, policy uncertainty, and stock returns of oil and gas corporations. *Journal of International Money and Finance* 70(C), 344-359.
- Kang, W. & Ratti, R. A. & Vespignani, J. L., 2017b. Oil price shocks and policy uncertainty: New evidence on the effects of US and non-US oil production. *Energy Economics*, Elsevier 66(C), 536-546.

- Liu, L., Zhang, T. , 2015. Economic policy uncertainty and stock market volatility. *Finance Res. Lett.* 15, 99–105 .
- Pastor, L., & Veronesi, P. 2012. Uncertainty about government policy and stock prices. *The Journal of Finance*, 67(4), 1219-1264.
- Pástor, L., & Veronesi, P. 2013. Political uncertainty and risk premia. *Journal of Financial Economics*, 110(3), 520-545
- Sadorsky, P., 2004. Stock markets and energy prices. *Encyclopedia of Energy*, vol. 5. Elsevier, New York 707–717.
- Twala, Z., Demirer, R., Gupta, R., 2018. Does Liquidity Risk Explain the Time-Variation in Asset Correlations? Evidence from Stocks, Bonds and Commodities. *Journal of Economics and Behavioral Studies* 10 (2), 120-132.
- Wang, Y., Zhang, B., Diao, X., & Wu, C. 2015. Commodity price changes and the predictability of economic policy uncertainty. *Economics Letters*, 127, 39–42.
- Watugala, S. W. 2014. Economic uncertainty and commodity futures volatility. http://people.csail.mit.edu/sumudu/docs/Sumudu_Watugala_CommodityVolatility.pdf.
- Wisniewski, T.P., Lambe, B.J., 2015. Does economic policy uncertainty drive CDS spreads? *Int. Rev. Financ. Anal.* 42, 447–458.
- Yu, H., Fang L., Du, D., Yan, P. 2017. How EPU drives long-term industry beta. *Finance Research Letters* 22, 249–258.
- Yin, L., & Han, L. 2014. Macroeconomic uncertainty: Does it matter for commodity prices? *Applied Economics Letters*, 21, 711–716.

Appendix. Political uncertainty and proxies for economic conditions.

The selection of the economic condition measures in our empirical analysis follows Pastor and Veronesi (2013) who also employ these indexes, along with political uncertainty, to study the effect of policy uncertainty on correlations across the stocks included in the S&P500 index.

Variable	Abbreviation	Definition	Frequency
Economic Policy Uncertainty	<i>PU</i>	U.S. economic policy uncertainty index of Baker et al. (2016). Heavily weighted on the news related to policy related uncertainty. For further details: https://www.policyuncertainty.com/us_monthly.html	Monthly
Volatility Index	<i>VIX</i>	A measure of aggregate stock market volatility implied by S&P 500 index options, computed and disseminated on a real-time basis by the Chicago Board Options Exchange (CBOE).	Monthly
<i>Macroeconomic measures of economic conditions</i>			
National Activity Index	<i>CFI</i>	The Chicago Fed National Activity Index, constructed by the Federal Reserve. This is a weighted average of 85 existing monthly indicators of national economic activity.	Monthly
Industrial Production Growth	<i>IPG</i>	Month-to-month industrial production growth (IPG) obtained from the Federal Reserve Bank of St. Louis.	Monthly
Recession dummy	<i>REC</i>	The National Bureau of Economic Research (NBER) recession dummy is equal to one during recession months and zero otherwise.	Monthly
<i>Stock market measures of economic conditions</i>			
Price-to-Earnings ratio	<i>P/E</i>	Cyclically adjusted price-to-earnings ratio for the aggregate stock market (P/E), available from Robert Shiller's website. http://www.econ.yale.edu/~shiller/data.htm	Monthly
Credit Default Spread	<i>DEF</i>	The difference between the yields on AAA and BBB rated corporate bonds.	Monthly

