U.S. Monetary Policy and Herding: Evidence from Commodity Markets

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Abstract This paper investigates the presence of herding behavior across a spectrum of commodities (i.e., agricultural, energy, precious metals, and metals) futures prices obtained from Datastream. The main novelty of this study is, for the first time in the literature, the explicit investigation of the role of deviations of U.S. monetary policy decisions from a standard Taylor-type monetary rule, in driving herding behavior with respect to commodity futures prices, spanning the period 1990-2017. The results document that the commodity markets are characterized by herding, while such herding behavior is not only driven by U.S. monetary policy decisions, but also such decisions exert asymmetric effects this behavior. An additional novelty of the results is that they document that herding is stronger in discretionary monetary policy regimes.

Keywords: Herd behavior; commodity futures prices; U.S. monetary policy

JEL Classification: E44; G10

Introduction

Financial markets often appear to behave frantically, which indicates dramatic changes in investors' behavior. The resulting price volatility is inconsistent with rational traders and informationally efficient markets and is attributed to investors' 'animal instincts' (Bikhchandani and Sharma, 2001). Such a stylized fact is associated with herding behavior in which investors follow the crowd. This herding can occur when agents' private information is swamped by the information derived from observing others and investors act against their private information and follow the crowd (Economou et al., 2011).

The literature explored the impact of monetary policy decisions on asset prices, where such decisions provided an informational mechanism that transmits expectations about the future course of interest rates and allowed investors to constantly revise their expectations about the impact of interest rates on asset prices (Bernanke and Kuttner, 2005; Rosa, 2013). Although a wide strand of the literature examined the impact of commodity prices on macroeconomic variables (Kilian, 2008, offered an excellent survey on evidence regarding the association between commodity prices and macroeconomic variables), less attention was spent on the impact of monetary policy decisions on asset commodity prices. According to theoretical arguments, monetary policy can affect asset pricing through four primary mechanisms/channels, i.e. the portfolio balance channel, the signaling or information channel, a confidence channel, and enhancing market liquidity and reducing risk premia. When it comes to commodity pricing, there exist additional channels, including through other financial variables, particularly interest rates and exchange rates, as well as additional channels, via (expectations of) inflation and economic growth (Barsky and Kilian,, 2004). These extra channels act in cooperation with the traditional for asset pricing channels since commodities are closely considered as substitutes to other assets (Rigobon and Sack, 2004).

This paper focuses, as this is the main novelty of this study, on exploring what is the role of deviations of U.S. monetary policy decisions from a standard Taylor-type monetary rule, in driving herding behavior in relevance to commodity futures prices. No study has explored so far the role of monetary policy deviations on forward commodity prices. In the presence of such deviations, the wrong signal is provided to the market participants and wrong portfolio decisions will be reached. Such wrong decisions have further repercussions for the course of the real economy as well, mainly through investment decisions and wealth distribution. This as explained below, is expected to further excarcebate any herding type of investment behaviors. The perceived credibility of monetary policy strategies were expected to influence the expectation formation process by market participants and was likely to establish the degree of volatility in these expectations (Bernanke, 2004; Coenen and Wieland, 2005; Issing, 2005). Alternatively, deviations of monetary policy decisions from their expected paths could induce herd behaviors in asset markets which may arise as the result of an informational cascades (Bikhchandani et al., 1992) coming from the wrong informational signals from interest rate and inflation trends that 'motivate' market participants to invest in asset markets, regardless of the presence of their possible negative own private signals. Thus, herding may be arising as the result of certain monetary policy news about the future course of interest rates and/or inflation that eventually failed to materialize (Christiano et al., 2007).

Over the recent years, commodities have played an increasingly significant role in the asset allocations of institutional investors. The investments in commodities take a variety of forms, including those in real assets, futures, indexes, equities, and hedge funds. In portfolio management, commodities can serve a variety of functions from volatility and/or inflation hedges to purely speculative plays. Based on this discussion, the paper truly emphasizes the investment approach when it comes to herding. When investors invest in the producers of commodities, rather than indexes or futures, they have a greater opportunity to confront social and environmental implications of their investment. In that respect, investments in the equities of commodities producers may actually, and counter-intuitively, turn out to be less correlated to the equities market as a whole than investments in the commodities themselves. The findings are expected to provide guidance for a monetary policy strategy that will be sufficient to monitor closely monetary, credit and financial developments as potential driving forces for inappropriate asset valuations.

Literature Review

In relevance to the herding behavior, a number of studies highlight the tendency of investors to follow each other and trade the same assets at the same time (Chiang et al., 2010). Herding examined in banking (Devenow and Welch, 1996), equity markets (Chiang and Zheng, 2010; Narayan et al., 2015; Economou et al., 2018), and analyst's forecasts and food commodities (Gleason et al., 2003).

A paper by Demirer et al. (2015) explores the role of stock markets in the presence of herding behavior in commodity futures markets. They test the presence of herding in a number of commodity sectors, while their findings document the presence of herding in grains only during the high volatility state. The literature has also tested the assumption of an efficient market, where all prices reflect the available information; this assumption was widely applied in the commodities market to explain whether prices were driven by fundamentals or sentiment (Hwang et al., 2018). In that sense, market traders could overreact and push prices away from fundamentals, with rational traders responding to imposing prices to equilibrium. Thus, prices may deviated from supply and demand fundamentals, but only momentary (Fishe and Smith, 2019). Recently, Gerson de Souza Raimundo Júnior et al. (2020) analyzed the behavior of food commodities between 2000 and 2018 to test the presence of herding. Their results suggested that betas herding may deviate from the fundamentals, although they tend to revert faster to stability between demand and supply disequilibrium conditions, which resulted in equilibrium in the long-run risk-return factor.

Certain papers in the literature of monetary policy rules (Taylor, 1993; Kahn, 2012) made use of policy interest rates as indicators of the monetary policy stance. Although such monetary rules have been a useful yardstick for assessing monetary policy behavior, policy rates have been away from the level implied by such rules, rendering monetary policy systematically accommodative from the perspective of this benchmark, as between the early 2000s and the outbreak of the recent global financial crisis (Ahrend et al., 2008). Nevertheless, the literature has not reached a consensus on this issue (Taylor, 2007; Bernanke, 2010; Zhang and Pan, 2019). Taylor (2010, 2012) argued that the presence of deviations from a standard monetary policy rule reflected a significant change in the policy regime, which he dubbed the 'Great Deviation', albeit this was rejected by Bernanke (2010).

