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A key determinant of commodity price Co-movement: The role of daily market liquidity

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ABSTRACT

Daily price co-movement across different commodity classes and its key determinant are investigated in this paper. Using co-integration and Granger causality analysis, we identify a common liquidity factor which drives prices of five commodities (oil, silver, gold, corn, live cattle) to move along a common trend. When the market becomes more (less) liquid, all commodity prices tend to move up (down) in the same direction. As a result, such liquidity-driven price co-movement across different commodity classes is likely to generate aggregate price shocks and amplify inflation volatility. As a practical implication of our findings, policy makers ought to be able to draw valuable lessons from monitoring daily commodity liquidity dynamics as a timely bellwether for incipient inflation and to more effectively control inflation risk.

1. Introduction

The last several decades have arguably witnessed the design of monetary policy turn into an ever more data-intensive and complex process. Central bank analysts now routinely scrutinize hundreds of historical time series which are as inputs into highly sophisticated models in order to first distill and then articulate policy recommendations based either on so-called “now-casted” coincident indexes or forward-looking forecasts. A continued adherence to the inflation-targeting paradigm has also compelled many central banks to engage in various commitment-enhancing “open-mouth” operations, which are regularly conducted and released to the public in the form of minutes, press conferences as well as comprehensively furnished inflation reports.

A considerably more “data-rich” environment (see Bernanke et al., 2005) faced by modern-day central banks notwithstanding, few would object to the view that trends in commodity prices continue to occupy a more prominent position on most central bankers' watch list of key economic indicators, not least because of their widely studied and accepted role in presaging changes to consumer prices. For example, Cody and Mills (1991) illustrate a close relationship between commodity prices and economic indicators such as the consumer price index (CPI), while Clarida et al. (1998) demonstrate that commodity prices strongly inform movements in inflation, interest rates and output. As a result, Bhar and Hamori (2008) show that commodity prices can be informative for formulating monetary policy, due to their role played as input factors to industrial production, while Stock and Watson (2003) argue that commodity prices are useful as predictors for inflation and output growth. Mallick and Sousa (2013) estimate a battery of modern dynamic macroeconometric models in order to robustly identify the importance of commodity price shocks, which lead to a rise in inflation and demand a more aggressive behavior from central banks towards inflation stabilization. In a more recent and related study, Holtemöller and Mallick (2016) employ both an estimated VARX as well as a small open-economy New Keynesian model to demonstrate that global food price shocks constitute an important contributor to cost-push inflation in India. Therefore, understanding the determinants of commodity price movements and price shocks can help to predict inflation dynamics and design effective monetary policy. Perhaps unsurprisingly then, Bernanke (2008) calls for the development of a better understanding of the factors that underpin commodity prices.

The present paper directly responds to this call by employing co-integration and Granger-causality analysis in order to identify a high-frequency market liquidity bellwether and investigate its potential in signaling changes in commodity price trends. Such an analysis should be of interest to policy-makers, not least because of the significant episodes of macroeconomic policy uncertainty often ushered in by elevated levels of commodity price volatility (Joëts et al., 2017). As a result, liquidity-induced changes to commodity price trends should be informative for anticipating episodes of future macroeconomic instability and may also help in deciding on timing and scope of optimal monetary

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policy responses, not merely to combat any incipient inflation pressure, but also to mitigate the fallout to the real economy from uncertainty shocks (Bernanke, 1983; Baker et al., 2016; Scheffel, 2016).

The main findings of this study are as follows. First, we statistically establish the existence of significant daily price co-movement among different commodity classes. Furthermore, we present evidence demonstrating how daily measures of liquidity observed across different commodity markets exhibit a tendency to co-move in accordance with the existence of a common liquidity factor. Finally, we show that such a common liquidity bellwether may be underpinning much of the observed co-movement of commodity prices, by presenting evidence from a series of co-integrating regressions and Granger causality tests. When the market becomes more (less) liquid, all commodity prices tend to move up (down) in the same direction. Thus, liquidity can drive aggregate price shock, which amplify inflation risk. Additional tests further suggest that the impact of liquidity on commodity price co-movement is stronger in a post-2008 financial crisis sub-sample of our complete data set.

A key result of this study is obtained through a co-integrating regression analysis similar to the one employed in Leybourne et al. (1994). By means of a dynamic linear regression carried out on lagged liquidity variables and the commodity market CRB index to control for changes in overall macroeconomic conditions, we establish the existence of a co-integrating and thus long-run equilibrium relationship between commodity price co-movements and a common liquidity factor. One additional and notable finding is that the liquidity effect on prices is not only found to spill over across different commodity sector boundaries, but also to propagate across different maturities of commodity futures securities.

Given that previous studies have tended to leave any predictors of commodity prices other than macroeconomic variables largely unexplored, we conduct a series of Granger causality tests in order to demonstrate that market liquidity may serve as a useful "real-time" variable for explaining changes in commodity prices. We thus contribute to the literature not only by developing a more in-depth understanding of the determinants of commodity price movements, but in contrast to many existing studies also by making use of data sampled at higher frequencies by exploiting the availability of commodity futures at daily intervals. Our analysis is therefore addressing an important research gap by establishing the existence and usefulness of a common commodity liquidity bellwether as an important market-derived, "real-time" predictor of cross-sectional commodity price co-movements. Its existence is implied via the presence of a series of long-run cointegrating relationships between the common liquidity bellwether and an array of commodity prices, while its predictive utility is established via a series of Granger-causality tests.

The paper is organized as follows. Section 2 briefly discusses the relevance of monitoring high-frequency market liquidity for monetary policy. Section 3 describes the data and suitable liquidity measures for commodity markets. In section 4, we investigate the daily price and return co-movement of both spot and future commodity products and conduct Granger-causality tests to investigate any causality between spot and future returns. In section 5, we study daily liquidity commonality for both spot and future security trading. In section 6, we establish a dynamic link between price co-movements and liquidity commonality by regressing daily prices on both individual as well as market levels of liquidity. The conclusions and policy implications derived from our study are summarized in section 7.

2. High-frequency market liquidity and monetary policy

The results presented in this study portend relevant lessons for optimal monetary policy design and implementation. During "frothier" times of comparatively more active or liquid market turnover, commodity prices tend to exhibit an upward trend. As a result, it may be optimal for policy makers to adopt a relatively tighter monetary policy stance so as to "lean against the wind" and head off any inflationary pressures. Conversely, during relatively placid or market-impairing illiquid trading periods, commodity prices often exhibit a downward trend. As a result, policy makers may prefer to adopt a more accommodating monetary policy stance with the aim of counteracting partially evaporated market liquidity.

Indeed, the question of whether central banks should respond more aggressively to either a broader class of assets or a more narrowly defined array of commodity prices has taken center stage again in the wake of the global financial crisis of 2008. While Bernanke and Gertler (2000) conduct a model simulation in order to argue that central banks are best served by responding to the general rate of inflation only, Jeanne and Bordo (2002) instead contend that specific circumstances characterized by an overoptimistic and excessively leveraged private sector may render a more active response to rapidly increasing nominal asset prices more optimal, by helping central banks insure against the possibility of a credit crunch.

Central banks may thus consider adopting a pre-emptive strategy of mitigating inflationary as well as other risks by responding also to changing trends in commodity prices, specifically by monitoring a market-based common liquidity measure available at high frequency, so as to inform policy makers on monetary policy formulation in a more timely manner (see Ramaprasad and Shigeyuki, 2008). Given that commodity prices may signal changes to the future state of the economy with important ramifications for optimal monetary policy design, an array of estimated commodity price co-movement measures may deliver an even richer and more informative set of policy-relevant indicators. Indeed, the existence of salient commodity price co-movement patterns has been well documented in the literature (Pindyck and Rotemberg, 1990; Ai et al., 2006; Natanelov et al., 2011; Byrne et al., 2013; Casassus et al., 2013; Daskalaki et al., 2014; Janzen et al., 2017; LePen and Sévi, 2017).

