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Three econometric essays in Stocks and Commodity markets

Georgios Bampinas

Thesis submitted for assessment with a view to obtaining the Degree of Doctor of Philosophy in Economics of the University of Macedonia

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Contents

PART I

INTRODUCTION

This PhD thesis discusses three central research topics in applied time series econometrics that generally belong in the fields of Macroeconometrics and Financial econometrics. It consists of three papers that are related to stocks and commodities investment in the context of hedging movements of inflation in the long-run, as well as the time-invariant and time-varying causal linkages of two major commodity markets. Particularly, the first two chapters inquire into the inflation hedging ability of stocks and commodity markets by relying on an empirical framework combined with economic theory. The third chapter examines the dynamic interrelationship between the most important commodities around the recent financial crisis.

The first chapter of this thesis deals with the inflation hedging properties of US individual stocks from a long-run (cointegration) perspective. In particular, we construct in- and out-of-sample portfolios based on the long-run inflation betas of stock prices with respect to consumer prices. The results show that the portfolio of stocks with the highest ex post long-run betas exhibit superior inflation hedging ability. We find some evidence of similar behavior for the out-of-sample portfolios with rebalancing periods one to four years. Stocks that outperform inflation tend to be drawn from the Energy and Industrial sectors. Moreover, the number of individual stocks that hedge inflation changes considerably following the period after the 2008 downturn of the economy.

The second chapter exploits the long-run inflation hedging ability of gold and silver prices against alternative measures of consumer price index from a historical perspective. We employ a dataset that spans over two centuries for the UK and the US. For the empirical analysis we employ both a time-invariant and a time-varying cointegration framework. We find that gold can fully hedge headline, expected and core CPI in the long-run. This ability tends to be stronger when we allow for the long-term dynamics to vary over time. More stability is observed in the long-run hedging ability of gold vs expected inflation during the last decades. The inflation hedging ability of gold is on average higher in the US compared to the UK. Silver does not hedge US con-

sumer prices albeit evidence emerges in favor of a time-varying long-run relationship in the UK.

The work of this thesis began little after the global economy was hit by the largest economic crisis since the Great Depression. Accordingly, the last chapter of this thesis is an empirical investigation of linear, nonlinear and time-varying causal linkages between the two most important commodities, namely crude oil and gold, around the recent financial crisis. The results show that before crisis causality is linear and unidirectional running from oil to gold. After crisis a bidirectional nonlinear causality relationship emerges, with volatility spillovers found as the source of the nonlinear linkage. The dynamic bootstrap causality analysis reveals that the causal linkage from gold to oil is time dependent and that the non-Granger causality null hypothesis rejection rate increased considerably in the post-financial crisis period. Moreover, probit analysis has shown that the probability of gold Granger causing oil in the short-run increases by more than 30% during the recent financial and euro crisis.

PART II

CHAPTERS

CHAPTER 1

HEDGING INFLATION WITH INDIVIDUAL STOCKS: A LONG-RUN PERSPECTIVE

ABSTRACT

We study the long-run inflation hedging ability of individual stocks. We construct in- and out-of-sample portfolios based on the long-run betas of stock prices with respect to consumer prices. We show that the portfolio of stocks with the highest ex post long-run betas exhibit superior inflation hedging ability, intensified in the left tail of the conditional distribution. The latter is also confirmed for the out-of-sample portfolios with rebalancing periods one to four years. Stocks that outperform inflation tend to be drawn from the Energy and Industrial sectors. The number of individual stocks that hedge inflation is reduced considerably following the downturn of the economy. Time variability in the composition of sectors and in the number of firms that hedge CPI movements is observed.

Keywords: stock prices, good prices, hedging, generalized Fisher effect, quantile regression.

1.1 Introduction

Recent developments in the US economy, notably the rise in government deficits and debt levels, the increase in macroeconomic volatility, dollar weakness and the large volume of reserves being created by Fed, raised consumers and investors concerns of a potential inflation surge. Inflation risk erodes purchasing power of retirement savings, redistributes wealth from lenders to borrowers, and intimidates investors' long-term objectives which are often specified in real terms (see e.g., Bodie, 1989; Doepke and Schneider, 2006). The theoretical framework in this area is attributed to the seminal work of Irving Fisher (1930), who posited that the market interest rate comprises the expected real interest rate and expected inflation.[1] Conventional financial theory holds that equities should compensate for movements in inflation since they represent claims against real rather than nominal assets (Mishkin, 1992; Boudoukh et al., 1994). However, empirical studies report a negative relation between inflation and stock returns in the US (Bodie, 1976; Nelson, 1976; Fama and Schwert, 1977; Jaffe and Mandelker, 1976; Geske and Roll, 1983), with this phenomenon being universal rather than country-specific (Solnik, 1983; Gultekin, 1983; Bekaert and Wang, 2010).

A range of competing hypotheses have emerged attempting to explain this negative short-term relationship: the "equity risk premium hypothesis" (Malkiel, 1979; Pindyck, 1984), the "tax effects hypothesis" (Feldstein, 1980; Summers, 1981), the "proxy hypothesis" (Fama, 1981; Bekaert and Engstrom, 2010), and the "inflation illusion hypothesis" (Modigliani and Cohn, 1979; Campbell and Vuolteenaho, 2004; Lee, 2010). Following attempts to provide an explanation for the puzzling negative short-run relationship between stock returns and inflation the literature has since moved towards investigating the long-run hedging properties of stocks. In order to recover the long-run (*LR*) information, two alternative methodologies have been adopted: regressions of long

[1]The Fisher Hypothesis about interest rates can be generalized to all assets in efficient markets. Jaffe and Mandelker (1976, pp. 450) term generalized Fisher effect, the hypothesis of independence between the expected real return in the stock market and the anticipated inflation rate.

holding-period stock returns on inflation using long span of data (Cagan, 1974; Lothian and McCarthy, 2001; Boudoukh and Richardson, 1993), and cointegration analysis of stock prices and consumer prices (Ely and Robinson, 1997; Anari and Kolari, 2001). Existing empirical evidence using both approaches comes along with a positive long-run relationship between stock returns (prices) and inflation (consumer prices) with estimated coefficients broadly in line with the generalized Fisher effect (*GFE*).

A considerable body of academic research has focused on how aggregate stock market indices covary with inflation. However only few consider the case of individual stocks as hedge against inflation. Johnson et al. (1971) conclude that the individual stocks in the Dow-Jones Industrial Average were not consistent inflation hedges. Ang et al. (2012) examine the inflation hedging ability of S&P 500 individual stocks by constructing portfolios based on short-run inflation betas.

We take the view that the reasoning underlying the relationship between returns and inflation could also be applied to the level of equity prices and the consumers price level. There are several important reasons to examine the inflation hedging ability of individual stocks in a long-run framework. First, in advanced economies where monetary policy focuses on price stability, investors and households are most concerned about long-run inflation risk (household saving for retirement, liabilities of pension funds and endowments, etc.) and to a lesser extent about inflation movements in short horizons. Second, constructing portfolios based on common stocks whose price comove strongly with consumers prices has the potential to provide a much better inflation hedge than the aggregate market index. Although the overall market may be a poor inflation hedge, companies from certain industry sectors and with specific characteristics may provide stronger long-run inflation hedging properties. Third, equity hedging techniques based on correlation have substantial weaknesses inherent to the very nature of correlation as a measure of dependence (Alexander and Dimitriu, 2004). Moreover, goods prices and stock prices are both known to be integrated processes with infinitely long memory, thus, estimating regressions in terms of their first (or higher)

order differences implies partial loss of valuable long-run information (Anari and Kolari, 2001). Fourth, examining individual stocks in the GFE framework, also allows us to investigate which types of stocks or sectors constitute effective inflation hedgers in the long-run. Blanchard (1982) examines the heterogeneity across sectors and finds that the variability of goods prices early in the chain production (food, energy) is larger than those of intermediate goods sector. In a similar vein, Clark (1999) argues that the response of producer prices to monetary shocks depends upon the manufacturing stage. Furthermore, there is a wide variation in the level of market pricing power across companies (Bresnahan, 1989). Fabiani et al. (2005) support that services firms change prices less often than others while retail firms do it more frequently. Gautier (2006) states that the sectoral heterogeneity in the frequency of price change is quite similar in the euro area and in the US, with the prices of primary goods frequently modified.

This study investigates the inflation hedging properties of individual stocks and strategic asset allocation from a long-run (cointegration) perspective. Within a GFE framework, we focus on the long-run hedging ability of individual stocks that have shown significant cointegrating relationship with consumer price index. We construct in-sample and out-of-sample portfolios sorted on the long-run stock-level prices betas.[2] In the first case, we conduct an ex-post analysis of which companies provided the strongest realized comovement with consumer prices using the entire dataset. In the second case, for the ex-ante analysis we use iterative estimation through which estimated parameters of the model used to test the stock prices/consumers prices relation are updated sequentially over time.[3] Iterative estimation is accomplished using rolling cointegrating regressions.

The results document how the magnitude of the inflation hedging ability varies across portfolios sorted on long-run betas. On the one hand, in-sample/ex-post esti-

[2]The stocks that have shown significant cointegration evidence with CPI in their vast majority exhibit positive sign. Thus, our analysis focuses on stocks with positive long-run betas.

[3]Alexander and Dimitriu (2005) argue that the theoretical benefits of trading strategies based on cointegration relationships are more robust out-of-sample than the relationships that are identified on returns.

mates of the stock prices/consumer prices model indicate substantial variation in how individual stocks comove with consumers prices in the long-run. While the long-run relation of the aggregate market with CPI is insignificant, there is a substantial subset of individual stocks with high, and significantly positive, consumers' price *LR* betas. Industrials and Energy sectors generally benefit from rising goods prices. We then sort stocks into quartile portfolios based on realized, ex-post inflation betas. The portfolios consisting of stocks with the highest ex-post long-run Fisher elasticities have inflation betas of 1.77 and 1.71 respectively, with the formers hedging ability to intensify on the left tail of the conditional distribution (lower returns). Moreover, stocks that have been good long-run inflation hedgers exhibit, on average, high nominal and real returns. On the other hand, out-of-sample/ex-ante evidence reveals that the portfolio with 3 years rebalancing period exhibits the stronger hedging ability, with beta estimate of 1.12. The rest of the out-of-sample portfolios also exhibit positive inflation betas estimates ranging from 0.93 to 1.01. Both the in-sample portfolio with the higher betas and the out-of-sample portfolio with one to four years rebalancing period posit higher beta coefficients in magnitude and statistically significance, at the lower quantile of the conditional distribution. There is also evidence of considerable time variation in the values of individual firms *LR* betas and the amount of firms that show partial or full inflation hedging ability. Further classification of stocks into sectoral portfolios shows that the Energy sector has the highest inflation beta, followed by the Materials and the Consumers Staples sectors. The sectoral inflation betas also exhibit pronounced time variation, with the Energy, Basic Materials and Industrials inflation betas moving closely during the sample period.

The remainder of this paper is organized as follows. The literature is reviewed in Section 2. Section 3 discusses the data and presents the empirical model. Section 4 describes the procedure for in- and out-of sample portfolio construction. The empirical results are presented in Section 5. Section 6 concludes.

1.2 Related literature

The relation between stock market returns and inflation remains a controversial issue. Early empirical studies focused on the US stock data provide voluminous evidence that common stocks are a poor hedge against both expected and unexpected inflation (see among others, Lintner, 1973; Oudet, 1973; Fama and Schwert, 1977). Contrary to the US studies, Firth (1979) provides evidence in favor of a positive Fisher effect for UK over the period 1955 to 1976, a finding further supported by Gultekin (1983). The latter study reports a negative relationship between stock returns and inflation in a multi-country context.

