**Time-Varying Effects of Financialization on Commodity-Equity Risk Sharing**

Key points

* KF is forward algorithm so without smoother (backwards algorithm) so
* Correlation is only direction, not magnitude like beta
* Your findings confirm Gorton and Rouwenhorst (2006)! S\&P and commodities negative pre-financialziation

Abstract

As financialization allowed more speculators enter the commodity market, greater risk-sharing occurs whereby commodity returns become more closely integrated with the returns of conventional assets. Previous studies have tested risk-sharing between commodity and equity markets using panel regressions or rolling correlations, which leave room for improvement on the granularity and interpretability of results. Turning to Bayesian modelling, this paper tests for co-integration between commodities and equities by the estimation of time-varying betas using Kalman filtering, which yields more comprehensive results. The findings suggest that financialization has eroded the diversification benefits of commodities for equity investors in the face of a secular convergence towards a ‘market of one’.

Structure:

1. Intro – lay down definitions, key theories and theoretical influences
2. Literature Review – say you’re ‘extending’ research that employed rolling correlation \& panel regressions
3. Model – maths presentation
4. Data – say where you got it plus summary statistics/visualization
5. Empirical Implementation (results) – present and discuss, split into WTI/gas then general indices
6. Conclusion – reiterate what you’ve written so people can skip over the other sections and just read this to understand implications

**Time-Varying Effects of Financialization on Commodity-Equity Risk Sharing**

1. Introduction

An investor holding a portfolio of stocks might look to diversify equity exposure by investing in the commodity market, but this line of thinking has come under empirical challenge. The original assumption that commodities and equities exhibit no positive correlation was established before the effects of commodity market financialization were evident, such as Gorton and Rowenhorst’s (c2006) study of commodity-equity correlations from 1959 to 2004. Over the next decade, commodities such as crude oil experienced an ‘unprecedented’ boom-bust cycle along with the equity market (cFattouh, Kilian and Mahadeva, 2013), leading academics to use dynamic and rolling correlation to assess how commodity-equity correlation has changed over time (cBüyüksahin, Haigh and Robe 2010; Tang and Xiong, 2012). This paper continues in that spirit of uncovering time-trends in the commodity-equity relationship, and may be placed in context with prior literature on commodity market financialization.

The concept of financialization surged to prominence along with commodity prices in the run-up to 2008, igniting fears that financialization caused increased speculative fervour that was distorting markets (cBrown and Sarkozy, 2009). However, both financialization and speculation remain ambiguous terms that have been inconsistently employed by both academics and policy makers alike (cFattouh, Kilian and Mahadeva, 2013). This paper will follow the definition adopted by Fattouh, Kilian and Mahadeva, such that financialization is ‘the increasing acceptance of [commodity] derivatives as a financial asset by a wide range of market participants’.

Correspondingly, the definition for speculation should capture the actions of new participants who would traditionally not have participated in the commodity market, though that is itself a challenge. Although the commodity markets’ traditional roles were the facilitation of hedging and consumption (Masters 2008), defining speculation by market actions based on expectation is broad enough to include producers. For example, an oil producer may sell some stockpiles now to invest in increasing production in expectation of rising long-run prices. Alternatively, an agent-based definition of speculation would fall unfairly strict on certain groups of participants and lax on others. All things considered, this paper will follow Working’s (c1960) definition of speculation as the volume of futures trading above that necessary to hedge spot positions. Despite the empirical critiques raised by Fattouh, Kilian and Mahadeva (2013), Working’s definition is the closest to an operational definition.

Overall, the effect of increased speculation falls roughly into three main theories in the literature. First is the idea that speculation is associated with mispricing in relation to economic fundamentals, causing asset price bubbles as the result of greed (Brown and Sarkozy 2009). Such a view of speculation is recognized by Fattouh, Kilian and Mahadeva (2013) as normative, imbuing speculation with a social dimension. Opposingly, another view is that an influx of speculators improves the market’s information discovery mechanism, allowing for new information to be better aggregated and resulting in better pricing (cCheng and Xiong, 2014). The information discovery theory thus assumes speculators are rational agents, unlike the more behavioural view of speculators by the asset price bubble theory. However, both theories remain elusive to prove empirically due to the difficulty in determining what makes prices ‘better’ or ‘worse’, especially when commodities form an alternative asset class that is difficult to price via conventional models (cDaskalaki . .. 2014). Hence, a third theory more neutral to the pricing ability of speculators has emerged – that of risk sharing. The risk sharing theory posits that because new participants in the commodity market will have traditionally invested in established assets, their capital allocation in the commodity market will reflect their allocation in other assets, bringing a closer degree of integration between the price movement of commodities and other assets. Undiversifiable market risk, or systematic risk, is thus shared between traditionally segmented markets.