In terms of the association between monetary policy and commodity prices, monetary conditions attracted attention as possible driving factors of commodity prices. Barsky and Kilian (2004) showed that monetary policy stance was a good predictor of commodity prices. They provided evidence that oil price increases in the 1970s could have been caused by monetary policy decisions. The majority of empirical studies in this strand of the literature attempt to assess the relationship between monetary policy and commodity prices, by making use of policy interest rates as the primary indicators of the monetary policy stance (Frankel and Rose, 2010). Hayo et al. (2012) analyzed the impact of U.S. monetary policy activities on commodity price volatility. Their results illustrated that U.S. monetary policy had a significant impact on price volatility. Hammoudeha et al. (2015) examined the effects of the U.S. monetary policy on sectoral commodity prices. Their reference documented that U.S. monetary contractions led to immediate rises in commodity prices, reflecting greater expected inflation and speculation, high production costs or some overshooting.

However, in certain times, monetary policy revealed not the expected messages (i.e., deviations from expected decisions) and thus, investors may over- or under-reacted to unexpected information changes (Bondt and Thaler, 1985), thus, leading to irrational investment choices. Galariotis et al. (2015) used the Fama-French three factor model, along with the momentum factor to reflect common risk factors in stock valuation, while they decomposed the reactions of market participants into fundamental and non-fundamental information parts. In addition, any deviations of expected monetary policy announcements from their trend tended to exacerbate herding irrationality.

Data

This paper measures herding on a number of commodities from January 1990 to December 2017. Daily data on a number of commodities futures prices are obtained: sugar, corn, wheat, oats, cocoa, cotton, coffee, oil, natural gas, gold, silver, platinum, copper, nickel, and aluminium. For the agricultural commodities the delivery months are January, March, May, July, and October), while for the remaining the delivery occurs across all months. Data were obtained from Datastream.

The results are reported in terms of 1-, 2- and 3-months ahead in the month where such a contract is allowed. Data on the overall commodity futures market index, offered as the Goldman Sachs Commodity Index (GSCI) futures contracts for one month through three months are also obtained. The GSCI is a world production weighted index and contains many commodity futures, with the weight of energy commodities in the index being about 75%. Returns are measured as first percentage differences in logs, while data are obtained as daily closing prices. A total of 6,300 observations (for each commodity) are considered.

The reason the empirical analysis focuses on commodity futures prices rather than spot prices is manyfold. First, the (forward) monetary rule is based on expected (forecasted) variables and in that sense it is more rational to assume that this type of monetary policy (i.e., forward looking policy) should more explicitly impact futures than spot commodity prices. Second, according to Reeve and Vigfusson (2011), futures prices can outperform random walk forecasting schems, while they outperform those schemes when there is a sizeable difference between spot and futures prices, third, commodity futures prices reveal useful information about global commodity demands and, thus, global economic strength (Sockin and Xiong, 2012), and fourth (a reason intrigued by a referee), financial investors almost entirely trade commodity futures, since they have no means to store physical commodities. The nearby futures contracts in particular are the most traded and most liquid futures contract. In particular, commodity exchange-traded funds (ETFs) that replicate commodity indices, such as the S&P Goldman Sachs Commodity Index (GSCI) or the Bloomberg commodity index are also long in nearby futures contracts; it is, therefore, natural to inspect the nearby futures contracts when looking at signs of herding behavior.

The timeframe covers highly interesting phases in the history of the U.S. monetary policy. In each phase, the Fed was confronted with a different policy problem (Williamson, 2014). The analysis covers the 1990-1991 recession, the slow recovery, and the disinflation to the end of 1993, the case of the Fed's preemptive tightening against inflation in 1994-1995, the long boom to 1999 and the near full credibility for low inflation and rising trend productivity growth, the tightening of monetary policy to slow the growth of aggregate demand in 1999 and 2000, the collapse of investment in late 2000 and the recession in 2001, the 2002-2007 new boom characterized by very low interest rates, and the 2007-2008 financial crisis, the strong recession, unconventional monetary policy and the stabilization phase.

We also obtain monthly real-time data on both U.S. real output gap and U.S. consumer price index forecasting prices (from Datastream), as well as on U.S. monetary policy interest rates, proxied by the federal funds rate. The federal funds rate is proxied by the shadow federal funds rate, calculated by Wu and Xia (2016), given that over the post 2008 crisis, interest rates were constrained by the lower zero bound and we need to maintain consistency across the time span under study.

Empirical Analysis

Baseline Results: The Herding Behavior Effect

The most common direction in the literature to explore herding is to study the collective behavior of all investors in addition to the market trend. The empirical analysis investigates the presence of herding through the cross-sectional absolute standard deviation (CSAD) methodology (Chang et. al, 2000) as a mesure of return dispersions:

$$CSAD_t = (1/N)\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right| \tag{1}$$

where $R_{i,t}$ is the return on commodity price i on day t, $R_{m,t}$ represents the returns on the corresponding market index and *N* is the number of commodity assets observations. The relationship between dispersion and market return is described through a non-linear equation (Demirer et al. (2015), which can easily detect herding, since it does not require large magnitudes of non-linearity. Thus, a new term was introduced in the CSAD methodology:

$$CSAD_t = c_0 + c_1\left|R_{m,t}\right| + c_2 R_{m,t}^2 + e_t \tag{2}$$

When herding is encountered during times of extreme market movements, the cross-sectional dispersion of asset returns is expected to decrease or increase considerably less than proportional with market returns. The squared market return is introduced as an additional term in the regression to capture this non-linear relationship through a negative estimate of the coefficient c_2.

To assess the impact of the deviations of monetary policy on herding, we need to retrieve the time-varying nature of the herding coefficient (c_2). We avoid certain econometric drawbacks by assuming a representation with time-varying coefficients for each commodity. Specifically, we assume a time-varying coefficient version of model (2):

$$CSAD_t = \gamma_{0,t} + \gamma_{1,t}|R_{m,t}| + \gamma_{2,t}R_{m,t}^2 + u_t,\ t = 1,2,\dots,T, \quad (3)$$