Barnes et al. (1999) examined the empirical relationship between inflation and a variety of asset returns of 25 countries for periods 1957 through 1996. They find that only in high inflation countries nominal returns provide some hedging properties against inflation. After examining several alternative hedging investments in the US, Attié and Roache (2009) conclude that of all the asset classes considered, equities are the least attractive hedge against inflation. Bekaert and Wang (2010) document higher inflation betas for emerging markets compared to developed markets. The authors argue that the positive coefficient for emerging markets is mainly due to the Latin American countries which have experienced high inflation shocks. Knif et al. (2008) employ event study methodology and conclude that stocks returns response to inflation is conditional on positive or negative inflation shocks in different states of the economy.

Despite this puzzling relationship, the literature has since moved towards the long-run hedging properties of stocks. Boudoukh and Richardson (1993) employ two century long time-series of annual stock and inflation returns for the US and UK, and strongly support a positive relation between nominal stock returns and inflation. Lothian and McCarthy (2001), using long span data for fourteen OECD countries over the post-World War II period and time series for the UK and the US over the longer period 1790 to 2000, conclude that equities constitute a good inflation hedge, but it takes "an exceedingly long time for this to happen." Ely and Robinson (1997) employ a multi-

variate model that incorporates real output and money in a cointegration framework. The authors, examine the period 1957 to 1992, and do not find evidence that stock and goods prices are important components in the cointegrating vectors for the majority of the 16 countries considered. They conclude that in the long-run, stocks maintain their value relative to goods prices following both real and monetary shocks. One notable exception is the failure of stocks to maintain their value relative to goods prices driven by real output shocks in the US. Anari and Kolari (2001) also employed a cointegration approach with data from 6 industrialized countries. They show that over the period 1953 to 1998, the long-run generalized Fisher elasticities of stock prices with respect to consumer prices exceed unity in four out of six cases ranging between 1.04 to 1.65. Nevertheless, none of the studies that employed cointegration has used common stocks to construct inflation hedging portfolios.

1.3 Data and methodology

1.3.1 Stock prices and stationarity tests

We use stock prices of companies that have been continuously constituents of the S&P 500 Index for almost two decades, from January 1993 until August 2012. For all common stocks present each month in the index, we obtain the monthly closing prices (cumulative stock price accounting for dividend gains and splits) from Yahoo Finance and market capitalization obtained from Datastream (Thomson Reuters). The US Consumer Price Index (headline CPI) is downloaded from Bureau of Labor Statistics. Following Ang et al. (2012), we also use CPI data at the time of the release ("real time" CPI series), provided by the Federal Reserve Bank of St Louis for the out-of-sample portfolio construction. For the CPI Series (headline and "real time") and all individual stocks, we have conducted four unit root and stationarity tests: (i) Dickey and Fuller (1979, (ii) Phillips and Perron (1988), (iii) the Ng-Perron (2001) and (iv) the KPSS. Our

final sample consists of 345 individual stocks and the two CPI indices (all *I(1)*).[4]

1.3.2 Long-run and short-run regression analysis

Several studies have explored the issue of cointegration and asset prices.[5] The Engle-Granger (1987) (E-G) method for cointegration testing is particularly appealing in this respect for its intuitive and straightforward implementation.[6]

Our definition of long-run inflation hedging applies on how strongly a security's nominal price comoves with consumers' prices in the following time-series regression:

$$S_{it} = \alpha + \beta_1 CPI_t + \varepsilon_t \tag{1}$$

where S_{it} is the monthly log nominal price of a stock i, CPI_t the monthly price level, and ε_t the error of the regression. We use the beta of a stock price with respect to consumer price index as a measure of individual securities' long-run inflation-hedging ability. Possible outcomes include $\beta_1 > 0$ partial *LR* hedge, $\beta_1 = 1$ one-to-one relationship, perfect *LR* hedge and $\beta_1 > 1$ stock performance superior. We construct portfolios sorted on long-run betas using both ex-ante and ex-post measures.

Next for the portfolios constructed on the basis of *LR* betas, we consider a simple concept of portfolios hedging ability (see eg., Ang et al., 2012; Bekaert and Wang, 2010), namely inflation beta, using the regression:

$$\Delta S_{pt} = a + \beta_2 \Delta CPI_t + e_t \tag{2}$$

[4]The unit root and stationarity tests results are available from the authors upon request.

[5]An extensive overview of this area is given in Alexander (1999b).

[6]See Alexander (1999a, pp. 2043) for a discussion about the virtues of Engle-Granger methodology on financial applications.

Here, ΔS_{pt} is the portfolio monthly nominal return, ΔCPI_t is the monthly inflation rate and e_t is the part of the return not explained by inflation. Our measure of inflation hedging is straightforward and involves the portfolio returns covariation with actual inflation. Given that the variables are expressed in logarithms, β_2 coefficient is the short-run elasticity of portfolio returns with respect to inflation.

1.4 Portfolio construction

We pick up stocks that have shown significant cointegration with consumer price index over the entire sample period. Equation (1) is estimated via Dynamic OLS (DOLS) for the stocks-CPI pairs that have shown significant cointegration at 10% level and the *LR* betas are saved. We sort stocks by their long-run betas to form quartile portfolios. Quartile 1 (Q1) is the portfolio with the highest betas, and Q4 is the portfolio with the lowest betas.[7]

We construct in-sample portfolios, selecting securities on the basis of betas calculated from January 1993 to August 2012 (see Section 5.2). Along with four portfolios (Quartiles 1 through 4, sorted from the highest inflation beta to the lowest) weighted at each date by market capitalization, we have also constructed portfolio Q5 that contains all stocks which have shown superior performance against consumer price movements (*LR* beta above unity).[8] For the regression analysis, we employ a robust HAC (Newey-West) covariance matrix estimator (Newey and West, 1987). The number of lags or leads in DOLS regression was selected according to Schwarz criterion. We record the returns of each portfolio as well as the portfolio inflation betas.

Proceeding in out-of-sample analysis, we construct dynamically rebalanced portfolios (see Section 5.3) on the basis of common stocks past cointegration ability (rolling E-G statistic) and long-run betas (rolling DOLS). The exercise is repeated for every

[7] A negative inflation beta implies that a stock price moves to the opposite direction in the long-run when CPI is high. Therefore stocks with negative inflation beta were excluded from our analysis.

[8] Note that as a robustness check, we have also constructed equally weighted quartile portfolios, with very similar results not reported here but available from the authors upon request.

rebalancing period (every 1, 3, 6, 12, 24, 36, 48 and 60 months). Since the CPI series is not announced until the middle of the subsequent month, we omit the most recent month in the regressions and use the "real time" CPI.

After constructing portfolios, we estimate the four factor model of Carhart (1997) which in addition to using the three factor loadings of Fama and French (1993) (FFC), also includes the momentum effect:

$$R_{pt} = a_p + \beta_p MKT_t + \gamma_p SMB_t + \delta_p HML_t + \eta_p MOM_t + \varepsilon_t \tag{3}$$

where R_{pt} is the monthly excess-return of portfolio p over the risk-free rate. We obtain from Kenneth French's online data library, monthly risk-free rates (on one month Treasury bills) and returns on risk factors which include MKT_t (market excess returns), SMB_t (small-minus-big firm returns), HML_t (high-minus-low book-to-market returns), and the MOM_t (winners-minus-losers returns).[9] All returns are at a monthly frequency. We compute standard errors and t-statistics using the Newey and West (1987) estimator with the number of lags equal to the recommendation in Newey and West (1994).[10] Following Alagidede and Panagiotidis (2012) that show a negative and significant relationship between S&P 500 returns and US inflation throughout the returns distribution, we also employ the quantile regression proposed by Koenker and Bassett (1978).[11]

1.5 Empirical results

1.5.1 The best long-run Inflation hedging Stocks

In this section, we examine the in-sample behavior of the comovement of stocks with goods prices. This ex-post exercise reveals which stocks have provided the best

[9] Available at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

[10] We follow Newey and West's (1994) recommendation to set the number of lags equal to the highest integer less than $4 \times (T/100)^{(2/9)}$, where T is the number of periods in the sample. Applying this formula to our sample of $T = 236$ months results in a lag length of four months.

[11] For a more detailed analysis of quantile regression see Koenker and Hallock (2001).

long-run inflation hedges over the entire sample period. Table 1 lists the 25 stocks with the highest *LR* betas in the S&P500 universe (obtained from DOLS regression), along with their sectors, annualized nominal and real return, and the FFC alpha. The top 25 betas range between 10.27 for Gilead Sciences Inc (Health Care) to 5.21 for HCP Inc (Financials). For the S&P 500 index, insignificant long-run relationship with CPI has been detected. Thus, specific individual stocks comove with consumer prices in the long-run even though the aggregate market index has not shown significant long-run inflation hedging ability. The best inflation-hedging stocks do not display particularly high abnormal returns above the FFC factors; five stocks out of these 25 have a significant FFC alpha coefficient. Within the top twenty five inflation-hedging stocks, the best-represented sectors are Health Care, Energy, Industrials and the Technology Sector (four of the top 25 stocks for each sector). Consumer Discretionary and Financials are represented by three companies. Other sectors represented include Basic Materials, Utilities and Consumer Staples.

A market map of all the inflation hedging stocks for each sector is presented in Figure 1. The surface of the rectangles is based on the individual stocks *LR* beta coefficient estimates. Larger surface corresponds to higher beta estimates. The color of the rectangles denotes companies mean annualized return. Within the universe of inflation-hedging S&P500 stocks, the best-represented sector is Industrials (companies engaged in the manufacture and distribution of capital goods, transportation services and infrastructure, construction, engineering and building products, electrical equipment and industrial machinery), followed by the Energy sector (companies engaged in the exploration, production, marketing, refining and/or transportation of energy products and other consumable fuels). The other sectors that are strongly represented are Financials, Healthcare, Technology and Utilities. In Figure 1, we also observe that stocks with high *LR* inflation betas (companies with sizeable surface of rectangles) also exhibit high annualized returns.

1.5.2 In-Sample Portfolios

As noted, we chose individual stocks that have shown significant long-run relationship with consumers prices over the entire sample. Next, we sort stocks at time t on the basis of their full sample long-run betas and hold the portfolio from t to $t + 1$. Table 2 presents descriptive statistics on returns obtained for the four (quartile) portfolios, the portfolio Q5 and the S&P500 over the entire sample. Quartile 1 (Q1) stocks, the stocks with the higher *LR* betas, have had higher average performance than portfolios with lower *LR* betas (Q2, Q3, Q4). Q5 (the portfolio containing all stocks with inflation betas above unity) also exhibits positive annualized mean returns. Real returns for the quartile portfolios are all positive. Monthly annualized real returns for the first two portfolios (Q1 and Q2) are 9.06% and 8.84%, well above those of the last two portfolios (Q3 and Q4) which are 5.06% and 1.99%. Thus, stocks that have been good inflation hedgers in the long-run have had, on average, higher nominal and real returns. It is noteworthy that the first two portfolios have more volatile performance than the last ones: Q1 and Q2 have volatilities of 6.13% and 5.82%, respectively, compared with volatilities of 4.51% and 4.7% for the last two quartile portfolios. They also exhibit higher extreme risks. Kurtosis ranges between 4.59 and of 5.63, reflecting distribution tails that are fatter than normal. The portfolios' success rates vary between 48% and 61%, with an average of 59% for the S&P500.