The problem of risk sharing has already been noted above for investors who want to diversify their portfolio by investing in the commodity market, but ironically the act of diversifying into commodities itself exacerbates the phenomenon. Recall that this paper’s definition of speculation covers any type of activity in the futures market that is not hedging, including portfolio diversification using index-tracking futures products. Masters (c2008) points to the rise of commodity index speculation, such as buying products benchmarked against the Goldman Sachs Commodity Index, as the cause of commodity price surges, but captures only the partial picture in his assessment. Cheng and Xiong (2014) note that subsequent papers fail to establish a linkage between changes in index speculation volume and commodity futures returns, finding instead more evidence that index speculation increases the level of integration of returns with previously segmented markets, including between different commodity sectors. It has since been generally accepted that institutional index speculation is the main cause of risk sharing (cBasak and Pavolova, 2016).

This paper will conduct empirical studies on commodity-equity risk sharing to determine whether the theory of index speculation holds, as well as determine its implications for individual commodities. However, instead of testing the linearity of integration using rolling correlation, a systematic risk approach will be used where co-movement coefficients are estimated using Kalman filters for each discrete time-step. This approach is motivated by literature that suggest the time-varying nature of systematic risk (cDaskalaki blah blaah; cIslemeiyyeh forthcoming), with Kalman filtering already established in equity market literature as a suitable estimator of time-variance (cFaff, Hillier and Hillier, 2003; Renzi-Ricci, 2016). In the estimation of systematic risk coefficients using monthly data from 1986 to 2021, this paper hopes to give a more direct and comprehensive picture of trends in commodity-equity risk sharing, which should be of interest for researchers, investors and policy makers.

The structure of this paper shall be as follows: [write something about structure and findings – consistent but new evidence or smth] [briefly explain models used]

1. Literature Review

Having already explored the linkage between financialization, speculation and risk sharing, this section will provide context on the motivation behind this paper’s focus on systematic risk. A methodological survey will also be conducted in choosing the Kalman filter, as well as its linear model specification.

Previous literature has focused mainly on the correlation of commodity and equity markets as a general test for integration. Gorton and Rouwenhorst (2006) computed the correlation between and equally-weighted commodity index and the S\&P 500 using data from 1959 to 2004, ultimately finding returns to be negatively correlated overall. However, as noted in the introduction, new evidence came to light later as market dynamics changed. Büyüksahin, Haigh and Robe (2010) assessed dynamic conditional correlation between investable commodity and equity indices in the US, finding that while correlations remain weak in general, the 2008 financial crisis induced a surge in correlation. Although their study did not give credence to the risk sharing theory overall, Büyüksahin, Haigh and Robe were significant in employing a dynamic time-varying approach to assessing correlation, which challenged the received wisdom of commodity diversification during market downturns. Tang and Xiong (2012) furthered this time-varying approach by employing one-year rolling correlation of daily returns to find an increase in commodity-equity correlation, and also provided evidence of increased inter-commodity correlation on average for indexed commodities. Silvennoinen and Thorp (c2013) and Basak and Pavlova (2016) employed dynamic conditional correlation models similar to Büyüksahin, Haigh and Robe, observing that cross-commodity and commodity-equity volatility correlations saw a sustained increase since 2008.

However, the strength of commodity-equity integration has been questioned. Dasklaski blah blah (c2014) finds that equity market asset pricing models have low explainability for commodity returns, concluding that equity and commodity markets remain segmented. Nevertheless, Dasklaski, blah blah’s analysis focused largely on average levels of $R^2$ (squared correlation) in factor models, despite observing and leaving unreported the significant time variation of the systematic risk coefficient $\beta$. As such, this paper believes Dasklaski blah blah’s study is in fact significant in recognizing the time-varying systematic risk relationship, and may be adjusted to test for the risk-sharing theory of integration through a focus on systematic risk.

Further evidence of changes in systematic risk can be found in risk premia literature. Baumeister and Kilian (c2016) found that stock returns can have statistical significance when included as regressors for crude oil futures risk premium at various horizons. Isleimeyyeh (cforthcoming) also builds a commodity futures risk premium model using hedging pressure and correlation-adjusted equity market (S\&P 500) returns, which was estimated for crude and heating oil over sample periods of 1995-2002, 2003-2008 and 2008-2015. Although hedging pressure is the significant regressor for all periods, Isleimeyyeh’s results showed substantial increase in the magnitude and statistical significance of the equity market coefficient, concluding that equity market systematic risk is the more salient factor for oil futures risk premium post-2008.

Placing this paper in context with prior literature, it shall aim to further past studies by explicitly testing whether systematic risk integration increased between commodity and equity markets as a result of financialization. For such purpose, it will employ a simplified model such that systematic risk may be tested directly without the inclusion of other explanatory variables. In so doing, this paper will not seek to build a detailed theory of risk transmission as with risk premia literature, but rather provide evidence on the premise that capital allocation from financialization results in increased commodity-equity integration overall. To fully analyse the effects of financialization, this paper will test for risk sharing between indices, as well as explore whether risk sharing affects individual commodities themselves. Should a time-varying relationship be found in line with that suggested by the theory of financialization, the results of this paper may also carry modelling implications for risk premia literature by reporting the changes in systematic risk sharing.