This time-varying modeling approach is motivated by the literature, which finds asset market return moments to be time-varying. In that sense, it is very likely that herding behavior, which actually is based on returns, is time-varying as well. This strand of the literature provided extensive empirical evidence of the presence of a time-varying market risk premium (Ferson and Harvey, 1991). This time-varying approach is based on the hypothesis that the level of aggregate risk aversion is time-varying. In a habit formation model, the representative agent's risk aversion changes with the difference between consumption and the habit-level of consumption. This habit-level was based on past consumption (Constantinides, 1990; Campbell and Cochrane, 1999). The analysis will estimate model (3) using the local linear approach proposed by Cai (2007), which allows for heteroskedasticity and serially correlated errors. Model (3) yields:

$$CSAD_t = X_t{}'\Gamma_t + u_t, \quad (4)$$

where, $X_t = (1,\ |R_{m,t}|,\ R_{m,t}^2)'$, $\Gamma_t = (\gamma_{0,t}, \gamma_{1,t}, \gamma_{2,t})'$, $E(u_t/X_t) = 0$, $E(u_t^2/X_t) = \sigma_t^2(X_t)$, $\{(u_t, X_t)\}$ is strictly stationary α-mixing, but $\{\varepsilon_t\}$ and $\{X_t\}$ may not be independent, with $\varepsilon_t = u_t/\sigma_t^2(X_t)$. To estimate Γ_t assume that $\gamma_j(\cdot)$ $(j = 0,1,2)$ has a continuous second derivative and can be approximated by a first degree Taylor polynomial at any fixed time point $\tau \in [0,1]$:

$$\gamma_j(t_t) \approx \gamma_j(\tau) + \gamma_j'(\tau)(t_t - \tau),\ j = 0,1,2, \quad (5)$$

where $\gamma_j'(\tau)$ the first derivative of $\gamma_j(\tau)$ and $t_t = t/T$. Hence, model (3) can be approximated by a local linear model:

$$CSAD_t = Z_t{}'\Theta + u_t, \text{ where } \quad Z_t = \begin{pmatrix} X_t \\ X_t(t_t - \tau) \end{pmatrix} \quad \text{and } \Theta = \begin{pmatrix} \Gamma(\tau) \\ \Gamma'(\tau) \end{pmatrix}.$$

The locally weighted sum of squares is:

$$\sum_{t=1}^{T}(CSAD_t - Z_t{}'\Theta)^2 K_h(t_t - \tau), \quad (6)$$

where $K_h(\nu) = K(\nu/S)$, $K(\cdot)$ is a kernel function, and S is the bandwidth parameter. We obtain the local linear estimate of $\Gamma_t = (\gamma_{0,t}, \gamma_{1,t}, \gamma_{2,t})'$, by minimizing (6) with respect to Θ. We use the Epanechnikov kernel $K(\nu) = 0.75(1-\nu^2)I(|\nu| \leq 1)$. Given that the bandwidth selection is important, we employ a nonparametric version of Akaike criterion to select the optimal bandwidth:

$$AIC(S) = \log(\hat{\sigma}^2) + \frac{2(T_S+1)}{T-T_S+2} \tag{7}$$

where $\hat{\sigma}^2 = (1/T)\sum_{t=1}^{T}\left(CSAD_t - \widehat{CSAD}_t\right)$, $\{\widehat{CSAD}_t\}$ is the fitted values of $\{CSAD_t\}$, T_S the trace of the smoother matrix, H_S associated with the bandwidth S, $\widehat{CSAD} = H_S\, CSAD$, and $CSAD = (1\,, CSAD_2, \ldots, CSAD_T)'$. The estimation results are shown in Table 1. The estimated coefficients are allowed to change over the course of the time span under consideration, while the reported estimates represent the average estimate over this time span. The negative and statistically significant estimates of γ_2 suggest the presence of herding across all commodity markets, as well as across the three frequency futures data. Cai's (2007) test clearly rejects the null hypothesis of the constancy of the $\gamma_{2,t}$ coefficient.

[Insert Table 1 about here]

Estimates of the Forward Monetary Rule

The behavior of central banks could be assessed through deviations of the federal funds rate from a benchmark monetary policy rule (Kahn, 2012). A Taylor-type (1993) of rule implied that central banks targeted stabilising inflation around its target and output around its potential. Positive (negative) deviations of the two variables from their target were associated with a tightening (loosening) of monetary policy.

The Fed, when announcing a decision, may change the target interest rate and also may hint at changes to the likely future trajectory of interest rates. Gürkaynak et al. (2005) argued that signaling future interest rate changes was the more important channel through which Fed's actions could affect bond prices. Moreover, we estimated the response of commodity futures prices to the deviations of monetary policy from a standard (forward) Taylor monetary rule.

Monetary authorities generally made policy decisions based on economic conditions expected in the future. Accordingly, a number of researchers prefered forward-looking, or forecast-based interest rate rules than contemporaneous rules. It was argued that using forward-looking data could implicitly include information that was not reflected onto inflation and output measures (Rudebusch and Svensson, 1999). Batini and Haldane (1999) argued that given that the presence of lags between the implementation of monetary policy and its first effects on inflation and output was well known, one could design forecast-based rules, such that they were taking into account these transmission lags. Failure to recognise these lags could result in cyclical instability. Moreover, expectations of monetary authorities were in general formulated based on a broad spectrum of information. In this sense, forecast-based rules were information encompassing rules. This was not necessarily a characteristic shared by other types of rules, such as the contemporaneous rules. A forward-looking monetary rule is described by the following process:

$$i_t = \alpha_1 + \beta_1 E_t \pi_{t+j} + \delta_1 y_{t+1} + \rho_1 i_{t-1} + \epsilon_t \tag{8}$$

where i_t is the nominal policy rate and y_{t+1} is the forecasted output gap, i.e., the deviations from trend output. $E_t \pi_{t+j}$ denotes the expectation or forecast formed today of inflation j periods in the future. To respond to questions on whether it makes sense to discuss about the Taylor rule when interest rates were so low and inflation below the announced target, the paper considers a Taylor rule in which the policy rate is based on Wu and Xia (2016) "shadow interest rate". This shadow policy rate accounts of the overall effect of diverse Fed instruments on the economy, including "forward guidance" over the path of future interest rates (with the idea of lowering today's real interest rate by raising the expectation of future inflation) and "quantitative easing" policies involving large-scale purchases of public and private bonds. These alternative tools, already battle-tested during the financial crisis, have been proven effective in stabilizing output and unemployment in a deep recession, following the crisis event.

Table 2 reports the estimates of the forward-looking rule [Equation (8)]. The estimations are derived through the Generalized Method of Moment (GMM) methodological approach (Clarida et al., 2000; Castro, 2011). The instrument list contains lagged values of inflation, the output gap, and interest rates. The empirical findings document an activist policy rule as the coefficient of inflation (β) exceeds one and that of the output gap (δ) exceeds zero, while they are both statistically significant. As the estimated coefficient of the output gap is positive and significant, the Fed has implemented a stabilising policy for the economic outlook. Table 2 points out that the monetary authorities have reacted more strongly to the market participants' perceptions about inflation compared to output stabilization.

