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Commodity futures hedge ratios: A meta-analysis

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A B S T R A C T

The derivative accounting standard requires hedging to satisfy the 80–125 rule to be eligible to apply the hedge accounting treatment. This means the hedging relationship should achieve hedging effectiveness within the 80%–125% level to qualify for hedge accounting. The appropriateness of this screening criterion is questioned in the existing literature, and there is hardly any empirical evidence to justify the suitability of this threshold level of hedge effectiveness. By applying meta-analysis methodology for 1699 hedge ratios collected from previous academic studies in commodity futures hedging, we show that the average optimal hedge ratio in commodity futures hedging in the academic literature mostly overlaps with the 80–125 threshold.

1. Introduction

Over the past few decades, the use of financial derivatives has increased substantially, thereby the importance of derivative accounting. A derivative is a financial security that derives its value from an underlying asset specified in the contract. Despite the fact

Abbreviations: ASU, Accounting Standards Update; BMA, Bayesian Model Averaging; Co-inte, Co-integration; DOR, Dollar Offset Ratio; ECM, Error Correction Model; FASB, Financial Accounting Standards Board; FAT, Funnel Asymmetry Test; GARCH, Generalized Autoregressive Conditional Heteroscedasticity Model; GAAP, Generally Accepted Accounting Principles; GLS, Ggeneralized Least Square; IASB, International Accounting Standards Board; IFRS, International Financial Reporting Standards; ML, Maximum Likelihood model; MV, Minimum Variance; OLS, Ordinary Least Square; PET, Precision Effect Test; PEESE, Precision Effect Estimation with Standard Errors test.

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that derivatives are designed to hedge the price risk exposure, firms can also use derivatives to earn a speculative profit by increasing their exposure to a specific risk. Corporate scandals, such as Metallgescellschaft[1] in 1993, provide evidence that the use of derivatives on commodities could destroy the value of a firm. These highly publicized corporate scandals reinforced the necessity to revise accounting standards on derivatives (Barnes, 2001).

The genuine question is why firms must be qualified to apply hedge accounting. The threshold of hedge effectiveness (80–125 rule) set up by hedge accounting is classified into effective and ineffective hedges. Both effective and ineffective hedges have the economic function of reducing a firm's risk exposure, but they have a different impact on a firm's earnings volatility. For effective hedges, the fair value changes of hedging derivatives are recorded in other comprehensive income (OCI) until the hedged item is recorded in earnings. For ineffective hedges, periodic fair value changes of hedging derivatives are reported directly in the income statement regardless of when the hedged item is recognized in the income statement. Therefore, qualifying or not qualifying for hedge accounting is essential from the accounting perspective.

The existing accounting literature provides evidence for the benefits of hedge accounting. According to Barton (2001), hedging reduces earnings volatility, and hedge accounting acts as a tool for earnings management. However, there is evidence that after implementing SFAS 133, hedging became less useful as a tool for smoothing earnings (Choi et al., 2015; Kilic et al., 2013). Furthermore, when a firm uses derivatives for hedging, it reduces the firm's cost of equity (Gay et al., 2011) and reduces the cost of debt (Chen and King, 2014). Dadalt, Gay and Nam (2002) conclude that eligibility to apply derivative accounting can reduce the information asymmetry of a firm. In contrast, Dewally and Shao (2013) and Lin and Lin (2012) find that firms using derivative accounting experienced increased information asymmetry.

A firm's eligibility to apply a derivative accounting standard is determined by the criteria set in accounting standards. There are two financial reporting guidelines for derivatives in the world. In 2014, the International Accounting Standards Board (IASB) issued IFRS 9: Financial Instruments.[2] IFRS 9 requires a hedge to have an economic relationship between the hedged item and the hedging instrument that offsets the risk. Furthermore, the optimal hedge ratio should remain appropriate to the firm's risk management strategy. In 2017, the Financial Accounting Standards Board (FASB) issued Accounting Standards Update (ASU) 2017–12 for Derivatives and Hedging (Topic 815): Targeted Improvements to Accounting for Hedging Activities. According to ASU 2017–12, the hedging relationships should be highly effective in achieving offsetting changes in fair values or cash flows attributable to the hedged risks. This effectiveness is required to be between 80 and 125 per cent. This is also known as the 80–125 test. According to the Comprehensive Guide to Derivatives and Hedging Report published by Ernst & Young Company (2019), in the mid-1990s, hedge accounting applied as long as the cumulative gains and losses from the futures contracts were between 60% and 167% of the offsetting cumulative losses and gains from the hedged items (i.e. a dollar-offset ratio range of 60%–167%). However, the Securities Exchange Commission (SEC) has objected to this wide range and revised the accounting policy to consider a dollar offset ratio of 80%–125%. Furthermore, this report mentions that SEC accepted the unofficial but "*generally accepted*" 80–125 rule. Nevertheless, there is no explanation as to why the 80–125 rule is ideal in this regard.

Albeit requiring hedging relationship to be "*effective*" is a prerequisite for hedge accounting, these accounting standards provide less clear guidance on measuring this effectiveness. Given the absence of specific guidelines, accounting practitioners following either US GAAP or IFRS have widely adopted two quantitative methods to measure the hedge effectiveness: dollar offset ratio (DOR) and regression method. DOR is the ratio of gains or losses of the hedging instrument to the gains or losses of the hedged position. Ideally, this ratio requires to be 1:1, but the accounting standard accepts this ratio to be between 80 and 125 per cent to consider an effective hedge. These boundaries of the hedge effectiveness test in the DOR method proved to be problematic during the periods when the volatility of prices of both the hedged position and the hedging derivative were nearly zero (Charnes et al., 2003; Finnerty and Grant, 2002; Frestad and Beisland, 2015; Kawaller and Koch, 2013).

In the regression model, we regress the cash market price of the hedged position on the price of the hedging instrument. The SEC in the US has indicated that firms can interpret both the R squared statistic and the slope coefficient of a regression output as measures of hedge effectiveness. According to the reports on derivative standards issued by KPMG (2020), it is "*generally accepted*" that a slope parameter (i.e. hedge ratio) within a range of negative 0.8 to 1.25 and an R squared parameter equal to or greater than 80% are considered as highly effective. However, it is noteworthy that the actual hedge ratio in practice can be different from this threshold level.

Existing studies introduce alternative techniques to estimate hedging effectiveness (Finnerty and Grant, 2002; Frestad and

[1] MG Refining and Marketing Inc. (MGRM) is a US subsidiary of Metallgesellschaft AG, a German conglomerate. In December 1993, the MGRM revealed an approximately USD 1.5 billion loss in their derivative-based trading strategy on oil. According to the US hedge accounting practices, MGRM could offset the unrealized loss on their futures contracts with the unrealized gain on their forward contracts. In contrast, German accounting principles on hedging allowed them to recognize only unrealized losses on the financial statements but did not allow them to recognize the unrealized gain on hedging. Therefore, MGRM reported a massive loss on derivative-related trading strategy on oil in the consolidated financial statements of Metallgesellschaft. If these differences in accounting standards did not prevail at that time, the story could have been different for Metallgesellschaft.

[2] FASB issues accounting standards applicable for the United States, whereas the rest of the world adopts accounting standards issued by the IASB. The information about the IFRS 9 and ASU 2017–12 is obtained from the reports issued by PricewaterhouseCoopers (PwC) (2017; 2018; 2019) and Ernst & Young (EY) (2019).

Beisland, 2015; Hailer and Rump, 2005; Kawaller and Koch, 2013). These studies conclude that the highly effective screening mechanism in FAS 133 and IAS39[3] is not an effective way to delineate the fine line between hedging and speculation (Frestad and Beisland, 2015; Hailer and Rump, 2005).

Surprisingly, a limited number of studies examine the appropriateness of this existing hedging effectiveness criterion of the 80–125 rule. Given the importance of being eligible to apply hedge accounting, such an effective screening criterion must be justifiable. Therefore, our study contributes to the current debate about the appropriateness of the hedging effectiveness screening test by using past academic literature. We scrutinize whether reported hedge ratios in the past academic literature met the 80 to 125 rule and were qualified for hedge accounting treatment.

We apply a meta-analysis methodology for this purpose. A meta-analysis is a statistical analysis of estimates collected from multiple studies to measure a similar effect. Our study synthesizes optimal hedge ratios from commodity futures hedging literature and analyses them. First, we estimate the average level of hedging effectiveness and the average optimal hedge ratio reported in the previous literature. The objective is to understand if these hedging strategies in the academic literature have been eligible to achieve the optimal hedge ratio between 80 and 125 per cent. Second, we examine whether there is a publication bias in reporting the optimal hedge ratios related to commodity futures hedging. The publication selection bias arises when there is a probability that researchers may either hide or not publish the estimates that are insignificant or have a different sign from what we expect to have. This is a problem as it distorts the accurate distribution of the effect. Finally, we investigate the factors determining the heterogeneity in the estimated hedge ratios in previous academic studies.

The rest of the paper is organized as follows. Section 2 briefly explains the evolution of derivative accounting. Section 3 summarizes the existing literature on hedging and possible factors affecting the optimal hedge ratio. In Section 4, we discuss the research design, including data characteristics. Section 5 introduces the meta-analysis methodology and presents the results thereof. Section 6 defines variables identified as potential determinants of the heterogeneity in hedge ratios. Section 7 describes the meta-regression methodology to evaluate the factors determining this heterogeneity in hedge ratios and discusses the results of each sub-sample. Finally, Section 8 summarizes the study's findings and concludes the paper.

2. Evolution of derivative accounting

FASB issues Generally Accepted Accounting Principles (GAAP) adopted in the United States, whereas IASB issues International Financial Reporting Standards (IFRS) adopted by approximately 120 nations globally.[4] Both FASB and IASB have published their reporting standards on derivative accounting and continuously updated them during the past decades. Table 1 provides a list of derivative-related accounting standards issued by the FASB and the IASB.

