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

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Abstract

As financialization allowed more speculators enter the commodity market in the early 2000s, systematic risk is shared whereby commodity returns became more closely integrated with the returns of conventional assets. In particular, systematic risk transmission is associated with commodity index speculation, which has been evidenced to occur between commodities and equities in prior correlation and risk premia studies. Using Kalman filters, this paper extends previous studies by estimating the time-varying systematic risk coefficients between commodity and equity markets directly. The findings suggest that financialization has indeed eroded the diversification benefits of commodity indices for equity investors in the face of a secular convergence, but individual commodities remain largely unaffected.

Keywords: *Financialization, Risk Sharing, Systematic Risk, Index Speculation, Kalman Filters, Commodities, Equities*

Acknowledgements

I owe much of any statistical understanding I currently possess to Fernando Zepeda and Patricio Hernandez, who patiently built my foundations when I had none. This paper also benefitted from general comments by Liza Kurenina and, of course, the guidance and challenge given by my supervisor Arie Gozluklu.

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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 prominent, such as Gorton and Rowenhorst's (2006) 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 (Fattouh, Kilian, and Mahadeva 2013), leading academics to find that the commodity-equity correlation has increased (Tang and Xiong 2012; Silvennoinen and Thorpe 2013). This paper continues in the spirit of uncovering trends in the commodity-equity relationship, and may be placed in context with prior literature on commodity market financialization.

Financialization surged to prominence along with commodity prices in the run-up to 2008, igniting fears that it was inducing a speculative fervour that distorted the pricing mechanism relied upon to allocate natural resources (Brown and Sarkozy 2009). However, both financialization and speculation remain ambiguous concepts that have been inconsistently employed by academics and policy makers (Fattouh, Kilian and Mahadeva 2013). This paper will follow the definition for financialization 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 whose actions do not fit traditional norms, though that has proven challenging. Traditionally, commodity spot and futures markets were created to facilitate immediate consumption and hedging (Masters 2008), but defining speculation as forward-looking actions is too broad for our purposes. 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 (1960) definition of speculation as the volume of futures trading in excess of what is necessary to hedge spot positions. Despite the empirical critiques raised by Fattouh, Kilian and Mahadeva (2013), Working's definition is at least unbiased.

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 (Tang and Xiong 2012). 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 (Daskalaki, Kostakis, and Skiadopoulos 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. Masters (2008) points to the rise of commodity index speculation, such as investors diversifying into 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 (Basak and Pavlova 2016).

This paper conducts 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 systematic risk is time-varying (Daskalaki, Kostakis, and Skiadopoulos 2014; Isleimeyyeh forthcoming), with Kalman filtering already established in equity market literature as a suitable model for estimating time-varying systematic risk (Faff, D. Hillier, and J. 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. Section 2 contextualizes the motivation and methodology of this paper with prior literature. Section 3 sketches a linear model for systematic risk and its state space transformation, followed by an explanation of the implementation strategy and data collection in Section 4. Section 5 discusses the results found, ultimately concluding in Section 6 that while increased commodity-equity risk sharing exists at the index level, there is an inconclusive effect on individual commodities.

2 Literature Review

Having already explored the linkage between financialization, speculation and risk sharing, this section provides 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 specification of its underlying dynamics.

Previous literature has focused mainly on the correlation between 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 does 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 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. Daskalaki, Kostakis, and Skiadopoulos (2014) finds that equity pricing models have low explainability for commodity returns, concluding that equity and commodity markets remain segmented. Nevertheless, the authors' analysis focused largely on average levels of R^2 (squared correlation) in factor models, and left unreported their observation of significant time variation of the systematic risk coefficient β. As such, this paper recognizes Daskalaki, Kostakis, and Skiadopoulos'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 (2016) found that stock returns can have statistical significance when included as regressors for crude oil futures risk premium at various horizons. Isleimeyyeh (forthcoming) 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 aims 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. For a comprehensive analysis on 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 (1994) 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 (1973) concluded that Kalman filters are a more efficient algorithm for simple linear models, though the advantage disappears when β is assumed to vary according to an extra 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 β. Renzi-Ricci (2016) further found that a random walk β outperforms rolling regressions upon a simulation of a structural shift in β.

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 contextualize the random walk β.

3 Model

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

3.1 Linear Model

The underlying linear model for systematic risk is simple and can be derived from first principles. To begin, let y and x represent returns. Systematic risk sharing can then be assumed to manifest through the proportionality $y \propto x$, such that $y = \beta x$ where β is non-zero. A perfect degree of integration will therefore result in a β of 1 such that returns are expected to co-move in the same direction and magnitude, while a β of -1 expects returns co-move in opposite directions but with the same magnitude. A near-zero β suggests little co-movement between the assets. Hence, if two assets are integrated under the risk sharing hypothesis, a positive β should exist, and the level of integration will be observable from the closeness of β to 1. Note that β beyond the range -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 β measure for risk integration over standard correlation testing prevalent in prior literature is that β 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. β, 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 β for x. Hence, it is possible to have a high correlation with a low β, and vice versa. Formally, a time-invariant β can be written in terms of correlation ρ and standard deviation σ such that:

$$\rho_{xy} = \frac{Covariance(x, y)}{\sigma_y \sigma_x} \tag{1}$$

$$\beta = \rho_{xy} \frac{\sigma_y}{\sigma_x} \tag{2}$$

However, although the benefits of β over correlation remain the same, the above equation is solely for a constant β. To observe whether the level of equity-commodity integration changes over time, β 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 ϵ:

$$y_t = \beta_t x_t + \epsilon_t \tag{3}$$

For Equation 3, 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.

Within financial literature, the linear model can also be derived using the Capital Asset Pricing Model (CAPM). From (Fama and Kenneth 2004), the original Sharpe-Lintner CAPM is expressed as:

$$E[R_i] = R_f + (E[R_m] - R_f)\beta \tag{4}$$

where E is the linear expectation operator, 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 β 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 the Daskalaki, Kostakis, and Skiadopoulos (2014) approach to test for integration using equity pricing models, which as noted by the authors necessitates a time-varying approach due to the (unreported) evolution of β_t observed.

3.2 State Space Transformation

Finding β_t is not as simple as dividing y by x for each t due to market noise ϵ: it necessitates some consideration for how β_t evolves given β_{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 β 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 variables given discrete state changes. For our purposes, the state shall be time t, such that the Kalman filter estimates 1) prior predictions at state $t-1$, and 2) new observations at state t. The general algorithm is as follows:

Algorithm 1 Kalman filter algorithm for state t $\forall$ $t \in \{0, 1, 2, ...T\}$

```
Initiate model inputs, which represent the posteriors at t = 0
for t = 1 to t = T do
    Predict the prior for t using the posterior estimate at t − 1
    Compute the posterior estimate using the prior and the observation at t
end for
```

β_t is thus estimated by posterior values for each timestep. To formalize subsequent notation, let $\hat{\beta}_t$ denote estimated β_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. We will also use standard Kalman filter assumptions that $\hat{\beta}_t$ and y_t can be modelled using Gaussian distributions, where the distribution for the time-dependent variable $\hat{\beta}_t$ is itself time-dependent and the distribution for observed variable y_t remains constant.

As such:

$$\hat{\beta}_t \sim N(\hat{\beta}_t, P_t) \tag{5}$$

$$y_t \sim N(y, R) \tag{6}$$

where P_t is the time-dependent $\hat{\beta}_t$ variance and R the constant y_t variance.