[Insert Table 2 about here]

Herding Behavior and Monetary Policy Deviations

To measure the deviations of monetary policy, we follow the approach recommended by Smales and Apergis (2016). In particular, such deviations of monetary policy (*DEV*) are measured as the difference between actual interest rates and their fitted values from (3). Next, the analysis explores whether Taylor-type monetary rule deviations drive asset commodity prices. However, we can also ask whether asset prices drive these deviations, which may reflect the central bank's reaction to asset price movements. Kuttner and Bernanke (2005) found that a typical unanticipated Fed funds rate cut of 25 basis points was associated with an increase of roughly one percent in the level of stock prices, while Rigobon and Sack (2003) found that a 5 percent decrease (increase) in the S&P500 over the course of a week raises the probability of a 25-basis-point interest rate cut (hike) by 64%. Although the data indicated that the Fed reacted directly to the stock market, statistical regressions did not reveal the motives behind this behavior. One possibility was that forward-looking policymakers viewed movements in the asset market as useful predictors of future economic activity. Similarly, forward-looking policy makers may view movements in commodity prices as useful predictors of future inflation. Therefore, the following model is considered:

$$\hat{\gamma}_{2,t} = k_0 + k_1 DEV_t + e_t \tag{9}$$

where $\hat{\gamma}_{2,t}$ is the estimate of $\gamma_{2,t}$ from (4), $DEV = i_t - \hat{\imath}_t$, with i_t being the observed (actual) interest rate and $\hat{\imath}_t$ the fitted interest rate from estimated rule (3).

To take explicitly the interdependence between the variables in Equation (9), as well as to avoid the presence of heteroskedasticity (Roodman, 2011), the equation is estimated through the maximum likelihhod methodological approach. This particular methodology generates heteroscedasticity consistent standard errors. To match monthly monetary policy deviations to the daily frequency of futures contracts we make use of the day of the month the contract is traded in relevance to the month that monetary policy deviations are considered. Moreover, since the asymptotic distribution of the $\hat{\gamma}_{2,t}$ estimator is not known, we cannot readily provide the standard errors for the estimated parameters. Therefore, we need to resort to bootstrap approximation for the distribution and subsequently obtain the bootstrap standard errors for the estimated parameters (a procedure as outlined in De Angelis et al., 1993).

The results are reported in Table 3. The findings in Panel A document that deviations from planned monetary policy provide 'informational' caskades/spillovers to market participants in commodity markets, leading them to behave as members of the herd. More specifically, for example in the case of gold futures prices, the estimates indicate that over the next month a 10-basis point surprise/deviation in interest rates increases gold futures prices by about 0.73%, while for the 2-month contracts this increase turns out to be 0.78%. However, for the case of the 3-month contracts the increase falls to 0.55%. Overall, the responses are higher for the case of precious commodities, vis-à-vis the case of agricultural commodities.

As emphasized by the longstanding hedging pressure theory of commodity futures prices, the stronger effects across the futures price frequencies occur with respect to the first two months, indicating an 'overshooting' effect (Hirshleifer, 1988), with the impact dissipating over longer time horizons. This observation received statistical support from the Z statistics, recommended by Clogg et al. (1995), which tested the null hypothesis that the coefficients k_1 and k_3 were equal across maturities for the same commodity.

Due to the important roles played by commodity prices in a range of policy issues, running from price inflation to energy security and to economic and political stability, policy makers across the globe have become increasingly concerned with greatly increased commodity price changes. Within such an environment, it is even more pressing to fully understand information contained in commodity futures prices and how this informational content affects deviations of monetary policy decisions from a forward-looking monetary rule. The findings in Panel B display a negative association between herding behavior and the reaction coming from the central bank. Such results support an active response of the monetary authorities to a 'herding' or 'bubble' trend coming from the commodity markets, which makes these results aligned to the rationale recommended by Bernanke and Gertler (1999). Once again, the estimates of the Zs statistic point out that the estimations are not equal across maturies for the same commodity.

[Insert Table 3 about here]

Robustness Checks: The Separation Between Rules- and Discretionary-Based Eras

In this part of the empirical analysis, we make use of the Nikolsko-Rzhevskyy et al. (2014) methodology who explicitly divided monetary policy into 'small' and 'large' deviations periods. Based on this methodological approach, we consider the periods 1990:1-1999:4 and 2006:3-2017:4 as rule-based eras and the period 2000:1-2006:2 as a discretionary era. Therefore, we investigate the behavior of the model described in Equation (9), across the three time windows mentioned above, along with the maximum likelihood methodological approach. The new results are reported in Table 4 and illustrate that deviations from planned monetary policy over the discretionary period provide stronger 'informational' spillovers to market participants in commodity markets than corresponding deviations over the rule-based eras. For instance, for the case of one-month gold futures contracts, the estimates clearly illustrate that a 10-basis point deviations of interest rates from their formal path initiate a 0.49% and 0.52% increase in the prices of those contract, while, by contrast, the same basis point deviations initiate a 0.84 increase in the same contracts. The results remain consistently robust across all commodity futures contracts, as well as across time (i.e., for 2- and 3-month contracts). Such findings imply a stronger herding behavior and indicate that rule-based eras seem to be characterized by signaling 'more accurate' monetary policies that transmit less uncertainty to commodity market participants.

Although the results display a negative association between herding and the reaction coming from the central bank in both monetary policy eras, supporting an active response of the monetary authorities to a 'herding' or 'bubble' trend in the commodity markets, the reaction of the monetary authorities is stronger over the discretionary-based era. Following a monetary rule in a more restrictive manner seems to constrain the monetary authorities from reacting excessively to herding in commodity markets. Finally, the estimates of the Zs statistics denote that the estimates are not equal across monetary policy eras for the same commodity.

[Insert Table 4 about here]

Conclusion

This paper investigated the presence of herding across major commodity markets, as well as the hypothesis that U.S. monetary policy could be a major driver for such a behavior. The empirical findings provided favorable evidence that herding was present in major energy, agricultural, metals and precious metals commodity markets, with the U.S. monetary policy potentially driving such a behavior. Additionally, the empirical analysis provided supportive evidence of stronger herding over a discretionary-based monetary policy era, probably reflecting higher uncertainty associated with the performance of the economy in such a period.

The empirical results highlighted that potentially extraordinary monetary policy decisions both on tranquil or distressed times, such as the recent financial crisis, are substantially likely to inflict commodity prices. The findings that the deviations of monetary policy from a standard rule impact commodity forward prices also indicates the presence of information asymmetry in investment markets, which makes herding behaviors more intense, since intensify the possibility of informational cascades, as well as of reputation and compensation based herding. What is needed is more and better disclosure rules, timely provision of data and better designed compensation contracts that are expected to make markets and institutions more transparent. This is expected to bring more and better information about market expectations into the public domain. Greater transparency will make it more likely that prices will closely track fundamentals.

The findings also point out that commodity prices could be used as an indicator for monetary policy; in that respect, policymakers could take commodity prices as signals for future inflation and real economic activity. This discussion implies that commodity price rises, as those occurred back in 2008, need not be necessarily taken as temporary, while potential swings in commodity markets do not necessarily reflect a speculative behavior of market participants. Finally, an interesting venue for future research could be the extension of this current work to investigate monetary policy schemes implemented in other primary monetary policy centers, i.e. the U.K., China, Japan, and the Eurozone.