FASB issued several accounting standards on derivatives early on.[5] FAS 52: Foreign Currency Translation in 1981 and FAS 80: Accounting for Futures Contracts in 1984. Due to their limited scope (they did not cover contracts like interest rate derivatives and options), FASB introduced three new standards: FAS 105, FAS 107 and FAS 119 in 1990, 1991 and 1994, respectively.[6] These accounting standards mainly focused on improving the disclosure requirements related to derivative accounting. Neither were applicable for commodity derivatives. Therefore, FAS 80, FAS 105 and FAS 119 were superseded in 1998 by FAS 133: Accounting for Derivative Instruments and Hedging Activities.

FAS 133 was the first comprehensive standard that standardised derivatives' accounting practices. Hedging should be 'highly effective' to qualify for hedge accounting under FAS 133. This condition is satisfied if the gain or loss on the derivative offsets the change in earnings associated with the hedged item within 80–125 per cent. This effectiveness should be evaluated at the beginning of the hedge and on an ongoing basis whenever financial statements are reported or at least every three months. However, FAS 133 also offers latitude on how to measure hedging effectiveness.

FASB issued Accounting Standards Update (ASU) 2017–12 in 2017.[7] The threshold level of hedge effectiveness remains, and there is still less clarity on estimating hedging effectiveness. However, ASU 2017–12 removes the need to estimate and report the hedge ineffectiveness to simplify the reporting. Statistical tests are only required if the criterion for qualitative testing is not satisfied, and hedge effectiveness is only evaluated at the beginning of the hedge. By introducing these amendments, FASB intended to simplify hedge accounting and reduce firms' costs of applying hedge accounting.

IASB has also issued two major accounting standards on derivatives.[8] First, IAS 39: Financial Instruments: Recognition and Measurement was published in 2003. IAS 39 required hedge effectiveness to be 80 to 125 per cent but did not provide specific

[3] FASB issued FAS 133: Accounting for Derivative Instruments and Hedging Activities in 1998 and it was replaced by the ASU 2017–12. IASB has also issued IAS 39: Financial Instruments: Recognition and Measurement issued in 2003 and it was superseded by IFRS 9: Financial Instruments in 2014.

[4] This information is obtained from https://www.ifrs.com/ifrs_faqs.html#q3.

[5] For more details about the accounting standards issued by the FASB, please refer to https://www.fasb.org/home.

[6] FAS 105: Disclosure of Information about Financial Instruments with Off-Balance-Sheet Risk and Financial Instruments with Concentrations of Credit Risk, FAS 107: Disclosures about Fair Value of Financial Instruments and FAS 119: Disclosure about Derivative Financial Instruments and Fair Value of Financial Instruments.

[7] Please refer to https://www.fasb.org/jsp/FASB/FASBContent_C/GeneralContentDisplay&cid=1176169280252 for more details.

[8] For more details about the accounting standards issued by the IASB, refer to https://www.iasplus.com/en/standards/ias and https://www.ifrs.org/issued-standards/list-of-standards/.

Table 1
Evolution of derivative accounting standards.

Issued by FASB		Issued by IASB	
Year	Accounting Standard	Year	Accounting Standard
1981	FAS 52: Foreign Currency Translation	2003	IAS 39: Financial Instruments: Recognition and Measurement
1984	FAS 80: Accounting for Futures Contracts	2014	IFRS 9: Financial Instruments
1990	FAS 105: Disclosure of Information about Financial Instruments with Off-Balance-Sheet Risk and Financial Instruments with Concentrations of Credit Risk	2017	Prepayment Features with Negative Compensation (Amendments to IFRS 9)
1991	FAS 107: Disclosures about Fair Value of Financial Instruments	2019	Interest Rate Benchmark Reform (Amendments to IFRS 7 and 9)
1994	FAS 119: Disclosure about Derivative Financial Instruments and Fair Value of Financial Instruments.		
1998	FAS 133: Accounting for Derivative Instruments and Hedging Activities		
2017	Accounting Standards Update (ASU) 2017-12		

This table summarizes the historical development of the derivatives accounting standards issued by the Financial Accounting Standards Board in the US and the International Accounting Standards Board in the UK. FASB issues Generally Accepted Accounting Principles (GAAP) adopted in the United States, whereas IASB issues International Financial Reporting Standards (IFRS) adopted by approximately 120 nations globally.

guidelines for calculating the hedge effectiveness. Due to the complex nature of IAS 39 superseded it by IFRS 9: Financial Instruments in 2014. IFRS 9 requires the hedge ratio to remain appropriate with the firm's risk management strategy and be economically meaningful, rather than achieving a threshold level of 80–125 per cent hedging effectiveness. It further removes the need to conduct retrospective effectiveness tests. However, under IFRS 9, unlike in IAS 39, firms cannot voluntarily reverse their decision to apply hedge accounting when they are eligible for using the hedge accounting standard. IFRS 9 also allows the discretion of the accounting standard users to decide how to evaluate the hedging effectiveness.[9]

3. Literature review

The empirical evidence on futures hedging in commodity markets is voluminous.[10] The previous literature on derivatives consists of studies determining the optimal hedge ratio, testing hedging effectiveness and examining the factors affecting hedging effectiveness. There is limited empirical evidence on whether these optimal hedge ratios meet the threshold level of hedging effectiveness in the derivative accounting standard.

Futures hedging involves creating a simultaneous position in the futures market and the spot market of the underlying commodity to hedge the fluctuations in commodity prices. The optimal hedge ratio is the proportion of the cash market position covered with an offsetting position in a futures market. Due to its simplicity, the minimum variance (MV) hedge ratio was popular in early studies (Ederington, 1979; Johnson, 1960; Stein, 1961). To calculate the MV hedge ratio, we require regressing changes in cash prices of the hedged commodity on the changes in the prices of the relevant futures contract. The slope coefficient of this regression is the MV hedge ratio, and the R squared indicates the hedging effectiveness.

Theoretically, the optimal hedge ratio calculated will differ based on the objective function of the optimisation process. The other static hedge ratio models in the literature are the mean-variance hedge ratio (Hsin et al., 1994), Sharpe hedge ratio (Howard and D'Antonio, 1984), Maximum expected utility hedge ratio (Cecchetti et al., 1988; Lence, 1995, 1996), Minimum mean extended Gini (MEG) coefficient hedge ratio (Cheung et al., 1990; Kolb and Okunev, 1992), Minimum generalized semi-variance (GSV) hedge ratio (Chen et al., 2001; De Jong et al., 1997) and Maximum mean-GSV hedge ratio (Chen et al., 2001).[11]

Initially, the MV hedge ratio was estimated using the ordinary least square (OLS) regression estimator. This method has its criticisms due to its assumptions of homoscedastic error terms and no autocorrelation in the residuals of price series. Another criticism is that the MV hedge ratio is static and not time-varying. In order to overcome these issues, later studies have adopted ARCH and GARCH models and calculated time-varying hedge ratios (Bekkerman, 2011; Cecchetti et al., 1988; Choudhry, 2009; Haigh and Holt, 2002;

[9] As per the IFRS 9, there are three broad hedge accounting models: 1) Fair value hedge, 2) Cashflow hedge, and 3) Net investment hedge. In a fair value hedge, the risk being hedged is a change in the fair value of an asset or liability or an unrecognized firm commitment that is attributable to a particular risk and could affect P&L. Changes in fair value might arise through changes in commodity prices. The carrying value of the hedged item is adjusted for fair value changes attributable to the risk being hedged, and those fair value changes are recognized in P&L. The hedging instrument is measured at fair value, with changes in fair value also recognized in P&L. In cashflow hedge, the risk being hedged is the exposure to variability in cash flows that is attributable to a particular risk associated with a recognized asset or liability, an unrecognized firm commitment (currency risk only) or a highly probable forecast transaction and could affect P&L. Future cash flows might relate to existing assets and liabilities, such as future interest payments or receipts on floating rate debt. Volatility in future cash flows might result from changes in commodity prices. Finally, a net investment hedge, includes hedging the currency risk associated with the translation of the net assets of these foreign operations into the parent entity's functional currency. Exchange differences arising from the consolidation of these net assets are deferred in equity until the foreign operation is disposed of or liquidated. They are recognized in P&L, on disposal or liquidation, as part of the gain or loss on disposal.

[10] Refer to Carlton (1984), Carter (1999), Chen et al. (2003), Garcia and Leuthold (2004) and Gray and Rutledge (1971) for literature surveys on commodity futures markets.

[11] Please refer to Chen et al. (2003) for a literature review on different futures hedge ratios.

Moschini and Myers, 2002; Myers, 1991). The error correction model (ECM) considered the long-term co-integration of commodities' spot and futures price series (Ghosh, 1993; Juhl et al., 2012; Lien, 1996; Tse, 1995). To cater to this autocorrelation issue, several other studies have used either the estimated generalized least square (EGLS) model (Brorsen et al., 1998; Franken and Parcell, 2003) or the generalized least square (GLS) model (Kim et al., 2015). These EGLS and GLS estimators correct the model for autocorrelation and heteroscedasticity in time series. The sample of the previous academic papers selected for this meta-analysis includes studies estimating the MV hedge ratio using OLS, GLS, Co-integration, ECM, GARCH model and the maximum likelihood (ML) model.

The existing literature suggests that the optimal hedge ratio and hedging effectiveness vary substantially between the adopted theoretical models and statistical estimators. We similarly identify several other factors affecting the heterogeneity in reported hedge ratios across academic literature. First, the hedge horizon affects the optimal hedge ratio and hedge effectiveness (Chen et al., 1987; Chen et al., 2004; Juhl et al., 2012). With a longer hedge horizon, the hedge ratio and hedge effectiveness increase (Chen et al., 1987, 2004).