Panel A in Table 3 presents the results of the regressions of monthly returns for each value-weighted portfolio against inflation. The explanatory power of these regressions is very small, as shown by the very low R^2.[12] Q1 and Q2 portfolios have inflation betas of 1.77 and 1.71 respectively over the entire sample period, but these are not significant. The other portfolios have positive betas, which range from 0.44 for Q3 to 0.81 for Q4, along with the S&P500's inflation beta of 0.65. Thus, all the subsets of stocks have

[12] Any asset that reduces the risk of a liability (in the current context changes in the value of a liability caused by inflation) can be considered a hedging instrument even if it does not eliminate the risk completely (Brealey and Myers, 1991). This is done by taking a long position in an asset with returns that are found to be positively related to changes in the value of a liability. Therefore, in the present study the fact that the R^2 statistics obtained are considerably low should not be of primary importance.

comoved positively with inflation and the average stock has been an adequate inflation hedge. The Q5 portfolio also exhibits inflation-hedging properties over the full sample, with a positive inflation beta of 1.33 but this is not significant.

We then proceed and employ quantile regression (three quantiles, see Panel B in Table 3). In the first quantile a significant and positive relation is revealed for Q1 compared to an insignificant OLS coefficient, with an inflation beta of 3.34. The same holds for the S&P500 index with an inflation beta of 2.43. Insignificant coefficients were found for the other two quantiles.

Table 4 breaks down the effects of exposure to the FFC factors for each portfolio. Q1 stocks have the highest 0.24% abnormal positive monthly return over the traditional factors and Q4, which contains stocks with the lowest long-run inflation betas, has the lowest alpha, which is significantly negative at -0.46% per month. Its' strong and significantly negative FFC alpha means that other systematic factors play a large role in explaining the differences of returns in stocks sorted by realized long-run inflation-hedging properties. For the S&P500, the size effect is negative and significant. This is consistent with smaller firms lacking the ability to raise their prices when the general inflation level rises compared with large firms; the best inflation hedgers have been the largest firms. The coefficient of the HML factor is positive and significant for Q1 to Q5 portfolios and the S&P500 index. Thus, the best inflation hedgers tend to be growth stocks. The fact that the poorest inflation hedgers tend to be value stocks is consistent with the low prices of value stocks in some cases reflecting low market power and the reduced ability of the products of these firms to command premium prices. The momentum factor is insignificant for the S&P500 and all the in- sample portfolios.

1.5.3 Out-of-Sample Porfolios

Given the strong in-sample relation between specific types of stocks and CPI, we now examine whether it would have been possible to pick good inflation-hedging stocks on an ex-ante basis.

We construct dynamically rebalanced portfolios consisting of stocks on the basis of the rolling window cointegration statistic and the DOLS betas, both estimated over the fixed-length 7 years (84 months) period preceding the rebalancing time.[13] We omit the current time t observation as inflation is not announced until the middle of the month and use "real time" inflation data. We hold this portfolio for one period and then rebalance every one month (Q*1m*), three months (Q*3m*), six months(Q*6m*), one year (Q*12m*), two years (Q*24m*), three years (Q*36m*), four years (Q*48m*) and five years (Q*60m*) .

The stock selection and allocation are calculated in a similar rolling framework. In each rebalancing we select the individual stocks that show significant long-run relationship with "real time" inflation (at 10% significance) level and pick up the stocks that provide partial or full hedge against consumer prices (positive long-run betas). Table 5 presents the performance of the out-of-sample portfolios in each rebalancing period. We compare the inflation hedging properties of out-of-sample portfolios, with US Government Inflation-Linked Bond Index (*GILB*) and the S&P 500 index.[14] Portfolios Q*3m*, Q*6m*, Q*12m*, Q*24m*, Q*36m*, Q*48m*, Q*60m* have on average higher nominal annualized returns than S&P 500 Index but lower than the GILB. Each out-of-sample portfolio success rate ranges between 53% to 57%, with GILB success rate is around 58%. The risks of each of the four portfolios are nearly equivalent, with volatility ranging from 4.13% to 4.66%. Kurtosis and skewness do not significantly differ across the portfolios.

Panel A in Table 6 reports the inflation betas on each portfolio from OLS regression. The inflation betas of all the out-of-sample portfolios are positive. Q*36m*, the portfolio

[13]As a robustness check, we conducted the same analysis based on rolling betas calculated on 60 and 108 months. While the results are similar between the 108 and 84 months analysis, the 60 months analysis slightly differs. This is may be attributed to the fact that 60 months period cannot be considered as an adequate time span in order to peform long-run analysis. The results are available from the authors upon request.

[14]The Barclays US Government Inflation-Linked Bond Index measures the performance of the US Treasury Inflation Protected Securities ("TIPS") market. The index history begins in February 1997 and includes TIPS with one or more years remaining maturity with total outstanding issue size of $500m or more. Available at: https://index.barcap.com/.

with the three years rebalancing period has the higher covariation with inflation, with beta point estimate to 1.12. Panel B in Table 6 shows that inflation beta coefficient in the 25th percentile is above unity for all out-of-sample portfolios except Q*6m*, ranging from 0.75 to 2.86. Still the Q*36m* portfolio exhibits the highest covariation with inflation, with a significant positive beta coefficient also found for Q*12m*, Q*24m*, Q*48m* and the S&P 500 Index. No significant relationship has been detected in neither of the other two quantiles.

In Table 7, exposure to the FFC factors reveals that the out-of-sample portfolios have similar factor loadings for the market and SMB factors. Exposures to the value factor are positive and significant for all portfolios except Q*1m*. The significant negative alpha in Q*1m* and Q*12m* portfolios indicates that the differences in returns may be explained by other systematic factors.

1.5.4 Long-run Fisher elasticities and Firms hedging Instability

Figure 2 presents the proportion of S&P 500 stocks that have shown significant cointegration relationship with consumers' prices (left axis) and the average positive long-run betas (right axis) during the period January 2000–July 2012. We observe that the number of individual stocks that have shown partial or full hedging ability against consumers prices vary substantially over time. Over the sample period, the amount of firms that have shown positive cointegration with consumers prices increased steadily until the US recession. Specifically, during the early 2000s, 12 to 15% of the firms in our sample have shown positive cointegration relationship with consumers prices. Precendently the US recession, this proportion rose to nearly 40%. Indeed, shortly after the beginning of US business cycle contraction the number of firms that partially or fully hedge movements in consumers' prices followed a downward trend, which exacerbated after the Lehman Brothers collapse with a decline approximately to 30%. This period coincided with a slightly fall in most stocks' long-run inflation betas (right axis). This phenomenon is clearly linked to the subprime crisis, when there was a large

decrease in US inflation from October to December 2008 and a simultaneous decline in equity markets during the same months. The financial crisis and the subsequent recession seem to aggravate the firms *LR* hedging ability in the US.

Figure 3 illustrates the average rolling seven-year inflation betas of the S&P 500 stocks that have shown positive long-run relationship with consumer prices over January 2000 to July 2012. We observe a decline of the positive *LR* betas, which ranged from high value of eight (early 2000) to near five (in the mid-2000s) falling slightly to four (during recent recession period). Figure 4 shows the beta distribution of S&P 500 stocks for two selected months within the study period, October 2000 and December 2008. The latter clearly illustrates that the *LR* beta dispersion was much lower in 2008 than in 2000. Moreover, in 2000, the distribution was symmetrical, while in 2008, it became asymmetrical with a positive skew. The proportion of companies with long-run inflation betas greater than zero remains high in both periods. This is in contrast with the result from the short-run betas in Ang et al. (2012) where the inflation beta dispersion differs substantially.

The cross section market map of the two months selected above is presented in Figure 5. The surface of the rectangles illustrate the value of the long-run beta for each firm, while the colour of the rectangles denotes the market capitalization weight of each individual stock. Darker areas denote higher weights. Financials and Information Technology are the two prevailing sectors in October 2000 followed by Industrials and Health Care sectors. After the outburst of financial crisis in September of 2008, the sectors that dominate are Energy and Utilities followed by Financials. Thus we observe that the composition of companies that show *LR* inflation hedging properties also change according to the sample period and the market conditions.

The fall in volatility of the aggregate economy occurring the last twenty years (Stock and Watson, 2002; Bernake, 2004), and the changing nature of inflation shocks (Briere and Signori, 2012), have been two plausible explanations of the changing correlation between stocks and inflation in the US. Bekaert and Wang (2010) evident this unstable

relationship in a panel of 50 countries. Ang et al. (2012) acknowledge companies related microeconomic characteristics (pricing power, market positioning, competitiveness) as a source of this instability. In addition to these macroeconomic and microeconomic factors, we note that company's long-run hedging ability varies over time, both in magnitude and in absolute numbers. Periods of low economic activity (recession) and high financial and macroeconomic volatility (subprime crisis) seem to contribute in the reduction of stocks average long-run hedging effectiveness.

1.5.5 Inflation hedging performance of sectors

We measure the inflation-hedging capacity of the nine S&P500 sectors, focusing to common stocks that have shown long-run relationship with CPI. Table 8 presents the results of the regression of returns for each sectoral value-weighted portfolio against inflation.

According to the OLS regression (Table 8, Panel A), all of the sector inflation betas were positive during the sample period, except for Utilities, whose beta was negative at -1.02 but not significantly different from zero. Our results differ from Ang et al. (2012) who find negative inflation betas for all sectors (except basic materials) during the period October 1989-May 2010. The Energy sector had the highest inflation beta of 2.51. This is not a surprising result since the best inflation hedges over the sample were drawn from the Energy sector. The Materials and the Consumer Staples sectors have also high inflation betas above unity, but statistically significant only for the latter (at 10% level). While Industrial sector stocks were over-represented in the best ex-post inflation hedging firms, the Industrial sector has a low inflation beta of 0.14 (not significant). Proceeding to the quantile regression analysis in Panel B, we observe a significant and positive Consumer Staple coefficient much higher than the OLS estimates in the 25th percentile. Negative and significant coefficients (at 10% level) were found for the Information Technology sector in the median (50th percentile) and higher (75th percentile) returns of the distribution. On the right tail of the distribution (higher

returns), though we observe positive and significant coefficient for the Energy sector, much higher than the OLS coefficient.

These aggregate results mask great variability over time and significant disparities among individual stocks. In Figure 6 we observe that sectors portfolios exhibit pronounced instability in inflation betas over time. For example, Financials over the whole sample have tended to be poor inflation hedges except the early 2000s period. During the financial crisis, the average financial inflation beta was positive; during this time Financials performed poorly and inflation was negative. Strong inflation beta variability is also noticeable for the Energy, Basic Materials, and Industrials sectors, with betas for the two latter sectors moving closely together during the sample period. Average betas for Energy, Information Technology, Utilities and Health Care sectors moved from negative in early 2000s to positive, especially after the US recession period. All sectoral portfolios have positive inflation betas after the financial crisis period, even the Utilities sector with a negative ex-post inflation beta.

1.6 Conclusions

This paper examines the long-run relationship between individual stock prices and goods prices to determine whether stocks market investment can provide a hedge against inflation. The literature so far has focused on aggregate stock market indices and short-run measures. We use individual stocks from S&P500 over the sample period 1993 to 2012 and find that specific individual stocks have the ability to be good inflation hedges over the long-run. During the last 20 years, the top 25 stocks with the strongest comovement with goods prices have had *LR* beta values above five. Industrials and Energy are the best representing sectors according to the total amount of stocks that comove with consumer prices. No significant cointegration relationship between S&P500 and CPI was detected over the sample period. Firms that have been good long-run inflation hedgers have had, on average, high nominal and real returns.