Methodology wise, this paper shall use the Kalman filter detailed by Hamilton (c1994) to estimate time-varying systematic risk in light of prior methodological comparisons. In a study of the filter’s mathematical properties with regards to rolling window regression, Belsley (c1973) concluded that Kalman filters are a more efficient algorithm for simple linear models, though the advantage disappears when $\beta$ is assumed to vary according to an extra linear systematic parameter. Faff, Hillier and Hillier (2003) made an empirical comparison of several types of autoregressive conditional heteroskedasticity models against the Kalman filter, using daily returns of equity indices for 32 different UK industry sectors. Their study found that the Kalman filter best minimizes in-sample error rates when estimating linear systematic risk, especially when a random walk assumption was made for the evolution of $\beta$. Renzi-Ricci (2016) further found that a random walk $\beta$ outperforms rolling regressions upon a simulation of a structural shift in $\beta$.

Overall, literature suggests that the Kalman filter is the best method for estimating time-varying coefficients in a simple linear model. To dive deeper into the technicalities, formal notation will be needed to discuss the relevance of the random walk $\beta$, which will be constructed below.

1. Model

In this section the intuition behind the linear model used to test for the level of commodity-equity systematic risk integration shall first be developed. Then, the linear model will be transformed into state-space representation using the Kalman filter, so that the systematic risk coefficient can be modelled as a time-dependent state.

1. Linear Model

The underlying linear model for systematic risk is simple and can be derived from first principles. To begin, returns may be used to build a general picture of price movements, expressed as $y$ and $x$. Systematic risk sharing can then be assumed to manifest through the proportionality $y \prop x$, such that $y = \beta x$ where $\beta$ is non-zero. A perfect degree of integration will therefore result in a $\beta$ of one such that returns are expected to co-move in the same direction and magnitude, while a $\beta$ of negative one expects returns co-move in opposite directions but with the same magnitude. A near-zero $\beta$ suggests little co-movement between the assets. Hence, if two assets are integrated under the risk sharing hypothesis, a positive $\beta$ should exist, and the level of integration will be observable from the closeness of $\beta$ to one. Note that $\beta$ beyond -1 and 1 is possible, but it is unlikely that commodity and equity returns will be so sensitive to each other.

The benefit of the $\beta$ measure for risk integration over standard correlation testing prevalent in prior literature is that $\beta$ tests for the level of price integration more directly. Correlation is a standardized form of covariance and only tests for the strength the linear relationship, with a large positive correlation value signalling a strong positive linear relationship. $\beta$, on the other hand, adjusts correlation to test for the sensitivity of co-movement itself, such that we can infer how much $y$ increases on average with $x$ given a strong positive $\beta$ for $x$. Hence, it is possible to have a high correlation with a low $\beta$, and vice versa. Formally, a time-invariant $\beta$ can be written in terms of correlation $\rho$ and standard deviation $sigma$ such that:

\rho = \frac{Covariance(x, y)}{\sigma\_y\sigma\_x}

[\beta$ = \rho\_{xy} \frac{\sigma\_y}{\sigma\_x}

However, although the benefits of $\beta$ over correlation remain the same, the above equation is solely for a constant $\beta$. To observe whether the level of equity-commodity integration changes over time, $\beta$ needs to be expressed as a time-varying coefficient for returns at different time points. To express the final model, I introduce time indexing and the market noise variable $\epsilon$:

[y\_t = \beta\_t x\_t + \epsilon\_t]

For equation [CITE], let $y$ denote commodity asset return and $x$ denote equity asset return. Hence for our study commodity assets will always be the dependent variable, and equity market the independent variable. Note that unless specified, commodity assets include commodity indices, and equity assets include equity indices, given the availability of index benchmarked products as discussed in the introduction.

In a more traditional context, the linear model can also be derived using the Capital Asset Pricing Model (CAPM). From Fama and French (c2004), the original Sharpe-Lintner CAPM is expressed as:

[E[R\_i] = R\_f + (E[R\_m] – R\_f)\beta]

Where $R\_i$ is the return of a single stock, $R\_f$ is the risk free rate, and $R\_m$ is the equity market return. The CAPM model thus describes systematic risk within the equity market such that $\beta$ represents the undiversifiable equity market risk inherent in a given stock. By altering the assumption for CAPM using the risk sharing theory such that systematic risk may exist between different asset classes, the notation of $y$ and $x$ may be retained such that $E[y] = R\_f + (E[x] – R\_f)\beta$, which results in the time-varying version of $y\_t = R\_{f, t} + (x\_t – R\_{f, t})\beta\_t + \epsilon\_t$. If using time-series data of sufficiently high frequency, the inter-period risk-free rate should also be negligible, rendering the final relationship the same as equation 1. In such a sense, the linear model used in this paper is a simplified form of Daskalaki blah blah’s (c2014) approach to test for integration using equity pricing models, which as noted by the authors necessitates a time-varying approach due to the evolution of $\beta\_t$ observed (though left unreported).