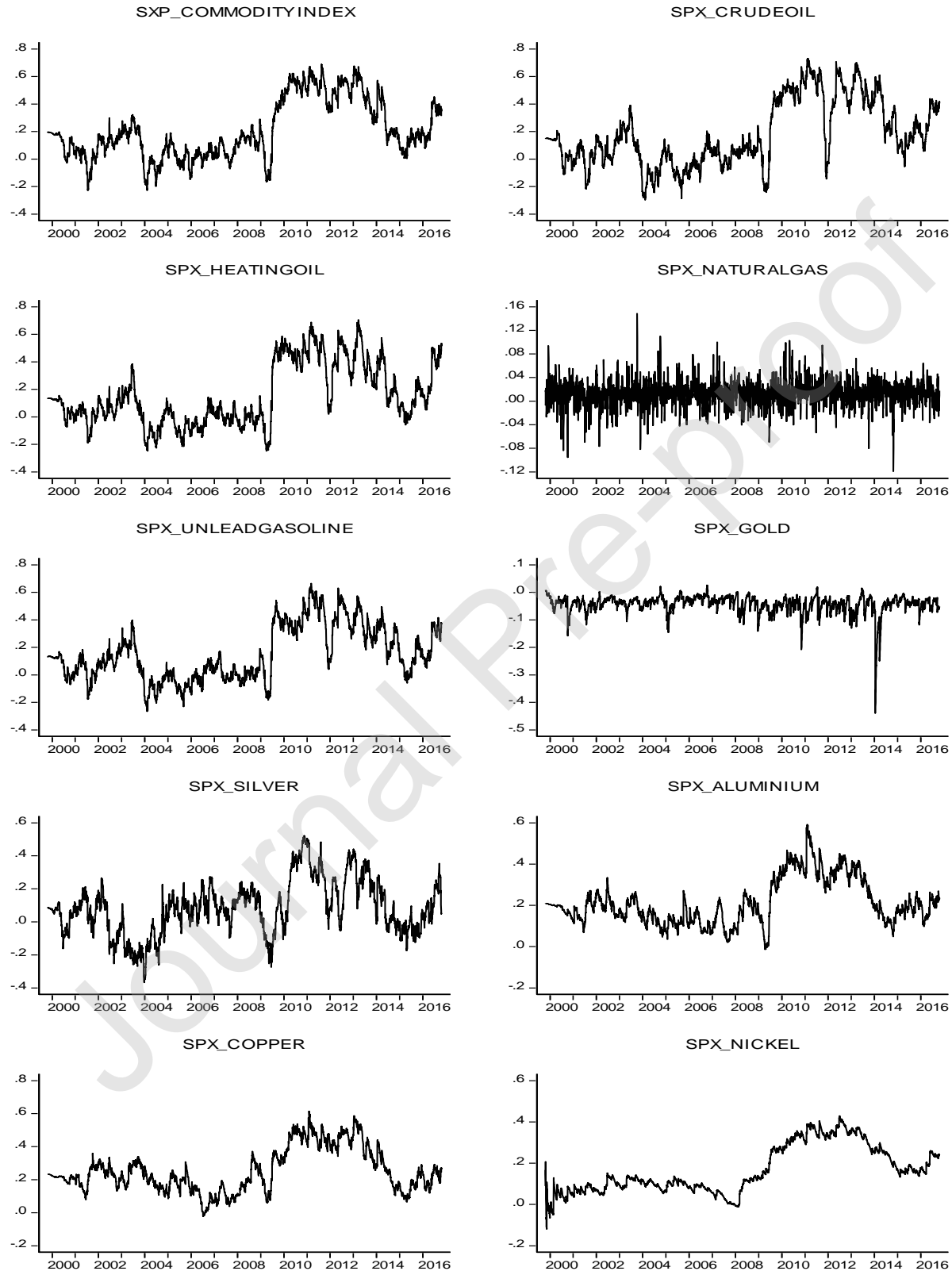
Figure 1. Dynamic conditional correlations between the S&P 500 index and commodities.

Figure 1. (Continued).