Commodity price movements therefore appear to be of immediate utility for predicting changes in the general price level, typically via the latter's lagged response to sustained changes in factory gate price inflation. Because of this close relationship, commodity prices have also been attributed with the role of an intermediate indicator for monetary policy (Garner, 1989). As a result, central banks may develop monetary policies by taking commodity price movements directly into account (see Garner, 1989; Awokuse and Yang, 2003; Gospodinov and Ng, 2013; Li et al., 2017). Indeed, it has long been suspected that the so-called "price puzzle" in the empirical macroeconometrics literature employing vector autoregressions arises from the econometrician's failure to incorporate a suitable leading indicator of inflation – such as a commodity price index – directly into the VAR model's specification (Eichenbaum, 1992; Sims, 1992). A more comprehensive understanding of commodity prices and their (co-)movements may consequently be more likely to deliver more accurate and timely insights into the prevailing state of the economy, as well as convey information helpful for formulating optimal monetary policies.

Given monetary policy's ultimate objective of managing the supply of money, the implications of our findings for the design of monetary policy can be best illustrated with reference to the celebrated equation of exchange or quantity theory, MV = Py, where M denotes the money supply, V the velocity of money (that is, the speed at which money circulates), P the price level and y the real level of GDP (Snyder, 1924). Browne and Cronin (2010) decompose the total price level P into two parts: $P = \omega P_s + (1-\omega)P_c$, where P_s represents the consumer goods, P_c the commodity and ω is a linear weight with $0<\omega<1$. Substituting this decomposition into the equation of exchange yields $MV = [\omega P_s + (1-\omega)P_c]^* y$, which in turn demonstrates theoretically how money supply responses are directly linked to commodity prices: $M = \frac{y}{V}(1-\omega)P_c + \frac{y}{V}\omega P_s$. Holding other variables constant, the money supply can thus be viewed as a linear function of commodity prices. It is this perspective which links the common liquidity bellwether identified in this study via commodity prices back to monetary aggregates and the conduct of monetary policy.

In order to better comprehend many of the sources underpinning commodity price movements, several studies have explored the role played by macroeconomic variables. Svensson (2008) argues that an increase in real interest rates decreases the future value of commodities due to its effect on market discount rates. Likewise, Akram (2009) employs quarterly data from 1990 to 2007 to empirically investigate the impact of real interest rates on commodity prices and attributes increases in commodity price to a fall in real interest rates. Vansteenkiste (2009) empirically investigates 32 commodities from 1957 to 2007 and finds that global demand, exchange rates and real interest rates all play a significant role in determining commodity prices. More recently, Byrne et al. (2013) have also presented evidence indicating that real interest rates constitute an important determinant of commodity prices, while Mo et al. (2018) employ a mixed-frequency Garch-MIDAS model in order to identify various domestic and international macroeconomic factors affecting the volatility of commodity futures traded in Chinese and Indian markets.

Previous studies on the role played by macroeconomic variables in informing commodity price movements have necessarily been limited to using low frequency (monthly or quarterly) data only. One important objective of this paper is to circumvent this limitation by exploring important liquidity-based determinants of price movements using market trading information obtainable at daily frequencies. Brockman et al. (2009) argue for the prevalence of a systematic liquidity factor in international stock markets and thus establish the existence of a common global liquidity factor. More recently, Mancini et al. (2013) have presented strong evidence in support of liquidity commonality in the foreign exchange market, while Gong et al. (2018) investigate liquidity interdependence based on bid-ask and return-spreads for Chinese stock index futures using a Copula-MIDA modelling approach drawing relevant lessons for the management of systemic liquidity risk. Recent works of Zhang and Ding (2018) and Zhang et al. (2018) show the significant role of liquidity in volatility spillover across different futures markets.

A liquidity factor has also been explicitly added to otherwise canonical theoretical asset pricing models, such as in Acharya and Pedersen (2005) and Liu (2006). For stock market data, the co-movement between asset returns and liquidity innovations has been documented by P'astor and Stambaugh (2003). Finally, a sizable number of studies have documented the existence of a common liquidity factor operating in both stock and commodity markets concurrently (Chordia et al., 2000; Frino et al., 2014; Korajczyk and Sadka, 2008; Marshall et al., 2013).

3. Data and methodology

According to Marshall et al. (2013), there exist five broad categories of commodities: energy (such as crude oil), agricultural (such as corn), livestock (such as live cattle), precious metals (such as silver) and industrial metal (such as gold). Gold is now also widely applied in the electronics industry and as a result primarily regarded as an industrial commodity (Tully and Lucey, 2007). We proceed by selecting one commodity from each family (as indicated in the brackets) to construct a cross-sectional commodity portfolio. We also allow our selection of representative commodities to be guided by the degree to which such markets are actively traded. Consequently, the trading volumes of crude oil, corn, gold, live cattle and silver are the highest of each commodity family (Kowalski, 2014).

Regarding the question of the preferred commodity liquidity measure, Marshall et al. (2012) explores a large number of liquidity proxies for 19 commodities. They find that the Amihud liquidity proxy possesses the maximal correction ratio among all proxies, leading them to strongly recommend the use of this proxy when modelling commodity liquidity. As a result, we will use this proxy first outlined in Amihud (2002) which takes the form:

$$Amihud = \frac{|R_t|}{Vol_t} \tag{1}$$

where R_t is the asset return and Vol_t is the asset trading volume at time t. Intuitively, whenever trading volume is high, this measure of asset liquidity is small and the asset is considered to be more liquid. In order to standardize this liquidity measure, we normalize all of our liquidity measures computed using the Amihud definition by dividing them by their respective standard deviation over time.

Throughout this study we employ the superscript *ca* to represent live cattle commodity futures, *co* corn commodity futures, *g* gold commodity futures, *o* oil commodity futures, *si* silver commodity futures and finally ML_t to represent an overall or aggregate indicator for market liquidity. Furthermore, the superscript s ("spot") denotes any asset data with a maturity of 1 month, while f ("future") denotes any asset data with a maturity of 6 months. L denotes the Amihud measure of liquidity, P the natural log of spot commodity prices, F the natural log of 6-month futures prices and finally r the return on various commodities.

Throughout we will be employing 1-month futures prices as spot prices. Our data was sourced from Thomson Datastream and ranges from 1st Jan, 2005 to 31st Dec, 2013. Nonlinearity present in various financial markets has often been cited as a reason for the adoption of non-linear co-integration tests, such as by Ghosh and Kanjilal (2016). However, as a result of failing to detect any significant non-linearity in the commodity price co-movement data explored in the present study, we confine our analysis to the use of purely linear regression model specifications. Moreover, as a result of focusing primarily on financial markets data at daily frequency, our regression models do not incorporate conventional macroeconomic predictors, which are instead proxied by using the global CRB aggregate commodity price index in natural logs, which itself is composed of 19 individual commodity series.

4. Commodity price Co-movements

4.1. Spot price Co-movements

This section presents the findings from a number of statistical tests in order to investigate the degree of co-movement present among our chosen set of commodity prices. To this end, we first plot all five spot commodity prices and returns in Fig. 1 and Fig. 2. Fig. 1 clearly demonstrates how commodity prices co-move with each other and that they exhibit a common moving trend. To illustrate this using but one instance, all commodity prices clearly exhibit a downward trend during the period of late 2008 to early 2009. Another conspicuous period occurs between the middle of 2010 to early 2011, during which all commodity prices evidently display an upward trend. As a result, significant co-movement appears to exist among the commodities under study here. In addition, high and low returns of different commodities also appear to occur at similar dates as well, which is well illustrated in Fig. 2.