We select stocks that have shown significant cointegration relationship with consumer prices and we sort them in a descending order according to their *LR* elasticity. The top portfolio, constructed on the basis of the highest ex-post long-run betas exhibits superior inflation hedging properties with a point inflation beta estimate of 1.77. Its inflation hedging ability is intensified in the left tail of the distribution (lower returns) both in magnitude and in statistical significance.

We proceed by constructing dynamically rebalanced portfolios consisting of stocks on the basis of the cointegration statistic and the *LR* (DOLS) betas. We find that the portfolio with three years rebalancing period has higher covariation with inflation, with beta estimates of 1.12. The rest out-of-sample portfolios also exhibit positive inflation betas. These findings are further supported by quantile regression analysis. When returns are low (left tail of the conditional distribution) almost all out of sample portfolios hedge inflation with statistically significant beta coefficients for the portfolios with rebalancing periods one to four years.

Additionally, in- and out-of-sample portfolios seem to follow similar pattern according to their exposure to the FFC factors. The amount of firms that show positive *LR* relationship with CPI declines during the recent crisis period. Similar pattern is observed for the average *LR* hedging ability of firms during the last two US recession periods. The composition of companies that hedge movements in goods prices also changes over time along with the shape of firms *LR* beta distribution.

Further classification of individual stocks into sector-level portfolios reveals that Energy sector has the highest inflation beta, followed by the Materials and the Consumers Staples sectors. We find that the sectors inflation betas exhibit similar time variation, as we move throughout our sample. All portfolios display positive inflation betas after the recent financial crisis period.

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Table1: Twenty five best inflation long-run hedging stocks, regression of monthly prices on CPI, January 1993-August 2012

Company name	Sector	Ann. Mean	Ann.Mean real	α		β_{CPI}	
Gilead Sciences Inc	Health Care	20.31%	17.88%	0.01	(1.31)	10.27***	(33.81)
Express Scripts Holding Co.	Health Care	24.77%	22.33%	0.01	(1.56)	10.03***	(49.69)
Amphenol Corp A	Inf. Tech.	21.23%	18.80%	0.01***	(2.12)	7.73***	(34.59)
Fossil Inc	Cons. Disc.	23.07%	20.64%	0.01	(1.1)	7.33***	(19.09)
Public Storage	Financials	20.05%	17.61%	0.01***	(2.69)	7.03***	(39.37)
O'Reilly Automotive	Cons. Disc.	20.31%	17.87%	0.01	(1.74)	6.86***	(32.97)
Apache Corp	Energy	12.13%	9.69%	0.00	(-0.27)	6.38***	(36.52)
ONEOK Inc	Utilities	17.52%	15.09%	0.00	(1.00)	6.28***	(32.74)
Fastenal Co	Industrials	18.16%	15.72%	0.01*	(1.61)	6.15***	(31.08)
Roper Industries Inc	Industrials	18.52%	16.09%	0.01*	(1.68)	6.01***	(38.03)
Helmerich & Payne Inc	Energy	13.70%	11.26%	0.00	(0.13)	5.95***	(31.9)
Bard, C.R. Inc	Health Care	11.23%	8.79%	0.00	(1.17)	5.94***	(36.56)
Praxair Inc	Materials	14.99%	12.56%	0.00	(1.17)	5.93***	(36.24)
Cerner Corp	Health Care	15.39%	12.96%	0.00	(0.48)	5.87***	(18.91)
Altria Group Inc	Cons. Staples	14.20%	11.76%	0.01	(1.35)	5.86***	(29.34)
Johnson Controls Inc	Cons. Disc.	12.88%	10.44%	0.00	(0.36)	5.85***	(29.21)
Microchip Technology Inc	Inf. Techn.	24.35%	21.91%	0.01*	(1.62)	5.68***	(13.87)
General Dynamics	Industrials	18.23%	15.79%	0.01	(1.32)	5.66***	(20.41)
Noble Corp	Energy	14.78%	12.34%	0.00	(0.06)	5.57***	(17.21)
Intuit Inc	Inf. Tech.	16.47%	14.03%	0.01	(0.91)	5.44***	(15.08)
Health Care REIT Inc	Financials	12.83%	10.39%	0.00	(1.21)	5.43***	(33.58)
Devon Energy Corp	Energy	10.57%	8.14%	0.00	(-0.60)	5.41***	(28.06)
Harris Corp	Inf. Tech.	13.28%	10.85%	0.00	(0.44)	5.37***	(24.81)
Caterpillar Inc	Industrials	15.00%	12.57%	0.00	(0.27)	5.35***	(23.35)
HCP Inc	Financials	13.23%	10.79%	0.00	(0.83)	5.21***	(34.34)
S&P500		5.97%	3.53%	-0.00	(-5.96)	-	-

***,**,* denote significance at the 1%, 5% and 10% level. α represents the constant of the FFC factor model. β_{CPI} is the *LR* elasticity of stock prices with respect to goods prices (Equation (1)) estimated via Dynamic OLS. Numbers in parentheses are the values of the *t*-statistic.

Table 2: Descriptive statistics of in sample portfolios.

	Q1	Q2	Q3	Q4	Q5	S&P500
Ann. Mean(%)	11.50	11.27	7.50	4.43	8.14	5.96
Ann.Mean real(%)	9.06	8.84	5.06	1.99	5.71	3.52
Median(%)	1.80	1.48	0.87	0.71	1.17	1.12
Max (%)	19.10	15.57	13.85	12.88	13.65	10.23
Min(%)	-26.56	-27.38	-18.77	-21.41	-21.74	-18.56
Std.Dev.(%)	6.13	5.82	4.51	4.70	4.64	4.45
Skewness	-0.88	-0.91	-0.42	-0.75	-0.75	-0.85
Kyrtosis	5.34	5.63	4.59	5.63	5.3	4.55
Success rate	0.58	0.53	0.50	0.48	0.61	0.59
#Obs	235	235	235	235	235	235

Quartile portfolios are formed from January 1993 to August 2012 by sorting common stocks on S&P 500 based on the long-run Fisher elasticity of each stock against CPI. The lowest (highest) quartile contains stocks with the lowest (highest) *LR* beta. Q5 portfolio contains all stocks with *LR* betas above unity. Success rate denotes the percentage of months when nominal returns are higher than inflation.

Table 3: In-sample portfolios sorted by long-run hedging capabilities, S&P500 universe, regression of monthly returns on inflation

	Percentiles	Q1	Q2	Q3	Q4	Q5	S&P500
Panel A: OLS regression							
ΔCPI_t		1.77	1.71	0.44	0.81	1.33	0.65
		(1.09)	(0.84)	(0.3)	(0.37)	(0.76)	(0.34)
R^2		0.00	0.00	0.00	0.00	0.00	0.00
Panel B: Quantile regression							
ΔCPI_t	25th	3.34***	-1.27	-0.61	0.006	0.06	2.43**
		(2.75)	(-0.51)	(-0.48)	(0.00)	(0.02)	(2.37)
Pseudo R^2		0.01	0.00	0.00	0.00	0.00	0.00
ΔCPI_t	50th	1.04	0.41	1.01	-0.4	-0.3	-0.32
		(0.64)	(0.21)	(1.06)	(-0.26)	(-0.17)	(-0.24)
Pseudo R^2		0.00	0.00	0.00	0.00	0.00	0.00
ΔCPI_t	75th	0.08	0.76	-0.37	-1.09	0.47	-2.55
		(0.05)	(0.40)	(-0.28)	(-0.82)	(0.35)	(-1.60)
Pseudo R^2		0.00	0.00	0.00	0.00	0.00	0.00

The coefficients reported in Panel A and B are for the following regression: $\Delta S_{pt} = a + \Delta CPI_t + e_t$ where ΔS_{pt} is the one month return and ΔCPI_t is the monthly inflation rate. ***,**,* denote significant at the 1%, 5% and 10% level. The sample period is from January 1993 through August 2012. Numbers in parentheses are the values of the *t*-statistic.

Table 4: In-sample portfolios sorted by long-run inflation hedging capabilities, regression of monthly returns on FFC factors

	Q1	Q2	Q3	Q4	Q5	S&P500
α(%)	0.24	-0.02	-0.16	-0.46***	-0.15	-0.23***
	(0.69)	(-0.09)	(-0.99)	(-3.18)	(-0.88)	(5.96)
MKT	0.71***	1.07***	0.85***	0.85***	0.88***	0.98***
	(9.75)	(17.72)	(17.84)	(18.97)	(19.86)	(83.90)
SMB	-0.02	-0.03	-0.13*	0.00	-0.05	-0.18***
	(-0.20)	(-0.32)	(-1.65)	(0.05)	(-0.67)	(-14.29)
HML	0.39**	0.48***	0.42***	0.63***	0.49***	0.02**
	(2.46)	(6.24)	(4.34)	(7.87)	(5.58)	(2.03)
MOM	-0.02	0.05	0.00	-0.05	-0.00	-0.01
	(-0.37)	(0.94)	(0.04)	(-0.90)	(-0.06)	(-0.94)
R^2	0.29	0.65	0.72	0.75	0.73	0.98

Quartile portfolios are formed from January 1993 to July 2012 by sorting common stocks on S&P 500 based on the long-run Fisher elasticity of each stock against CPI. The lowest (highest) quartile contains stocks with the lowest (highest) beta. Q5 portfolio contains all stocks with positive betas.The sample period is from January 1993 through July 2012. The alpha raw shows Fama–French–Cahart four-factor alphas. All returns are expressed in percent per month. Newey and West (1987) adjusted t-statistics are shown in parentheses

Table 5. Descriptive statistics of out-of-sample portfolios.

	Q*1m*	Q*3m*	Q*6m*	Q*12m*	Q*24m*	Q*36m*	Q*48m*	Q*60m*	GILB	S&P 500
Ann. Mean(%)	-0.18	1.93	2.43	1.09	2.8	2.29	2.44	2.56	5.33	-0.5
Ann.Mean real(%)	-2.59	-0.47	0.02	-1.32	0.39	-0.12	0.03	0.15	2.91	-2.92
Median(%)	0.78	0.59	0.78	0.78	0.95	0.82	0.98	0.67	0.55	0.71
Max (%)	10.43	10.43	9.37	9.81	11.22	7.53	12.28	9.88	5.56	10.23
Min(%)	-20.73	-16.07	-17.73	-20.68	-20.68	-17.34	-20.68	-15.63	-8.92	18.56
Std.Dev.(%)	4.5	4.13	4.29	4.55	4.45	4.08	4.66	4.3	1.85	4.7
Skewness	-1.15	-0.78	-0.94	-1.09	-0.99	-0.96	-0.79	-0.82	-1.06	-0.63
Kurtosis	6.08	4.57	4.69	5.36	5.78	4.71	5.04	4.77	7.46	3.95
Success rate	0.54	0.53	0.57	0.55	0.56	0.55	0.56	0.53	0.58	0.52
#Obs	151	151	151	151	151	151	151	151	151	151

Out-of-sample portfolios are formed every rebalancing period from January 2000 to July 2012 by: 1) selecting stocks that have shown cointegration with consumers' prices and 2) sorting stocks based on the long-run beta, both estimated over a rolling calibration period of 84 months. Success rate denotes the percentage of months when nominal returns are higher than inflation.