Under the index speculation theory, β_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 β_t fits well with the random walk assumption that inter-period evolution is solely due to stimuli exogenous to the process itself (Malkiel 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 β estimates for the CAPM in their study. Hence for the predictive step the following set of equations are used:

$$\hat{\beta}_{t|t-1} = \hat{\beta}_{t-1|t-1} + \theta_t \tag{7}$$

$$P_{t|t-1} = P_{t-1|t-1} + Q \tag{8}$$

where θ_t in Equation 7 represents the error of the $\hat{\beta}_{t-1|t-1}$ estimate and Q in Equation 8 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 θ_t. Hence a lower Q implies a higher ϵ_t in Equation 3, where ϵ is not estimated directly by the Kalman filter. This follows since if one assumes $\theta_t = 0$, then β_t is deterministic and the fluctuations of y_t and x_t can be explained by market noise ϵ_t alone.

To compute the posterior estimates the following set of equations are used:

$$K = \frac{P_{t|t-1}}{P_{t|t-1} + R} \tag{9}$$

$$\hat{\beta}_{t|t} = \hat{\beta}_{t|t-1} + K(y_t - \hat{\beta}_{t|t-1}x_t) \tag{10}$$

$$P_{t|t} = (1 - K)P_{t|t-1} \tag{11}$$

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. Notice also that Equation 7 is embedded into Equation 10 as the residual controlled by the Kalman gain.

4 Implementation

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

4.1 Methodology

To implement the model, real dollar returns shall be used for x and y. Deflation is necessary for a robust analysis since inflation information is embedded in commodity prices (Garrat 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 0.6% per month since the 1980s (Appendix A). To make the data suitable for our model, returns are 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 involves calculating the difference between actual returns and in-sample monthly averages. Note that due to the two-step data transformation, it matters little whether simple or log returns are used. For this paper simple returns is 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 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 is 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 uses 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 (2015) to implement the Kalman filter. Recall that the Kalman filter detailed in Section 3.2 is a forward (in time) algorithm that calculates the most likely position of β_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 β_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 standard Rauch-Tung-Striebal smoother implemented by FilterPy.

4.2 Data

The data used for this paper falls into three categories: index prices, index trading volume and single commodity prices. 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 36×12 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 when many commodity futures in the US began trading (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 (CPI) from the Federal Reserve Bank of St. Louis. The formula used for deflation is:

$$Price_{real,t} = Price_{nominal,t} \times \frac{CPI_T}{CPI_t} \tag{12}$$

such that T represents December 2021.

4.2.1 Indices

Index data include both commodity and equity indices, all of which was collected from Bloomberg. Commodity indices collected are the S&P Goldman Sachs Commodity Index (GSCI), S&P Dow Jones Commodity Index (DJCI), Bloomberg Commodity Index (BCI), and Commodity Research Bureau Index (CRBI). Equity indices used are the S&P 500 (SPX), MSCI World (MSCI-W) and MSCI Emerging Markets (MSCI-EM).

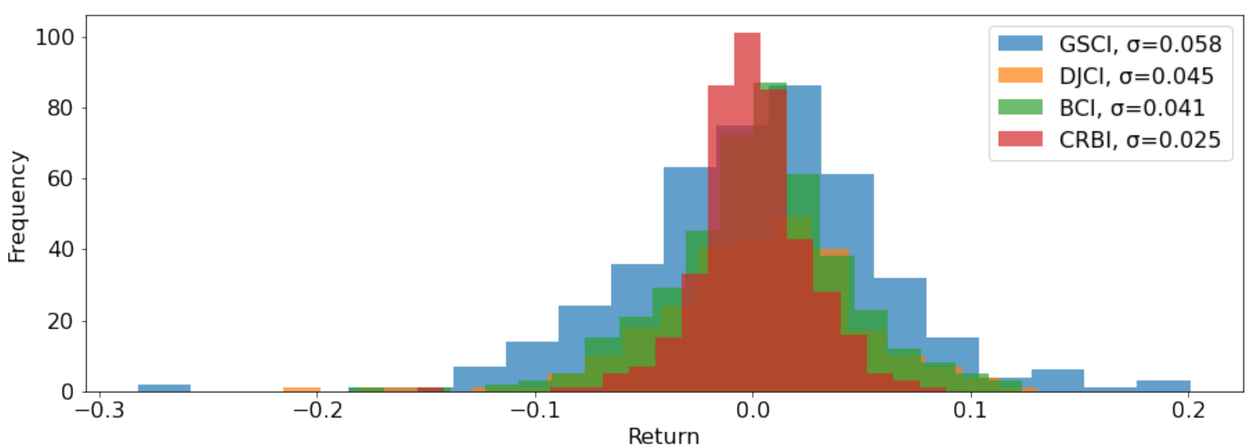

Figure 1: Return distributions of commodity indices

Figure 1 displays the real return distributions for the commodity indices used. GSCI, DJCI and BCI all include the broad sectors of energy, agriculture, livestock and metal. 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.

Despite their broad similarities, key differences exist in the methodology of GSCI, DJCI and BCI. GSCI is a production-weighted index, with weights determined by five-year average world production data (S&P Global 2022a). As such, it has a momentum-driven weighting that has seen significant historical exposure to the energy sector, which leads to critique of over-exposure to idiosyncratic event risks (Anson 2008), evident from the high standard deviation of returns. By contrast, BCI aims to create a well-diversified index by implementing a 15% weight cap for constituents (Bloomberg 2022). Aside from 5-year average production data, it also incorporates the 5-year average trading volume of each commodity when assigning weights, which makes it more attractive to institutional investors due to improved liquidity (ibid). Note that BCI is the original version of the DJCI before S&P decided to relaunch the index, removing any consideration of production data in the weighting of DJCI (S&P Global 2021).

An interesting index to include is the CRBI, which is now maintained as part of the cmdty BLS Index by Barchart.com. CRBI is a niche index composed of commodities used in the initial stages of production, which renders its composition entirely different from the three indices above (Barchart.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). As such, CRBI may be a proxy for usually non-indexed commodities, and it is also an un-investable index (see Section 4.2.2).

The equity indices used – SPX, MSCI-W, MSCI-EM – are all weighted by market capitalization (S&P Global 2022b; MSCI 2022), differing only in geography. SPX captures the

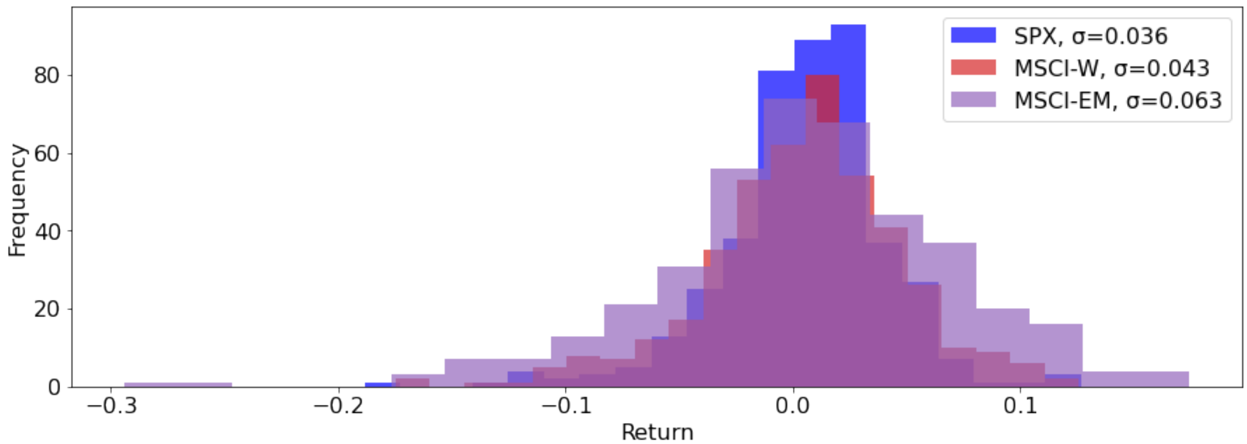

Figure 2: Return distributions of equity indices

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 2 shows, the prices and return distributions are especially different between equity indices from developed and developing economies.