Following our visual inspection, we compute a series of correlation matrices for the five commodities, which reveal that the correlation between commodity prices is always positive, and that all the correlation coefficients are larger than 0.5 (see Tables 4-1) as well as statistically significant. Cross-sectional correlations therefore suggest that all the spot commodity prices move in the same direction, which explains why these commodity prices tend to closely track each other along a common moving average trend. Similarly, for the correlation matrix computed based on commodity returns, again all the spot commodity returns appear to be positively correlated with each other (see Tables 4-2). More importantly, the p-values again indicate that all the correlation coefficients are statistically significant as well. It can thus be argued that prices and returns of different commodities are positively and statistically significantly correlated with each other and that this correlation may result in price co-movement.

4.2. 6-Month future price Co-movements

We will now extend the analysis of the previous section by

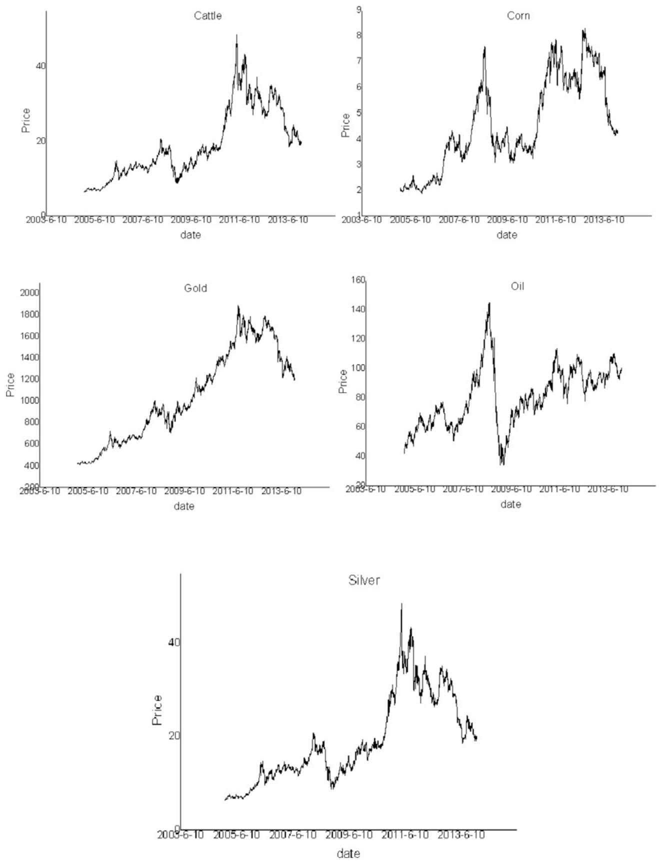

Fig. 1. Spot commodity daily prices.

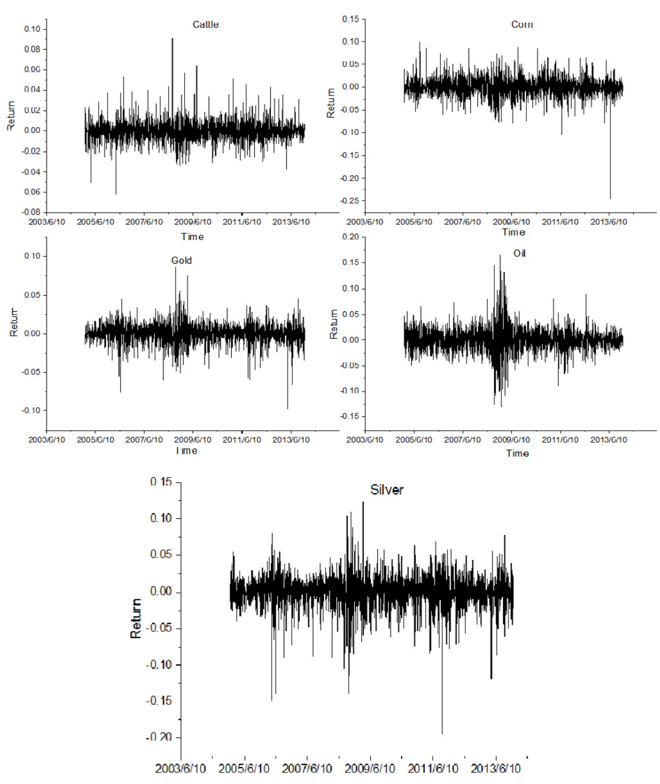

Fig. 2. Spot commodity daily returns.

investigating also the maturity effect of commodity prices, by replicating relevant statistical computations using commodities futures with a maturity of 6 months instead.

Plotting all five commodity future prices and returns in Figs. 3 and 4 again makes evident a common moving trend shared by all of the series. For example, from the middle of 2010 to early 2011, all future commodity prices display an upward trend. As a result, not only the spot commodity prices scrutinized in the previous section, but also the future commodity prices may exhibit significant co-movement. In addition, Fig. 4 reveals how high and low returns for future prices of different commodities cluster at similar dates.

We continue our analysis by again computing two correlation matrices for future prices and returns, which again demonstrate how prices are positively and statistically significantly correlated with each other, all exhibiting correlation coefficients which are all larger than 0.5 (see Table 4-3). As a result, any price co-movement appears to occur not just for the specific case of spot prices, but is in evidence also across different maturities. Based on the computed correlation matrix of returns data, all the commodity futures appear to be statistically significantly correlated with each other (see Tables 4-4), safe for the return correlation between cattle and corn which is negatively signed.

Next we conduct a two-way Granger causality test in order to investigate any predictive power our chosen set of return measures may exhibit. The results of these F-tests are summarized in Tables 4-5 and 4-6. For spot returns, cattle and oil possess any predictive power for commodity future returns. By contrast, only the silver future return fails to predict spot returns. Therefore, the overall results indicate that the spot return fails to predict future returns in general, while at the same time future returns appear to be more successful at predicting spot returns.

5. Liquidity commonality

While the statistical evidence presented in the previous section served to establish co-movement of the five commodity series, the present section will be devoted to identifying and clarifying the role played by any liquidity commonality present among the commodity series. In order to facilitate this task, the sample correlation matrix for the five commodity liquidities is presented in Tables 5-1 and 5-2. For the Amihud liquidity measure correlation matrix for spot prices presented in Table 5-1, all liquidity measures exhibit positive and statistically significant correlation. This suggests that – similar to our earlier analysis conducted for price levels and returns – the commodities' corresponding liquidity measures may also share a common trend or liquidity commonality. By contrast, the correlations computed for the Amihud liquidity measures associated with the commodity futures appear to be statistically insignificant as evidenced by the almost unanimously high p-values. The evidence obtained from our sample therefore suggests that liquidity commonality is only likely to exist for spot price data, which motivates our decision of confining our subsequent analysis to investigating any relationship between the commodity price series and their corresponding *spot* liquidity measures only.

Furthermore, it has been argued elsewhere that individual asset

Table 4-1
Spot Commodity Prices Correlation Matrix with p-value.

	P^{ca}_t	P^{co}_t	P^{g}_t	P^{o}_t	P^{s}_t
$\mathbf{P^{ca}_t}$	1				
$\mathbf{P^{co}_t}$	0.7634	1			
	(0.00)				
$\mathbf{P^{g}_t}$	0.808	0.8652	1		
	(0.00)	(0.00)			
$\mathbf{P^{o}_t}$	0.6384	0.7237	0.6018	1	
	(0.00)	(0.00)	(0.00)		
$\mathbf{P^{s}_t}$	0.7727	0.8822	0.9371	0.6235	1
	(0.00)	(0.00)	(0.00)	(0.00)	

Note: Values in brackets are p-values.

Table 4-2
Spot Commodity Returns Correlation Matrix with p-value.

	$r^{ca,s}_t$	$r^{co,s}_t$	$r^{g,s}_t$	$r^{o,s}_t$	$r^{s,s}_t$
$r^{ca,s}_t$	1				
$r^{co,s}_t$	0.1564	1			
	(0.00)				
$r^{g,s}_t$	0.0488	0.2014	1		
	(0.02)	(0.00)			
$r^{o,s}_t$	0.155	0.2999	0.3118	1	
	(0.00)	(0.00)	(0.00)		
$r^{s,s}_t$	0.1145	0.2586	0.8123	0.3574	1
	(0.00)	(0.00)	(0.00)	(0.00)	

Note: Values in brackets are p-values.