Table 6: Out-of-sample portfolios sorted by long-run hedging capabilities, regression of monthly returns on inflation

	Percentiles	Q*1m*	Q*3m*	Q*6m*	Q*12m*	Q*24m*	Q*36m*	Q*48m*	Q*60m*	GILB	S&P 500
Panel A: OLS regression											
ΔCPI_t		0.19	0.38	0.46	1.01	0.89	1.12	1.0	0.33	0.36	0.88
		(0.10)	(0.22)	(0.24)	(0.53)	(0.45)	(0.67)	(0.51)	(0.17)	(0.69)	(0.47)
R^2		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Panel B: Quantile regression											
ΔCPI_t	25th	1.03	1.83	0.75	2.57**	2.77***	2.86***	2.48**	1.48	-0.1	2.65**
		(0.37)	(1.59)	(0.25)	(2.57)	(2.66)	(2.74)	(2.01)	(0.73)	(-0.21)	(2.42)
ΔCPI_t	50th	-1.13	-0.90	-1.01	-0.94	-0.41	-0.37	-0.45	-0.87	-0.23	-0.04
		(-0.88)	(-0.75)	(-0.82)	(-0.73)	(-0.30)	(-0.29)	(-0.3)	(-0.67)	(-0.60)	(-0.02)
ΔCPI_t	75th	-0.06	-1.60	-0.63	-0.41	-0.65	-0.55	-0.43	-1.68	0.16	-0.73
		(-0.04)	(-1.56)	(-0.56)	(-0.36)	(-0.53)	(0.5)	(-0.33)	(-1.40)	(0.43)	(-0.51)
Pseudo R^2		0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.01

The coefficients reported in Panel A and B are for the following regression: $\Delta S_{pt} = a + \Delta CPI_t + e_t$ where ΔS_{pt} is the one month return and ΔCPI_t is the monthly inflation rate. ***,**,* denote significant at the 1%, 5% and 10% level. The sample period is from January 2000 through July 2012. Numbers in parentheses are the values of the *t*-statistic.

Table 7: Out-of-sample portfolios, regression of monthly returns on FFC factor

	Q1m	*Q3m*	*Q6m*	*Q12m*	*Q24m*	*Q36m*	*Q48m*	*Q60m*
α(%)	-0.30**	-0.19	-0.13	-0.27*	-0.01	-0.14	-0.17	-0.15
	(-2.33)	(-1.29)	(-1.05)	(-1.79)	(-1.07)	(-1.03)	(-1.4)	(-0.98)
MKT	0.87***	0.80***	0.84***	0.85***	0.84***	0.78***	0.91***	0.81**
	(22.01)	(17.3)	(15.8)	(15.03)	(14.53)	(15.93)	(16.36)	(14.66)
SMB	-0.10*	-0.09*	-0.10**	-0.06	-0.09	-0.14**	-0.12**	-0.12
	(-1.96)	(-1.70)	(-1.99)	(-0.96)	(-1.45)	(-2.48)	(-2.2)	(-1.92)
HML	0.06	0.20***	0.18***	0.20***	0.28***	0.22***	0.26**	0.27***
	(0.81)	(4.33)	(3.74)	(3.01)	(5.22)	(3.77)	(5.15)	(4.04)
MOM	0.09**	0.05	0.04	0.01	0.01	0.02	0.03	-0.00
	(3.17)	(1.39)	(1.02)	(0.23)	(0.27)	(0.71)	(1.02)	(-0.16)
R^2	0.77	0.82	0.83	0.80	0.83	0.81	0.85	0.84

Out-of-sample portfolios are formed every rebalancing period from January 2000 to July 2012 by: 1) selecting stocks that have shown cointegration with consumers' prices and 2) sorting stocks based on the long-run beta, both estimated over a rolling calibration period of 84 months. The FFC alpha raw shows Fama–French–Cahart four-factor alphas. All returns are expressed in percent per month. Newey and West (1987) adjusted *t*-statistics are shown in parentheses

Table 8: S&P500 Sector level value-weighted portfolios, regression of monthly returns on inflation, February 1993-August 2012

		Energy	Inf.Tech.	Materials	Indust.	Utilities	Heal.Care	Cons.St.	Cons.Disc.	Financials
Panel A: OLS regression										
ΔCPI_t		2.51	0.41	1.74	0.14	-1.02	0.84	2.5*	0.37	0.21
		(1.21)	(0.13)	(0.55)	(0.06)	(-0.94)	(0.78)	(1.65)	(0.11)	(0.10)
R^2		0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
Panel B: Quantile regression										
ΔCPI_t	25th	1.53	2.21	0.88	-0.14	-1.77*	0.61	4.24***	0.84	0.12
		(0.68)	(0.67)	(0.39)	(-0.09)	(-1.89)	(0.40)	(3.01)	(0.48)	(0.03)
ΔCPI_t	50th	2.2	-4.03*	-1.89	-1.04	-0.52	2.14	2.43*	-3.31	-0.69
		(1.42)	(-1.66)	(-0.91)	(-0.46)	(-0.52)	(1.53)	(1.72)	(-1.13)	(-0.40)
ΔCPI_t	75th	4.12**	-4.83*	1.58	-1.83	0.42	1.56	0.7	-3.17	-0.46
		(2.5)	(-1.84)	(0.49)	(-1.09)	(0.52)	(0.76)	(0.49)	(-1.63)	(-0.36)
Pseudo R^2		0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.00	0.00

Sectoral portfolios are formed from January 1993 to August 2012 by grouping common stocks that have shown positive long-run relation with CPI, according to the sector they belong. The coefficients reported in Panel A and B are for the following regression: $\Delta Sp_t = a + \Delta CPI_t + e_t$ where ΔSp_t is the one month return and ΔCPI_t is the monthly inflation rate. ***,**,* denote significant at the 1%, 5% and 10% level. Numbers in parentheses are the values of the *t*-statistic.

Figures

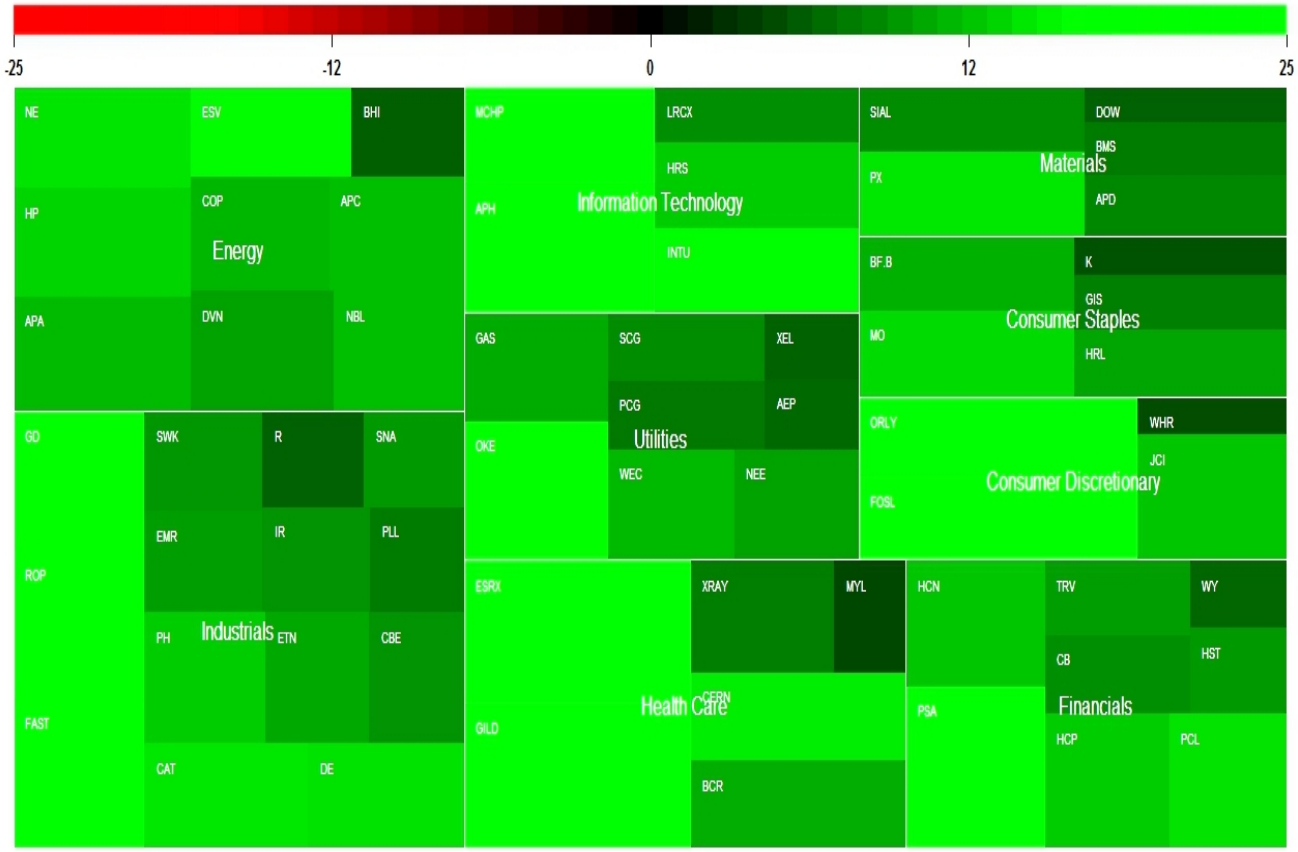


Fig. 1. Market map of the best long-run inflation hedging Individual stocks, Annualized Returns

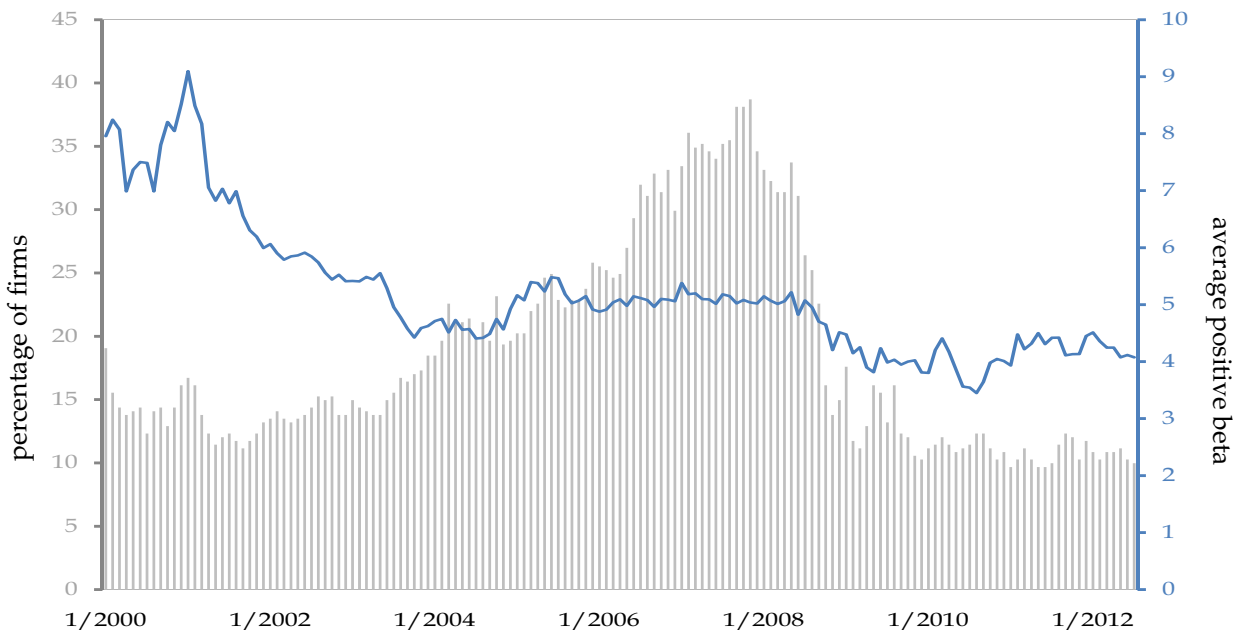


Fig. 2. Average seven-year rolling inflation betas and inflation hedging firms, January 2000-July 2012