4.2.2 Index Trading Volumes

Monthly trading volume of financial products benchmarked against the indices in Section 4.2.1 is collected from Bloomberg to proxy the level of index speculation, with each data series running from product inception to December 2021. BlackRock's iShares exchange traded fund was used for GSCI, and its iPath exchange traded notes were used for BCI (its iShares variant only launched in 2018). Given that BCI was the original version of DJCI, no products benchmarked against the S&P DJCI was found. No products also exist for the CRBI (Barchart.com BLS).

Total of SPGI and BCI averages are plotted in Figure 3 as a proxy for the aggregate

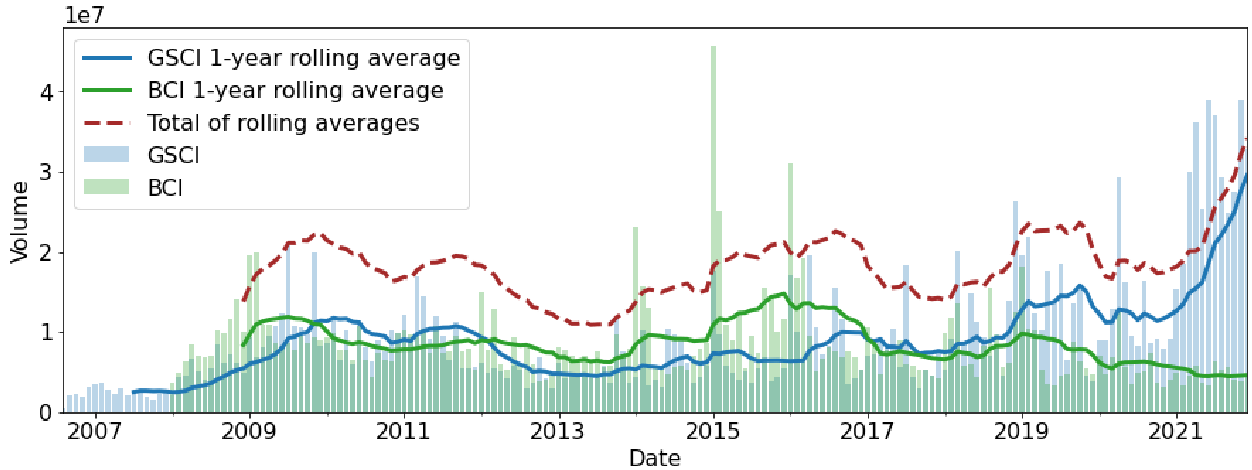

Figure 3: Trading volume for BlackRock iShares GSCI and iPath BCI products

level of index speculation, which should affect GSCI, DJI and BCI similarly as they capture broadly the same basket of commodities. This figure will be referred back to later during our analysis. Although a more accurate method would be to construct replicating portfolios of each index, then estimate the level of speculation from the US Commodity Futures Trading Commission data for each commodity, this study is constrained by the restricted access to historical index component weights on the academic Bloomberg subscription.

4.2.3 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 crude oil (WTI) were collected from the US Energy Information Administration. Front-month future prices for generic contracts in gold, lean hogs, wheat, lumber, oats, palladium and rubber were collected from Bloomberg. Note that while the volumes of index speculation and historical index 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. The implication of these limitations will be mentioned in the relevant sections during analysis.

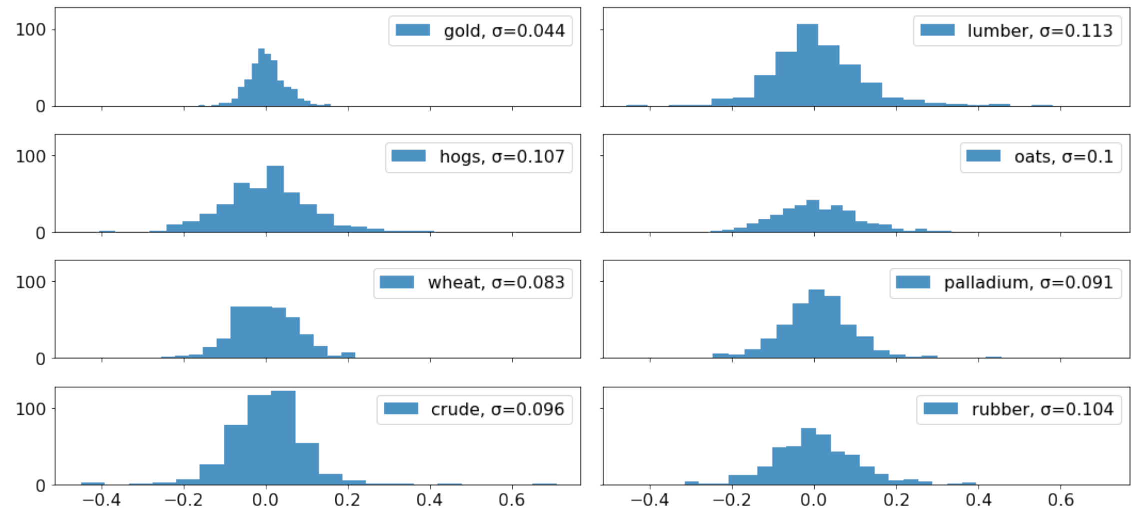

Figure 4: Return distributions of individual commodities

5 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.

5.1 Commodity Indices

The differences in commodity index construction may be observed through the difference in real returns. Although these differences are zero on average (Appendix B), it has more of a time-varying relationship. Figure 5 shows the rolling average of a difference in monthly returns constructed using 6, 9 and 12 year windows for robustness (blank periods due to different data availability). 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. Different equity indices will also be used to see if any trends remain consistent across economies.