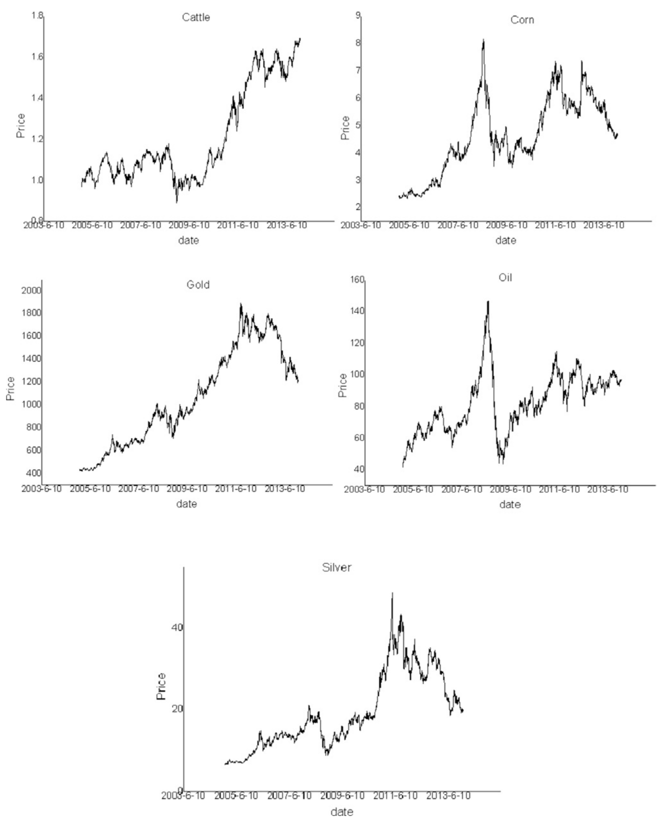

Fig. 3. 6-month futures commodity daily prices.

liquidity may also be correlated with some overall level of market liquidity, which may for instance be proxied via an equally weighted average of individual liquidity series (Chordia et al., 2000). As a result, commodity liquidity may be decomposed into a market liquidity as well as an idiosyncratic liquidity component as follows: $L_{c,t} = \lambda * ML_t + (1 - \lambda) * IL_t$, where $L_{c,t}$ is the commodity liquidity, λ a linear weight, IL_t the idiosyncratic and ML_t the market part of commodity liquidity. Since all correlations have been found to be positive, the coefficient λ should be both positive and bounded $0 < \lambda < 1$. This is one possible way of explaining how various commodity prices may be connected to levels of liquidity associated with other commodities. Whenever liquidity changes significantly, it induces a synthetical effect, by triggering variation in both market liquidity and idiosyncratic liquidity.

In preparation for the co-integration analysis presented in the section to follow, we also present the results from Dick-Fuller tests, which have been carried out for both spot and future liquidity measures computed using the Amihud formula. Tables 5-3 and 5-4 and the p-values summarized therein all result in the rejection of the null hypothesis of non-stationarity for both spot and future Amihud liquidity series.

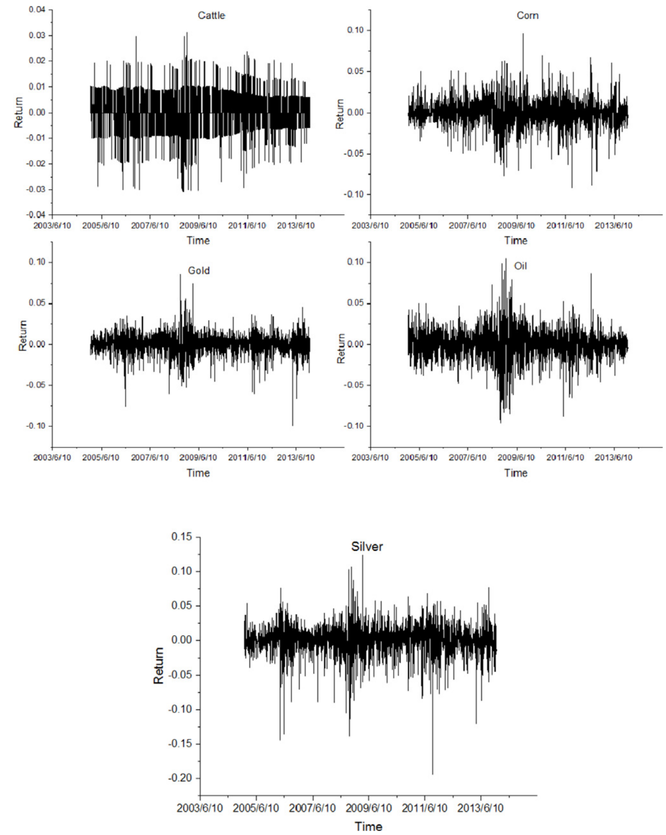

Fig. 4. 6-month future commodity daily returns.

Table 4-3
Commodity Futures Prices Correlation Matrix with p-value.

	F^{ca}_t	F^{co}_t	F^{g}_t	F^{o}_t	F^{s}_t
F^{ca}_t	1				
F^{co}_t	0.6201	1			
	(0.00)				
F^{g}_t	0.8066	0.8126	1		
	(0.00)	(0.00)			
F^{o}_t	0.5992	0.805	0.6333	1	
	(0.00)	(0.00)	(0.00)		
F^{s}_t	0.7593	0.8219	0.9373	0.656	1
	(0.00)	(0.00)	(0.00)	(0.00)	

Note: Values in brackets are p-values.

Table 4-4
Commodity Futures Returns Correlation Matrix with p-value.

	$r^{ca,f}_t$	$r^{co,f}_t$	$r^{g,f}_t$	$r^{o,f}_t$	$r^{s,f}_t$
$r^{ca,f}_t$	1				
$r^{co,f}_t$	−0.045	1			
	(0.02)				
$r^{g,f}_t$	0.0195	0.2305	1		
	(0.34)	(0.00)			
$r^{o,f}_t$	0.1681	0.3384	0.3281	1	
	(0.00)	(0.00)	(0.00)		
$r^{s,f}_t$	0.0671	0.2792	0.8121	0.3908	1
	(0.00)	(0.00)	(0.00)	(0.00)	

Note: Values in brackets are p-values.

6. Link between liquidity commonality and price Co-movements

In light of the observation that both commodity price and liquidity series exhibit co-movement individually, this section will enquire into the degree with which these two types of series may be linked to each

Table 4-5
Granger causality test from spot to 6-month future.

IV	DV				
	$r^{ca,f}_t$	$r^{co,f}_t$	$r^{g,f}_t$	$r^{o,f}_t$	$r^{s,f}_t$
r^s_t (Lags)	1	4	3	1	1
F-Value	9.20	1.47	1.74	4.36	1.82
	(0.00)	(0.21)	(0.16)	(0.04)	(0.18)

Note: H0: spot commodity returns do not Granger-cause 6-month future commodity returns. Values in brackets are p-values.

Table 4-6
Granger causality test from 6-month future to spot.

IV	DV				
	$r^{ca,s}_t$	$r^{co,s}_t$	$r^{g,s}_t$	$r^{o,s}_t$	$r^{s,s}_t$
r^f_t (Lags)	1	4	3	4	4
F-Value	3.55	2.02	2.55	6.74	1.95
	(0.06)	(0.09)	(0.05)	(0.00)	(0.16)

Note: H0: spot commodity returns do not Granger-cause 6-month future commodity returns. Values in brackets are p-values.

Table 5-1
Spot commodity amihud liquidities correlation matrix.