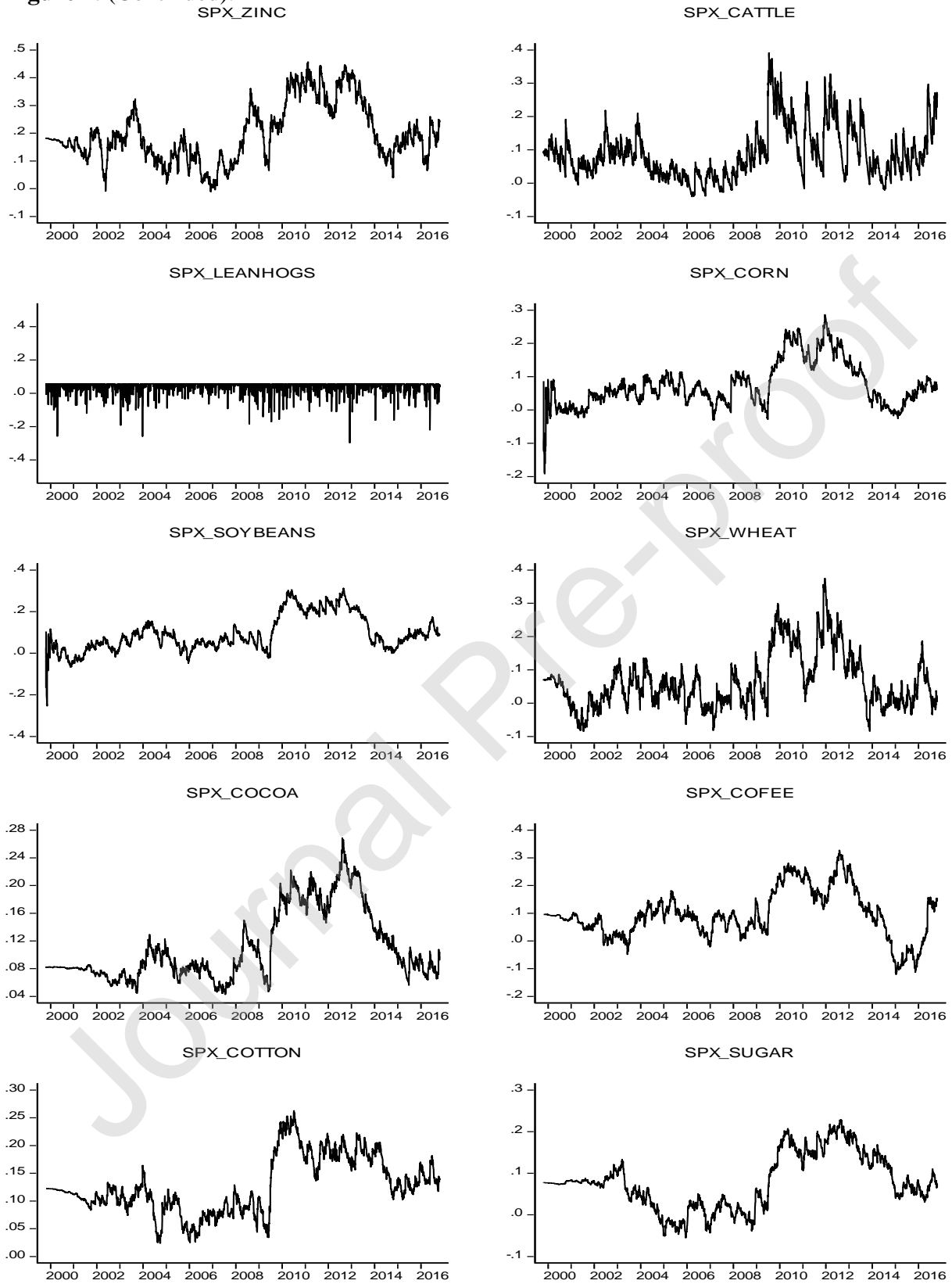


Table 1: Uncertainty and time-varying correlations

The table reports the β_2 estimates from **Model 1**: $Cor_t = \beta_1 + \beta_2 U_t + \epsilon_t$ and **Model 2**: $Cor_t = \beta_1 + \beta_2 U_t + \beta_3 Cor_{t-1} + \epsilon_t$ where Cor_t is the correlation between the S&P 500 index and a given commodity in month t , computed as the average of the estimated daily correlations from the DCC model within a month. We use two measures of uncertainty (U_t): the U.S. policy uncertainty index of Baker et al. (2016) (**PU**) and the implied stock market volatility measured by the average of the daily CBOE VIX index values within a month (**VIX**). The significance of the coefficients is based on Newey-West standard errors with five lags. ***, **, * and represent significance at 1, 5 and 10 percent level, respectively.