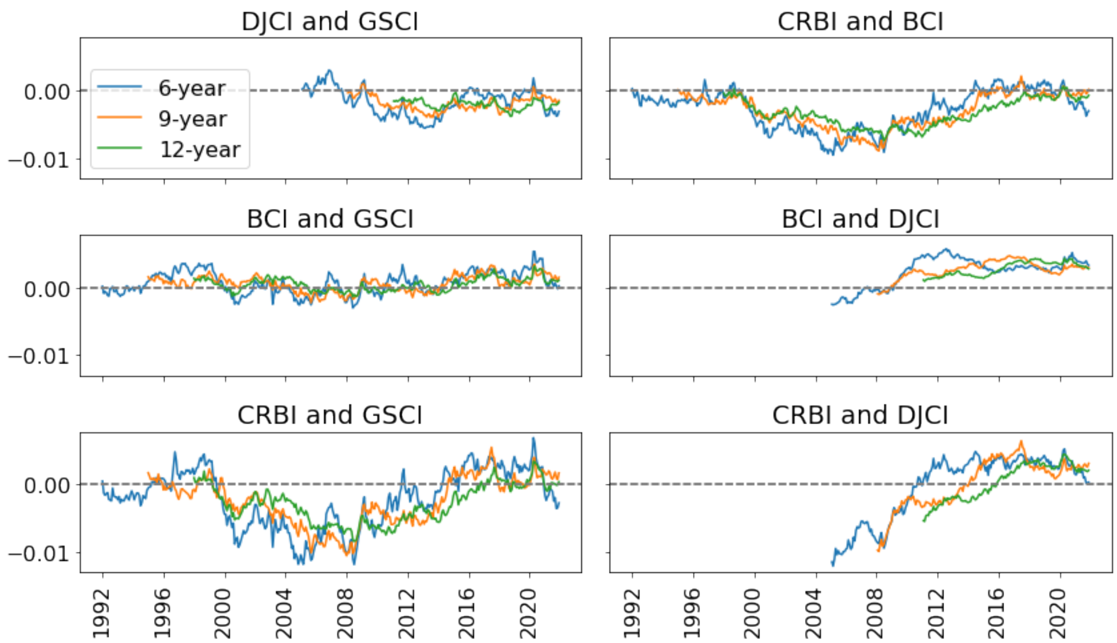

Figure 5: Rolling averages of differences in commodity index return

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 for each equity index. 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 investable commodity indices (GSCI, DJCI and BCI) due to financialization. This follows because although there are some deviations of magnitude, 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 investable indices due to the lack of capital allocation.

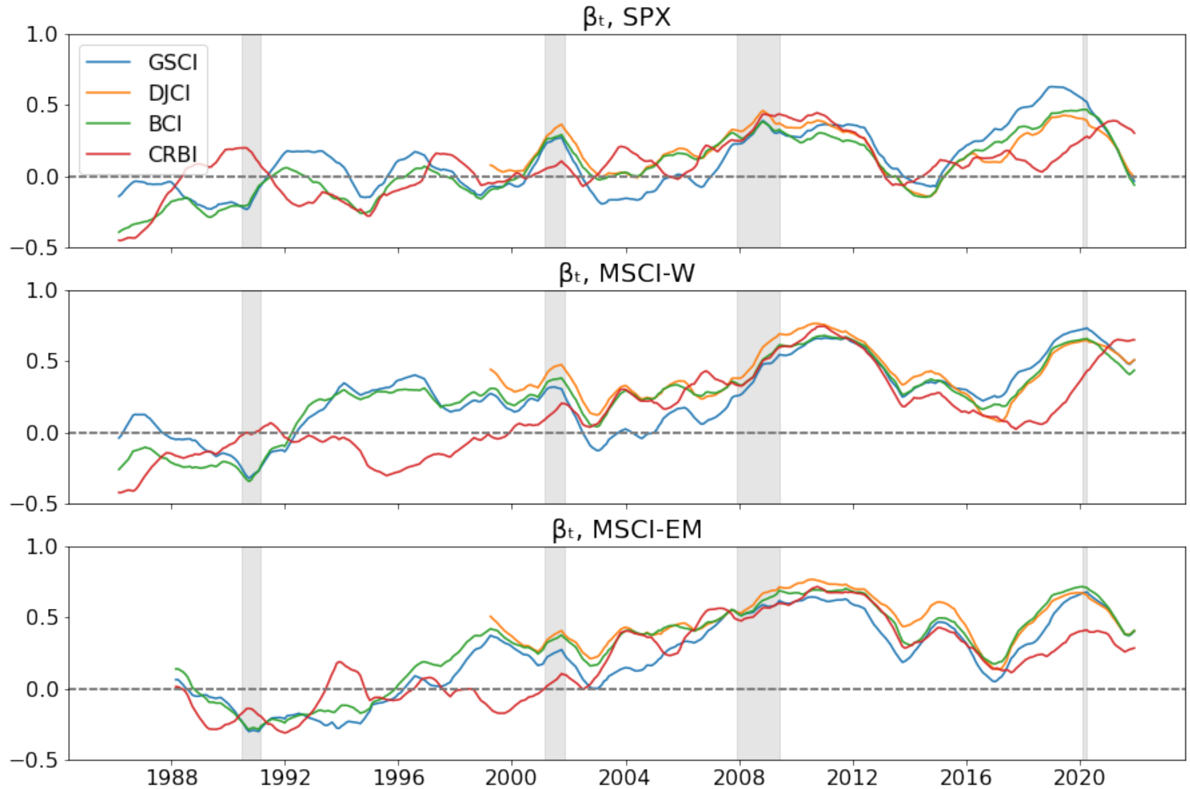

Figure 6: $\hat{\beta}_t$ values obtained

Figure 6 presents the smoothed $\hat{\beta}_t$ values between the commodity indices tested and the SPX, MSCI-W and MSCI-EM. Due to our data cleaning, $\hat{\beta}_t$ 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 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 (global recessionary periods shaded in grey), though slight spikes are observed during recessionary periods for SPX integration.

Risk sharing caused by index speculation is evidenced by the fluctuations in integration similar to trends observed for speculative trading volumes in Figure 3. Furthermore, there is a slower increase in integration for CRBI, which is our un-investable 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 investable indices, which this study alone is unable to explain (but is discussed in the conclusion of Section 5.2). Overall, the fluctuations in integration roughly corresponds with our crude measure of index speculation in Figure 3, which is supportive of the index speculation theory. Appendix C further reports a significant lead-lag relationship such that changes in index speculation volume may Granger cause the $\hat{\beta}_t$ observed.

$\hat{\beta}_t$ only represents the most likely position of β_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 7 represents the credible level of positive integration where $\hat{\beta}_t > 0$, constructed using variance term P_t. Note that under the Bayseian philosophy of the Kalman filter, the state probabilities should not 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.