1. State-Space Transform

Finding $\beta\_t$ is not as simple as dividing $y$ by $x$ for each $t$ due to market noise $\epsilon$, necessitating some consideration for how $\beta\_t$ evolves given $\beta\_{t-1}$ to separate trend from noise. Hamilton (1994) details the suitability of state-space models, such as Kalman filtering, for including autoregressive assumptions while accounting for time variance. The literature review also suggests that the standard Kalman filter is best approach to modelling a time-varying $\beta$ given the simplicity of the linear systematic risk model used in this paper.

The Kalman filter is a recursive model that estimates the most likely value of hidden states given 1) prior predictions at $t-1$, and 2) new observations at $t$. The general algorithm is as follows:

\begin{verbatim}

1. Initiate model inputs, which represent posteriors at time t = 0
2. For t = 1 to t = T:
3. Predict the prior for t using the posterior estimate at t-1
4. Compute the posterior estimate using the prior and the observation at t

\end{verbatim}

$\beta\_t$ is thus estimated by posterior values for each timestep. To formalize subsequent notation, let $\hat\beta\_t$ denote estimated $\beta\_t$ such that $\hat\beta\_{t|t-1}$ represents the predicted prior at $t$, and $\hat\beta{t|t}$ represents the posterior estimates at $t$. We can let $y\_t$ and $x\_t$ remain as per prior notation, since I am only constructing a one-dimensional Kalman filter and so can forego matrix representation. Kalman filtering also assumes that $\hat\beta\_t$ and $y\_t$ can be modelled using Gaussian distributions, where the distribution for the state variable $\hat\beta\_t$ is time-dependent and the distribution for observed variable $y\_t$ time-invariant. As such:

\hat\beta\_t \sim N(\hat\beta\_t, P\_t)

y\_t \sim N(y, R)

where $P\_t$ is the time-varying variance for $\hat\beta\_t$ and $R$ the constant variance for $y\_t$.

Under the index speculation theory, $\beta\_t$ should be most influenced by the exogenous factor of capital allocation rather than exhibit any endogenous properties such as mean reversion. Such an assumption of $\beta\_t$ fits well with the random walk assumption that inter-period evolution is solely due to informational stimuli (cMalkiel 1973). A random walk assumption will also follow prior studies conducted by Faff, Hillier and Hillier (2003) and Renzi-Ricci (2016), which was found to yield the most accurate $\beta$ estimates for the CAPM in their study. Hence for the predictive step I use the following set of equations:

\hat\beta\_{t|t-1} = \hat\beta\_{t-1|t-1} + \theta\_t

P\_{t|t-1} = P\_{t-1|t-1} + Q

where $\theta\_t$ represents the error of the \hat\beta\_{t-1|t-1} estimate and $Q$ is a time-invariant assumption of process noise. Essentially, a lower value of $Q$ restricts the variance around the prior, which necessitates the posterior to give greater consideration to the prior than the observation, increasing $\theta\_t$. Hence a lower $Q$ implies a higher $\epsilon\_t$ in the linear model, where $\epsilon$ is not estimated directly by the Kalman filter. This follows since if one assumes $\theta\_t = 0$, then $\beta\_t$ is deterministic and the fluctuations of $y\_t$ and $x\_t$ can be explained by market noise $\epsilon\_t$ alone.

To compute the posterior estimates I use the following set of equations:

K = \frac{P\_{t|t-1}}{P\_{t|t-1} + R}

\hat\beta\_{t|t} = \hat\beta\_{t|t-1} + K(y\_t - \hat\beta\_{t|t-1}{x\_t})

P\_{t|t} = (1 – K) P\_{t|t-1}

$K$ above is commonly known as the ‘Kalman gain’ between each time-step, which decides how much weight should be given to the new residual computed using the prior prediction. Intuitively, it controls how the error of the prediction is used to update the posterior.

1. Implementation

This section will focus on developing the practical methodology used to obtain my results. First will be a discussion of general strategy around building the models using empirical data, before an explanation of how data was obtained.