	$L^{ca,s}_t$	$L^{co,s}_t$	$L^{g,s}_t$	$L^{o,s}_t$	$L^{s,s}_t$
$L^{ca,s}_t$	1				
$L^{co,s}_t$	0.4326	1			
	(0.00)				
$L^{g,s}_t$	0.3185	0.0797	1		
	(0.00)	(0.00)			
$L^{o,s}_t$	0.1726	0.0795	0.3004	1	
	(0.00)	(0.00)	(0.00)		
$L^{s,s}_t$	0.2856	0.0076	0.6921	0.1935	1
	(0.00)	(0.00)	(0.00)	(0.00)	

Note: Values in brackets are p-values.

Table 5-2
Future commodity amihud liquidities correlation matrix.

	$L^{ca,f}_t$	$L^{co,f}_t$	$L^{g,f}_t$	$L^{o,f}_t$	$L^{s,f}_t$
$L^{ca,f}_t$	1				
$L^{co,f}_t$	0.0155	1			
	(0.47)				
$L^{g,f}_t$	0.0118	0.0123	1		
	(0.58)	(0.56)			
$L^{o,f}_t$	0.0772	0.0495	0.212	1	
	(0.00)	(0.02)	(0.00)		
$L^{s,f}_t$	0.0747	−0.0265	−0.0059	−0.0184	1
	(0.00)	(0.23)	(0.79)	(0.40)	

Note: Values in brackets are p-values.

other. To this end, we demonstrate the existence of a long-run co-integrating relation between liquidity commonality and price co-movements, by employing a methodology similar to the one outlined in Leybourne et al. (1994). Instead of specifying our regression model with various macroeconomic predictors – which are typically only available at quarterly or monthly frequencies – we proxy changes to the macroeconomic environment by regressing individual commodity prices on the natural log of the CRB index (P^{crb}_t) instead and include also lagged Amihud liquidity measures as additional controls.

$$\begin{aligned}
P_{ca,t} &= \beta_1 P_{crb,t} + \alpha_{11} L_{ca,t-1} + \alpha_{12} L_{co,t-1} + \alpha_{13} L_{g,t-1} + \alpha_{14} L_{o,t-1} + \alpha_{15} L_{s,t-1} + \varepsilon_{ca,t-1} \\
P_{co,t} &= \beta_2 P_{crb,t} + \alpha_{21} L_{ca,t-1} + \alpha_{22} L_{co,t-1} + \alpha_{23} L_{g,t-1} + \alpha_{24} L_{o,t-1} + \alpha_{25} L_{s,t-1} + \varepsilon_{co,t-1} \\
P_{g,t} &= \beta_3 P_{crb,t} + \alpha_{31} L_{ca,t-1} + \alpha_{32} L_{co,t-1} + \alpha_{33} L_{g,t-1} + \alpha_{34} L_{o,t-1} + \alpha_{35} L_{s,t-1} + \varepsilon_{g,t-1} \\
P_{o,t} &= \beta_4 P_{crb,t} + \alpha_{41} L_{ca,t-1} + \alpha_{42} L_{co,t-1} + \alpha_{43} L_{g,t-1} + \alpha_{44} L_{o,t-1} + \alpha_{45} L_{s,t-1} + \varepsilon_{o,t-1} \\
P_{s,t} &= \beta_5 P_{crb,t} + \alpha_{51} L_{ca,t-1} + \alpha_{52} L_{co,t-1} + \alpha_{53} L_{g,t-1} + \alpha_{54} L_{o,t-1} + \alpha_{55} L_{s,t-1} + \varepsilon_{s,t-1}
\end{aligned} \tag{2}$$

Table 5-3
Dickey-Fuller tests for spot liquidity.

	$L^{ca,s}_t$	$L^{co,s}_t$	$L^{g,s}_t$	$L^{o,s}_t$	$L^{s,s}_t$
DF	−14.70	−30.61	−20.78	−29.77	−35.52
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Note: Values in brackets are p-values. Statistics shown for five spot commodity markets. Liquidity is based on the Amihud measure.

Table 5-4
Dickey-Fuller tests for future liquidity.

	$L^{ca,f}_t$	$L^{co,f}_t$	$L^{g,f}_t$	$L^{o,f}_t$	$L^{s,f}_t$
DF	−31.69	−78.47	−42.95	−22.91	−25.38
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Note: Values in brackets are p-values. Statistics shown for five spot commodity markets. Liquidity is based on the Amihud measure.

We also adjust all coefficients' standard errors using Newey-West robust variance-covariance matrix estimates, in order to account for any autocorrelation in our regression model residuals. The regression equations and results are shown in equation (2), where all co-integration relations are documented and robustly established via Dick-Fuller tests for the stationarity of each estimated model's regression residuals.

Table 6-1 shows that all coefficients are statistically significant, suggesting not only that the level of liquidity of the commodity itself, but also liquidity of other commodities from different families explains variation in the price level. More importantly, all signs of the coefficients are negative, which indicates that liquidity may be driving commodity prices toward a common attractor. Likewise, in Table 6-5, spot liquidities display similar results, with the single exception of the spot silver liquidity failing to significantly explain the price of the corn future. Overall, these results show that the liquidity effect can propagate across products with different maturities. In contrast, the future liquidity results are perceptibly different (see Tables 6-3 and 6-7). Several coefficients are estimated to be statistically insignificant, suggesting that a number of liquidity measures exhibit weak explanatory power.

More importantly, a number of coefficients turn out to be estimated with a positive sign, albeit one which is statistically indistinguishable from zero. As a result, future liquidities may not exhibit any commonality, which is consistent with our previous conclusion. Finally, in order to test for the presence of co-integration, we also investigated the stationarity of all regression residuals, for all of which the null of non-stationarity is strongly rejected (see Tables 6-2,6-4,6-6 and 6-8).

Given that our data set covers both pre- and post-2008 financial crisis periods, we investigate the robustness of our findings by adopting a series of regressions based on model equation (2), so as to be able to compare

Table 6-1
Regression results for spot liquidity and log spot prices.

IV	DV				
	P^{ca}_t	P^{co}_t	P^{g}_t	P^{o}_t	P^{s}_t
P^{crb}_t	0.16***	0.92***	0.04	1.21***	0.70***
	(5.44)	(16.36)	(0.65)	(40.62)	(8.36)
$L^{ca,s}_{t-1}$	−0.22***	−0.17***	−0.28***	−0.13***	−0.32***
	(-10.37)	(-3.01)	(-4.70)	(-5.47)	(-1.59)
$L^{co,s}_{t-1}$	−0.13***	−0.53***	−0.52***	−0.11***	−0.52***
	(-9.47)	(-12.92)	(-11.09)	(-6.34)	(-6.79)
$L^{g,s}_{t-1}$	−0.09***	−0.62***	−0.61***	−0.19***	−0.54***
	(-4.69)	(-9.56)	(-9.49)	(-7.87)	(-2.13)
$L^{o,s}_{t-1}$	−0.10***	−0.15***	−0.37***	−0.24***	−0.37***
	(-6.26)	(-2.97)	(-7.17)	(-11.67)	(-2.72)
$L^{s,s}_{t-1}$	−0.14***	−0.14*	−0.31***	−0.11***	−0.46***
	(-6.99)	(-1.84)	(-4.03)	(-3.97)	(-0.95)
F-value	137.71***	212.03***	199.37***	793.92***	193.37***

Note: Values in brackets are p-values. *, **, *** indicate statistical significance at 10%, 5% and 1% levels, respectively. Liquidity is based on the Amihud measure.

Table 6-2
Dickey-Fuller tests for residuals from Table 5-1 regressions.

	$\varepsilon^{ca,s}_t$	$\varepsilon^{co,s}_t$	$\varepsilon^{g,s}_t$	$\varepsilon^{o,s}_t$	$\varepsilon^{s,s}_t$
DF	−13.64	−18.61	−20.85	−17.74	−19.09
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Note: Values in brackets are p-values.

Table 6-3
Regression results for futures liquidity and log spot prices.