Second, Laws and Thompson (2005) suggest that the success of futures-based hedging varies depending on whether the hedge is direct hedge or cross-hedge.[12] The findings of cross-hedging strategies are inconclusive regarding whether cross-hedging or direct hedging is better. The cross-hedging has been effective in the case of hedging ethanol (Franken and Parcell, 2003) and dairy commodities (Bialkowski and Koeman, 2018). Cross-hedging was ineffective in hedging ethanol (Dahlgran, 2009) and winter Canola (Kim et al., 2015). Given these findings, one might expect the effectiveness of cross-hedging to vary with the type of commodity being hedged.

Another alternative for direct hedging is multi-product hedging. It involves hedging using futures contracts of more than one commodity. Multi-product hedging proved to be more beneficial than single-product hedging and proportional hedging in locations where the prices of multiple products are highly correlated (Fackler and McNew, 1993; Franken and Parcell, 2011; Miller, 1982a, 1982b; Tejeda and Goodwin, 2011).

Third, the existing literature has modified the traditional regression model of estimating the optimal hedge ratio by including additional explanatory variables in the model. Previous studies conclude that adding year dummies could improve the hedging effectiveness (Carter, 1984; Revoredo-Giha and Zuppiroli, 2013). Furthermore, controlling the transaction cost has also significantly affected the optimal hedge ratios (Mattos et al., 2008). Accordingly, the heterogeneity in optimal hedge ratio is possibly determined based on the design of the hedge, hedging horizon, type of contract used, and the type of commodity hedged in each study.

In addition, based on the meta-analysis literature (Arestis et al., 2015; Astakhov et al., 2017; Bessler et al., 2019; Bialkowski and Perera, 2019; Churchill and Yew, 2017; Geyer-Klingeberg et al., 2018; Zigraiova and Havranek, 2016), we add publication characteristics also as explanatory variables of the heterogeneity in optimal hedge ratio in previous literature.

4. Research design

4.1. Alternative regression models in original studies

There are three types of regression models used to estimate the MV hedge ratio in the previous literature:

$$S_t = a_0 + a_1 F_t + e_t \tag{1}$$

$$\Delta S_t = a_0 + a_1 \Delta F_t + e_t \tag{2}$$

$$R_s = a_0 + a_1 R_f + e_t \tag{3}$$

Equation (1) regresses the spot prices of the commodity on day t (S_t) on the prices of the futures contract used to hedge on day t (F_t) in price levels. In equation (2), ΔS_t and ΔF_t denote the price changes of spot prices and the futures prices of commodities and futures contracts. Equation (3) regresses commodity spot returns (R_s) on the returns of futures contracts (R_f). In all three regression models, a_1 denotes the MV hedge ratio. We have collected these hedge ratio estimates, their respective standard errors or t statistics from the sample of studies selected for this meta-analysis.

There is a debate in the existing literature regarding whether to use price levels, price changes or percentage changes of prices (returns) in the regression model mentioned above. Studies argue that return-based regressions are statistically more valid than price-level regressions because residuals of the cash and futures prices are likely to be highly correlated in price-level regressions (Benninga et al., 1984; Brown, 1985; Hill and Schneeweis, 1981). Despite this debate, price-level regression has been used even in recently published studies (Altman et al., 2008; Brinker et al., 2009; Chen et al., 2004). A recent study concludes that a hedge ratio calculated based on the price level regressions is superior to a hedge ratio calculated based on price change regressions (Jiang et al., 2016).

Additionally, it is essential to understand that there are different interpretations for the optimal hedge ratios estimated under each of the above three regression models. The hedge ratio derived from equation (1) is the ratio of the number of futures contract units to the number of cash position units hedged to offset the cash position price volatility. The price change regression in equation (2) provides the ratio of the proportional number of units of the futures contracts to the proportional number of units of the spot contract. The hedge ratio in equation (3) is the ratio of the futures position's value to the cash position's value that must be hedged to mitigate the cash position's return volatility.

[12] Cross-hedging involves hedging the cash prices of a selected commodity using the futures prices of another (but related) commodity.

Due to these differences in the interpretation of the optimal hedge ratios, we are unable to combine all the collected hedge ratio estimates into one sample for the meta-analysis. Unfortunately, we do not have the sample sizes (or the degrees of freedom) of the hedge ratio estimates in the original studies. Therefore, we could not calculate the partial correlation coefficient (PCC) (i.e. the standard practice in meta-analysis) to remove the problem of this different measurement unit in regression models. Hence, this study analyses data in three sub-samples depending on the type of regression model: price level, price change and return.

4.2. Data sample

The first step of a meta-analysis is collecting relevant studies on the selected research theme. Then, based on the findings of these selected studies, a meta-analyst estimates the overall effect of the selected relationship after controlling for publication bias. Our research aims to provide research-based evidence regarding the average optimal hedge ratio. In other words, we aim to identify the overall optimal hedge ratio or its range based on the previous academic literature after controlling for any publication bias.

For this purpose, we have searched for papers using these keyword combinations (and/or): "Hedge ratio and commodity markets", "Hedging effectiveness and commodity markets", "Minimum variance hedge ratio and commodity markets", "Optimal hedge ratio and commodity markets", "Futures hedging and commodity markets" and "Cross-hedging and commodity markets". We have collected papers from these electronic databases: Google Scholar, Ebscohost, JSTOR, Science Direct, Research Gate, SSRN and EconRep. There is no precise answer for how many papers must be collected or selected for a meta-analysis study. The practice is to conduct a comprehensive search by collecting papers on a particular topic and then choose the best comparable papers to code[13]. According to Stanley and Doucouliagos (2012), the average number of studies included in 87 meta-analyses was 41, with the median being 35.

Given the variety of theoretical models adopted to measure the optimal hedge ratio, we have restricted this study to collecting MV hedge ratios estimated using OLS, GLS, EGLS, ARCH, GARCH, co-integration, ECM and ML estimators. In order to conduct the meta-analysis, we require effect sizes (estimated hedge ratios) and their respective standard errors from the original studies. Thus, we had to omit the studies that do not provide standard errors or any other statistical measures that allow us to calculate the standard error of the estimated hedge ratio in the original research. Furthermore, we concentrate only on futures contracts–based hedging and exclude the studies on option-based hedging. We have collected papers written in English and excluded those reported in other languages.

We terminated the search for papers in this study on July 5, 2019. After considering and eliminating papers based on the above criteria, we selected only 38 papers for coding from a total sample of 406 research papers. We have collected 1699 hedge ratio estimates from these 38 papers. The selected papers represent four commodities included in the Bloomberg Commodity Index: energy, agriculture, precious metals and livestock. We have gathered direct hedge, cross-hedge, multi-product hedge, and proportional hedge ratios. We have aggregated these hedge ratio estimates for different countries, for different exchanges, on different commodities for different periods in one database, assuming the market conditions at the time of each study are similar across countries, exchanges, commodity sectors and periods.

4.3. Sample characteristics

The papers selected for the study were published from 1972 to 2018. There are nine studies (25.5 per cent of estimates) published before 1990, five studies (39.5 per cent of estimates) published between 1990 and 1999 (inclusive) and 13 studies (35 per cent of estimates) published on or after 2000. The sample includes papers published in ranked (31) and non-ranked journals (7). Based on the ABDC Journal Ranking system,[14] there are 19 studies published in A- and A*-ranked journals, 4 in B-ranked journals and 7 in C-ranked journals. Furthermore, these studies are published in 17 different journals.

Table 2 provides descriptive statistics of the hedge ratios, standard errors and *t* statistics collected for these three sub-samples. The sub-samples are created based on the type of regression model used. Accordingly, the mean hedge ratio is 1.33, 0.63 and 0.60 for the level, price change and return sub-samples, respectively. These mean hedge ratios in the sub-samples do not fall under the expected threshold level of 0.8–1.25 required by the accounting standard. Therefore, it is reasonable and valid to examine whether the optimal hedge ratio of these academic studies falls upon this 80-125 band using a meta-analysis methodology.

In addition, we have summarized the descriptive statistics for hedge ratios, standard errors, and *t* statistics based on each commodity type. We graphically present the average hedge ratio of each commodity sector in Fig. 1. These graphs show that the mean hedge ratio varies depending on the commodity sector. Surprisingly, none of these commodity sectors has reported a hedge ratio within the expected threshold level required by the accounting standard to be eligible for applying derivative accounting practices, except the precious metals sector.

[13] Coding is the process of collecting data from the selected studies. In the meta-analyses, researchers expect effect sizes to vary across studies. Coding the original studies highlights the contexts, participants, and methods used in relevant studies so that the reviewer understands the limits of the external validity of the review (Wood and Eagly, 2009). The meta-analyst extracts these data from the acceptable studies when the literature search is completed. Coding data for a meta-analysis is context specific. Meta-analysts must code the data required to calculate effect sizes and other variables that could explain the heterogeneity in the acceptable studies. According to the standard practice in the meta-analysis, each selected paper will be coded by two individuals to ensure consistency and accuracy.

[14] Journal ranks are based on the ABDC Journal Ranking System published in 2017. Retrieved from http://www.abdc.edu.au/master-journal-list.php.

Table 2
Descriptive statistics.