1. Strategy

To implement the model, real returns shall be used for $x$ and $y$. Deflation is necessary for a robust analysis since commodity prices are found to embed inflation information (cGarrat and Petrella 2022). I shall also use series of monthly data to make the linear model compatible with the CAPM under the aforementioned assumption of negligible inter-period risk-free rate. This is a realistic assumption since the US Federal Funds rate has remained below 0.5% per month since the 1980s (Appendix CITE). To make the data suitable for our model, returns shall be standardized at an annual basis to remove any leptokurtosis that undermines the Kalman filter’s normality assumption, as well as de-seasonalized to remove the influence of seasonal demand/supply patterns. De-seasonalization will involve calculating the difference between actual returns and in-sample monthly averages. Note that due to two-step the data transformation, it matters little whether simple or exponential returns are used. For this paper simple returns will be used.

Recall also that the initial parameters $\hat\beta\_0$, $P\_0$, $R$ and $Q$ for the Kalman filter must be specified. Since I am testing for integration, I shall first assume no integration with $\hat\beta\_0 = 0$, and let the model provide evidence for the contrary. $R$ is easy to specify as the in-sample variance of $y$, which should remain consistent throughout the period given the standardization of returns. $P\_0$ will be assumed to be the same as $R$, though the initial specification matters little because it is a dynamic variable that will be updated with each iteration. This paper shall use 0.01 for $Q$, which reflects the assumption that the level of integration between markets is not volatile given that financialization is a gradual process.

For computation this paper uses the Python package FilterPy (v.1.4.5) by Labbe (c2015) to implement the Kalman filter. Recall that the Kalman filter is a forward (in time) algorithm that calculates the most likely position of $\beta\_t$ given data at $t-1$, making it useful for real-time updating. However, for inference it is sometimes desirable to compute the most likely evolution of $\beta\_t$ given observations at $t+1$ as well, which requires adjusting the Kalman filter estimates using a backward algorithm known as a ‘smoother’. For the analysis below smoothing will refer to the Rauch-Tung-Striebal smoother implemented by FilterPy, which I shall not detail here given its standard nature and implementation.

1. Data

The data used for this paper falls into two categories: single securities and indices. Time-series data was collected at monthly intervals as detailed above, utilizing first-of-month values. I collected the maximum historical sample available for all data, with in-sample cut-off points being January 1986 and December 2021, giving a maximum of $36 \times 12$ datapoints for any series. The in-sample period was decided based on the scope of the research being aimed at uncovering risk sharing with regards to financialization in the 2000s, as well as the late 1980s being the period from which many commodity futures records in the US began (Tang and Xiong 2012). Prices were all collected in US dollar denomination, and deflated to December 2021 terms using the monthly US Consumer Price Index from the Federal Reserve Bank of St. Louis. The formula used for deflation is:

\Price\_{real, t} = Price\_{nominal, t} \times \frac{CPI\_T}{CPI\_t}

such that $T$ represents December 2021.

1. Indices

Index data include both commodity and equity indices, all of which was collected from Bloomberg. Commodity indices collected are the Goldman Sachs Commodity Index (GSCI), Dow Jones Commodity Index (DJCI), Bloomberg Commodity Index (BCI), and Commodity Research Bureau Index (CRBI). The energy component of GSCI (GSECI), and the non-energy component (GSNECI) was also collected to test for cross-sector integration within the commodity market itself. Equity indices used are the S\&P 500 (SPX), MSCI World (MSCI\_W) and MSCI Emerging Markets (MSCI\_EM).

[graph of commodity indices]

Figure [CITE] visualizes the real price and return distributions of the different commodity indices used in this paper. Although GSCI, DJCI and BCI all include the broad sectors of energy, agriculture, livestock and metal, their weighting differs, which contributes to their price differences. CRBI will be discussed separately as its constituents differ from the other three indices entirely. All commodity indices used are constructed based on rolling futures prices, usually one to two months from expiry.

The GSCI and DJCI represent the most common indices for investors who want to gain commodity exposure (Anson 2008; Tang and Xiong 2012). GSCI is a production-weighted index, with weights determined by five-year average world production data (cS\&P Global 2022). As such, it is a momentum-driven construction that has seen significant historical exposure to the energy sector, which leads to critique of over-exposure to idiosyncratic event risks (cAnson 2008), evident from the high standard deviation of returns. By contrast, DJCI is designed to maximise diversification with equal weighting of the sectors, and designed with liquidity in mind by weighing individual commodities using five-year average trading volumes (cS\&P Global 2021). DJCI is hence more investable than the GSCI from an institutional standpoint due to its liquidity and diversification benefits (ibid). Also designed with attracting institutional investment in mind, BCI takes both production and liquidity into consideration, with a weight cap of 15% for individual commodities (cBloomberg, 2022).

An interesting index to include is the CRBI, which is now maintained as part of the cmdty BLS indices by Barchart.com. CRBI is a relatively niche index composed of commodities used in the initial stages of production, which renders its composition entirely different from the three indices above (cBarchart.com 2019). Specifically, energy commodities and ‘highly fabricated commodities’ are avoided as part of the index’s aim to serve as an indicator for manufacturing activity (ibid). Hence, scrap metal is included in place of regular metals, and fats like butter and tallow further differentiate the index from regular commodity indices. The CRBI is also unweighted, using instead the geometric mean of price relatives (ibid). Given the constraints faced when collecting the volumes of index speculation, the CRBI is included in the analysis to proxy a commodity index with low institutional speculation.