IV	DV				
	P^{ca}_t	P^{co}_t	P^{g}_t	P^{o}_t	P^{s}_t
P^{crb}_t	0.22***	0.97***	0.17***	1.29***	0.86***
	(7.96)	(16.37)	(2.76)	(44.34)	(10.11)
$L^{ca,f}_{t-1}$	−0.18***	−0.13***	−0.32***	−0.14***	−0.37***
	(-9.21)	(-2.21)	(-5.21)	(-5.54)	(-5.65)
$L^{co,f}_{t-1}$	−0.19***	−0.68***	−0.81***	−0.21***	−0.82***
	(-8.65)	(-10.46)	(-11.12)	(-7.55)	(-11.04)
$L^{g,f}_{t-1}$	−0.17***	−0.94***	−1.07***	−0.38***	−1.03***
	(-6.30)	(-9.98)	(-11.76)	(-11.60)	(-11.15)
$L^{o,f}_{t-1}$	−0.26***	−0.71***	−0.92***	−0.35***	−0.98***
	(-14.42)	(-13.63)	(-19.07)	(-17.64)	(-18.74)
$L^{s,f}_{t-1}$	−0.07***	0.05	−0.06	−0.01	−0.09
	(-3.06)	(1.06)	(-0.99)	(-0.31)	(-1.49)
F-value	95.93***	120.87***	122.28***	671.45***	136.12***

Note: Values in brackets are p-values. *, **, *** indicate statistical significance at 10%, 5% and 1% levels, respectively. Liquidity is based on the Amihud measure.

Table 6-4
Dickey-Fuller tests for residuals from Table 5-3 regressions.

	$\varepsilon^{ca,f}_t$	$\varepsilon^{co,f}_t$	$\varepsilon^{g,f}_t$	$\varepsilon^{o,f}_t$	$\varepsilon^{s,f}_t$
DF	−9.99	−13.19	−15.43	−13.30	−14.51
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Note: Values in brackets are p-values.

Table 6-5
Regression results for log futures price and spot liquidity.

IV	DV				
	F^{ca}_t	F^{co}_t	F^{g}_t	F^{o}_t	F^{s}_t
P^{crb}_t	0.12***	0.92***	0.04	1.04***	0.72***
	(3.71)	(16.36)	(1.03)	(39.66)	(8.67)
$L^{ca,s}_{t-1}$	−0.25***	−0.08*	−0.27***	−0.10***	−0.31***
	(-11.4)	(-1.76)	(-4.74)	(-4.60)	(-5.34)
$L^{co,s}_{t-1}$	−0.11***	−0.42***	−0.52***	−0.12***	−0.51***
	(-7.52)	(-12.38)	(-11.87)	(-7.73)	(-11.45)
$L^{g,s}_{t-1}$	−0.06***	−0.52***	−0.59***	−0.18***	−0.54***
	(3.56)	(-9.68)	(-9.31)	(-7.57)	(-8.24)
$L^{o,s}_{t-1}$	−0.14***	−0.098***	−0.36***	−0.19***	−0.37***
	(-7.85)	(-2.30)	(-72.21)	(-10.60)	(-6.69)
$L^{s,s}_{t-1}$	−0.21***	−0.04	−0.31***	−0.096***	−0.46***
	(-10.16)	(-0.54)	(-4.07)	(-3.29)	(-6.03)
F-value	142.99***	205.46***	195.9***	708.72***	193.46***

Note: Values in brackets are p-values. *, **, *** indicate statistical significance at 10%, 5% and 1% levels, respectively. Liquidity is based on the Amihud measure.

the results from before and after the 2008 financial crisis. Tables 6-1,6-3,6-5 and 6-7 show that the F-values computed from the spot liquidity regressions are significantly larger than those obtained from comparable regressions involving only commodity futures. In view of this, we choose to employ only spot liquidity measures as independent variables for the following regressions. We divide the full data set into a pre-crisis sub-sample ranging from 2005 to 2008 as well as a post-crisis sub-sample from 2009 to 2013. Tables 6-9–6-12 clearly reveal that most F-values computed for the post-crisis period are considerably higher than those for the pre-crisis period. This result suggests that any co-movement among

Table 6-6
Dick-Fuller tests for residuals from Table 6-5 regressions.

	$\varepsilon^{ca,s}_t$	$\varepsilon^{co,s}_t$	$\varepsilon^{g,s}_t$	$\varepsilon^{o,s}_t$	$\varepsilon^{s,s}_t$
DF	−13.04	−18.61	−20.76	−18.64	−19.29
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Note: Values in brackets are p-values.

Table 6-7
Regression results for futures liquidity and log futures prices.

IV	DV				
	F^{ca}_t	F^{co}_t	F^{g}_t	F^{o}_t	F^{s}_t
P^{crb}_t	0.21***	0.82***	0.19***	1.11***	0.87***
	(7.96)	(16.37)	(3.07)	(45.68)	(10.43)
$L^{ca,f}_{t-1}$	−0.22***	−0.05	−0.31***	−0.09***	−0.37***
	(-9.21)	(-1.07)	(-5.13)	(-3.99)	(-5.67)
$L^{co,f}_{t-1}$	−0.17***	−0.51***	−0.80***	−0.21***	−0.81***
	(-8.65)	(-9.03)	(-11.15)	(-7.70)	(-11.03)
$L^{g,f}_{t-1}$	−0.20***	−0.77***	−1.03***	−0.36***	−1.01***
	(-6.30)	(-9.95)	(-11.71)	(-11.69)	(-11.60)
$L^{o,f}_{t-1}$	−0.32***	−0.52***	−0.91***	−0.34***	−0.96***
	(-14.42)	(-12.34)	(-19.02)	(-18.92)	(-18.10)
$L^{s,f}_{t-1}$	−0.08***	0.08*	−0.06	0.02	−0.09
	(-3.06)	(1.88)	(-0.99)	(0.85)	(-1.47)
F-value	100.63***	104.26***	121.98***	674.48***	137.07***

Note: Values in brackets are p-values. *, **, *** indicate statistical significance at 10%, 5% and 1% levels, respectively. Liquidity is based on the Amihud measure.

Table 6-8
Dick-Fuller tests for residuals from Table 6-7 regressions.

	$\varepsilon^{ca,f}_t$	$\varepsilon^{co,f}_t$	$\varepsilon^{g,f}_t$	$\varepsilon^{o,f}_t$	$\varepsilon^{s,f}_t$
DF	−10.38	−13.34	−16.21	−12.02	−15.06
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Note: Values in brackets are p-values.

Table 6-9
Pre-crisis regression results for spot liquidity and log spot prices.

IV	DV				
	P^{ca}_t	P^{co}_t	P^{g}_t	P^{o}_t	P^{s}_t
P^{crb}_t	0.18***	1.57***	1.10***	1.78***	1.36***
	(8.75)	(16.21)	(13.52)	(75.79)	(19.42)
$L^{ca,s}_{t-1}$	−0.06***	−0.05	0.05	0.04**	−0.01
	(-3.51)	(0.80)	(1.11)	(2.56)	(-0.31)
$L^{co,s}_{t-1}$	−0.05***	−0.27***	−0.16***	−0.01	−0.15***
	(-5.10)	(-6.59)	(-5.20)	(-0.88)	(-4.67)
$L^{g,s}_{t-1}$	−0.04***	−0.30***	−0.13***	−0.04**	−0.05
	(-3.29)	(-5.57)	(-3.25)	(-3.01)	(-1.15)
$L^{o,s}_{t-1}$	−0.02	−0.02	−0.02	0.00	−0.10**
	(-1.45)	(-0.42)	(-0.64)	(0.02)	(-2.90)
$L^{s,s}_{t-1}$	0.03*	0.20***	0.15***	0.05**	0.03
	(1.88)	(3.02)	(3.07)	(2.68)	(0.59)
F-value	39.61***	140.32***	94.37***	149.52***	108.83***

Note: Values in brackets are p-values. Results reported for pre-crisis period (2005–2008) and *, **, *** indicate statistical significance at 10%, 5% and 1%. Levels, respectively.

commodity markets is stronger for the post-crisis period, which is consistent with existing findings (Kang et al., 2017; LePen and Sévi, 2017). This result indicates a seemingly much strong impact of liquidity spillovers occurring over the post-crisis years.