	Model 1		Model 2	
	PU	VIX	PU	VIX
Commodity Index	0.5488***	0.069	0.0357**	0.0035
Energy				
Crude Oil	0.5454***	0.0152	0.0347**	0.0006
Heating Oil	0.486***	0.0227	0.0402**	0.0041
Natural Gas	0.0012	0.0042	0.0013	0.0017
Unleaded Gasoline	0.4685***	0.0482	0.0428**	0.0061
Precious Metals				
Gold	-0.0253**	-0.0089	-0.0122*	-0.0053
Silver	-0.1851*	-0.0941	-0.0115*	-0.0204
Industrial Metals				
Aluminum	0.2854***	0.0942	0.0138**	-0.0008
Copper	0.3837***	0.1247	0.036**	0.0044
Nickel	0.2976***	-0.0424	0.0133**	0.006
Zinc	0.3682***	0.1769***	0.0405**	0.0088
Live Stock				
Live Cattle	0.1454***	0.1151***	0.0161	0.0114
Lean Hogs	-0.0044	0.0116***	-0.0043	0.0059***
Grains				
Corn	0.1413***	0.0262	0.015**	0.0081
Soybeans	0.1877***	0.0086	0.0066***	0.0054
Wheat	0.1548***	0.1085***	0.0221**	0.0159***
Softs				
Cocoa	0.1176***	-0.0098	0.0011	-0.0005
Coffee	0.1291***	0.0021	0.0159	0.0047
Cotton	0.1251***	0.0217	0.0133	0.0037
Sugar	0.2048***	0.0625	0.0104**	0.0058***

Table 2: Policy uncertainty, economic conditions and time-varying correlations

The table reports the β_2 estimates from **Model 3**: $Cor_t = \beta_1 + \beta_2 U_t E_t + \beta_3 U_t + \beta_4 E_t + \beta_5 Cor_{t-1} + \epsilon_t$ and **Model 4**: $Cor_t = \beta_1 + \beta_2 U_t E_t + \beta_3 U_t + \beta_4 E_t + \beta_5 Cor_{t-1} + \epsilon_t$ where Cor_t is the correlation between the S&P 500 index and a given commodity in month t , computed as the average of the daily correlations from the DCC model within a month. Uncertainty (U_t) in month t is measured by the U.S. policy uncertainty index of Baker et al. (2016). Five proxies are used for economic conditions (E_t): the AAA/BBB corporate bond default spread (**DEF**), industrial production growth (**IPG**), Shiller's price to earnings ratio for the aggregate stock market (**PE**), the Chicago Fed National Activity Index (**CFI**) and the NBER recession dummy (**REC**) which is equal to one during recession months and zero otherwise. The significance of the coefficients is based on Newey-West standard errors with five lags. ***, **, * and represent significance at 1, 5 and 10 percent level, respectively.