Type of the Regression	Variable	Observations	Mean	Minimum	Maximum	Standard Deviation	Skewness	Kurtosis
Price level	Effect size (Hedge ratio)	863	1.3332	−2.9500	7.0600	0.9753	1.4207	8.8162
	Standard error	863	0.1409	0.0032	1.7791	0.1534	3.4751	25.1519
	T statistic	863	25.0600	−7.3600	255.0000	38.8193	3.4561	15.7748
Price change	Effect size (Hedge ratio)	625	0.6326	−1.1710	4.8100	0.6402	−0.5507	7.9024
	Standard error	625	2.4258	0.0015	42.7200	6.5029	3.1208	12.8158
	T statistic	625	59.1767	−27.3750	728.0000	156.0817	3.6801	15.4043
Returns	Effect size (Hedge ratio)	211	0.6013	−1.2220	3.0540	0.5275	0.1097	6.1638
	Standard error	211	0.1146	0.0041	1.5208	0.1751	4.7585	30.7186
	T statistic	211	18.2678	−12.2375	241.4800	38.2271	3.2410	14.1602

This table summarizes the mean, minimum and maximum values, standard deviations, skewness and the kurtosis of the minimum variance (MV) hedge ratios, standard errors and *t* statistics in the original studies. The results are reported for three sub-samples based on the type of the regression: price level, price change and returns. The data are collected from 38 selected papers given in the appendix.

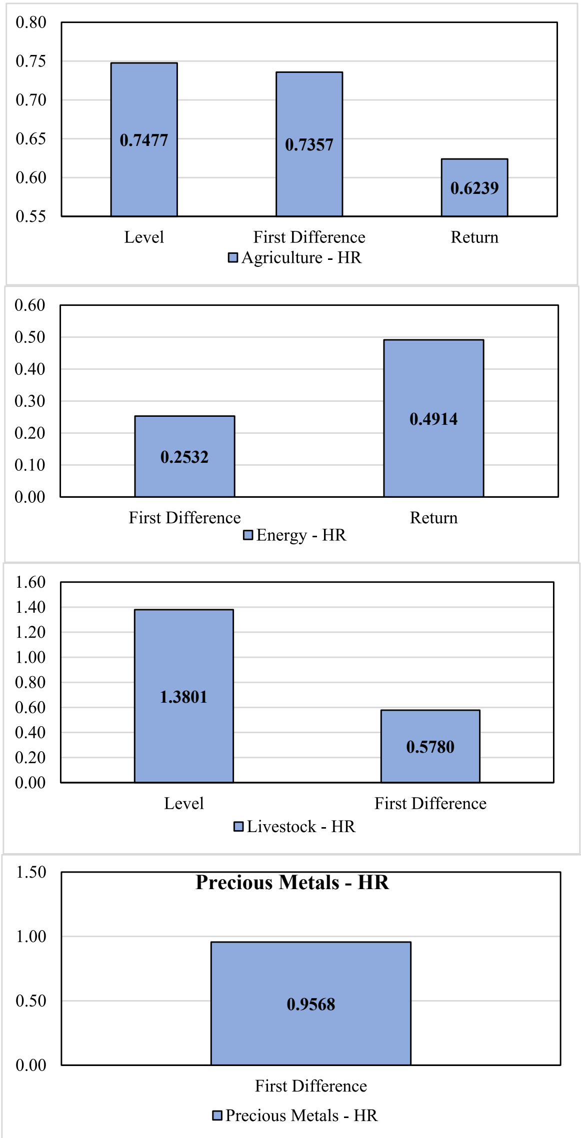

Fig. 1. Mean hedge ratios (HR) by commodity sector.

5. Testing for publication bias

5.1. FAT-PET-PEESE approach

The meta-analysis methodology is an emerging methodology in finance; hence, only a handful of meta-analysis studies have been published in finance to date.[15] This study adopts the standard FAT-PET-PEESE[16] approach in the meta-analysis methodology to examine the publication bias.[17]

We initially test the publication bias using a visual test called funnel plot (Egger et al., 1997) and then test statistically using the funnel asymmetry test (FAT) (Card and Krueger, 1995). Figs. 2–4 depict the funnel plots of the estimated hedge ratios collected from the original studies on the horizontal axis and their respective precision (i.e. the inverse of the standard error of the estimate) on the vertical axis. Figs. 2 and 4 display the possible existence of a positive publication bias relating to the MV hedge ratios calculated based on the price level and return sub-samples. The wide dispersion in the funnel plot indicates the heterogeneity of the MV hedge ratio estimates in the original studies. Fig. 3 shows the estimated MV hedge ratios based on price changes are equally distributed with less dispersion.

Next, we conduct the FAT that analyses the relationship between the estimated effect size and standard errors using the following meta-regression model. If there is publication bias, the relationship between the estimated hedge ratios and their respective standard errors is expected to be statistically significant.

$$\alpha_{ij} = \beta_0 + \beta_1 SE_{ij} + \varepsilon_i \tag{4}$$

where α_{ij} is the estimated MV hedge ratio from regression j in study i and SE_{ij} is the standard error of the estimated MV hedge ratio from regression j in study i. The constant (β_0) measures the overall hedge ratio corrected for potential publication bias, slope coefficient (measures the extent of publication bias and ε_i is the error term. Testing the hypothesis $H0$: $\beta 1 = 0$ is known as FAT, and testing the hypothesis $H0$: $\beta 0 = 0$ is known as the precision effect test (PET). If $H0$: $\beta_1 = 0$ is rejected, implying a publication bias related to commodity market estimated hedge ratios. The direction of the publication bias depends on the sign of the slope coefficient. If $H0$: $\beta_0 = 0$ is rejected; it can be concluded that the model has estimated the true hedge ratio after correcting for publication bias.

The OLS estimation of equation (4) above can suffer from heteroscedasticity. Therefore, we estimate equation (4) using either a fixed effect (FE) or a random effect (RE) model and using two weighting schemes: weight 1 and weight 2 (Please refer to Appendix B for more details of this weighting scheme). The FE model assumes that one true effect size underlies all the studies. In contrast, the RE model assumes a distribution of true effects. These differences in the estimated MV hedge ratios across studies arise due to sampling error and genuine differences in the underlying hedge ratio estimate in the original studies. Therefore, the total variability in a hedge ratio estimate consists of two components under the RE model: fixed effect error variance (υ_i) and the estimated variance of the population hedge ratios across studies (τ^2).

In the Precision Effect Test (PET), when the results reject $H0$: $\beta_0 = 0$, concludes that β_0 is the true effect after controlling for publication bias. Stanley and Doucouliagos (2012) suggest using a non-linear model instead of the standard error because they argue that the effect is related to the variance, i.e., the square of the standard error in the original study. They claim that this is a more accurate correction for publication bias. This regression model (Eq. (5)) is known as the precision-effect estimation with standard errors (PEESE) test.

$$\alpha_{ij} = \beta_0 + \beta_1 SE_{ij}^2 + \varepsilon_i \tag{5}$$

where α_{ij} is the estimated MV hedge ratio from regression j in study i, SE_{ij}^2 is the square of the standard error of the estimated MV hedge ratio from regression j in study i and ε_i is the disturbance term. Similar to FAT-PET, we use weight 1 and weight 2 with PEESE as well. For example, the PEESE regression in equation (5) will be as follows after weighting with weight one under the FE model.

$$t_{ij} = \beta_1 SE_{ij} + \beta_0 \left(\frac{1}{SE_{ij}}\right) + \upsilon_i \tag{6}$$

This regression model in equation (6) does not include a constant term. In PEESE also, the hypothesis test is $H0$: $\beta_0 = 0$. If β_0 is significant, the study further convinces us that the model provides a genuine hedge ratio estimate after controlling for publication bias.

[15] These are examples of a few recent applications of meta-analysis in finance: Arestis et al. (2015); Asongu (2015); Astakhov et al. (2017); Bessler et al. (2019); Bialkowski and Perera (2019); Ewjik et al. (2012); Geyer-Klingeberg et al. (2018); Rusnak et al. (2013), and Wimmer (2021) and Winkelried (2021) and Zigraiova and Havranek (2016).

[16] This FAT-PET-PEESE procedure is a valid method of analysis and has been adopted in several recent studies in economics and finance literature: Churchill and Yew (2017), Costa-Font et al. (2011), Efendic et al. (2011), Havránek (2010), Iwasaki and Tokunaga (2014), Kim et al. (2014) and Linde Leonard, Stanley and Doucouliagos (2014). Therefore, this study also follows the same methodology adopted by the previous meta-analysis researchers since the findings in the PET of this study were significant.

[17] According to Card and Krueger (1995), publication selection bias may arise for three reasons. First, journal editors may tend to publish papers that have effects consistent with the expected theoretical relationship. Second, it is likely that statistically significant effects will have a greater probability of getting published or being reported. Third, research can be biased by selecting models which confirm the expected results. Related to this publication bias, Doucouliagos and Stanley (2013) find that most studies in empirical economics suffer from publication bias.

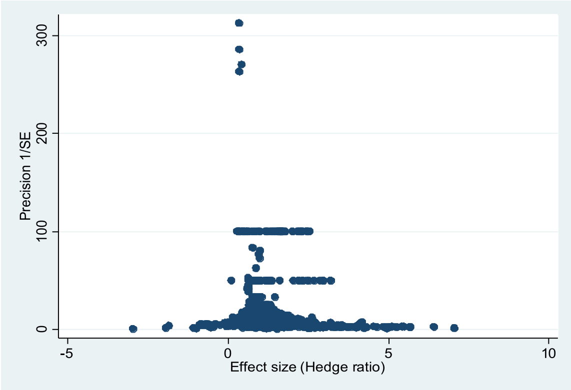

Fig. 2. Funnel plot of hedge ratios – Price level.

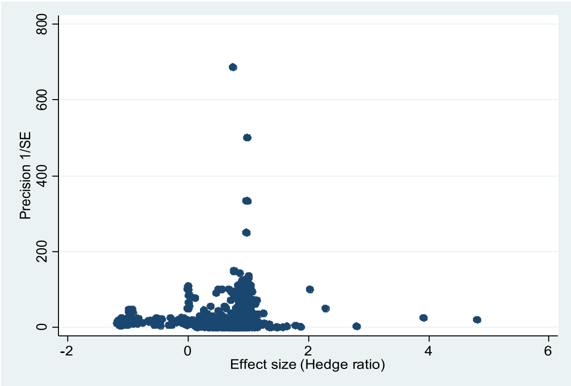

Fig. 3. Funnel plot of hedge ratios – Price change.