We also test for any predictive power liquidity commonality may possesses in explaining observed commodity price co-movement by incorporating a commodity liquidity commonality proxy as an additional explanatory variable for commodity price co-movement. Following Chordia et al. (2000), we use an equally weighted average liquidity measure as a proxy indicator of overall market liquidity or liquidity

Table 6-10
Post-crisis regression results for spot liquidity and log spot prices.

IV	DV				
	P^{ca}_t	P^{co}_t	P^{g}_t	P^{o}_t	P^{s}_t
P^{crb}_t	0.63***	1.88***	1.18***	1.20***	2.58***
	(12.66)	(28.79)	(18.25)	(19.22)	(39.81)
$L^{ca,s}_{t-1}$	−0.32***	−0.19***	−0.22***	−0.21***	−0.16***
	(-8.99)	(-3.56)	(-5.89)	(-6.35)	(-3.39)
$L^{co,s}_{t-1}$	−0.14***	−0.27***	−0.16***	0.04	−0.17***
	(-5.16)	(-6.60)	(-5.57)	(1.58)	(-5.16)
$L^{g,s}_{t-1}$	0.25***	0.00	−0.01	0.12*	−0.05
	(4.25)	(0.05)	(-0.19)	(1.80)	(-0.76)
$L^{o,s}_{t-1}$	−0.05*	0.30***	0.05	−0.32***	0.23***
	(-1.83)	(6.69)	(1.47)	(-9.50)	(5.70)
$L^{s,s}_{t-1}$	−0.33***	−0.11	−0.28***	−0.29***	−0.20***
	(-6.55)	(-1.21)	(-5.39)	(-4.69)	(-2.74)
F-value	146.63***	186.81***	189.80***	185.53***	383.42***

Note: Values in brackets are p-values. Results reported for post-crisis period (2009–2013) and *, **, *** indicate statistical significance at 10%, 5% and 1%. Levels, respectively.

Table 6-11
Pre-crisis regression results for spot liquidity and log futures prices.

IV	DV				
	F^{ca}_t	F^{co}_t	F^{g}_t	F^{o}_t	F^{s}_t
P^{crb}_t	0.21***	1.49***	1.10***	1.63***	1.36***
	(17.55)	(16.47)	(13.69)	(53.07)	(19.42)
$L^{ca,s}_{t-1}$	−0.03***	0.06	0.05	0.04***	−0.02
	(-4.26)	(1.16)	(1.06)	(2.59)	(-0.44)
$L^{co,s}_{t-1}$	0.00	−0.23***	−0.15***	−0.01	−0.15***
	(0.19)	(-6.54)	(-5.14)	(-0.74)	(-4.65)
$L^{g,s}_{t-1}$	0.00	−0.26***	−0.12***	−0.03*	−0.04
	(0.42)	(-5.70)	(-3.05)	(-1.80)	(-1.09)
$L^{o,s}_{t-1}$	−0.02***	−0.00	−0.03	0.02	−0.11***
	(-2.63)	(-0.06)	(-0.81)	(1.47)	(-3.03)
$L^{s,s}_{t-1}$	−0.02***	0.20***	0.15***	0.06***	0.02
	(-2.82)	(3.32)	(2.96)	(3.01)	(0.47)
F-value	94.22***	153.56***	92.36***	594.38***	109.07***

Note: Values in brackets are p-values. Results reported for pre-crisis period (2005–2008) and *, **, *** indicate statistical significance at 10%, 5% and 1%. Levels, respectively.

Table 6-12
Post-crisis regression results for spot liquidity and log futures prices.

IV	DV				
	F^{ca}_t	F^{co}_t	F^{g}_t	F^{o}_t	F^{s}_t
P^{crb}_t	0.63***	1.31***	1.18***	1.05***	2.57***
	(10.34)	(27.51)	(18.18)	(24.59)	(39.63)
$L^{ca,s}_{t-1}$	−0.40***	−0.09**	−0.21***	−0.15***	−0.17***
	(-9.58)	(-2.51)	(-5.84)	(-6.68)	(-3.42)
$L^{co,s}_{t-1}$	−0.15***	−0.16***	−0.16***	0.02	−0.17***
	(-4.27)	(-6.01)	(-5.58)	(1.39)	(-5.15)
$L^{g,s}_{t-1}$	0.29***	0.01	−0.01	0.10	−0.05
	(4.01)	(0.13)	(-0.23)	(2.40)	(-0.75)
$L^{o,s}_{t-1}$	−0.09**	0.25***	0.05	−0.23***	0.23***
	(-2.43)	(8.18)	(1.53)	(-11.07)	(5.64)
$L^{s,s}_{t-1}$	−0.40***	−0.01	−0.28***	−0.20***	−0.20***
	(-6.49)	(-0.13)	(-5.34)	(-5.30)	(-2.79)
F-value	140.30***	152.58***	187.33***	408.51***	381.67***

Note: Values in brackets are p-values. Results reported for post-crisis period (2009–2013) and *, **, *** indicate statistical significance at 10%, 5% and 1%. Levels, respectively.

commonality. Based on equation (3), we regress all five commodity log spot and log future prices against the commodity market liquidity measure. To proxy for liquidity, we again employ the Amihud measure, while for the futures, we employ the relevant measures with a 6-month future maturity. The regression results are presented in Tables 6-13 and 6-14.

Table 6-13
Regression results for log spot prices and spot liquidity.

IV	DV				
	P^{ca}_t	P^{co}_t	P^{g}_t	P^{o}_t	P^{s}_t
ML^{s}_{t-1}	−0.45***	−0.94***	−1.24***	−0.46***	−1.31***
	(-18.92)	(-14.96)	(-19.18)	(-18.09)	(-20.22)
P^{crb}_t	0.24***	1.09***	0.32***	1.34***	1.01***
	(8.78)	(16.92)	(4.57)	(45.61)	(10.81)
F-value	301.97***	231.51***	189.82***	1575.67***	257.46***

Note: Values in brackets are p-values. *, **, *** indicate statistical significance at 10%, 5% and 1% levels, respectively. Liquidity is based on the Amihud measure.

Table 6-14
Regression results for log 6 m futures prices and spot liquidity.

IV	DV				
	F^{ca}_t	F^{co}_t	F^{g}_t	F^{o}_t	F^{s}_t
ML^{s}_{t-1}	−0.51***	−0.66***	−1.21***	−0.41***	−1.29***
	(-19.70)	(-12.96)	(-19.16)	(-17.64)	(-20.24)
P^{crb}_t	0.23***	0.92***	0.35***	1.16***	1.03***
	(7.08)	(15.92)	(4.89)	(45.56)	(11.10)
F-value	305.03***	182.95***	190.55***	1742.61***	261.3***

Note: Values in brackets are p-values. *, **, *** indicate statistical significance at 10%, 5% and 1% levels, respectively. Liquidity is based on the Amihud measure.

$$\begin{aligned} P_t^{ca} &= \alpha_1 + \beta_{11} ML_{t-1} + \beta_{12} P_t^{CRB} + \varepsilon_t^{ca} \\ P_t^{co} &= \alpha_2 + \beta_{21} ML_{t-1} + \beta_{22} P_t^{CRB} + \varepsilon_t^{co} \\ P_t^{g} &= \alpha_3 + \beta_{31} ML_{t-1} + \beta_{32} P_t^{CRB} + \varepsilon_t^{g} \\ P_t^{o} &= \alpha_4 + \beta_{41} ML_{t-1} + \beta_{42} P_t^{CRB} + \varepsilon_t^{o} \\ P_t^{s} &= \alpha_5 + \beta_{51} ML_{t-1} + \beta_{52} P_t^{CRB} + \varepsilon_t^{s} \end{aligned} \tag{3}$$