[equity indices summary graphics \& table]

The equity indices used – SPX, MSCI\_W, MSCI\_EM – are all weighted by market capitalization (cS\&P Global 2022b; cMSCI 2022), differing only in geography. SPX captures the 500 largest US companies, MSCI\_W captures some 1,500 eligible companies from developed economies such as the US and UK, while MSCI\_EM captures roughly the same number of companies from developing economies such as China and Russia. By comparing levels of commodity-equity integration across different economies, this study also tests whether risk-sharing is consistent across equity markets, or if it is an anomaly that only occurs in developed/developing economies. As figure [CITE] shows, the prices and return distributions are especially different between equity indices from developed and developing economies.

1. Individual Commodities

Individual commodities data are used to analyse whether indexed commodities and non-indexed commodities exhibit differences in equity market integration. The historical prices of front-month futures for oil (WTI) were collected from the US Energy Information Administration. Front-month future prices for generic contracts in gold, hog, wheat, lumber, oats, palladium and rubber were collected from Bloomberg.

[summary stats of mean, std]

Due to the number of individual commodity data collected and their lack of consistent price levels, Table [CITE] provides for a quick overview of their characteristics. Note that while the volumes of index speculation and historical component weights of individual commodities would have made the following analyses more rigorous, I was unable to access the relevant data on Bloomberg due to the university’s subscription constraints. Such limitations will be mentioned in the relevant sections below.

1. Results

In this section I detail my findings in two parts. First, I present the level of integration found between commodity and equity indices. Then, I analyse individual commodities, comparing the effect of financialization on indexed and non-indexed commodities. Note that ‘indexed’ denotes commonly indexed commodities for this paper, since niche indices like CRBI exist to capture every tradeable commodity imaginable.

1. Commodity Indices

[table of rolling average return differences]

The differences in commodity index construction may be observed through the difference in real returns. Although these differences are zero on average (Appendix [CITE]), it has more of a time-varying relationship. Figure [CITE] shows the rolling average of a difference in monthly returns constructed using 6, 9 and 12 year windows for robustness. The relatively large difference between the CRBI and other indices from 2000-2008 is attributable to the non-inclusion of energy commodities like crude oil in the CRBI, which experienced significant price surges in that period. Some effects of weighting differences can also be seen between the GSCI, DJCI and BCI, which are otherwise effectively homogenous in composition. Since we are employing a time-varying method, the idea is that these time-varying differences in returns will cause inconsistent levels of integration over periods such as 2000 to 2008 should there be no common driver for risk-sharing, which makes it important to compare the level of integration across different commodity indices. Different equity indices will also be used to for the same reason, since the MSCI\_W and MSCI\_EM captures markets with different levels of economic development.

Given the differences in commodity index construction, which results in different inter-period returns, the null hypothesis is that inconsistent levels of $\hat\beta\_t$ is observed through the sample period. Such a result would imply that the levels of systematic risk integration is not driven by homogenous factors, rather dependent on commodity index construction and equity market conditions. However, should the index speculation theory of risk sharing hold, $\hat\beta\_t$ would be significantly non-zero after the 2000s, with a consistent trend observed for the $\hat\beta\_t$ of the popular commodity indices (GSCI, DJCI and BCI) due to financialization. This follows because although there are some deviations on average, the direction of individual monthly returns should align. As part of the index speculation theory, $\hat\beta\_t$ for CRBI should also be less than the $\hat\beta\_t$ for the popular indices due to the lower level of capital allocation necessary for commodity-equity integration.

[beta plot]

Figure [CITE] presents the smoothed $\hat\beta\_t$ values between the commodity indices tested and the SPX, MSCI\_W and MSCI\_EM. Note that due to our data cleaning, a $\hat\beta\_t$ should be interpreted to represent the co-movement of the annual standard deviations of returns rather than returns itself. Overall, it appears that commodity-equity systematic risk has increased substantially from 1990 to 2012, but has decreased in magnitude from between 2014 and 2017 before rising again. A $\hat\beta\_t$ of around 0.7 is also observed at the peak levels of integration for both MSCI\_W and MSCI\_EM, suggesting risk sharing is a global phenomenon that remains consistent across economies. The roughly 0.3 higher peak integration reached for the MSCI indices than the SPX further indicates that risk sharing is more pronounced across a basket of economies than any single economy. In general, the trend consistency of how $\hat\beta\_t$ for each commodity index evolves is a strong indicator of risk sharing, with the level of integration being invariant to commodity index construction and equity market idiosyncrasies. The level of integration is also mostly invariant to business cycles (US recessions shaded in grey), though slight spikes are observed during recessionary periods for SPX integration.