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Table 1 Herding estimates between futures commodity prices and deviations of monetary policy from a Taylor's rule: January 1990 to December 2017 (1-, 2-, 3-month futures prices)

Commodity	$\gamma_{0,t}$	$\gamma_{1,t}$	$\gamma_{2,t}$	R^2	Cai test
Futures prices: 1-month					
Gold	0.236	0.374	-0.476	0.35	[0.00]
	[0.00]	[0.03]	[0.00]		
Silver	0.216	0.297	-0.459	0.27	[0.00]
	[0.00]	[0.01]	[0.00]		
Platinum	0.155	0.251	-0.409	0.26	[0.01]
	[0.01]	[0.01]	[0.00]		
Natural gas	0.126	0.580	-0.677	0.43	[0.00]
	[0.05]	[0.02]	[0.00]		
Copper	0.125	0.458	-0.592	0.39	[0.00]
	[0.03]	[0.00]	[0.00]		
Aluminium	0.146	0.483	-0.598	0.44	[0.00]
	[0.00]	[0.00]	[0.00]		
Nickel	0.124	0.396	-0.564	0.33	[0.01]
	[0.01]	[0.00]	[0.00]		
Sugar	0.135	0.386	-0.561	0.35	[0.00]
	[0.02]	[0.01]	[0.00]		
Corn	0.139	0.395	-0.552	0.37	[0.00]
	[0.01]	[0.00]	[0.00]		
Wheat	0.141	0.418	-0.573	0.35	[0.00]
	[0.02]	[0.00]	[0.00]		
Oats	0.154	0.473	-0.562	0.39	[0.00]

	[0.01]	[0.00]	[0.00]		
Cocoa	0.166	0.493	-0.580	0.40	[0.00]
	[0.00]	[0.00]	[0.00]		
Cotton	0.142	0.511	-0.563	0.38	[0.00]
	[0.03]	[0.00]	[0.00]		
Coffee	0.157	0.536	-0.572	0.39	[0.00]
	[0.00]	[0.00]	[0.00]		
Futures prices: 2-month					
Gold	0.239	0.381	-0.482	0.36	[0.00]
	[0.00]	[0.02]	[0.00]		
Silver	0.220	0.299	-0.463	0.29	[0.00]
	[0.00]	[0.00]	[0.00]		
Platinum	0.158	0.255	-0.416	0.28	[0.00]
	[0.00]	[0.00]	[0.00]		
Natural gas	0.128	0.586	-0.681	0.44	[0.00]
	[0.04]	[0.01]	[0.00]		
Copper	0.129	0.462	-0.596	0.41	[0.00]
	[0.02]	[0.00]	[0.00]		
Aluminium	0.149	0.487	-0.602	0.46	[0.00]
	[0.00]	[0.00]	[0.00]		
Nickel	0.128	0.399	-0.568	0.35	[0.01]
	[0.00]	[0.00]	[0.00]		
Sugar	0.139	0.458	-0.539	0.32	[0.00]
	[0.02]	[0.00]	[0.00]		
Corn	0.146	0.477	-0.516	0.34	[0.01]

	[0.01]	[0.00]	[0.00]		
Wheat	0.155	0.462	-0.539	0.36	[0.00]
	[0.01]	[0.00]	[0.00]		
Oats	0.142	0.483	-0.551	0.41	[0.01]
	[0.02]	[0.00]	[0.00]		
Cocoa	0.139	0.466	-0.548	0.37	[0.00]
	[0.02]	[0.00]	[0.00]		
Cotton	0.157	0.493	-0.586	0.39	[0.00]
	[0.00]	[0.00]	[0.00]		
Coffee	0.142	0.474	-0.571	0.38	[0.00]
	[0.01]	[0.00]	[0.00]		
Futures prices: 3-month					
Gold	0.234	0.379	-0.468	0.35	[0.00]
	[0.00]	[0.01]	[0.00]		
Silver	0.221	0.295	-0.461	0.28	[0.00]
	[0.00]	[0.00]	[0.00]		
Platinum	0.152	0.253	-0.414	0.26	[0.01]
	[0.00]	[0.00]	[0.00]		
Natural gas	0.124	0.582	-0.678	0.43	[0.00]
	[0.05]	[0.00]	[0.00]		
Copper	0.123	0.460	-0.591	0.39	[0.00]
	[0.04]	[0.00]	[0.00]		
Aluminium	0.141	0.479	-0.602	0.45	[0.01]
	[0.00]	[0.00]	[0.00]		

Nickel	0.122	0.394	-0.562	0.33	[0.00]
	[0.00]	[0.00]	[0.00]		
Sugar	0.144	0.462	-0.563	0.38	[0.00]
	[0.02]	[0.00]	[0.00]		
Corn	0.150	0.474	-0.559	0.35	[0.01]
	[0.01]	[0.00]	[0.00]		
Wheat	0.159	0.481	-0.593	0.40	[0.00]
	[0.00]	[0.00]	[0.00]		
Oats	0.138	0.460	-0.574	0.36	[0.01]
	[0.02]	[0.00]	[0.00]		
Cocoa	0.169	0.485	-0.597	0.42	[0.00]
	[0.01]	[0.00]	[0.00]		
Cotton	0.142	0.448	-0.552	0.37	[0.00]
	[0.01]	[0.00]	[0.00]		
Coffee	0.154	0.426	-0.541	0.36	[0.00]
	[0.00]	[0.00]	[0.00]		

Notes: 1-, 2- and 3-month results indicate the next three months such contracts are allowed to negotiate. Estimated equation is:. $CSAD_t = \gamma_{0,t} + \gamma_{1,t}\left|R_{m,t}\right| + \gamma_{2,t}R_{m,t}^2 + u_t$. The model has been estimated using the local linear approach proposed by Cai (2007), which allows for heteroskedasticity and serially correlated errors. Figures in brackets denote p-values. The Cai test examines the validity of the null hypothesis of the constant parameter of $\gamma_{2,t}$.

Source: Data come from the Thomson Reuters database

Table 2 Forward-looking monetary policy rule estimates (output is measured as GDP): January 1990 to December 2017

α_1	β_1	δ_1	ρ_1	*Adj. R^2*	*J-statistic*
0.097***	3.682***	0.058***	0.296***	0.67	[0.98]
[0.00]	[0.00]	[0.00]	[0.00]		

Notes: The estimations were derived through the Generalized Method of Moment (GMM) methodology. The instrument list contained lagged values of inflation, the output gap, and interest rates. The J-statistic indicates that the employed instruments are valid. Figures in brackets denote p-values. *** denotes significance at the 1% level.