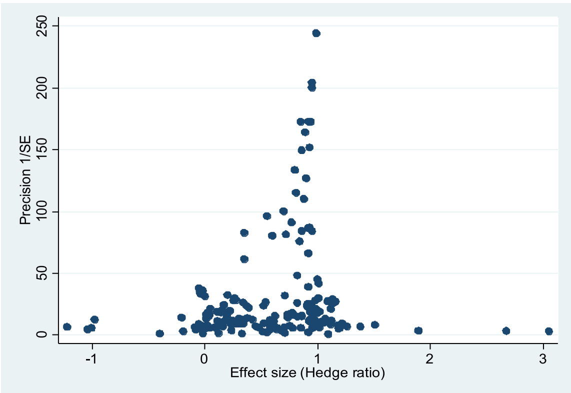

Fig. 4. Funnel plot of hedge ratios – Returns.

5.2. FAT-PET-PEESE results

Table 3 summarizes the FAT and PET results for each sub-sample: price level, price change and return. The second and third columns provide results for the FE model with weights 1 and 2, respectively. The fourth and the fifth columns offer results to the RE model with weights 1 and 2, respectively.

In the price level sub-sample, the evidence for publication bias related to hedge ratio estimates in commodity markets is inconsistent across different models. We find evidence to reject the $H0$: $\beta_0 = 0$ under all models, except the RE model with weight 2. This

Table 3
Funnel asymmetry test (FAT) and precision effect test (PET) results.

	FE with Weight 1	FE with Weight 2	RE with Weight 1	RE with Weight 2
Price level				
FAT (β_1)	**4.5324*****	**−4.7037*****	**2.1706*****	−2.5948
	0.0414	1.2709	0.2255	15.1872
PET (β_0)	**0.9760*****	**0.6953*****	**1.0333*****	0.6578
	0.0011	0.0245	0.0403	0.6552
Observations	863	863	863	863
Price change				
FAT (β_1)	**−5.1769*****	**2.1777****	−0.0117	−1.0747
	0.0464	0.8681	0.1006	6.1567
PET (β_0)	**0.9066*****	**1.1197*****	**0.6049*****	**1.1663****
	0.0007	0.0179	0.0303	0.5797
Observations	625	625	625	625
Returns				
FAT (β_1)	**−5.0911*****	**−5.2340*****	−0.3823	0.2028
	0.0843	1.5711	0.3484	12.4709
PET (β_0)	**0.9040*****	**0.7735*****	**0.6395*****	0.5088
	0.0017	0.0579	0.0459	0.9091
Observations	211	211	211	211

This table reports the coefficients of β_1 (FAT) and β_0 (PET), respectively, for the three sub-samples: price level, price change and returns. The top value is the coefficient estimate, and the value in parentheses is the associated standard error. The first two columns provide the results under the fixed effect (FE) model with weights 1 and 2, respectively. The third and fourth columns provide the results under the random effect (RE) model with weights 1 and 2, respectively. With weight 1, each estimate is given equal weight, and with weight 2, each study is given equal weight. FE and RE estimates have robust standard errors clustered by the StudyID. Price level, price change, and return sub-samples have 863, 625 and 211 observations. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

study finds positive publication bias under the FE and RE models with weight 1 but negative publication bias under the FE model with weight 2. The average hedge ratio estimate of the price level sub-sample lies between 0.6953 and 1.0333. Thus, we conclude that these models have estimated the true hedge ratios after correcting publication bias in this sub-sample.

Table 4
PEESE test results.

	FE with Weight 1	FE with Weight 2	RE with Weight 1
Price level			
β_0 (True Effect)	**1.0411****	**0.6208*****	**1.2456*****
	0.0009	0.0121	0.0308
SE	**6.7346*****	−16.8576	
	0.1649	12.6184	
SE/SQRT (Total Variance)			**2.0192*****
			0.3232
Price change			
β_0 (True Effect)	**0.8654*****	**1.1475*****	**0.6041*****
	0.0006	0.0141	0.0295
SE	−0.0048	−0.0305	
	0.0058	0.5465	
SE/SQRT (Total Variance)			0.0006
			0.0058
Returns			
β_0 (True Effect)	**0.8468*****	**0.6480*****	**0.6088*****
	0.0014	0.0399	0.0351
SE	**−5.6241*****	−20.0422	
	0.3311	13.6690	
SE/SQRT (Total Variance)			−0.1726
			0.4249

This table reports the coefficients of the PEESE test for the three sub-samples: price level, price change and return. The top value is the coefficient estimate, and the value in parentheses is the associated standard error. The second and third columns provide the results under the fixed effect (FE) model with weights 1 and 2, respectively. The fifth column provides the results under the random effect (RE) model with weight 1. With weight 1, each estimate is given equal weight, and with weight 2 each study is given equal weight. FE and RE estimates have robust standard errors clustered by StudyID. Price level, price change, and return sub-samples have 863, 625 and 211 observations. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

We also find mixed evidence on publication bias for the price change sub-sample. There is a negative publication bias with weight 1 of the FE model, whereas there is a positive publication bias with weight 2 of the FE model. The average hedge ratio estimate is positive and lies between 0.6049 and 1.1663 after correcting publication bias.

Concerning the return sub-sample, the FE regression model provides evidence for negative publication bias related to the hedge ratio of commodity markets. The RE models do not provide evidence of publication bias. Furthermore, the results suggest that the overall hedge ratio is positive and lies between 0.6395 and 0.9040 after controlling for publication bias.

In summary, there is no consistent evidence on the direction of the publication bias related to the hedge ratio estimates in commodity markets. Our findings confirm that the true hedge ratio estimate, on average, lies between the range of 0.60 and 1.20 for all sub-samples. Given these findings, we conclude that most commodity hedging strategies reported in the academic literature satisfy the minimum threshold level of the hedge ratio set by the accounting standard.

However, the hedging strategies with an average optimal hedge ratio between 0.60 and 0.79 will not be qualified to apply the standard. Hedge accounting allows for recognising gains and losses on both hedging instruments and hedged items in the statement of comprehensive income in the same accounting period. The problem arises when the optimal hedge ratio is close to 0.80 but still not eligible to apply derivative accounting standards, as it increases earnings volatility in the statement of comprehensive income. All the hedges reported in the academic literature in commodity markets with an optimal hedge ratio of 0.6–0.8 will not be eligible to apply

Table 5
Determinants of the heterogeneity in hedge ratios.

Variable	Description
Data Characteristics	
T statistic	The estimated hedge ratio divided by the respective standard error of the estimate
Precision	The inverse of the standard error of the estimated hedge ratio
MidYear	The mean year of the sample period
Hedge Horizon	
Daily	Equals 1 if the daily data are used in the original study
Weekly	Equals 1 if the weekly data are used in the original study
Reference: Other	Equals 1 if any other frequency of data is used in the original study
Design of the Hedging	
Direct hedge	Equals 1 if commodity hedged and the underlying commodity of the futures contract is the same
Cross-hedge	Equals 1 if commodity hedged and the underlying commodity of the futures contract are close substitutes or highly correlated
Multi-hedge	Equals 1 if multiple futures contracts on different commodities used to hedge at the same time
Reference: Other	Equals 1 if any other hedging strategy is involved
Commodity Type	
Agriculture	Equals 1 if hedging involves an agricultural commodity (excluding livestock)
Energy	Equals 1 if hedging involves a commodity from the energy sector
Livestock	Equals if hedging involves a livestock
Reference: Other	Equals 1 if hedging involves a precious metal
Estimation Method	
OLS	Equals 1 if ordinary least squares method is used to estimate the hedge ratio
GLS	Equals 1 if generalized least squares method is used to estimate the hedge ratio
Co-inte	Equals 1 if the co-integration estimator is used to estimate the hedge ratio
ECM	Equals 1 if error correction model is used to estimate the hedge ratio
Reference: Other	Equals 1 if any other estimation method is used to estimate the hedge ratio
Control Variables	
Lag	Equals 1 if lags of cash prices and/or futures prices are included in the estimation equation
Other commodities	Equals 1 if multiple commodities are included in the estimation equation
Time dummies	Equals 1 if time dummies (monthly dummies, year dummies, seasonal dummies) are included in the estimation equation
Basis	Equals 1 if basis lags or basis at the beginning are included in the estimation equation
Reference: Other	Equals 1 if any other control variables are included in the estimation equation
Publication Characteristics	
PubYear	The year in which the paper is published
Impact factor	The impact factor of the journal in which the paper is published obtained from https://ideas.repec.org
Rank A	Equals 1 if the ABDC ranking of the journal is A or A*
Rank B	Equals 1 if the ABDC ranking of the journal is B
Rank C	Equals 1 if the ABDC ranking of the journal is C
Reference: No Rank_ABDC	Equals 1 if there is no ABDC ranking for the journal
Scimago < 1	Equals 1 if the Scimago ranking of the journal is less than 1
Scimago < 2	Equals 1 if the Scimago ranking of the journal is less than 2 but greater than 1
Scimago > 2	Equals 1 if the Scimago ranking of the journal is greater than 2
Reference: No Rank_Scimago	Equals 1 if there is no Scimago ranking for the journal

This table defines the variables included in the meta-regression analysis as possible explanatory variables of the heterogeneity in the estimated hedge ratios in the original studies. These variables are coded from the list of studies included in the appendix.

hedge accounting.

As a robustness check and to improve the accuracy of the true hedge ratio estimate, the analysis is extended to conduct the PEESE test. Table 4 presents the results of the PEESE test. We exclude the RE model with weight 2 in the PEESE test, as β_0 coefficients of the PET analysis of that model were not significant. The results show that the hedge ratio estimates are positive and significant. On average, the optimal hedge ratio lies between 0.62 and 1.24, 0.60–1.15 and 0.60–0.85 for the price level, price change and return sub-samples, respectively. Our PEESE test findings also identify that not all the hedging strategies applied in academic studies are qualified to use the hedge accounting standard as the lower level of the hedge ratio lies around 0.6.