	Model 3					Model 4				
	DEF	IPG	REC	PE	CFI	DEF	IPG	REC	PE	CFI
Commodity Index	0.2325	0.8646	0.7788***	-0.0241	-0.2903**	0.1927**	0.2244	0.1197**	0.0064	-0.0969**
Energy										
Crude Oil	0.2731	0.8399	0.7351***	-0.0133	-0.3445***	0.2142**	0.1537	0.0611**	0.0086	-0.0915*
Heating Oil	0.3903*	0.3629	0.6746***	-0.0049	-0.365***	0.2251**	0.8922	0.1014***	0.0082	-0.1092**
Natural Gas	0.0177*	-0.6543	0.0036	0.0001	-0.0099**	0.0148	-0.7094*	0.0033	0.0001	-0.0091**
Unleaded Gasoline	0.3003**	0.4151	-0.5771	-0.0117	-0.2929**	0.1502**	0.2352	0.0685	0.0071	-0.0688*
Precious Metals										
Gold	0.0234	0.8813	-0.0599**	-0.0004	-0.0111	0.0097	-0.3169	-0.0501**	0.0012	-0.0115
Silver	-0.0442	0.7172	-0.4543***	-0.0107	0.1418	0.0531	0.0628**	-0.1432**	0.0029	0.0717***
Industrial Metals										
Aluminum	0.2486**	0.6041	0.3785***	0.0042	-0.1428**	0.0737*	1.5779	0.1583**	0.001	-0.0531**
Copper	0.1090	0.5551	0.3182**	-0.0164	0.0798	0.1171***	2.3552	0.2012***	0.0018	-0.0748**
Nickel	0.1967**	-0.0607*	0.4043***	-0.0025	-0.1701***	0.0282**	0.5411	0.0701***	0.0004	-0.0257***
Zinc	0.0947	0.7856	0.3561***	-0.0223***	-0.0946***	0.0574	1.8212	0.1229***	0.0001	-0.0403***
Live Stock										
Live Cattle	0.2449***	0.6842	0.1901***	-0.0054	-0.1246**	0.1019**	-0.0453***	0.0763***	-0.0012	-0.0668**
Lean Hogs	-0.0149	-0.0331	0.0023	-0.0016**	-0.007	-0.0151	-0.0424	0.0022	-0.0009***	-0.007
Grains										
Corn	0.1070	0.8815	0.2436***	-0.0076	-0.0604**	0.0333	0.7839	0.0551**	-0.0009	0.0197
Soybeans	0.1164**	6.3004	0.2504***	-0.0107	-0.0857**	0.055**	1.3992	0.0746***	0.0014	-0.0336**
Wheat	0.0553	0.5466	0.1226**	-0.0214**	0.0301	0.033	-0.3517	0.0031	-0.0029	0.0184
Softs										
Cocoa	0.0196	0.1548	0.1997***	-0.0065	-0.0521***	0.0389***	0.9521	0.0511***	0.0011	-0.0198***
Coffee	-0.1082	-0.9216	-0.1082	-0.0147**	-0.0138	0.0211	-0.0815*	-0.0093	-0.0007*	0.0031
Cotton	0.0594	0.4687	0.1867***	-0.0026	-0.0815***	0.0496**	-0.7311	-0.0646**	0.0011	-0.0291**
Sugar	0.0969	-0.2443**	0.2614***	-0.0042	-0.1173***	0.0037	-0.7906	-0.031	-0.001	0.007

Table 3: Stock market volatility, economic conditions and time-varying correlations

The table reports the β_2 estimates from **Model 3**: $Cor_t = \beta_1 + \beta_2 U_t E_t + \beta_3 U_t + \beta_4 E_t + \beta_5 Cor_{t-1} + \epsilon_t$ and **Model 4**: $Cor_t = \beta_1 + \beta_2 U_t E_t + \beta_3 U_t + \beta_4 E_t + \beta_5 Cor_{t-1} + \epsilon_t$ where Cor_t is the correlation between the S&P 500 index and a given commodity in month t , computed as the average of the daily correlations from the DCC model within a month. Uncertainty (U_t) in month t is measured by the implied stock market volatility, computed as the average daily value of the CBOE VIX index within a month. Five proxies are used for economic conditions (E_t): the AAA/BBB corporate bond default spread (**DEF**), industrial production growth (**IPG**), Shiller's price to earnings ratio for the aggregate stock market (**PE**), the Chicago Fed National Activity Index (**CFI**) and the NBER recession dummy (**REC**) which is equal to one during recession months and zero otherwise. The significance of the coefficients is based on Newey-West standard errors with five lags. ***, **, * and represent significance at 1, 5 and 10 percent level, respectively.