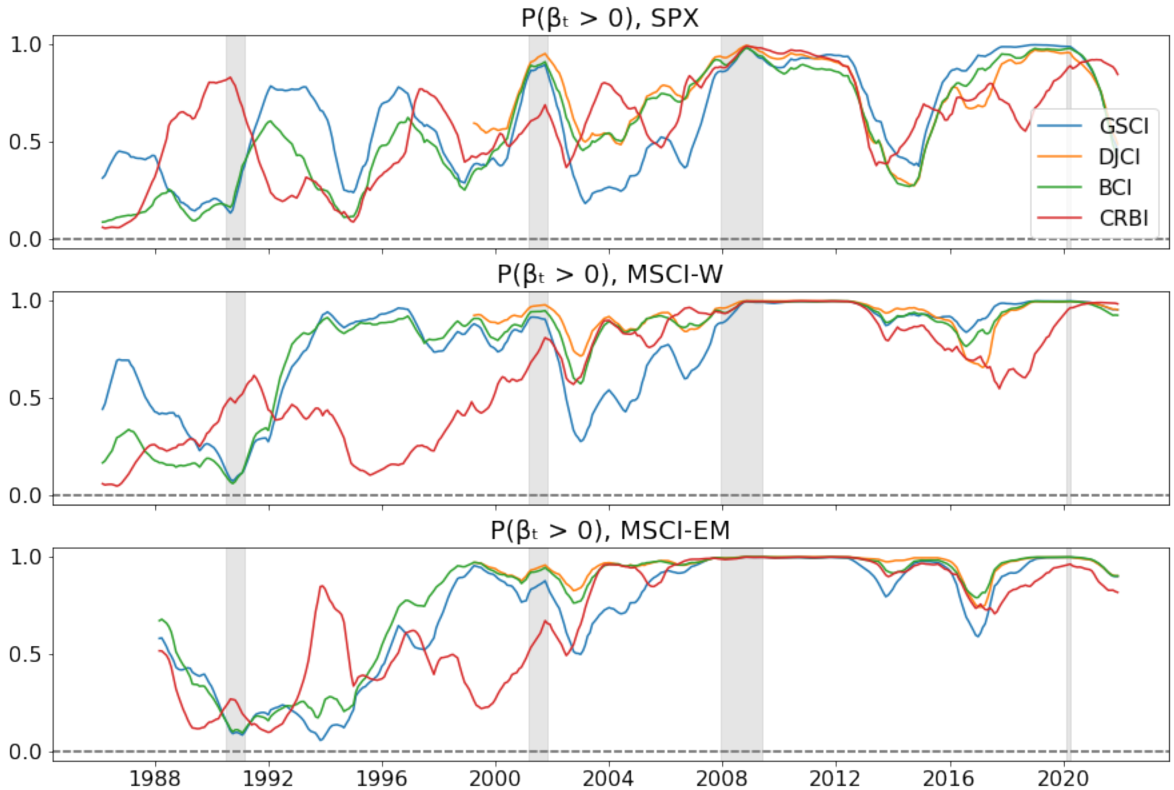

Figure 7: $P(\hat{\beta}_t > 0)$ for $\hat{\beta}_t$ values in Figure 6

	OLS $\hat{\beta}$	**KF** $\hat{\beta}_t$ **Mean**	**RW RMSE**	**OLS RMSE**	**KF RMSE**
GSCI	0.2430	0.1908	0.9933	0.9681	0.8983
DJCI	0.3673	0.3659	0.9933	0.9768	0.7358
BCI	0.3489	0.2070	0.9933	0.9732	0.9109
CRBI	0.2598	0.1371	0.9933	0.9643	0.9500

Table 1: Backtest results averaged across SPX, MSCI-W and MSCI-EM

To justify my results against a time-invariant approach, Table 1 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 on average) and the time-invariant $\hat{\beta}$ estimated using ordinary least squares (OLS) regression. Backtesting was performed for all three equity indices tested, with the average result reported. The OLS coefficient is seen to differ from the average $\hat{\beta}_t$ obtained, which raises the question of which measure is better. From the root mean squared errors (RMSE), the random-walk assumption is worst at describing the sample data, while the OLS assumption of a constant β is worse than the time-varying model employed by this paper. Note that the RW RMSE is the same across indices due to the two-step transformation process detailed in Section 4.1 to remove leptokurtosis evident in Figures 1, 2 and 4 to respect the normality assumption of the Kalman filter. Overall, backtesting 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.

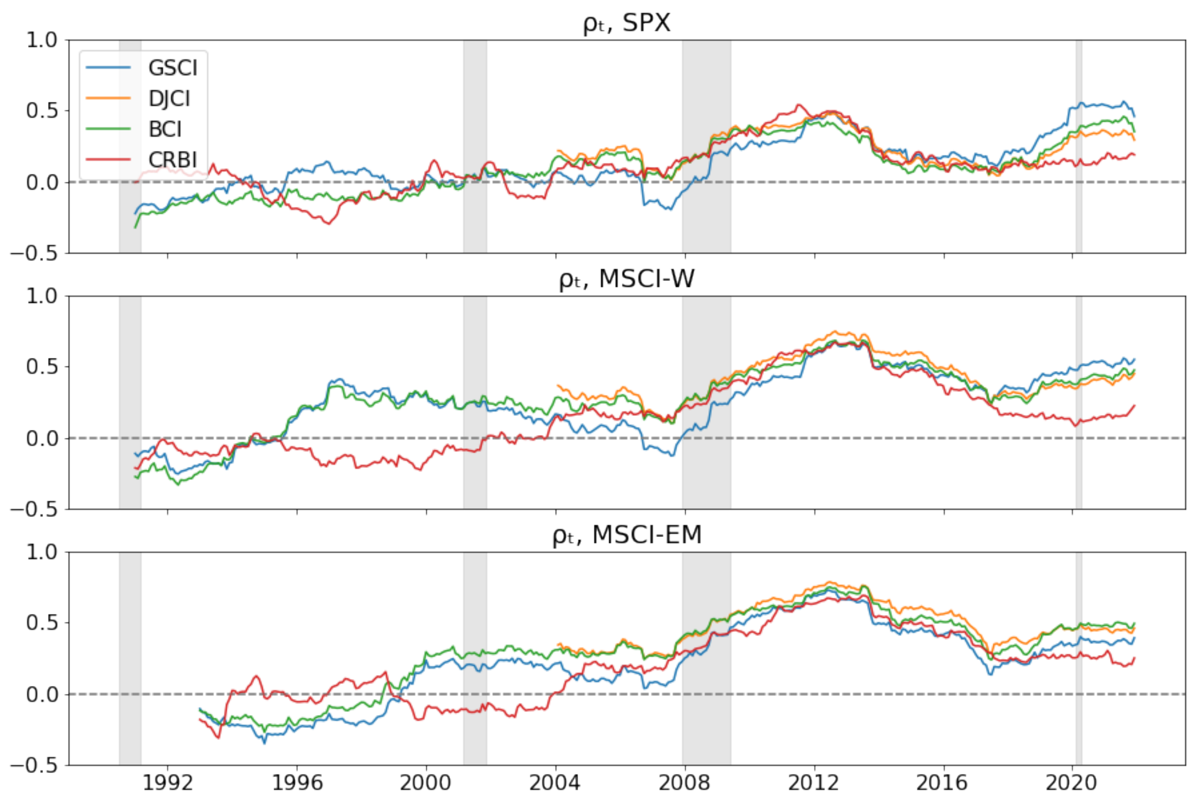

Figure 8: 5-year rolling correlation values (ρ_t)

For robustness, a comparison with the traditional rolling correlation method is made. Figure 8 presents 5-year rolling correlation coefficients in the same format as Figure 6 above.

The correlations computed correspond closely with the series of $\hat{\beta}_t$ in Figure 6, 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) method. However, the benefit of the systematic risk model is its interpretability (of how much a one standard deviation change in x would affect y), and also its ability to be backtested for accuracy. Nevertheless, Figure 8 remains a beneficial exercise to confirm that a linear assumption for the β_t model is valid, especially when integration has been highest.

Overall, the study provides evidence that the trend in commodity-equity risk sharing at the index level 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) is invariant to economic cycles, and 5) is consistent with evidence from 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 (Daskalaki, Kostakis, and Skiadopoulos 2014; Isleimeyyeh forthcoming) is validated by our study, which may now be contextualized within the financialization literature.

5.2 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 hypothesis 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.

This paper's definition 'indexed' refers to commodities included in the investable indices as opposed to all indices. In our data, it represents GSCI, DJCI (for to its history with BCI) and BCI. Due to 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), gold, lean hogs, wheat and crude oil (WTI) are chosen as our sample. Respectively, each of the individual commodities represent the metal, livestock, agricultural and energy sectors shared across the GSCI, DJCI and BCI.