The results from our regression models show that the signs of all coefficients estimated for the liquidity measures are not only negative, but also statistically significant. According to Leybourne et al. (1994), if the sign of the first derivative with respect to the same variable is the same in the regression model, then the variable drives the price toward a common attractor:

$$sign\left(\frac{dP_{ca,t}}{dML_{t-1}}\right) = sign\left(\frac{dP_{co,t}}{dML_{t-1}}\right) = sign\left(\frac{dP_{g,t}}{dML_{t-1}}\right) = sign\left(\frac{dP_{o,t}}{dML_{t-1}}\right) = sign\left(\frac{dP_{s,t}}{dML_{t-1}}\right)$$

$$sign\left(\frac{dF_{ca,t}}{dML_{t-1}}\right) = sign\left(\frac{dF_{co,t}}{dML_{t-1}}\right) = sign\left(\frac{dF_{g,t}}{dML_{t-1}}\right) = sign\left(\frac{dF_{o,t}}{dML_{t-1}}\right) = sign\left(\frac{dF_{s,t}}{dML_{t-1}}\right)$$

As a result, all the commodity liquidities drive the commodity prices to toward a common attractor, which may help to explain the presence of commodity price co-movement. We therefore argue that the common factor lying at the core of each individual commodity liquidity series may also be a major causal determinant in driving all commodity prices toward a common attractor. Consequently, commodity liquidity commonality may act as an important driving force behind commodity price co-movement, since it influences all of the commodity prices negatively, which in turn can be explained by the fact that whenever commodities turn more illiquid, they become more difficult to sell. Given that the Amihud definition of liquidity is relatively sensitive to changes in trading volume and tends to fall as volume rises, trading volume should exhibit a positive relation with commodity prices. This conclusion is consistent with existing studies in the literature.

Previous inquiries into the relevance of trading volume strongly suggest that this particular measure of trading activity plays an important and informative role within financial markets. For example, Blume et al. (1994) present evidence for the potential usefulness of trading volume in financial market. They assert that trading volume can provide investors with additional information the market price by itself cannot offer. In addition, Lee and Swaminathan (2000) suggest that trading volume may be helpful in predicting cross-sectional stock returns and that it may also be closely related to price momentum.

Trading volume may affect asset prices along three different dimensions. First, trading volume has been found to be positively correlated with price changes (see Karpoff, 1987), which may be partially attributable to the disposition effect, causing investors holding a particular security to be less willing to sell after a price decline than a price rise. For example, Odean (1998) shows that stocks with gains are sold by individual investors at twice the rate of stocks incurring losses. Secondly, trading volume appears to be correlated with transactions costs. Karpoff (1987) shows that trading volume will increase with a growing number of active traders, resulting in a lower Amihud measure and a more active market. Since sellers are more likely to sell the asset under more heavily traded market conditions, the cost of asset trades declines. Similarly, Admati and Pfleiderer (1988) develop a model which exhibits a negative relationship between trading volume and transactions costs.

Finally, there are several studies focusing on the relationship between trading volume and asset price volatility in future markets. Bessembinder and Seguin (1993) present evidence suggesting that trading volume exerts a strong effect on price volatility, especially in case of sudden volume shocks, which tend to translate directly into more pronounced levels of price volatility. Similarly, Wang and Yau (2000) also develop evidence indicating the existence of a positive relationship between trading volume and asset price volatility in future markets.

Given that our findings indicate that a negative relationship between commodity prices and market illiquidity is likely to exist, we proceed by also investigating any possible causal link between the two variables by carrying out a series of Granger causality tests, the results of which are summarized in Tables 6-15 and 6-16. Except for the price of corn, the computed F-tests suggests that spot market liquidity may generally be a good predictor of spot commodity prices. By contrast, the spot market liquidity appears to be of less utility in predicting future prices, where the predictive power for cattle and corn turn out to be insignificant. As a result, commodity liquidity commonality may be useful in predicting commodity price co-movement along a common trend or attractor.

Table 6-15
Granger-causality test from spot market liquidity to spot commodity prices.

IV	DV				
	P^{ca}_t	P^{co}_t	P^{g}_t	P^{o}_t	P^{s}_t
ML^s_t (Lags)	2	4	1	2	1
F-Value	2.74	0.44	3.74	2.69	4.78
	(0.07)	(0.77)	(0.01)	(0.10)	(0.03)

Note: H0: spot market liquidity does not have Granger-cause toward spot commodity prices. Values in brackets are p-values. Liquidity is based on the Amihud measure.

Table 6-16
Granger-causality test from spot market liquidity to futures commodity prices.

IV	DV				
	F^{ca}_t	F^{co}_t	F^{g}_t	F^{o}_t	F^{s}_t
ML^s_t (Lags)	2	1	4	2	4
F-Value	0.75	0.54	3.66	3.37	4.70
	(0.52)	(0.70)	(0.01)	(0.06)	(0.03)

Note: H0: spot market liquidity does not have Granger-cause toward futures commodity prices. Values in brackets are p-values. Liquidity is based on the Amihud measure.

7. Research implications and conclusions

This study shows that liquidity commonality existent in commodity markets drives commodity prices toward a common trend. In fact, spot and future prices are driven toward this common stochastic trend not only by their own liquidity, but also by measures of liquidity computed from other commodity classes. This result suggests that liquidity effects can penetrate through and spill over across commodity sector boundaries. Our results also indicate that liquidity spillovers associated with commodity price co-movement appear to be significantly stronger in post-2008 data. In addition, spot and future prices are not only driven by liquidities over their own maturities, but also by liquidities over different maturities, implying that the liquidity effect also propagates across asset maturities. Finally, we also investigate the causal relationship between commodity prices and liquidity and find that spot commodity liquidity Granger-causes spot commodity prices. Given the widely studied role of commodity prices in driving the inflation rate of consumer goods and services, our results imply that the common commodity liquidity bellwether we identify can be of significant utility in the design and timely implementation of optimal monetary policy responses.

We arrive at these findings more specifically by first computing a series of correlation matrices and their p-values, which demonstrate that significant daily price and return co-movement exists in both spot and future commodity markets. Secondly, additional econometric analysis reveals that commodity futures returns Granger-cause commodity spot returns. While significant daily liquidity co-movement is found to exist in commodity spot securities, the same does not hold true for commodity futures. This in turn implies that a common liquidity factor appears to exist only in spot trading. We accordingly choose to employ only a measure of spot market liquidity as an indicator for our final regression model specification.

Commodity prices clearly impact macroeconomic variables such as inflation, as for example argued by Beckerman and Jenkinson (1986) and Garner (1989), both of whom promulgate the view that commodity prices often exert strong effects on various measures of inflation. Clarida et al. (1998) observe that many developed economies employ inflation-targeting as their main operational mechanism for formulating monetary policy. As a result, because co-moving commodity prices exert a more amplified effect on the inflation rate than other less inter-correlated security classes, they may exhibit a significantly more pronounced impact on other key macroeconomic variables such as GDP, inflation expectations, interest and exchange rates, the trade balance and so on. Common trends in commodity prices therefore clearly exert an indirect influence on monetary policy via the inflation and the central bank's target rate. As a result, a common commodity liquidity bellwether and its impact on commodity price co-movements may be pivotal for uncovering changing trends in commodity price movements and optimal monetary policy design.

The co-movement of commodity prices exerts an amplifying effect on the general rate of inflation. Policy makers charged with the remit of controlling inflation are thus likely to benefit from a better understanding of existing patterns in commodity price co-movements. In this paper, we have shed light on this issue by empirically testing and establishing a robust link between commodity price co-movements and a common liquidity factor. A more in-depth understanding of the role played by this common liquidity bellwether ought to help policy makers better exploit the availability of one important as well as regularly observable candidate determinant of salient commodity price co-movements. Finally, we show that market liquidity can convey crucial information about trends in commodity price movements and provide market signals to policy makers, who may accordingly be better prepared for formulating monetary policy in a timely manner by appropriately responding to inflationary pressures and improve overall economic performance.

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