Furthermore, we also conducted the FAT-PET-PEESE test for each commodity type under each sub-sample (price level, price change, and return). We do not present these results in this paper, but the results are available from the authors upon request. According to our findings, estimated hedge ratios vary significantly between the type of commodity, and there is no consistent evidence of publication bias in relation to each commodity type. Therefore, we question the appropriateness of setting a single common threshold hedge ratio for all different types of commodities and other assets.

6. Heterogeneity of estimated hedge ratios

The factors explaining the heterogeneity in meta-regression can be classified into two broad categories: structural heterogeneity and methodological heterogeneity. Structural heterogeneity includes differences among the primary studies, whereas methodological heterogeneity explains the differences in the design and the methodology used. We have identified data characteristics, commodity sector and publication characteristics to describe the structural heterogeneity in the original studies. The design of the hedge, estimation method, and other control variables included in the model also explain the methodological heterogeneity in those studies.

Accordingly, Table 5 lists the different variables identified from the original studies that could explain the variation in the estimated hedge ratios in commodity markets. The existing literature confirms that the estimation method, hedging strategy, hedge horizon, and other control variables affect the optimal hedge ratio. This study adds publication characteristics, following the previous meta-analysis studies in economics and finance (Arestis et al., 2015; Astakhov et al., 2017; Bessler et al., 2019; Churchill and Yew, 2017; Geyer-Klingeberg et al., 2018; Zigraiova and Havranek, 2016).

All these variables are manually coded by reading the sample of 38 papers selected. A selection bias is involved here because the variables are selected based on data available in the original studies in the sample. Table 6 summarizes these unweighted and weighted (by 1/SE) descriptive statistics (mean and standard deviation) of the coded variables.

6.1. Data characteristics

Data characteristics include the standard error (*SE*) of the estimated hedge ratio and the *MidYear* of the sample period in the original study. Theoretically, the meta-regression model suggests that the estimated hedge ratios in the initial studies relate to their respective standard errors. The average *SE* is 0.14, 2.43 and 0.11 for the sub-samples of the price level, price change and returns, respectively.

MidYear variable is the midpoint of the sample period in the original studies included to control for any structural changes in the period of the original research. The average *MidYear* is 1987, 1992 and 2004 for the price level, price change, and return sub-samples, respectively. It indicates that researchers have first used the price level–based regression model and then moved into the price change regression model due to the statistical issues with price levels. In recent years, the return-based regression model has become popular among researchers.

6.2. Hedge horizon

To account for the differences in the hedge horizon, we use the data frequency in the original studies. We have created three dummy variables: *Daily, Weekly* and *Reference Frequency* (includes all the other data frequencies). More than 50 per cent of the original studies used daily frequency data in all sub-samples. The price level and return sub-samples use weekly data as the second-best popular data frequency. The price change sub-sample has both weekly (17 per cent) and reference frequency data (17 per cent) equally.

6.3. Design of the hedge

As discussed in the literature review, the type of hedging will affect the hedge ratio estimates. We have created three dummy variables to represent the type of hedging involved. The *Direct-hedge* variable equals one if the futures contract's underlying commodity is the same as the commodity hedged in the study. The *Cross-hedge* variable equals one when the original study uses a futures contract of a closely related commodity to hedge the exposure of the commodity in concern. *Cross-hedge* involves using a single related commodity to hedge the commodity in concern. The *Multi-hedge* variable equals one when the original study uses more than one cross-hedge contract to hedge the commodity's exposure in concern. Ninety-six per cent of the studies in the price level sub-sample used a cross-hedging strategy, 66 per cent of the price change sub-sample used a direct-hedging strategy, and 40 per cent of the return sub-sample used a multi-hedging strategy.

Table 6
Descriptive statistics of meta-regression variables.

Variable	Price level		Price change		Return		Price level		Price change		Return	
	Mean	SD	Mean	SD	Mean	SD	Weighted Mean	Weighted SD	Weighted Mean	Weighted SD	Weighted Mean	Weighted SD
Data Characteristics												
Standard Error/FE Precision	0.1409	0.1534	2.4258	6.5029	0.1146	0.1751	20.9900	30.2952	32.3254	54.9687	28.4920	40.3843
MidYear	1987.5900	5.9566	1992.3500	13.4118	2004.1040	9.1557	41,750.0740	60,439.3299	64,304.7000	109,268.4000	57,059.7600	80,830.7400
Hedge Horizon												
Daily	0.5562	0.4971	0.6560	0.4754	0.6493	0.4783	8.7070	20.7459	26.6339	56.7269	24.6072	42.1870
Weekly	0.4299	0.4953	0.1696	0.3756	0.2844	0.4522	11.8498	26.2822	3.0794	8.4858	3.1139	6.2531
Reference: Other	0.0116	0.1071	0.1744	0.3798	0.0664	0.2495	0.2558	2.7528	2.6121	7.1682	0.7709	2.9952
Design of the Hedging												
Direct hedge	0.0382	0.1919	0.6608	0.4738	0.3270	0.4702	0.7415	6.1485	25.0149	54.5356	18.9134	43.4573
Cross-hedge	0.9606	0.1947	0.1728	0.3784	0.2654	0.4426	20.1906	30.1580	4.7956	19.6292	4.0064	7.9906
Multi-hedge	0.0012	0.0340	0.1648	0.3713	0.4076	0.4926	0.0579	1.7020	2.5012	7.2496	5.5722	9.3495
Reference: Other			0.0016	0.0400					0.0136	0.3390		
Commodity Type												
Agriculture	0.0742	0.2622	0.7248	0.4470	0.8294	0.3771	4.5986	24.2826	19.9874	45.4715	27.0834	41.1602
Energy			0.2176	0.4129	0.1706	0.3771			9.2307	35.8003	1.4086	3.6591
Livestock	0.9258	0.2622	0.0288	0.1674			16.3914	21.8880	0.8181	5.4360		
Reference: Other			0.0288	0.1674					2.2891	14.0673		
Estimation Method												
OLS	0.6292	0.4833	0.6032	0.4896	0.4739	0.5005	12.8978	30.5126	11.3523	30.9354	20.3481	43.0828
GLS	0.3685	0.4827			0.1137	0.3183	8.0922	13.9915	0	0	2.1083	6.8512
Co-integration			0.1872	0.3904					9.6585	24.0482		
ECM			0.1312	0.3379					2.9104	15.6768		
GARCH			0.0160	0.1256	0.1896	0.3929			1.8267	14.5442	1.5930	3.8635
MLE					0.1896	0.3929			0	0	3.8700	8.9145
Reference: Other			0.0448	0.2070	0.0332	0.1795			2.2521	13.8025	0.5726	3.2681
Control Variables												
Lag	0.0116	0.1071	0.3824	0.4864	0.0284	0.1666	0.3423	4.1609	16.0663	31.4072	0.4234	2.5738
Other commodities	0.0290	0.1678	0.1392	0.3464	0.4028	0.4916	1.6221	11.4247	2.1623	6.5011	5.4612	9.2753
Time dummies	0.0359	0.1862	0.0416	0.1998	0.1280	0.3348	0.5413	4.6379	0.9456	5.6938	5.7409	18.7785
Basis	0.4171	0.4934	0.0928	0.2904			2.6903	4.1030	1.9351	7.0189		
Reference: Other	0.0012	0.0340	0.2496	0.4331	0.0095	0.0971	0.0579	1.7020	9.7911	44.2504	0.1283	1.3158
Publication Characteristics												
PubYear	1993.4820	5.6928	2001.6450	10.7176	2009.9810	8.0445	41,878.7800	60,654.9000	64,689.2700	109,968.6000	57,314.7200	81,305.2300
Impact factor	2.9353	0.7518	2.9847	0.8364	3.4391	1.5602	59.0204	77.2182	93.4590	161.3460	69.5342	65.6019
Rank A	0.0301	0.1710	0.8768	0.3289	0.3223	0.4685	0.8776	6.5017	27.1297	54.2903	3.5703	6.4857
Rank B	0.0695	0.2545	0.0432	0.2035	0.0284	0.1666	0.6843	2.5568	3.3742	17.7252	0.4234	2.5738
Rank C	0.8343	0.3720	0.0352	0.1844	0.6351	0.4826	15.5990	22.2918	0.7741	5.5171	24.0788	42.3054
Reference: No rank_ABDC	0.0660	0.2485	0.0448	0.2070	0.0142	0.1187	3.8292	23.5293	1.0473	5.0795	0.4195	3.5221
Scimago < 1	0.5805	0.4938	0.8704	0.3361	0.5545	0.4982	9.1491	20.7956	27.3126	54.3858	20.7070	42.7303
Scimago < 2	0.0023	0.0481	0.0448	0.2070			0.1774	3.6867	3.1695	17.3320		
Scimago > 2	0.0035	0.0589			0.0142	0.1187	0.2581	4.4029			0.4279	3.7181
Reference: No rank_Scimago	0.4137	0.4928	0.0848	0.2788	0.4313	0.4964	11.4054	26.0638	1.8432	7.0220	7.3572	11.0206

This table summarizes the mean and the standard deviation (SD) of the explanatory variables included in the meta-regression analysis to explain the heterogeneity in the estimated hedge ratios in the original studies. These variables are coded from the list of studies included in the appendix. The weighted descriptive statistics are calculated by dividing the value of each variable by the respective standard error of the hedge ratio estimate.