Source: Data come from the Thomson Reuters database

Table 3 Estimates of the effect of monetary policy deviations on futures commodity prices: January 1990 to December 2017

Panel A

Equation: $\hat{\gamma}_{2,t} = k_0 + k_1 DEV_t + e_t$

Commodity	k_0	k_1	$Adj. R^2$	*Zs-statistic*
1-month				
Gold	-3.314 [0.03]	7.019 [0.02]	0.07	[0.00]
Silver	-2.346 [0.01]	5.875 [0.00]	0.10	[0.00]
Platinum	-2.006 [0.03]	5.472 [0.01]	0.12	[0.01]
Oil	-1.764 [0.02]	5.146 [0.01]	0.08	[0.00]
Natural gas	-1.498 [0.04]	5.072 [0.01]	0.11	[0.00]
Copper	-1.543 [0.03]	5.084 [0.01]	0.12	[0.03]
Aluminim	-1.374 [0.03]	5.092 [0.00]	0.13	[0.01]
Nickel	-1.089 [0.05]	3.963 [0.01]	0.09	[0.01]
Sugar	-1.148[0.04]	4.281 [0.00]	0.13	[0.00]
Corn	-1.179[0.03]	4.274 [0.01]	0.12	[0.01]
Wheat	-1.167[0.03]	4.651 [0.00]	0.13	[0.00]
Oats	-1.238[0.03]	4.352 [0.00]	0.14	[0.03]
Cocoa	-1.156[0.03]	4.658 [0.01]	0.12	[0.01]
Cotton	-1.164[0.04]	4.349 [0.00]	0.15	[0.00]
Coffee	-1.251[0.03]	4.568[0.01]	0.14	[0.01]
2-month				
Gold	-3.034 [0.01]	7.429 [0.00]	0.09	[0.01]
Silver	-2.096 [0.04]	6.466 [0.01]	0.10	[0.00]

Platinum	-1.675 [0.04]	5.664 [0.01]	0.14	[0.00]
Oil	-1.613 [0.05]	5.618 [0.01]	0.11	[0.00]
Natural gas	-1.364 [0.04]	5.149 [0.01]	0.15	[0.00]
Copper	-1.175 [0.05]	5.493 [0.01]	0.16	[0.01]
Aluminim	-1.045 [0.05]	5.491 [0.01]	0.15	[0.00]
Nickel	-1.148 [0.04]	4.682 [0.01]	0.10	[0.01]
Sugar	-1.062[0.05]	4.952 [0.00]	0.16	[0.01]
Corn	-1.207[0.04]	4.576 [0.01]	0.14	[0.01]
Wheat	-1.173[0.05]	4.718 [0.01]	0.15	[0.00]
Oats	-1.263[0.04]	4.563 [0.01]	0.13	[0.01]
Cocoa	-1.016[0.05]	5.067 [0.00]	0.14	[0.01]
Cotton	-1.066[0.05]	4.485 [0.01]	0.16	[0.00]
Coffee	-1.032[0.05]	4.671[0.01]	0.15	[0.00]

3-month

Gold	-2.378 [0.03]	5.409 [0.01]	0.06	[0.01]
Silver	-1.896 [0.04]	5.644 [0.00]	0.09	[0.00]
Platinum	-1.315 [0.05]	5.062 [0.01]	0.11	[0.01]
Oil	-1.279 [0.05]	5.146 [0.00]	0.09	[0.00]
Natural gas	-1.086 [0.07]	5.095 [0.01]	0.12	[0.01]
Copper	-1.059 [0.06]	5.168 [0.00]	0.13	[0.00]
Aluminim	-1.063 [0.06]	5.117 [0.01]	0.12	[0.01]
Nickel	-1.048 [0.05]	4.052 [0.01]	0.09	[0.00]
Sugar	-1.053[0.06]	4.375 [0.01]	0.13	[0.00]
Corn	-1.144[0.04]	4.126 [0.01]	0.11	[0.01]
Wheat	-1.126[0.05]	4.419 [0.01]	0.10	[0.01]

Oats	-1.013[0.06]	4.286 [0.01]	0.10	[0.01]
Cocoa	-0.953[0.08]	4.582 [0.01]	0.11	[0.01]
Cotton	-1.058[0.05]	4.129 [0.01]	0.13	[0.01]
Coffee	-1.078[0.05]	4.316[0.01]	0.11	[0.00]

Panel B

Equation: $DEV_t = \kappa_2 + \kappa_3 \hat{\gamma}_{2,t} + \nu_t$

Commodity	$\boldsymbol{\kappa_2}$	$\boldsymbol{\kappa_3}$	$\boldsymbol{Adj. R^2}$	***Zs-statistic***
1-month				
Gold	0.037 [0.32]	0.083 [0.02]	0.17	[0.01]
Silver	0.116 [0.24]	1.065 [0.01]	0.12	[0.00]
Platinum	1.048 [0.08]	1.175 [0.01]	0.07	[0.01]
Oil	-0.048 [0.17]	0.078 [0.01]	0.07	[0.01]
Natural gas	-1.005 [0.10]	0.647 [0.02]	0.10	[0.01]
Copper	-0.062 [0.26]	2.185 [0.01]	0.12	[0.02]
Aluminim	-1.002 [0.10]	0.713 [0.01]	0.12	[0.01]
Nickel	-0.226 [0.20]	0.734 [0.01]	0.08	[0.01]
Sugar	-0.835[0.09]	1.382[0.01]	0.13	[0.02]
Corn	-0.915[0.07]	1.329[0.01]	0.14	[0.01]
Wheat	-0.835[0.09]	1.396[0.02]	0.12	[0.01]
Oats	-0.895[0.07]	1.452[0.01]	0.14	[0.02]
Cocoa	-0.874[0.07]	1.448[0.01]	0.13	[0.00]
Cotton	-0.753[0.10]	1.446[0.01]	0.14	[0.01]
Coffee	-0.867[0.07]	1.461[0.01]	0.12	[0.00]
2-month				