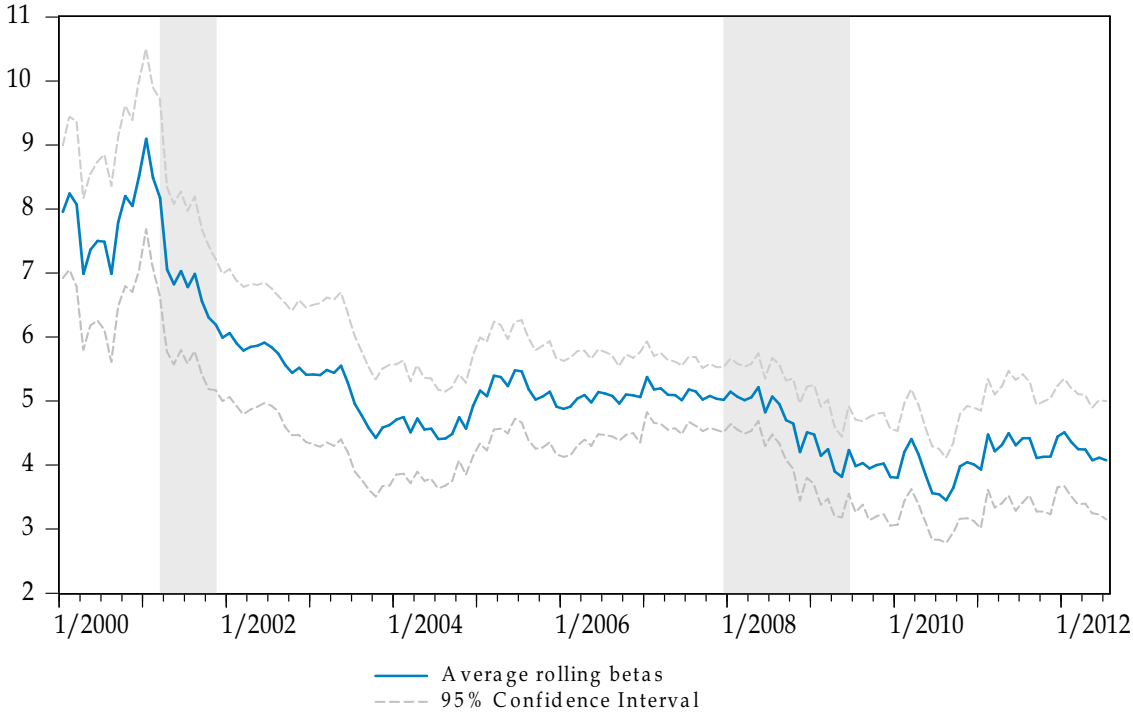
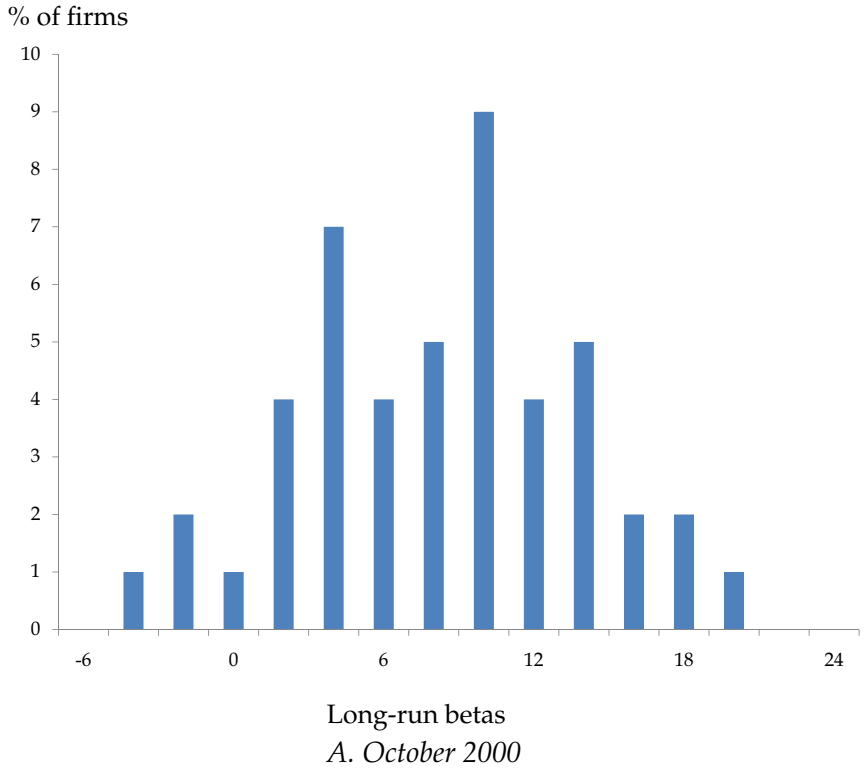
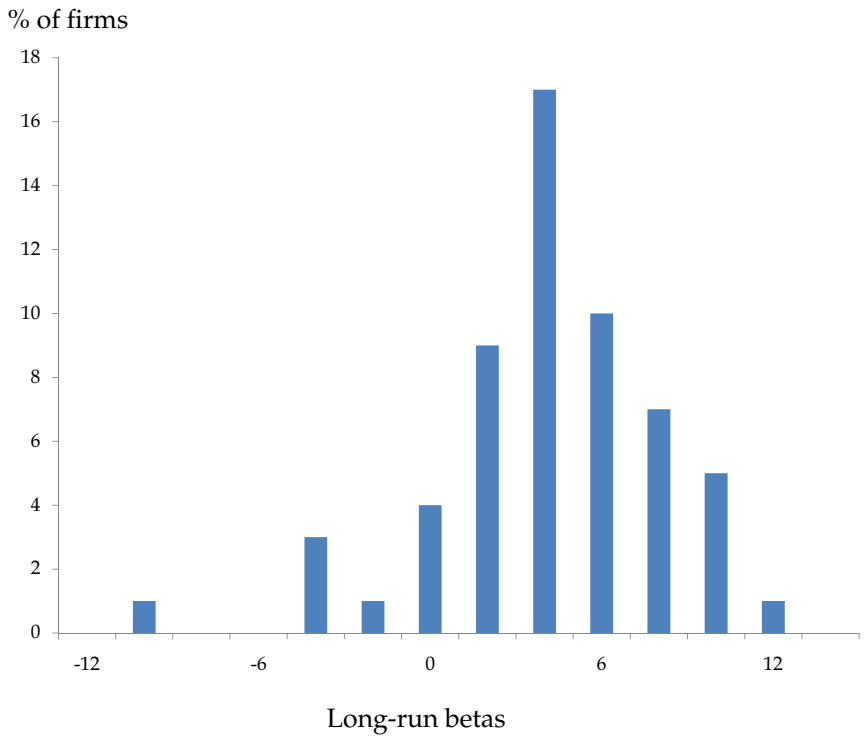


Fig. 3. Average rolling seven-year inflation betas, January 2000-July 2012



A. October 2000



B. December 2008

Fig. 4. Cross-Sectional distribution of long-run consumer prices betas of S&P 500 stocks, October 2000 and December 2008

A. October 2000

B. December 2008

Fig. 5. Cross-section market map of the best long-run inflation hedging Individual stocks, October 2000-December 2008.

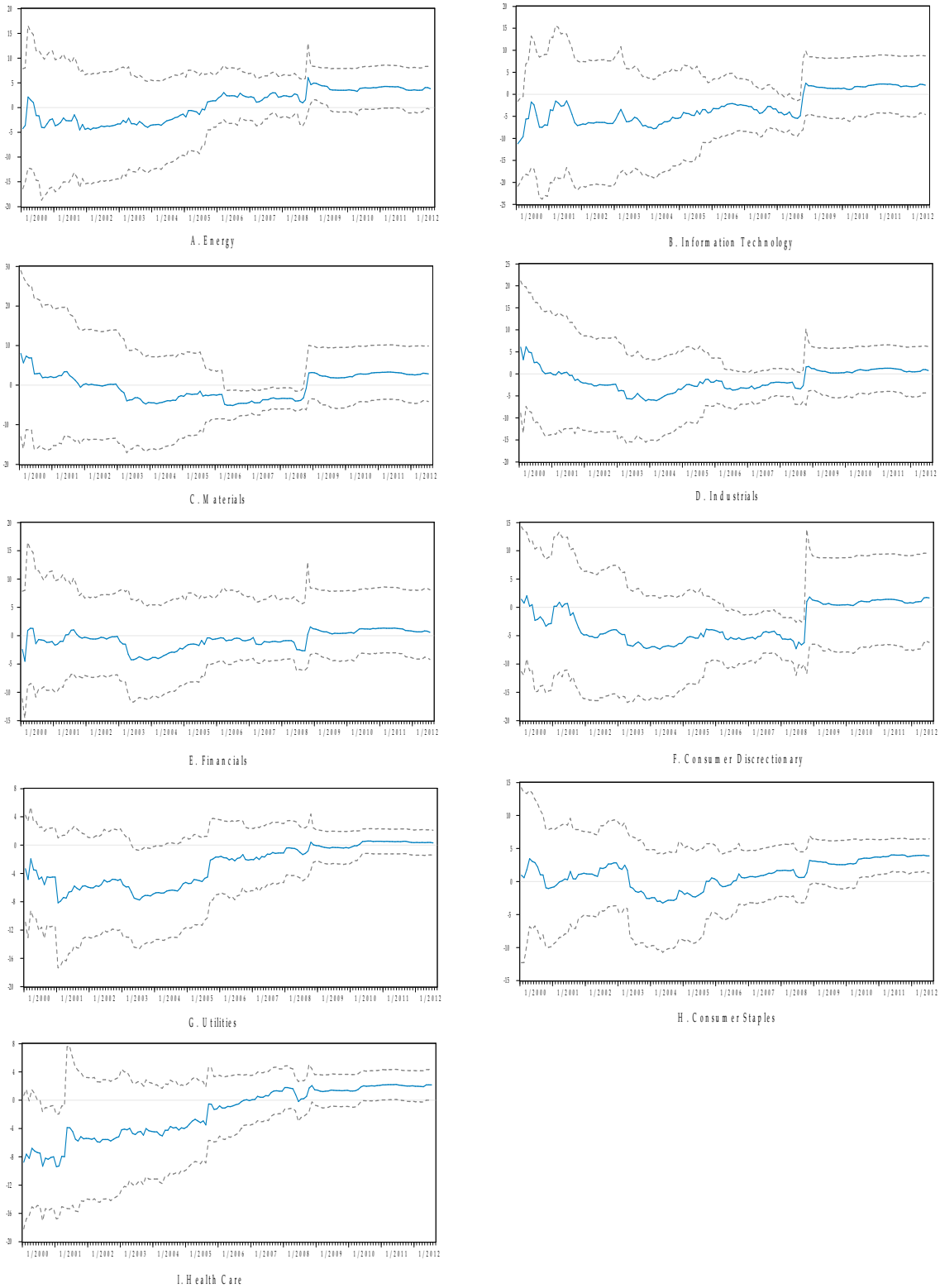


Fig. 6. Seven-year rolling inflation betas of S&P Sectors, January 2001-July 2012

CHAPTER 2

ARE GOLD AND SILVER A HEDGE AGAINST INFLATION? A TWO CENTURY PERSPECTIVE

ABSTRACT

This study examines the long-run hedging ability of gold and silver prices against alternative measures of consumer price index for the UK and the US. We employ a dataset that spans from 1791 to 2010, and both a time-invariant and a time-varying cointegration framework. We find that gold can at least fully hedge headline, expected and core CPI in the long-run. This ability tends to be stronger when we allow for the long term dynamics to vary over time. The inflation hedging ability of gold is on average higher in the US compared to the UK. Silver does not hedge US consumer prices albeit evidence emerges in favor of a time-varying long-run relationship in the UK.