	Model 3					Model 4				
	DEF	IPG	REC	PE	CFI	DEF	IPG	REC	PE	CFI
Commodity Index	0.5323***	0.0276	0.3564*	-0.1377***	-0.2628**	0.0955***	0.1216	0.0722	-0.0142***	-0.0487**
Energy										
Crude Oil	0.4607*	0.5871	-0.3107	-0.1426***	-0.334***	0.0908**	0.2518	0.0465	-0.0172**	-0.0429**
Heating Oil	0.5482**	0.7137	0.4181**	-0.1402***	-0.3536**	0.0930**	0.4876	0.0564	-0.0145***	-0.0488**
Natural Gas	0.0078*	-0.6781**	0.0097*	0.001	-0.0092***	-0.0025	-0.5619**	-0.0044	0.0006	-0.0042***
Unleaded Gasoline	0.4837**	0.1015	0.3047*	-0.1209***	-0.2833***	0.0721**	0.9136	0.0288	-0.0136***	0.0319
Precious Metals										
Gold	-0.0151	0.0317**	0.0046	0.0046**	-0.0051	-0.0022	0.0649	-0.0079	0.0005	-0.0046**
Silver	-0.0379	0.4825	-0.1919	0.0562**	0.1315**	-0.0486*	0.3373**	-0.0717**	0.0085**	0.0353**
Industrial Metals										
Aluminum	0.4058***	-0.8801*	0.2776**	-0.0729***	-0.1513**	0.0653***	-0.2071**	0.0556*	-0.0064**	-0.0286**
Copper	0.2983**	0.1191	-0.0715	-0.0814***	-0.0751	0.0792***	-0.0548**	0.0675*	-0.0089***	-0.0387**
Nickel	0.2170*	0.0583	0.1055	-0.0591***	-0.0665	0.0172**	0.1155	-0.0103	-0.0014	-0.0077
Zinc	0.2775**	-0.6410	0.0421	-0.0561***	-0.0876***	0.0502***	-0.5254**	0.0539*	-0.0066***	0.0261**
Live Stock										
Live Cattle	0.2581***	-0.9095	0.0951	-0.0270***	-0.083**	0.0493**	-0.3245	0.0260	-0.0029	-0.0192**
Lean Hogs	0.0195***	-0.5303	0.0221**	-0.0021***	-0.0101***	0.0106**	-0.5451*	0.0167**	-0.0011**	-0.0065**
Grains										
Corn	0.2490***	0.2259	0.1338*	-0.0374***	0.0428	0.026***	1.0925	0.0365**	-0.0035**	-0.0124***
Soybeans	0.2774***	0.3174	0.0478	-0.0449***	-0.0579	0.0317***	0.8429	0.0419**	-0.0032**	-0.0177**
Wheat	0.2865***	-0.8868	-0.0779	-0.0345**	0.0148	0.034**	-0.5615	-0.0218	-0.0027	-0.0104
Softs										
Cocoa	0.0744	-0.711	-0.6404	-0.0299***	0.0226	0.0196***	0.3773	-0.0168	-0.0021**	-0.0074**
Coffee	0.0214	-0.5636	0.0271	-0.0354**	-0.0333	0.0244**	-0.5152	0.0009	0.0018	-0.0014

Cotton	0.1365**	0.7477	0.1392**	-0.0325***	-0.0692**	0.0281***	-0.2832	0.0255*	-0.0030**	-0.0124**
Sugar	0.1870**	-0.5751*	0.2317***	-0.0494***	-0.1109**	0.0094	-0.3303	-0.0015	0.0009	0.0014

Journal Pre-proof

Table 4: Policy uncertainty and optimal hedge ratios

The table reports the effect of policy uncertainty on the optimal hedge ratios for each commodity via Eq. (7). The significance of coefficients is based on Newey-West standard errors with five lags. ***, **, * and represent significance at 1, 5 and 10 percent level, respectively.

Commodity	θ_0	θ_1	Adj. R ²
Aluminum	0.0251***	-0.0259***	0.052
Cattle	0.0115**	-0.0091**	0.028
Cocoa	0.0179	-0.0112	0.004
Coffee	0.0161	-0.0269*	0.015
Commodity	0.0231***	-0.0183***	0.048
Copper	0.0760***	-0.0570***	0.075
Corn	-0.0320*	0.0152	0.005
Cotton	0.0077	-0.0112	0.003
Crude oil	0.0448**	-0.0487***	0.040
Gold	0.0164***	-0.0099**	0.026
Heating oil	0.0216	0.0217	0.011
Lead	0.1015***	-0.0681***	0.055
Lean hogs	0.0017	-0.0086	0.005
Natural gas	-0.0151	-0.0033	0.001
Nickel	0.0626	-0.0499	0.013
Silver	0.0385	-0.0291	0.012
Soybeans	0.0077	-0.0017	0.001
Sugar	-0.0090	0.0089	0.002
Unlead. gasoline	0.0261	-0.0249	0.006
Wheat	-0.0191	0.0015	0.001
Zinc	0.0684***	-0.0576***	0.081