Risk sharing caused by index speculation is also evidenced by the slower increase in integration for CRBI, which is our low-speculation index. As the theory posits, lower levels of capital allocation to an index would result in lower levels of equity integration. However, it is surprising that CRBI reached the same level of equity integration from 2008 to 2012 as the more popular indices, which suggests some spillover effects from index speculation in the main commodity indices into the less-speculated CRBI. Recall also our earlier observation that the difference between CRBI returns and the three main commodity indices was noticeably sustained through 2000 to 2008, which makes the consistent level of integration with the three main indices across that period more evident that integration is invariant to index construction.

[probability of betas]

$\hat\beta\_t$ only represents the most likely position of $\beta\_t$, so for rigour we also need to check the magnitude of $P(\hat\beta\_t > 0)$ to confirm the significance of positive integration. Figure [CITE] represents the credible level of positive integration where $\hat\beta\_t > 0$, constructed using variance term $P\_t$. Note that unlike an ordinary regression, the state probabilities cannot be summarized into one confidence level, which will also defeat the purpose of the Kalman filter in uncovering time trends. However, one can assign an arbitrary cut-off if so disposed, for example assigning significance using $P(\hat\beta\_t > 0) > 0.9$, such that anything below the 0.9 threshold would be inconclusive of integration. I will make no such cut-off, because it is evident positive integration was reached around the 2008 global financial crisis and for periods thereafter. The credible levels are also useful for visualizing the speed of integration, with CRBI noticeably lagging the other commodity indices in integration with MSCI\_W and MSCI\_EM.

[backtesting results against RW, OLS – also give KF mean and OLS mean]

To justify my results against a time-invariant approach, Table [CITE] shows the back-testing results for the $\hat\beta\_t$ from the Kalman filter (KF) compared to the random-walk (RW) assumption that $\beta = 0$ (no systematic risk exists) and $\hat\beta$ estimated using ordinary least squares (OLS) regression. The results suggest that the random-walk assumption is worst at describing the sample data, while assuming a constant $\beta$ is worse than the time-varying model employed by this paper. Hence, back testing confirms the methodology behind this paper – that the commodity-equity risk-sharing relationship should not be assessed ‘on average’, but with regards to time due to the changing dynamics of the market.

[correlation plot]

For robustness, a comparison with the traditional rolling correlation method is made. Figure [CITE] presents 5-year rolling correlation coefficients in the same format as Figure [CITE] above. The correlations computed correspond closely with the series of $\hat\beta\_t$ in Figure [CITE], which implies this study’s conclusion is consistent with the conclusion of commodity-equity integration that would have been reached under the Tang and Xiong (2012) rolling correlation analysis detailed in the literature review. The magnitude of the rolling correlations is also indicative that my linear assumption for the $\beta\_t$ model is valid.

Overall, the study above provides evidence that commodity-equity risk for sharing for commodity indices 1) is consistent with the theory of index speculation, 2) is invariant to commodity index construction, 3) is invariant to levels of economic development in equity markets, 4) persists regardless of economic cycles, and 5) exhibits patterns consistent with prior literature. Pre-financialization papers finding little correlation between commodity indices and the SPX are captured by our results (Gorton and Rouwenhorst 2006), as are papers pointing to spikes in SPX integration during recessionary periods (Büyüksahin, Haigh and Robe 2010; Silvennoinen and Thorpe 2013). Moreover, the time-varying commodity-equity systematic risk observed in risk premia studies (cDaskalaki; Isleimeyyeh forthcoming) is confirmed by our study, which may now be contextualized within the financialization literature.

However, though the evolution of $\hat\beta\_t$ is harmonious across the commodity indices, it remains that the level of integration is not sustained at a consistent level post-2012, which this paper is unable to offer explanations for. Empirical data on the levels of index speculation could have helped in explaining why integration is not sustained post-2012, but the author was constrained by limitations in data access detailed in Section 4. Moreover, this data constraint also limits the rigour of using the CRBI as a low-speculation proxy. since the study has relied on inductive reasoning using index methodology rather than empirical observation. This paper thus recognizes the limitations above, and invites future studies to address these issues.

1. Individual Commodities

Having established that commodity-equity risk-sharing exists for commodity indices, this paper will further examine whether that has affected the level of equity integration for individual commodities. The general idea is that since products benchmarked against indices of commodity futures will necessitate similar futures positions, index speculation would also cause increased systematic risk integration in individual commodities (Cheng and Xiong 2014). As mentioned in the literature review, past literature is sympathetic to this direction: Tang and Xiong’s (2012) empirical study noted a substantially higher average inter-commodity correlation between baskets of indexed commodities than non-indexed, and Isleimeyyeh’s (forthcoming) futures risk premium study found increased equity systematic risk coefficient for crude and heating oil.