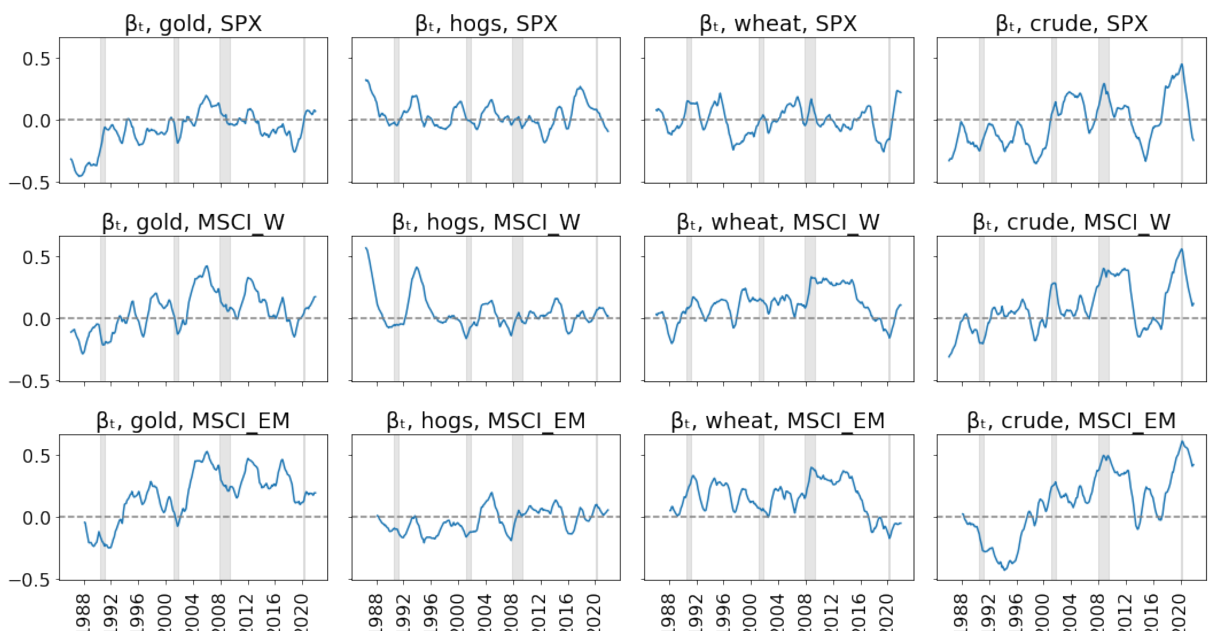

Figure 9: $\hat{\beta}_t$ obtained for indexed commodities

Overall the $\hat{\beta}_t$ values for indexed commodities in Figure 9 are inconclusive of index speculation increasing equity integration, which is backed up by the $P(\hat{\beta}_t > 0)$ values (Appendix

D.1). 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 (Schroders 2022). Wheat appears to have some positive relation to global 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.

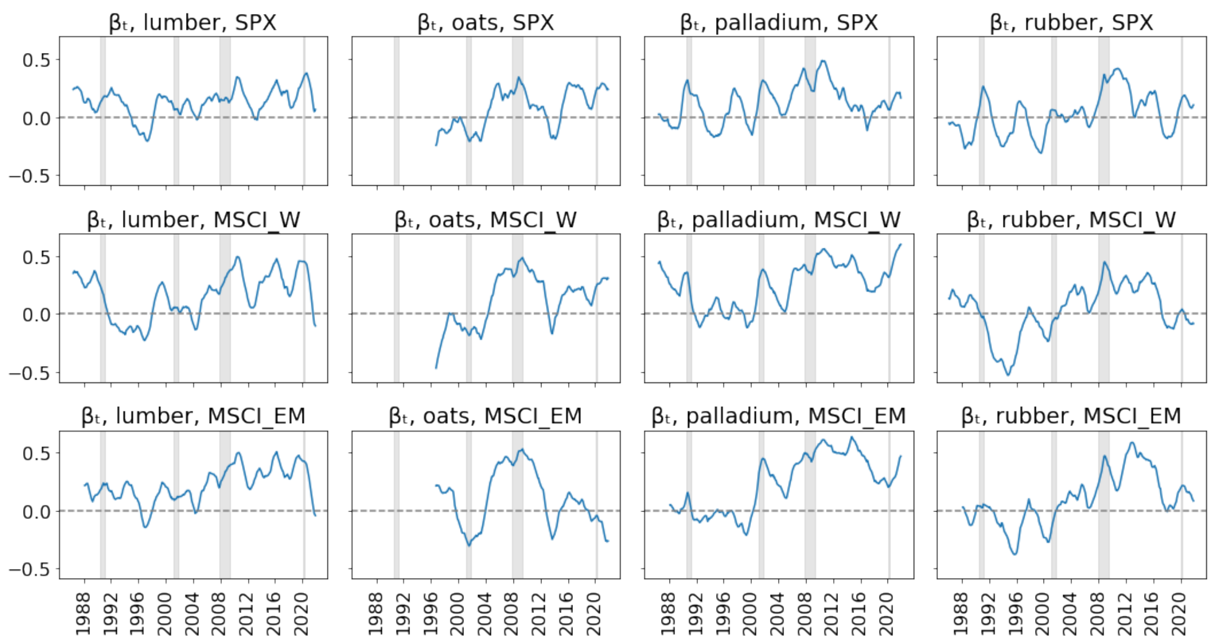

Figure 10: $\hat{\beta}_t$ obtained for non-indexed commodities

Lumber, oats, palladium and rubber in Figure 10 represent non-indexed commodities. Overall, no coherent trend exists in integration ($P(\hat{\beta}_t > 0)$ included in Appendix 10), much like the indexed commodities. 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 (Pfeifer et al. 2007). Since car demand is cyclical and dependant on economic strength, it makes sense for positive integration between palladium and equity markets. Rubber and lumber also exhibited some periods of increasing integration post-2000, though is inconclusive from the probabilities in Appendix 10, while oats peaked at 2008.

Ultimately, it appears that equity risk sharing for individual commodities is driven more by idiosyncratic factors than a common cause in index speculation. As such, integration occurs when the specific uses of those commodities themselves 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 (2012) used an impulse response model to demonstrate that positive surprises in forecasted economic growth positively affects crude oil prices. Furthermore, Hamilton and Wu (2015) observed that notional positions of index speculators cannot forecast price changes for agricultural futures, but has some weak predictive abilities for crude oil.

Although Hamilton and Wu (2015) dismissed the index speculation theory of risk sharing based on its weak effect for individual commodities, this paper reiterates the *sine qua non* of index speculation: that speculators buy the index not the commodity. Capital inflow into products benchmarked against an index would almost never transmit equally or immediately to all constituents due to the weights assigned to each commodity and maturity of futures contracts used (see Section 4.2.1). Given that commodity indices are commonly weighted based on demand/supply related factors such as recent production or trading volume, it follows that capital inflows to index-linked products are distributed to individual commodities based on existing fundamentals, which re-enforces rather than disrupts existing market trends.

Hence, rather than cause all indexed commodities to integrate similarly to the equity market, index speculation likely amplifies existing momentum for individual commodities. Although individual effects of increased momentum are barely noticeable in our test, index speculation likely culminates in expediting risk sharing at the index level from the amplification of price momentum – but that is not to say equity integration is dependent on index speculation. This idea is reflected in Figure 6, where CRBI is slower to increase in equity integration, but reaches the same level as the investable indices. Furthermore, Appendix E demonstrates that monthly volatility of investable indices consistently increases more than the un-investable CRBI, giving credence to the amplification theory. Finally, given the physical nature of commodities, it is unlikely that they will undergo endogenous changes upon indexing, unlike when changes in corporate practices occur after a company's stock is included in a well-regarded equity index (Bennet, Stulz, and Wang 2021).

Nevertheless, there is insufficient scope for this paper to conclusively study this theory of capital transmission between indices and underlying commodities, which paves way for future research. This study can only conclude that index speculation has little effect on systematic risk sharing between individual commodities and equity indices.