Keywords:gold prices, silver prices, inflation hedge, time-varying cointegration.

2.1 Introduction

Gold and silver have played a major role in the history of money and monetary policy. They have traditionally acted as medium of exchange, store of wealth, and a unit of value (Goodman, 1956; Solt and Swanson, 1981). In contrast to many other multi-faceted commodities, they are durable, relatively transportable, universally acceptable and easily authenticated. Gold as the most acclaimed precious metal in human history, still plays a pronounced role as a store of value especially in times of uncertainty. This feature stems from the 'flight to quality' behavior of investors who purchase gold in search for safer assets (Baur and Lucey, 2010). As precious metals represent claims to real rather than nominal assets, under the Fisher (1930)'s framework, gold and silver are expected to hedge against inflation.[1] An expected increase in consumer price level may induce individuals to convert their current liquid assets into gold, influencing its price (Fortune, 1987).[2] Therefore, gold and silver prices could effectively gauge inflation expectations since, commodity prices are generally considered to be able to incorporate new information faster than consumer prices (Mahdavi and Zhou, 1997).

To the best of our knowledge, historical data have not being employed so far to examine the long-run (*LR*) hedging ability of gold and silver. This article fills this gap by looking at over 200 years of annually data for the UK and the US gold and silver markets. The renewed attention for the role of precious metals, as fundamental investment strategy against the eroding impact of inflation, further reinforces the goals of this study: (i) assess the historical role of gold and silver prices as a hedge against headline, expected and core CPI measures and (ii) examine the hedging ability of these two precious metals in a time-invariant (TI) and a time-varying (TV) cointegration framework that allows for nonlinear adjustment and the smooth evolution of the long-

[1]The proposition that *ex ante* nominal asset returns contain the market's perception of anticipated inflation rates can be applied to all assets in efficient markets, also known as Generalized Fisher Effect (GFE, henceforth) (see, Jaffe and Mandelker, 1976).

[2]The theoretical argument developed in Fortune (1987) emphasized the substitution effect rather than the wealth effect. The author developed an equilibrium model, focusing on the US demand side of gold.

run relationship.

Laurent (1994) notes that during the 1800 to 1992 period, the price of gold and the general level of prices (wholesale prices) in the US have corresponded quite closely. Jastram (1978) indicates that the study of gold in the US is a logical companion piece to the study of UK, given that economic institutions are akin and common factors influence their commerce and finance. London was the undisputed center of the world capital markets during the gold standard, since the Bank of England could exert a powerful influence on the money supplies and price levels of other gold-standard countries (Bordo and Schwartz, 1994). Moreover, the US has been a prime mover in silver markets since the last quarter of the nineteenth century (Jastram, 1981). Concerning inflation, Siegel (2008) ascertains a similar pattern between the US and the UK consumer price level in the last 150 years, which is characterized by a significant overall inflation until World War II and protracted inflation later. Thus, the UK and the US can be considered as the most preferable cases for examining the historical long-run hedging ability of gold and silver.

Our paper is broadly related to a literature that used cointegration to study the hedging abilities of an asset in the long-run (Ely and Robinson, 1997; Anari and Kolari, 2001). Research into the gold/CPI relationship, though, produced mixed evidence. Garner (1995), Mahdani and Zhou (1997) and Tully and Lucey (2007) have documented an insignificant *LR* relationship between gold price and CPI, while Gosh et al. (2004) and Worthington and Pahlavani (2007) assert a significant positive relationship in the US.[3] On the other hand, the empirical literature for the hedging ability of silver is less extensive. Adrangi et al. (2003) argue that investment in gold and silver may be reliable inflation hedges in both the short- and long-term. McCown and Zimmerman (2006, 2007) provide evidence in favor of the hedging ability of gold and silver against inflation risk, especially over longer time horizons. Aggarwal and Lucey (2007) study

[3]See also Chua and Woodward (1982), Kaufmann and Winters (1989) and Tkacz (2007) who document a positive relationship between gold and inflation in the US.

psychological barriers in gold prices. A recent study of Wang et al. (2011) observes that time and market selection are the keys to inflation hedge. They employ a threshold cointegration framework and find that the low cross elasticity, the incomplete price adjustment and the short-run rigidity of the price adjustment between gold price and CPI might eliminate the inflation hedge ability of gold.

The 2007-09 financial crisis, the rise in volatility of commodity prices in conjunction with the tendency of central banks to become net buyers of bullion have revived the discussion on the role of precious metals.[4] In March 2011, Chatham House Gold Taskforce was founded in order to captivate the multiple role of gold (including that of hedge against inflation) as a means of enhancing the performance of the international monetary system.[5] One widely held argument for a renewed role for gold is that its countercyclical qualities can serve as a hedge against specific risks, such as bouts of inflation or financial contagion. However few would argue that a return of gold as an anchor in the international monetary system is feasible.[6] Nevertheless, from an investor's point of view, an examination of whether gold and silver prices historically maintain their value relative to consumer prices becomes increasingly important for several reasons.

From a practical perspective, many investors hold precious metals over long holding periods. Therefore, it is crucial to examine whether gold and silver prices move together with consumers prices over longer horizons. This applies to both long-term institutional and individual investors, for whom real-term capital preservation is a

[4]Speaking in the Financial Times before the G20's core reform agenda in Cannes, Robert Zoellick, the president of the World Bank, has stated that a new monetary system should 'consider employing gold as an international reference point of market expectations about inflation, deflation and future currency values'(see, Zoellick, R. 'The G20 must look beyond Bretton Woods II', Financial Times, 7 November 2010).

[5]Between 1929 and 1931, Chatham House convened a special Study Group having John Maynard Keynes as a member, in order to examine the problems arising from the post-war international monetary settlement, which contributed to the Great Depression and ultimately led to the suspension of the Gold Standard by the British government in September 1931. Available at: http://www.chathamhouse.org/publications/papers/view/178235

[6]The term anchor refers to whether gold has a role in being tied to or linked with the expansion or contraction of the global monetary base.

primary objective. In addition, the puzzling results of previous studies as well as the provided evidence for instabilities in precious metals and goods prices further reinforce the case for employing a time-varying approach (see, e.g. Beckmann and Czudaj, 2013; Batten et al., 2014). In our analysis, the *LR* coefficients quantify the intensity of the relationship between the two precious metals and alternative consumer price measures. Gold and silver could be a poor hedge against inflation in the short-term, but as the investment horizon increases they may provide adequate *LR* hedging properties. Furthermore, while investors and central banks have been buying gold in order to protect themselves against inflation risk, less attention has been given to silver. Silver, as one of the most attractive naturally occurring elements, may also provide inflation hedging properties.[7] Lastly, precious metals and consumers prices are both known to be integrated processes, thus estimating regressions in terms of their first (or higher order) differences implies partial loss of valuable long-run information (Anari and Kolari, 2001).

With these concerns in mind, this study examines the generalized Fisher effect using over two centuries of data for gold, silver and consumer prices. We employ time-invariant and time-varying cointegration analysis, that allows us to utilize the long-run information and account for different regimes. The key findings of the paper are as follows: (i) the real price of gold and silver is stationary when we account for structural breaks, (ii) we get moderate (strong) evidence of time-invariant (time-varying) cointegration between the precious metal prices and alternative CPI's for the US and the UK, (iii) the average *LR* betas for gold are above unity indicating superior hedging ability, (iv) the average long-run beta for gold is higher in the US compared to the UK, (v) more stability is observed in the long-run hedging ability of gold vs expected inflation during the last decades and (vi) the long-run relationship between silver and CPI in the UK emerges only when we consider the case of time-varying cointegration.

[7]The time period that central banks viewed silver on par with gold as a reserve can be traced back to 1923. The St Louis Fed's report on this issue is available at: http://fraser.stlouisfed.org/docs/publications/FRB/pages/1920-1924/43097_1920-1924.pdf

The remaining parts are as follows: Section 2 describes the data, Section 3 presents the methodology. The results are discussed in Section 4 and Section 5 concludes.

2.2 Literature review

Gold has been under investors spotlight for a long time and the idea of gold hedging against inflation is not new. The theoretical foundation lies on Fisher (1930)'s seminal work. A widely adopted view in the economic literature is that an asset is a good hedge against inflation if the Fisher hypothesis holds. Numerous studies have addressed the extent to which various assets have been useful to economic agents interested in hedging against the eroding effects of inflation (Bodie 1976, Jaffe and Madelker 1976, Gultekin 1983 and Solnik 1983 for stocks, Boughton and Branson 1991 and Pecchenino 1992 for commodities). Furthermore regression analysis have been employed to examine whether assets can act as a hedge against both expected and unexpected inflation. Chua & Woodward (1982) employed monthly and bi-annual data of six major industrial countries for the period 1975 to 1980 and found that gold appears to have been a hedge against both expected and unexpected inflation in the US. Kaufmann and Winters (1989) conclude that there is a significant positive relation between the GNP deflator and the price of gold in the US during the period from 1974 to 1988.

Mahdavi and Zhou (1997), used quarterly data of gold price, CPI, an industrial material index, the 3-month treasury bill and real GDP for the sample period 1970 to 1994, and conclude that multivariate models do not support the cointegration hypothesis between gold prices and CPI. Their conlusions are in line with the findings of Garner (1995), Cecchetti et al. (2000) and Tully and Lucey (2007) who were also unable to provide empirical evidence for the existence of a long-run relationship between gold price and CPI. On the contrary, Gosh et al. (2004) employing monthly US data that ranges from 1976 to 1999 and applying cointegration techniques, detect an effective hedge of gold against inflation in the long-run. Worthington and Pahlavani (2007) employ monthly observations of the price of gold and monthly US inflation rate

for two overlapping sample periods from 1945 to 2006 and from 1973 to 2006, and also provide evidence in favor of long-run relationship between the price of gold and inflation in both sample periods as long as one takes into account structural changes in the US gold market and inflationary regimes. Tkacz (2007) use monthly gold prices, consumer price indexes and exchange rates for 14 countries spanning the period from 1994 to 2005, and find that gold is a significant predictor for US inflation at a 12 month horizon. In addition, gold is a significant predictor of inflation for many developed inflation-targeting countries (especially OECD countries) with the optimal horizons to vary across 12 and 18 months. Wang et al. (2011), within a threshold cointegration framework employ monthly observations for the period 1971 to 2010, and conclude that the keys of inflation hedge are time and market selection. They have also noted that the low cross elasticity, the incomplete price adjustment and the short-run rigidity of the price adjustment between gold price and CPI might eliminate the inflation hedge ability of gold. Beckmann and Czudaj (2013) adopt a MS-VECM approach for a sample period ranging from January 1970 to December 2011 and show that gold is partially able to hedge future inflation in the long-run and this ability is stronger for the US and the UK compared to Japan and the Euro Area. They argue that during some periods where no price adjustment is observed, gold is not able to shield a portfolio in the sense that the adjustment of the general price level is characterized by regime-dependence.

While the majority of academic research has focused on the hedging role of gold, the empirical literature for the hedging ability of silver is less extensive. Adrangi et al. (2003) find that gold prices are positively correlated with expected inflation and conclude that a gold and silver investment may be a reliable inflation hedge in both the short- and long-run. They also reveal an insignificant relationship between these two precious metals returns and unexpected inflation. McCown and Zimmerman (2006), use annual, quarterly and monthly spot prices for gold, silver and several other variables including US consumer prices for the period 1970 to 2003, and provide evidence of favorable gold and silver hedging against inflation risk over the longer time horizon.