Recall that this paper’s definition ‘indexed’ refers to commodities commonly included in the popular indices, rather than any commodity included in an index. Given the constraint that I was unable to access the historical composition of the various commodity indices, some faith will be required that index composition remained roughly consistent. By comparing the current composition of the GSCI, DJCI and BCI, as well as data recorded in Anson (2008), four indices prevalent across all are chosen: gold, lean hogs, wheat and crude oil (WTI). Respectively, each of the individual commodities represent the metal, livestock, agricultural and energy sector prevalent in the GSCI, DJCI and BCI.

[split view of betas for indexed]

Overall the $\hat\beta\_t$ values for indexed commodities in Figure [CITE] are inconclusive of index speculation increasing equity integration, which is backed up by the $P(\hat\beta\_t > 0)$ values (Appendix [CITE]). The results indicate that unlike the indices they are a part of, these commodities exhibit significant variation in integration between each other and equity markets, which leaves index speculation unlikely as a salient common driver for any integration observed. For example, gold exhibits sustained positive integration with the MSCI basket of emerging markets from 2004, while it fails to do so for developed markets. Interestingly, gold differs from other commodities in exhibiting decreased equity risk sharing during most recessionary periods, which lends some credence its common perception as a haven asset (cSchroders 2022). Wheat appears to have some slight positive relation to world equity markets, while lean hogs exhibit no signs of equity risk sharing at all. The only integration akin to that exhibited by indices themselves can be observed in crude oil, which has exhibited a sustained positive trend across all markets.

[split view of betas for non-indexed]

Lumber, oats, palladium and rubber in Figure [CITE] represent non-indexed commodities, and the results are similar to that observed in indexed commodities ($P(\hat\beta\_t > 0)$ included in Appendix [CITE]). Interestingly, palladium appears to have high equity market integration since the 2000s, which may be attributable to its main usage in catalytic converters as car manufacturers committed to the reduction of pollutants (cPfeiffer blah blah 2007), thereby causing increased economic integration. Rubber and lumber also exhibited some periods of increasing integration post-2000, while oats peaked at 2008.

Ultimately, it appears that equity risk sharing for individual commodities is driven more by idiosyncratic factors than index speculation. As such, integration more likely occurs when the specific uses of those commodities are economically integrated. Within our sample, sustained periods of high equity market integration are observed for oil and palladium, which are both influenced by the cyclical demand for shipping and transportation. In support of this conclusion, Kilian and Hicks (c2012) used an impulse response model to demonstrate that surprises in forecasted economic growth can predict crude oil prices. Furthermore, Hamilton and Wu (c2015) evidenced that index speculation volumes does not directly translate to futures price changes for individual commodities.

Although Hamilton and Wu (2015) dismissed the index speculation theory of risk sharing based on its non-effect on individual commodities, this paper reiterates the sine qua non of index speculation: that speculators *buy the index not the commodity*. Essentially, capital inflow into products benchmarked against an index would almost never transmit equally to all constituents due to the weights assigned to each commodity. Given that commodity indices are commonly weighted based on demand/supply related factors such as recent production or trading volume, it implies that capital will be distributed to individual commodities based on some fundamentals themselves, which re-enforces existing market realities rather than create noticeable trends. Hence, index speculation may be thought of as the invisible hand in a Sorosian feedback loop (cSoros ) that reinforce market perceptions based on pre-determined metrics. As such, we would expect a basket of indexed commodities to increase in volatility compared to a basket of non-indexed commodities over the financialization period, which will form this paper’s final test.

[BCI CRBI vol comp final]

Due to the time constraints of this study, commodity indices BCI and CRBI shall be used to proxy indexed and non-indexed baskets. BCI is chosen to represent indexed commodities due to its 15% weight-cap to prevent price-distortion from one commodity, and because it stretches back further than DJCI. CRBI is equal-weighted as detailed in section 4.2. Figure [CITE] plots the BCI less CRBI difference in monthly rolling standard deviation. Windows of 6, 9, 12 and 15 years are plotted for robustness. From the results, it appears that indexed commodities have grown more volatile relative to non-indexed commodities at every window-length, which is intuitively consistent with price trends in Figure [CITE]. Given that both indices exhibited similar levels of equity market integration in Figure [CITE], and the aforementioned weight cap in BCI and equal-weighting of CRBI, there is no reason why we might expect to see a persistent increase in BCI volatility relative to CRBI – other than persistently increase in levels of speculation in BCI than CRBI.

Nevertheless, the conclusion above relies again on CRBI being a reliable proxy for low index speculation, which [get volume data from bberg for popular indices, leave CRBI off as ‘too niche’, find better explanation for CRBI reaching same level of integration (maybe because tied to economic activity?)]

[then explain that other factors like economic news shocks more contributaory, Kilian oil analysis]