6 Conclusion

The systematic risk relationship between commodities and the equity market has fundamentally changed over the last few decades, which was hinted in studies on commodity-equity correlation (Buyuksahin, Haigh, and Robe 2010; Tang and Xiong 2012; Silvennoinen and Thorpe 2013) and risk premia (Daskalaki, Kostakis, and Skiadopoulos 2014; Baumeister and Kilian 2016; Isleimeyyeh forthcoming). Contextualizing time-varying systematic risk as an effect of financialization, this paper seeks to test the strength and direction of changes in systematic risk, and whether it is impacted by index speculation. Risk integration between commodities and equities was directly tested using a simple linear model, then Kalman filtering was employed to extract time-varying β coefficients. Kalman filters were not previously used in the literature to assess commodity market risk sharing, which forms the main contribution of this paper in providing new statistical evidence directly from a systematic risk perspective. Using monthly price data from 1986 to 2021, commodity-equity integration was found to have increased secularly for commodity indices, consistent with the results of prior literature. However, equity market integration remains idiosyncratic across individual commodities, which invites further research into capital transmission from index-linked products to individual commodities.

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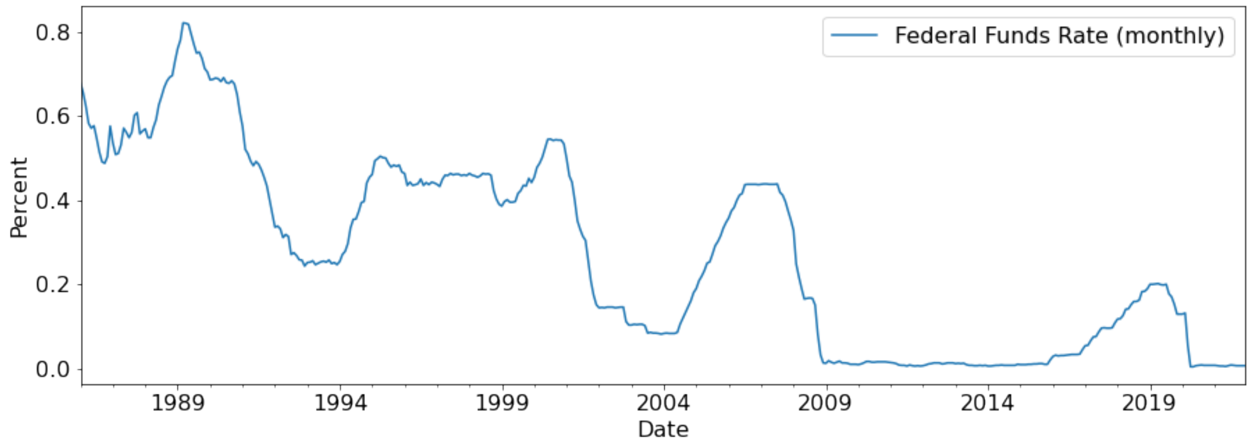
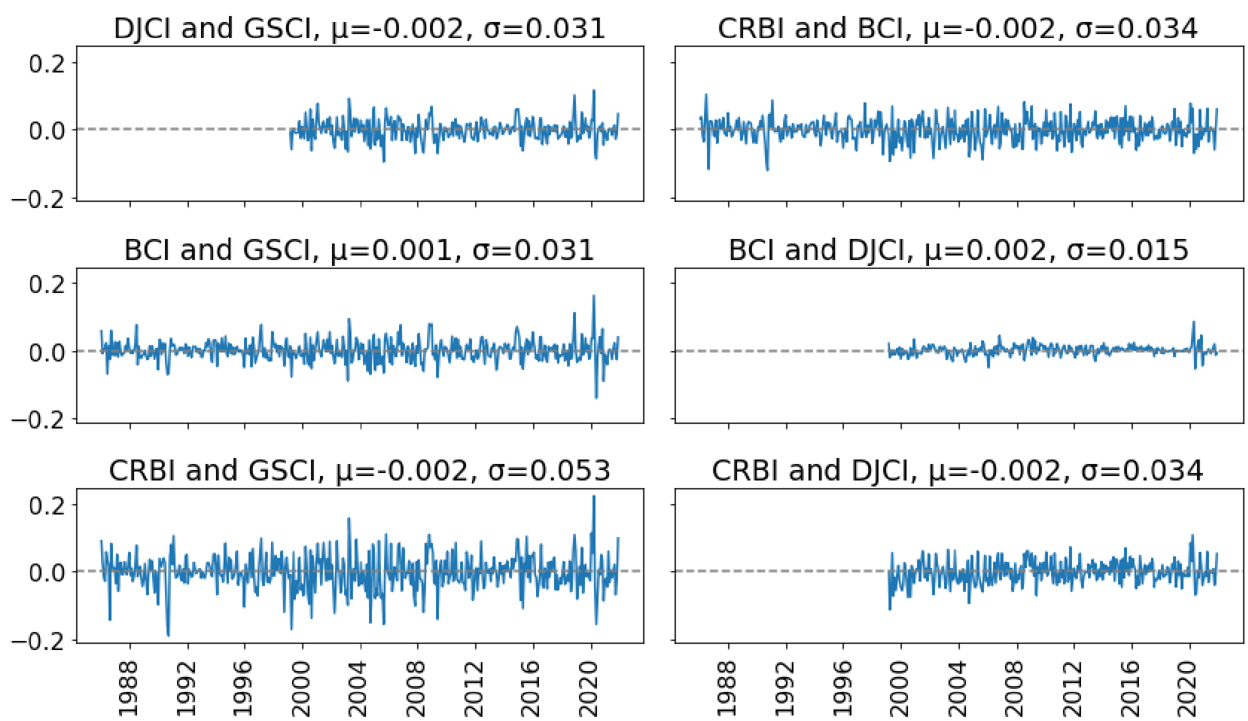
Appendices

A Federal funds rate since 1980



Source: Federal Reserve Bank of St. Louis

B Differences in commodity index returns



C Lead-lag relationship between index speculation and risk sharing

To investigate if a lead-lag relationship between index speculation and commodity-equity integration, I perform a standard Granger causality test to determine whether percentage changes in index speculation Granger cause the estimated $\hat{\beta}_t$ values in Figure 6. The total between the two rolling average trading volumes in Figure 3 is used as a crude proxy for the level of index speculation. Due to the lack of rigour behind this proxy's construction, this test is not reported in the main body. However, given the limitations for this paper with regards to time and data collection, it is the best measure available.