Gold	-0.502 [0.21]	0.509 [0.00]	0.13	[0.00]
Silver	-0.335 [0.28]	0.615 [0.01]	0.15	[0.01]
Platinum	-0.411 [0.24]	0.565 [0.01]	0.17	[0.00]
Oil	-0.915 [0.17]	1.242 [0.01]	0.16	[0.01]
Natural gas	-0.914 [0.08]	1.348 [0.01]	0.19	[0.00]
Copper	-0.416 [0.25]	1.632 [0.01]	0.22	[0.01]
Aluminim	-0.373 [0.28]	0.621 [0.01]	0.17	[0.02]
Nickel	-0.212 [0.44]	0.608 [0.01]	0.14	[0.01]
Sugar	-0.483[0.23]	0.909 [0.01]	0.21	[0.00]
Corn	-0.304[0.42]	0.725 [0.01]	0.22	[0.01]
Wheat	-0.486[0.22]	0.903 [0.01]	0.19	[0.01]
Oats	-0.227[0.43]	0.792 [0.01]	0.22	[0.01]
Cocoa	-0.327[0.28]	1.049 [0.01]	0.19	[0.00]
Cotton	-0.426[0.23]	1.005 [0.01]	0.24	[0.01]
Coffee	-0.322[0.38]	1.001[0.01]	0.23	[0.02]
3-month				
Gold	-0.314 [0.25]	0.429 [0.01]	0.10	[0.00]
Silver	-0.115 [0.54]	0.584 [0.01]	0.13	[0.01]
Platinum	-0.231 [0.36]	0.514 [0.01]	0.14	[0.01]
Oil	-0.125 [0.45]	1.013 [0.01]	0.15	[0.00]
Natural gas	-0.329 [0.23]	1.071 [0.01]	0.19	[0.01]
Copper	-0.242 [0.28]	1.084 [0.00]	0.20	[0.00]
Aluminim	-0.302 [0.25]	0.513 [0.01]	0.14	[0.01]
Nickel	-0.225 [0.42]	0.414 [0.01]	0.12	[0.01]
Sugar	-0.342[0.25]	0.639 [0.01]	0.18	[0.02]

Corn	-0.215[0.33]	0.606 [0.01]	0.19	[0.01]
Wheat	-0.224[0.35]	0.653 [0.01]	0.18	[0.01]
Oats	-0.226[0.34]	0.539 [0.01]	0.19	[0.00]
Cocoa	-0.235[0.35]	0.832 [0.00]	0.16	[0.00]
Cotton	-0.326[0.30]	0.864 [0.01]	0.20	[0.01]
Coffee	-0.257[0.34]	0.731[0.01]	0.22	[0.01]

Notes: Estimations were obtained through the three stage least squares (3SLS) methodological approach. The endogenous variables estimates are built on the maximum–likelihood estimator (MLE), while it generates heteroscedasticity consistent standard errors. The Zs statistic tests the null hypothesis that the coefficients k_1 and k_3 are equal across maturities for the same commodity. Figures in brackets denote p-values based on bootstrap standard errors coming from 1000 bootstrap replications.
Source: Data come from the Thomson Reuters database.

Table 4 Estimates of the effect of monetary policy deviations (across both rule-based 1990:1-1999:4 and 2006:3-2014:4, and discretionary-based 2000:1-2006:2, eras).

Equation: $\hat{\gamma}_{2,t} = \mathrm{k}_0 + \mathrm{k}_1\mathrm{DEV}_\mathrm{t} + \mathrm{e}_\mathrm{t}$

1-month

Commodity	k_1(1990:1-1999:4)	k_1(2006:3-2014:4)	k_1(2000:1-2006:2)	*Zs-statistic*
Gold	4.775 [0.00]	5.139 [0.00]	8.175 [0.00]	[0.01]
Silver	4.255 [0.00]	5.774 [0.00]	8.052 [0.00]	[0.00]
Platinum	3.065 [0.00]	5.615 [0.00]	8.148 [0.00]	[0.01]
Oil	2.764 [0.00]	5.524 [0.00]	9.043 [0.00]	[0.01]
Natural gas	2.519 [0.01]	5.193 [0.01]	8.205 [0.00]	[0.01]
Copper	2.358 [0.00]	5.264 [0.00]	9.291 [0.00]	[0.01]
Aluminim	2.548 [0.00]	5.586 [0.00]	8.259 [0.00]	[0.00]
Nickel	3.179 [0.00]	4.665 [0.00]	8.248 [0.00]	[0.00]
Sugar	3.163[0.00]	5.139 [0.00]	9.186 [0.00]	[0.04]
Corn	2.639[0.00]	4.714 [0.00]	9.005 [0.01]	[0.01]
Wheat	2.658[0.00]	5.149 [0.00]	8.763 [0.00]	[0.00]
Oats	3.295[0.00]	4.782 [0.00]	8.351 [0.01]	[0.02]
Cocoa	2.548[0.00]	4.681 [0.00]	9.072 [0.00]	[0.02]
Cotton	3.174[0.00]	5.274 [0.00]	8.437 [0.01]	[0.01]
Coffee	3.154[0.00]	4.752 [0.01]	8.784 [0.01]	[0.01]

2-month

Commodity	k_1(1990:1-1999:4)	k_1(2006:3-2014:4)	k_1(2000:1-2006:2)	*Zs-statistic*
Gold	4.758 [0.00]	5.263 [0.00]	8.447 [0.00]	[0.01]

Silver	4.542 [0.00]	6.084 [0.00]	8.271 [0.00]	[0.01]
Platinum	3.177 [0.00]	5.752 [0.00]	8.594 [0.00]	[0.01]
Oil	2.785 [0.00]	5.516 [0.00]	9.187 [0.00]	[0.01]
Natural gas	2.785 [0.01]	5.437 [0.01]	8.554 [0.01]	[0.01]
Copper	2.524 [0.01]	5.437 [0.01]	9.452 [0.00]	[0.01]
Aluminim	2.582 [0.00]	5.675 [0.01]	8.662 [0.01]	[0.01]
Nickel	3.291 [0.01]	4.872 [0.01]	8.493 [0.01]	[0.02]
Sugar	3.216[0.01]	5.065 [0.01]	9.264 [0.01]	[0.01]
Corn	2.537[0.00]	5.036 [0.01]	9.321 [0.00]	[0.02]
Wheat	2.674[0.01]	5.244 [0.00]	9.081 [0.01]	[0.00]
Oats	3.569[0.00]	5.073 [0.00]	8.615 [0.01]	[0.02]
Cocoa	2.854[0.01]	4.688 [0.01]	9.374 [0.01]	[0.01]
Cotton	3.447[0.01]	5.392 [0.00]	8.679 [0.01]	[0.01]
Coffee	3.285[0.01]	5.042 [0.01]	9.256 [0.01]	[0.00]

3-month

Commodity	***k_1*(1990:1-1999:4)**	***k_1*(2006:3-2014:4)**	***k_1*(2000:1-2006:2)**	***Zs-statistic***
Gold	4.569 [0.01]	4.916 [0.01]	8.052 [0.00]	[0.02]
Silver	4.029 [0.01]	5.621 [0.00]	7.884 [0.01]	[0.02]
Platinum	3.064 [0.01]	5.268 [0.01]	8.144 [0.01]	[0.02]
Oil	2.586 [0.01]	5.421 [0.01]	8.879 [0.01]	[0.02]
Natural gas	2.544 [0.00]	5.132 [0.01]	8.254 [0.01]	[0.04]
Copper	2.194 [0.01]	5.064 [0.00]	9.109 [0.00]	[0.04]
Aluminim	2.375 [0.01]	5.276 [0.01]	8.199 [0.01]	[0.05]
Nickel	2.911 [0.01]	4.465 [0.01]	8.073 [0.01]	[0.05]
Sugar	3.065[0.01]	4.921 [0.01]	9.003 [0.01]	[0.06]