6.4. Commodity sector

The differences in the commodity type involved is another crucial variable in the original studies. We have collected MV hedge ratio estimates for different commodity types: agriculture, energy, livestock and precious metals.[18] We have created four dummy variables for these commodity types: Agriculture, Energy, Livestock and Other (includes precious metals). One of these variables will be the reference category depending on the data availability in each sub-sample. In the price level sub-sample, 92 per cent of the hedge ratios are estimated for *Livestock*. In the price change and return sub-samples, 72 per cent and 82 per cent of the hedge ratios, respectively, are calculated for *Agriculture.*

6.5. Estimation methods

As discussed in the literature review, the original studies used different estimation procedures to calculate the MV hedge ratio. These other estimators are captured by creating seven dummy variables: *OLS* (ordinary least square), *GLS* (generalized least square), *Co-inte* (co-integration), *ECM* (error correction model), *GARCH* (generalized autoregressive conditional heteroscedasticity model), *ML* (maximum likelihood model) and *Other* (any other estimators). The widely adopted estimator is *OLS* in all three sub-samples: 62 per cent in the price level sub-sample, 60 per cent in the price change sub-sample and 47 per cent in the return sub-sample.

6.6. Differences in control variables

Some original studies have included other control variables in the regression model when estimating the MV hedge ratio depending on the estimation method. We have categorized these control variables broadly into four categories: *Lags* (including lags of future prices and spot prices), *Other commodities*, *Time dummies* and *Basis* variables. The *Omitted category* represents any other control variables included. Adding the *Basis* variable is the most common (41 per cent) in the price level sub-sample; adding *Lags* is the most common (38 per cent) in the price change sub-sample, and adding *Other commodities* is the most common (40 per cent) in the return sub-sample.

6.7. Publication characteristics

To account for differences in publication quality, we include the publication year (*PubYear*), the journal's *Impact factor*, and dummy variables to show the journal rankings. The *Rank A, Rank B,* and *Rank C* dummy variables take the value of one when the ABDC rank of the journal is A and A*, B or C, respectively. The *No Rank_ABDC* variable includes journals that do not have any ABDC ranking. Furthermore, we have added the Scimago rankings of journals as well. The *Scimago* < 1*, Scimago* < 2 and *Scimago* > 2 dummy variables equal to one when the Scimago ranking is less than one, Scimago ranking is less than two but greater than one and Scimago ranking is greater than two. The *No Rank_Scimago* variable includes the journals that do not have a Scimago ranking. Depending on the data availability in each sub-sample, we have selected the omitted category for these variables.

7. Results of meta-regression analysis

7.1. Methodology

When there are many explanatory variables in a regression model, there is model uncertainty regarding the best predictors of the dependent variable and, hence, uncertainty regarding what variables should be included in the final model. Bayesian model averaging (BMA) (Zeugner, 2011) handles this model uncertainty problem. BMA is used to resolve the model uncertainty problem in previous meta-regression studies in economics (Churchill and Yew, 2017; Zigraiova and Havranek, 2016).

BMA will run possible combinations of regressions with explanatory variables in the study. We do not have a fixed set of omitted variables for all sub-samples. Depending on the data availability for each sub-sample, we have considered one variable under each category as the omitted variable. BMA calculates three vital statistics: posterior mean, posterior standard deviation and posterior inclusion probability (PIP). The posterior mean is the average of the coefficients over all models. Posterior standard deviation describes the uncertainty in the coefficient. The PIP indicates the probability of a specific variable being included in the final regression model. Following Zigraiova and Havranek (2016), the effect is considered weak when the PIP lies within the range of 0.5–0.75, substantial when the PIP is between 0.75 and 0.95, strong when the PIP is between 0.95 and 0.99, and extremely strong when the PIP exceeds 0.99.

This study conducted the BMA regression model with weighted variables (weighted by 1/SE) for the three sub-samples separately. We estimated the following meta-regression model after selecting the variables included in the meta-regression model based on the PIP values. We have set variables with a PIP value greater than 0.5 to be included in this meta-regression model.

$$t_{ij} = \beta_1 + \beta_0 \frac{1}{SE_{ij}} + \sum_{k=1}^{K} \delta_k \frac{Z_{ik}}{SE_{ij}} + \eta_j + \varepsilon_{ij} \tag{7}$$

[18] This classification of commodity markets is based on the types of commodities used in the Bloomberg Commodity Index.

where t_{ij} is the t statistic of the estimated MV hedge ratio from regression j in study i and $(\frac{1}{SE_{ij}})$ is the inverse of the standard deviation or the precision from regression j in study i. Z_{ik} is a vector of explanatory variables likely to explain the heterogeneity in estimated hedge ratios, and k represents the number of moderating variables. These explanatory variables are also weighted by the $(\frac{1}{SE_{ij}})$ of the regression j in study i. The hypotheses tested are $H0$: $\beta_0 = 0$ and $H0$: $\delta_k = 0$, i.e. whether each coefficient of these explanatory variables equals zero. If any δ_k coefficient is significant; then, we conclude that variable is an important factor determining the heterogeneity in estimated hedge ratios in commodity markets.

7.2. Results of the price level sub-sample

Table 7 summarizes the meta-regression results of the price level sub-sample. After removing the multicollinear reference categories and variables, only 17 variables (including *Precision*) were included in the BMA exercise of the price level sub-sample. All these variables (except the *Rank A* dummy variable) have a decisive impact on the estimated hedge ratio, as their PIP value exceeds 0.99. Therefore, the OLS regression included 16 variables identified as necessary in the BMA. The standard errors are clustered at the individual study level in the OLS regression.

These results indicate a negative and significant coefficient for *Precision*, providing evidence after controlling for publication bias and all other explanatory variables. The constant of this regression is positive and significant. It means that the positive and significant hedge ratio coefficients are likely to get reported and published more than the negative ones.

Furthermore, our results suggest that the following variables significantly explain the heterogeneity in hedge ratios. When the *MidYear* increases (i.e., for recent studies), the hedge ratio will likely increase by 0.55. The hedge ratio estimates are likely to be more significant for *Daily* and *Weekly* hedge horizons than monthly frequency. The hedge ratio is higher for *Cross-hedging* by 17.8 compared with *Direct hedging*. The models including *Time dummies* are likely to report a higher estimated hedge ratio in the original studies than models including any *Other* control variables. The higher the journal's *Impact factor*, the higher the value of the hedge ratio reported.

In contrast, the hedge ratio estimates for *Livestock* commodities are lower by 5.8 compared with those for *Agriculture* commodities. The hedge ratio estimated using the *OLS* estimator is likely to be lower than that calculated using the *GLS* estimator. In the original studies, models including *Other commodities*, *Lags* of futures or spot prices and the *Basis* variable also estimate a lower hedge ratio than models including any *Other* control variables. For the recently published studies (i.e. higher the *PubYear)*, the hedge ratio would be lower. Finally, studies published in ranked journals with *Rank B* in ABDC ranking or *Scimago* < 2 are likely to report a lower hedge ratio.

In summary, these results support the notion that the characteristics of data, commodity sector, design of the hedge, estimation methodology, other control variables included in the original study and publication characteristics affect the heterogeneity in the hedge ratios in the price level sub-sample.

Table 7
Bayesian model regression – Price level sub-sample.

	Bayesian Model Averaging (Weighted 1/SE)			OLS		
	Post. Mean	Post. SD	PIP	Coefficient	Standard Error	P value
Precision	−882.6500	113.1419	1.0000	−878.7522	21.4853	0.0000***
MidYear	0.5576	0.0652	1.0000	0.5574	0.0046	0.0000***
Daily	18.6706	2.7437	1.0000	19.2382	0.5753	0.0000***
Weekly	15.2087	2.3610	1.0000	15.6039	0.6021	0.0000***
Cross-hedge	17.8232	2.6326	1.0000	18.4749	0.7289	0.0000***
Livestock	−5.8226	1.1792	0.9989	−6.3093	0.0889	0.0000***
OLS	−4.0383	0.5411	1.0000	−4.0973	0.1902	0.0000***
Lag	−3.1565	0.6334	0.9999	−3.0711	0.5416	0.0000***
Other commodities	−3.8810	0.4582	1.0000	−3.8807	0.0280	0.0000***
Time dummies	37.5439	5.5447	1.0000	38.6951	1.1901	0.0000***
Basis	−0.7535	0.1031	1.0000	−0.7578	0.0663	0.0000***
PubYear	−0.1332	0.0170	1.0000	−0.1355	0.0094	0.0000***
Impact factor	4.9512	0.7363	1.0000	5.1460	0.1687	0.0000***
Rank A	0.4344	0.7849	0.2833			
Rank B	−9.4908	1.2571	1.0000	−9.6759	0.2414	0.0000***
Scimago < 2	−37.9523	5.4650	1.0000	−39.1145	1.4355	0.0000***
(Intercept)	3.0297	NA	1.0000	3.0380	0.6619	0.0010***

This table summarizes the meta-regression analysis results of the price level sub-sample. The dependent variable of this regression is the t statistic of the estimated MV hedge ratio from regression j in study i (t_{ij}). Post. Mean = Posterior Mean and Post. SD = Posterior Standard Deviation and PIP = Posterior Inclusion Probability. The OLS frequentist check includes the explanatory variables with PIP>0.5 only. The standard errors in the OLS are clustered at the study level. A detailed definition of the explanatory variables is included in Table 5. *** means significant at 5%.

7.3. Results of the price change sub-sample

Table 8 reports the BMA results of the price change sub-sample. This test included only 25 variables (including the *Precision*) representing different characteristics. Only 13 variables were selected based on the PIP value to include in the OLS regression model.

According to these results, the optimum hedge ratio after controlling for all other variables is positive and significant (i.e., coefficient of *Precision*). As the intercept is insignificant, we do not find evidence for publication bias after controlling for all other explanatory variables for the price change sub-sample. The PIP values are insufficient to include the variables indicating the data characteristics, design of hedging and other controlling variables included in the original studies. This implies that these variables do not affect the heterogeneity in the estimated hedge ratios in the price change sub-sample.