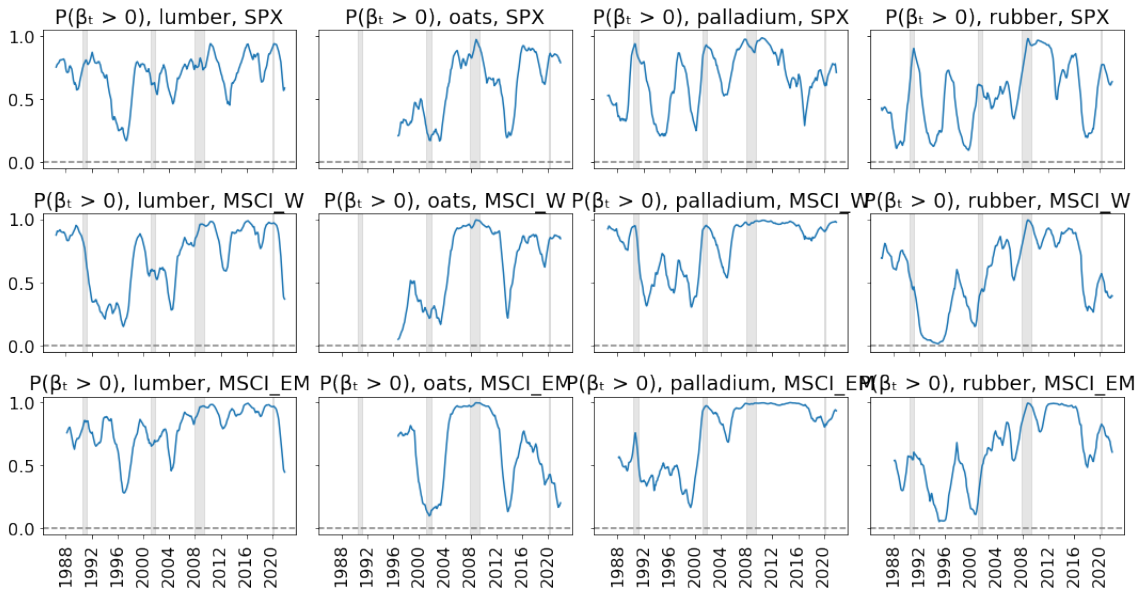
	GSCI	**DJCI**	**BCI**	**CRBI**
SPX	0.3597	0.1902	0.0696	0.8258
MSCI-W	0.0804	0.0660	0.0283	0.1202
MSCI-EM	0.3345	0.5732	0.7038	0.8976

Table 2: Granger F test results for different $\hat{\beta}_t$ combinations

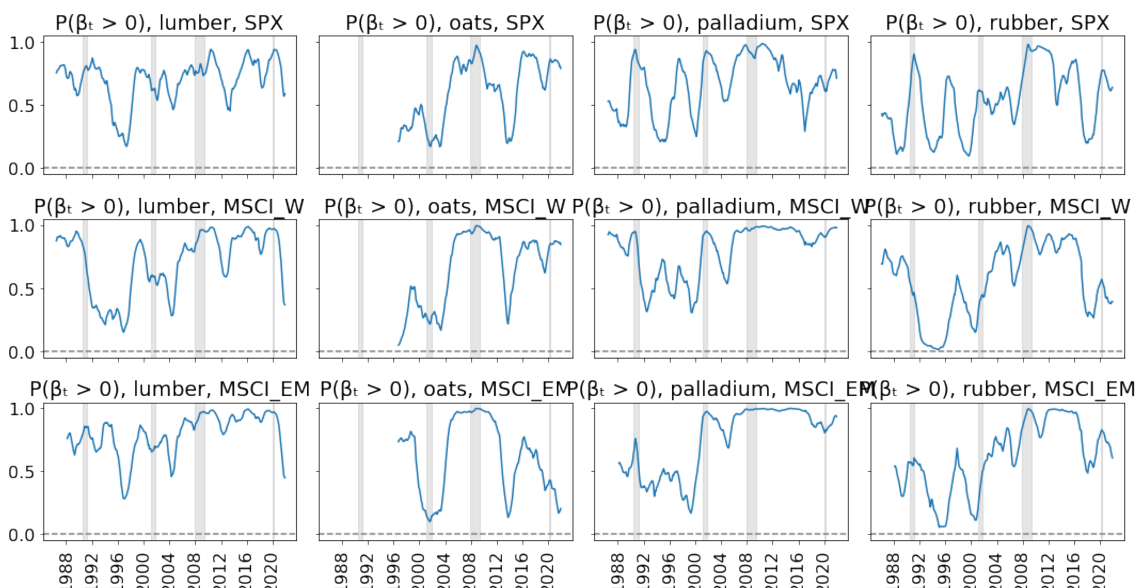
The F-statistics are reported in Table 2 above. The table is to be interpreted as the probability of a percentage change in trading volume Granger causing the $\hat{\beta}_t$ between the row and column indices. At the 10% level, there is significant lead-lag relationship between change in trading volumes and the level of integration between the investable commodity indices and MSCI-W, which lends credibility to the theory that index speculation is the driver behind commodity-equity risk sharing present at the index level. The lack of lead-lag relationship for CRBI is also indicative that the level of integration between equity markets and niche commodities captured by the CRBI is driven by other factors.

D Credible levels of integration for individual commodities

D.1 Indexed commodities



D.2 Non-indexed commodities



E Volatility comparison of indexed and non-indexed baskets

Due to the time constraints of this study, commodity indices BCI and CRBI shall be used to proxy indexed and non-indexed baskets.[1] BCI is chosen to represent indexed commodities due to its 15% weight-cap to prevent price-distortion from one commodity, and CRBI is equal-weighted as detailed in section 4.2.1. I calculate dynamic standard deviation using a rolling window, then subtract the series for CRBI from the values for BCI.

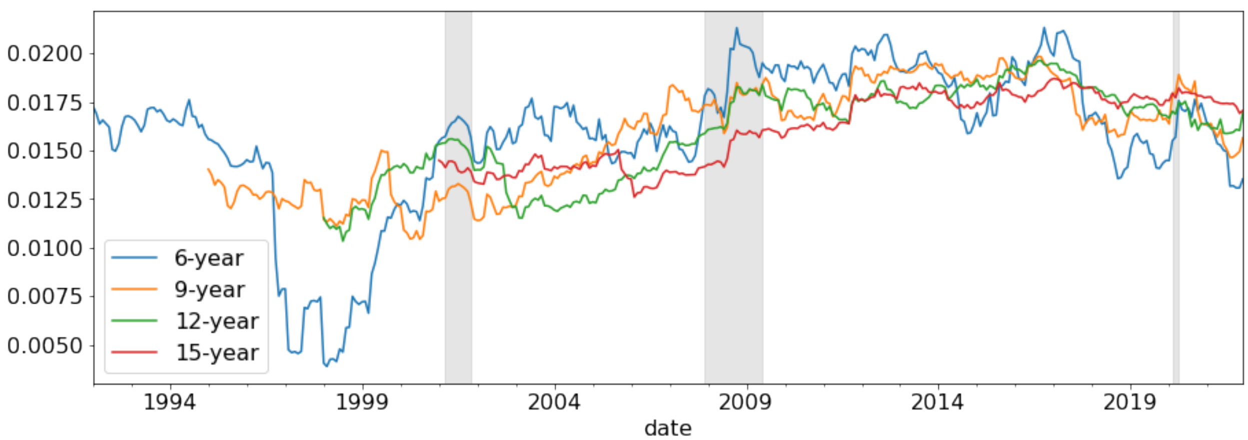


Figure 11: BCI rolling standard deviation less CRBI rolling standard deviation

Figure 11 plots the results calculated using windows of 6, 9, 12 and 15 years for robustness. It appears that indexed commodities have grown more volatile relative to non-indexed commodities, which does not appear upon first glance at Figure 1. Given that both BCI and CRBI exhibited similar levels of equity market integration in Figure 6, and the aforementioned weight cap in BCI and equal-weighting of CRBI, it is hard to explain a persistent increase in BCI volatility relative to CRBI. In Section 5.2, I reason that it could be due to a persistent increase in levels of speculation in BCI amplifying the movements of individual commodities, given that no coherent level of integration was reached between individual

[1] Recall that this paper defines indexed commodities as constituents of investable indices, so an index may be composed of non-indexed commodities

commodities, yet the investeable indices integrated much faster with the equity market than the non-investeable index CRBI. However, this study alone is inconclusive, and capital transmission from index to constituent remains an area for future research.