Corn	2.293[0.01]	4.634 [0.01]	9.005 [0.01]	[0.03]
Wheat	2.385[0.01]	5.084 [0.01]	8.654 [0.01]	[0.04]
Oats	3.179[0.01]	4.762 [0.01]	8.092 [0.01]	[0.05]
Cocoa	2.274[0.01]	4.459 [0.01]	9.026 [0.01]	[0.03]
Cotton	3.135[0.02]	5.104 [0.01]	8.139 [0.01]	[0.02]
Coffee	3.052[0.01]	4.674 [0.01]	8.762 [0.01]	[0.01]

Equation: $DEV_t = \kappa_2 + \kappa_3\hat{\gamma}_{2,t} + \nu_t$

1-month

Commodity	***k₃*(1990:1-1999:4)**	***k₃*(2006:3-2013:4)**	***k₃*(2000:1-2006:2)**	***Zs-statistic***
Gold	-0.025 [0.01]	-0.038 [0.02]	-0.102[0.01]	[0.01]
Silver	-0.023 [0.01]	-0.049 [0.00]	-0.101[0.00]	[0.01]
Platinum	-0.032 [0.01]	-0.043 [0.01]	-0.077[0.01]	[0.01]
Oil	-0.036 [0.01]	-0.053 [0.00]	-0.078[0.00]	[0.01]
Natural gas	-0.019 [0.02]	-0.051 [0.00]	-0.095[0.01]	[0.01]
Copper	-0.042 [0.01]	-0.080 [0.00]	-0.113[0.00]	[0.02]
Aluminim	-0.053 [0.02]	-0.070 [0.01]	-0.109[0.00]	[0.03]
Nickel	-0.068 [0.00]	-0.069 [0.00]	-0.103[0.00]	[0.01]
Sugar	-0.032[0.01]	-0.071[0.01]	-0.096[0.01]	[0.03]
Corn	-0.059[0.01]	-0.083[0.00]	-0.109[0.00]	[0.01]
Wheat	-0.042[0.02]	-0.051[0.01]	-0.081[0.00]	[0.00]
Oats	-0.056[0.01]	-0.081[0.00]	-0.114[0.00]	[0.03]
Cocoa	-0.049[0.02]	-0.083[0.00]	-0.116[0.01]	[0.01]
Cotton	-0.042[0.02]	-0.074[0.00]	-0.107[0.01]	[0.02]
Coffee	-0.045[0.01]	-0.082[0.00]	-0.112[0.00]	[0.01]

2-month

Commodity	k_3(1990:1-1999:4)	k_3(2006:3-2013:4)	k_3(2000:1-2006:2)	*Zs-statistic*
Gold	-0.023 [0.00]	-0.032 [0.00]	-0.085[0.00]	[0.01]
Silver	-0.022 [0.00]	-0.046 [0.00]	-0.079[0.01]	[0.02]
Platinum	-0.027 [0.03]	-0.038 [0.01]	-0.072[0.00]	[0.02]
Oil	-0.034 [0.01]	-0.045 [0.01]	-0.070[0.00]	[0.01]
Natural gas	-0.015 [0.03]	-0.044 [0.02]	-0.080[0.00]	[0.01]
Copper	-0.036 [0.01]	-0.073 [0.00]	-0.092[0.01]	[0.02]
Aluminim	-0.045 [0.01]	-0.061 [0.00]	-0.088[0.01]	[0.03]
Nickel	-0.061 [0.00]	-0.053 [0.01]	-0.084[0.02]	[0.01]
Sugar	-0.026[0.01]	-0.065[0.00]	-0.075[0.01]	[0.03]
Corn	-0.051[0.00]	-0.072[0.00]	-0.086[0.02]	[0.02]
Wheat	-0.035[0.01]	-0.042[0.01]	-0.069[0.01]	[0.01]
Oats	-0.045[0.01]	-0.064[0.00]	-0.101[0.00]	[0.02]
Cocoa	-0.041[0.01]	-0.072[0.00]	-0.097[0.01]	[0.01]
Cotton	-0.036[0.01]	-0.066[0.00]	-0.085[0.01]	[0.01]
Coffee	-0.042[0.01]	-0.075[0.00]	-0.092[0.01]	[0.01]

3-month

Commodity	k_3(1990:1-1999:4)	k_3(2006:3-2013:4)	k_3(2000:1-2006:2)	*Zs-statistic*
Gold	-0.020 [0.01]	-0.031 [0.01]	-0.078[0.00]	[0.03]
Silver	-0.017 [0.02]	-0.043 [0.00]	-0.080[0.00]	[0.02]
Platinum	-0.027 [0.01]	-0.036 [0.01]	-0.077[0.00]	[0.03]
Oil	-0.031 [0.01]	-0.045 [0.00]	-0.072[0.00]	[0.02]
Natural gas	-0.016 [0.01]	-0.043 [0.01]	-0.092[0.01]	[0.02]

Copper	-0.035 [0.01]	-0.074 [0.01]	-0.090[0.00]	[0.02]
Aluminim	-0.043 [0.00]	-0.064 [0.00]	-0.093[0.01]	[0.02]
Nickel	-0.055 [0.00]	-0.060 [0.00]	-0.090[0.00]	[0.02]
Sugar	-0.024[0.01]	-0.058[0.01]	-0.081[0.01]	[0.03]
Corn	-0.052[0.00]	-0.077[0.00]	-0.083[0.01]	[0.03]
Wheat	-0.035[0.01]	-0.044[0.01]	-0.074[0.01]	[0.03]
Oats	-0.051[0.00]	-0.064[0.00]	-0.103[0.00]	[0.05]
Cocoa	-0.046[0.00]	-0.072[0.00]	-0.105[0.00]	[0.02]
Cotton	-0.035[0.01]	-0.070[0.00]	-0.102[0.00]	[0.02]
Coffee	-0.042[0.00]	-0.075[0.00]	-0.093[0.01]	[0.03]

Notes: Estimations were obtained through the three stage least squares (3SLS) methodological approach. The endogenous variables estimates are built on the maximum–likelihood estimator (MLE), while it generates heteroscedasticity consistent standard errors. The Zs statistic tests the null hypothesis that the coefficients k_1 and k_3 are equal across maturities for the same commodity. Figures in brackets denote p-values based on bootstrap standard errors coming from 1000 bootstrap replications. Here, the Zs statistic tests the null hypothesis that the coefficients k_1 and k_3 are equal across monetary policy eras for the same commodity.
Source: Data come from the Thomson Reuters database.