The *Weekly, Livestock, ECM*, publication year *(PubYear*) and *Rank A* and *B* variables report a negative and significant relationship with the t statistics of the optimal hedge ratio. The *Daily, OLS* and *Co-inte* methods, *Scimago ranks*, and *Rank C* report a positive and significant relationship in this regression. In conclusion, data characteristics, commodity type, estimation method, and publication characteristics affect the heterogeneity in optimal hedge ratios in the price change sub-sample.

7.4. Results of the return sub-sample

Table 9 presents the BMA results of the return sub-sample. After removing reference categories, only 19 variables (including the *Precision*) were included in the BMA exercise. Except for the *Direct hedge*, all other variables reported a PIP value of 1. Hence, they were selected to be included in the OLS regression model.

The OLS regression excludes the *Precision* variable due to multicollinearity. Hence, we do not find the optimum hedge ratio coefficient for this sub-sample, and the constant is also positive but not significant. Therefore, these results do not support publication bias in this return sub-sample. Out of the variables added to the OLS regression, only three were statistically significant: *Daily*, *Other commodities*, and *Rank C*. Accordingly, hedge ratio estimates in the return sub-sample are likely to be high when using the *Daily* hedge horizon, and *Rank C* in ABDC ranking. The hedge ratio estimates are likely to be low for studies including *Other commodities* in the original model. In conclusion, only a few variables representing the hedge horizon, other control variables and publication characteristics affect the hedge ratio estimates in the return sub-sample. We do not find strong evidence to support a majority of the selected variables were the determinants of the optimal hedge ratios in this sub-sample.

8. Conclusion

This study aims to fill the gap in the existing literature by adding empirical evidence on whether hedging strategies in academic literature have been qualified to apply derivative accounting standards. The accounting standard requires hedging effectiveness between 80 and 125 per cent to be eligible to apply the standard. We aim to find the range of the average optimal hedge ratios reported in the previous literature. We have conducted a meta-analysis using a sample of 1699 hedge ratio estimates (collected from 38 previous papers), examining the relationship between spot prices and futures prices for different types of commodities in different markets.

Our findings provide evidence on three aspects. First, the results indicate the average hedge ratio in the commodity market lies approximately between 0.60 and 1.20 after controlling for publication bias. Thus, the estimated average hedge ratio level based on academic literature overlaps with the 80 to 125 per cent threshold of hedge accounting to a large extent. Second, we do not find consistent evidence of publication bias related to the hedge ratio estimates in commodity markets. Finally, we support the notion that reported hedge ratios in commodity markets vary depending on data characteristics, commodity sector, estimation methodology, other control variables included and publication characteristics.

Our findings are important as there is limited evidence in the existing literature regarding how this 80-125 threshold level is selected for the accounting standard. We find evidence that the optimal hedge ratio in the previous academic literature lies in a broader band between 60 and 120 per cent. The problem arises when hedging with a hedge ratio of 79 per cent effective does not qualify for applying hedging accounting under the 80–125 rule. The main objective of this threshold level in earlier SFAS 133, IAS 39 and now in ASU 2017 is to differentiate effective and ineffective hedges. However, IFRS 9 does not require to meet such a screening criterion; instead, it requires hedging strategies to align with the firm's risk management strategy. Hence, IFRS 9 provides more opportunities for firms to be qualified for applying hedge accounting, thereby reducing the income volatility of these firms. Whereas ASU 2017 still requires maintaining this threshold, the US firms have limited opportunities to be qualified for applying hedge accounting treatments.

Furthermore, our conclusions have a tangible implication for policymakers. Our results suggest that lowering the minimum level of hedging effectiveness to 60 per cent would be beneficial, as several commodity futures hedging strategies reported in past academic literature would have qualified to be treated as hedge accounting. In addition, we find that the optimal hedge ratio varies among different commodities. Therefore, setting a single threshold level for all commodities and other assets is questionable. The best screening criterion would be to introduce different threshold levels of hedging effectiveness depending on the type of the asset.

CRediT author statement

Jedrzej Bialkowski: Conceptualization, Idea, Methodology selection, **Devmali Perera**: Data curation, Software, Writing – original draft, **Devmali Perera**: Visualization, Investigation., **Jedrzej Bialkowski and Martin T. Bohl**: Supervision. **Jedrzej Bialkowski, Devmali Perera, Martin T. Bohl**: Writing- Reviewing and Editing.

Table 8
Bayesian model regression – Price change sub-sample.

	Bayesian Model Averaging (Weighted 1/SE)			OLS		
	Post. Mean	Post. SD	PIP	Coefficient	Standard Error	P value
Precision	35.1456	7.2665	1.0000	39.5567	3.2373	0.0000***
MidYear	−0.0009	0.0046	0.2110			
Daily	0.4557	0.1686	0.9673	0.4367	0.0790	0.0000***
Weekly	−1.1449	0.1458	1.0000	−1.1887	0.0895	0.0000***
Direct hedge	−0.2027	0.2989	0.3620			
Cross-hedge	−0.2091	0.3066	0.3659			
Agriculture	−0.0031	0.0135	0.0814			
Energy	−0.0011	0.0101	0.0473			
Livestock	−0.5113	0.0741	1.0000	−0.5081	0.0727	0.0000***
OLS	0.0490	0.0531	0.5378	0.0884	0.0311	0.0047***
Co-inte	0.1108	0.0582	0.8760	0.1473	0.0266	0.0000***
ECM	−0.3292	0.0462	1.0000	−0.2997	0.0371	0.0000***
GARCH	−0.0004	0.0109	0.0396			
Lag	0.0021	0.0242	0.1027			
Other commodities	−0.2287	0.2933	0.4472			
Time dummies	0.0139	0.0638	0.0777			
Basis	−0.0011	0.0177	0.0451			
PubYear	−0.0160	0.0076	0.8688	−0.0192	0.0016	0.0000***
Impact factor	0.0032	0.0320	0.0811			
Rank A	−2.0986	0.2607	1.0000	−2.0545	0.1773	0.0000***
Rank B	−0.8334	0.2366	0.9836	−0.8288	0.1457	0.0000***
Rank C	0.9991	0.2022	1.0000	1.0551	0.1674	0.0000***
Scimago < 1	1.4231	0.1782	1.0000	1.4066	0.1421	0.0000***
Scimago < 2	0.6656	0.1881	0.9853	0.7123	0.1067	0.0000***
(Intercept)	−0.6895	NA	1.0000	−1.0704	0.5717	0.0617

This table summarizes the meta-regression analysis results of the price change sub-sample. The dependent variable of this regression is the *t* statistic of the estimated MV hedge ratio from regression *j* in study i (t_{ij}). Post. Mean = Posterior Mean and Post. SD = Posterior Standard Deviation and PIP = Posterior Inclusion Probability. The OLS frequentist check includes the explanatory variables with PIP>0.5 only. The standard errors in the OLS are clustered at the study level. A detailed definition of the explanatory variables is included in Table 5. *** means significant at 5%.

Table 9
Bayesian model regression – Return sub-sample.

	Bayesian Model Averaging (Weighted 1/SE)			OLS		
	Post Mean	Post SD	PIP	Coefficient	Standard Error	P value
Precision	−265457.6000	68,054.8000	1.0000	(omitted)	(omitted)	
MidYear	0.0116	0.0045	1.0000	0.0045	0.0047	0.3377
Daily	−1565.9840	401.6370	1.0000	0.6622	0.3344	0.0491***
Weekly	1974.0300	506.0383	1.0000	0.1561	0.5976	0.7942
Direct hedge	0.0000	0.0000	0.0000			
Cross-hedge	0.1217	0.1876	1.0000	0.1249	0.2165	0.5647
Agriculture	−0.1878	0.3612	1.0000	−0.2294	0.4167	0.5826
OLS	265.4452	68.0299	1.0000	0.0869	0.2861	0.7617
GLS	265.4907	68.0335	1.0000	0.1190	0.3216	0.7119
GARCH	−2372.4040	608.0318	1.0000	−0.6917	0.5225	0.1871
ML	265.6272	68.0297	1.0000	0.2708	0.3149	0.3910
Other commodities	−0.6223	0.1853	1.0000	−0.6386	0.2139	0.0032***
Time dummies	−0.0174	0.0345	1.0000	−0.0484	0.03881	0.2142
PubYear	132.6348	34.0045	1.0000	−0.0047	0.0047	0.3239
Impact factor	−93.9835	24.1044	1.0000	0.0386	0.1221	0.7519
Rank A	−216.5689	55.6926	1.0000	0.6651	0.4934	0.1792
Rank C	−249.3180	64.0149	1.0000	0.3828	0.1599	0.0176***
Scimago < 1	−146.3366	37.4598	1.0000	0.2210	0.1489	0.1395
Scimago > 2	753.4016	1.9307	1.0000	0.3185	0.7588	0.6751
(Intercept)	0.8383	NA	1.0000	0.8096	1.1700	0.4898

This table summarizes the meta-regression analysis results of the price change sub-sample. The dependent variable of this regression is the *t* statistic of the estimated MV hedge ratio from regression j in study i (t_{ij}). Post. Mean = Posterior Mean and Post. SD = Posterior Standard Deviation and PIP = Posterior Inclusion Probability. The OLS frequentist check includes the explanatory variables with PIP>0.5 only. The standard errors in the OLS are clustered at the study level. A detailed definition of the explanatory variables is included in Table 5. *** means significant at 5%.

Data availability statement

The data supporting this study's findings are available upon request from the authors. Variables included in the data set are explained in Table 5, and the data are collected from the list of papers selected for coding mentioned in the Appendix.

Declaration of competing interest

None of authors have any financial and personal relationships with other people or organizations that could inappropriately influence (bias) their work.

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Appendix A.List of papers selected for coding

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