Cointegration analysis reveals that both gold and silver have the ability to hedge against inflation. McCown and Zimmerman (2007), employ monthly spot prices for the period 1970 to 2006 and support that the correlations for both metals and expected inflation are positive and generally higher for gold, especially for the time horizon greater than ten years. They also conclude that gold has a generally higher correlation with expected inflation than silver and is more useful for indicating long-term expectations.

One part of the literature is also related to our discussion of 'safe haven' assets (protect wealth in case of high-risk market conditions). Baur and McDermott (2010) indicate that what sets gold apart from other commodities is its behaviour during periods of falling asset values. The authors provide evidence that the 'haven effect' is generally only present in developed markets and not in emerging markets. They conclude that gold was a strong 'safe haven' for most developed countries (US and Canada) during the peak of recent financial crisis (1987 stock market crash). In the same line, Baur and Lucey (2010) employ an asymmetric GARCH approach and argue that gold is a hedge for stocks (bonds) in US and UK (Germany) but not in Germany (US and UK) and is a short-lived 'safe haven' for stocks only after extreme negative market shocks.

Another strand of the literature analyzes the role of gold as a hedge against key currencies, finding evidence of the exchange-rate hedging potential of gold. Capie et al. (2005), use weekly observations of the price of gold (in US$), sterling-dollar and yen-dollar exchange rates, estimate GARCH type of models and find that gold has served as a hedge against fluctuation in the foreign exchange value of the dollar but the strength of that relationship varied over time. Sjaastad (2008) provide evidence that during 1980's the world gold market was dominated by the European currency bloc, while in the 1990's and the early years of the current century, the dollar area appears to have become dominant (along with Japan). Joy (2011) uses weekly data for gold prices and 16 US dollars exchange rate pairings for the period 1986 to 2008. Within a multivariate DCC-GARCH framework, finds that gold operates as an effective hedge against the US dollar but its role as a safe haven was found negligible. Wang and Lee

(2011), for the sample period 1986 to 2007, estimate a non-linear TVAR model using yen's exchange rate as a threshold variable to divide between high and low depreciation regime. Their conclusion is that the investor view of gold as hedge depends on whether the yen depreciation rate is lower or higher than the variation margin (or risk premium that works as threshold).

2.3 Data

The empirical analysis is conducted using annual data on consumer prices, gold prices and silver prices in the UK and US over the period 1791 to 2010.[8] The sample period for silver prices starts in 1792 for both countries. The inflation series are obtained from Reinhart and Rogoff (2011) (RR series).[9] Gold and silver prices are obtained from Officer and Williamson (2011) and the Kitco Metals Inc, respectively.[10] Following Bekaert and Wang (2010), the precious metals prices were converted into local currency (USD $ and GBP £ per ounce), therefore, their hedging ability may also be due to currency movements, rather than to changes in their prices *per se*. The data (in logarithms) for the US and the UK are presented in Figures 1 and 2, respectively. An initial observation suggests that gold, silver and consumers price data went through many shifts over time, in both countries. We observe that for long periods in the 19th and 20th century gold and silver prices remain constant, reflecting the nominal price rigidity under periods of *monometallic* or *bimetallic* regimes.

In order to extract expected CPI measures, we employ two methodologies: the linear Hodrick and Prescott (1980, henceforth HP) filter and the asymmetric band-pass filter proposed by Christiano and Fitzgerald (2003, henceforth CF).[11] Each of these filters produce a long-term trend component of a series that may then be used to examine

[8] A detailed description of the data is given in the Appendix.

[9] Note that the base of the CPI was set to 100 in 1791.

[10] http://www.measuringworth.com/gold/ and http://www.kitco.com

[11] For the HP method, we follow Ravn and Uhlig (2002) by setting the penalty parameter equal to 6.25, for annual data.

the long-run relationship of the historical prices of gold and silver and the expected consumer price level.[12]

We employ two different estimates for core CPI: the exponentially smoothed core inflation estimator proposed by Cogley (2002) and a wavelet method proposed more recently by Dowd et al. (2011).[13] The later compare the wavelet-based core measures against a number of alternative measures (including Congley's low pass filter) and conclude that the former generally performs better. We utilize both the single exponential smoothing (*ses*) and two core inflation measures based on wavelets analysis namely *d*4, *la*8.[14]

Figure 3 summarizes the different measures. For the CPI series (headline, expected and core) and the nominal gold and silver prices of both countries under investigation, we have conducted three unit root tests. The augmented Dickey and Fuller (1979, ADF henceforth), the Phillips and Perron (1988, PP henceforth), and the Ng and Perron's (2001, NP henceforth) all seem to suggest that the maximum order of integration (*d*) is 1. The results are reported in Table 1.

[12]Ash et al. (2002), using long annual data, evaluate the usefulness of HP-filtered time series as a proxy for rational expectations applying a battery of tests for rationality. From their analysis of the US inflation data, they conclude that over the long period of 120 years the HP filter is weakly rational, being unbiased but inefficient. Orr et al. (1995) and Martin and Scarpetta (1999) also proxy inflation expectations with the HP filter. Smant (1998) argues that the HP filter generates a price series which is consistent with price expectations formed rationally indicating that HP filter incorporates a substantial element of 'perfect foresight' price expectations.

[13]Wavelet analysis involves the application of successive approximations to remove more and more high-frequency detail, or noise, and so help reveal an underlying signal (or shape) of the data. The procedure for the selection of plausible wavelet-based measures of core inflation is described in Dowd et al. (2011, pp. 521-522).

[14]The wavelets were calculated using the R package: "wavelets", covering four classes of wavelet transform filters: Daubechies, Least Asymetric, Best Localized and Coiflet. The prefixes for filters of these classes are *d*, *la*, *bl* and *c*, respectively. The optimal number of wavelets level was selected according the lowest value of the Shannon entropy (R package: "wavethresh").

2.4 Methodology

In order to assess the underlying long-run dynamics, we employ two cointegration methodologies; the trace test proposed by Johansen (1995) and the Bierens and Martins (2010) time-varying (TV) vector error correction model, in which the cointegrating relationship varies smoothly over time and the adjustment can be nonlinear. Johansen (1995) cointegration procedure is restrictive in the sense that it assumes that the cointegrating vector is constant and the adjustment is linear.

The time-invariant Vector Error Correction model (TI-VECM) of order p, used to construct the Johansen tests can be written as:

$$\Delta Z_t = \Pi Z_{t-1} - \gamma_0 - \gamma_1 t + \sum_{j=1}^{p-1} \Gamma_j \Delta Z_{t-j} + \varepsilon_t, \quad \varepsilon_t \sim N_k(0, \Omega), \quad t=1,\ldots,T, \tag{1}$$

where Z_t is a $k \times 1$ vector of variables observed at time t, Ω and Γ_j, j=1,. . . , $p-1$, are $k \times k$ matrices. Johansen (1995) used full information maximum likelihood cointegration analysis to test for a long-run relationship.[15] If cointegration exists, one can decompose $\Pi = \alpha\beta'$ and (1) can be rewritten as:

$$\Delta Z_t = \alpha(\beta' Z_{t-1} - \beta_0 - \beta_1 t) - \gamma_0 - \gamma_1 t + \sum_{j=1}^{p-1} \Gamma_j \Delta Z_{t-j} + \varepsilon_t, \tag{2}$$

where α is a $k \times r$ matrix of coefficients (where r is the cointegrating rank of the system), β is a $k \times r$ matrix of coefficients which defines the r cointegrating vectors in the system, β_0 is an $r \times 1$ vector of intercepts for the cointegrating vectors, β_1 is a $r \times 1$ vector of coefficients which allows for linear deterministic trends in the cointegrating vectors, γ_0 and γ_1 are $k \times 1$ vectors of the VECM's intercepts and linear trend coefficients respectively.

In line with Bierens and Martins (2010), for the $k \times 1$ sequence Z_t, we assume that

[15] Cheung and Lai (1993) have documented that the trace test shows more robustness to both skewness and excess kurtosis in the residuals than the maximal eigenvalue test.

for some t there are fixed $r < k$ linearly independent columns of the time-varying $k \times r$ matrix $\beta_t = (\beta_{1t}, \ldots, \beta_{rt})$, that forms the time-varying space of the cointegrating vectors. We can write the time-varying Vector Error Correction model (TV-VECM) of order p as:

$$\Delta Z_t = \gamma_0 + \alpha\beta_t' Z_{t-1} + \sum_{j=1}^{p-1} \Gamma_j \Delta Z_{t-j} + \varepsilon_t, \quad t = 1 \ldots T \tag{3}$$

where $\varepsilon_t \sim N_k(0, \Omega)$, α is a fixed $k \times r$ matrix with rank r, β_t is a time-varying $k \times r$ matrix also with rank r, T is the number of observations, Ω and Γ_j are $k \times k$ matrices. We test the null hypothesis of time-invariant (TI) cointegration $\Pi_t' = \Pi' = \alpha\beta'$, against the alternative time-varying (TV) cointegration of the type $\Pi_t = \alpha\beta_t'$.

Bierens and Martins (2010) (Lemma 1) prove that under standard smoothness and orthonormality conditions, the parameters of the TV cointegrating vector β_t can be approximated for some fixed m by a finite sum of Chebyshev time polynomials $P_{i,T}(t)$ of decreasing smoothness:

$$\beta_t = \beta_m(t/T) = \sum_{i=0}^{m} \xi_{i,T} P_{i,T}(t), \quad t = 1 \ldots T, \tag{4}$$

where $1 \leq m < T - 1$ and $\xi_{i,T} = \frac{1}{T}\sum_{t=1}^{T} \beta_t P_{i,T}(t)$ for $i = 0, \ldots, T$-1, are unknown $k \times r$ matrices. Chebyshev time polynomials are defined by: $P_{0,T}(t) = 1$ and $P_{1,T}(t) = \sqrt{2}\cos\left(\frac{i\pi(t-0.5)}{T}\right)$, $t = 1, 2, \ldots T$, $i \geq 1$, such that, for all couples of integers i, j, the following orthonormality property holds: $\frac{1}{T}\sum_{t=1}^{T} P_{i,T}(t) P_{j,T} = 1 (i = j)$.

Testing for TV cointegration corresponds to the null and alternative hypothesis:

For TI: $H_0 : \xi_{i,T} = O_{k \times r}$ for i=1,$\ldots, m$, and $\xi_i = O_{k \times r}$ for $i > m$.

For TV: $H_1 : lim_{T \to \infty} \xi_{i,T} \neq O_{k \times r}$ for some $i = 1, \ldots, m$, and $\xi_i = O_{k \times r}$ for $i > m$.

Substituting (4) in (3), we get: $\Delta Z_t = \gamma_0 + \alpha\left(\sum_{i=0}^{m} \xi_i P_{i,T}(t)\right)' Z_{t-1} + \sum_{j=1}^{p-1} \Gamma_j \Delta Z_{t-j} + \varepsilon_t$, which can be rewritten as:

$$\Delta Z_t = \gamma_0 + \alpha\xi' Z_{t-1}^{(m)} + \sum_{j=1}^{p-1} \Gamma_j \Delta Z_{t-j} + \varepsilon_t, \tag{5}$$

where $\xi' = \left(\xi_0', \xi_1', \ldots, \xi_m'\right)$ and $Z_{t-1}^{(m)} = P_{i,T}(t) \otimes Z_{t-1}$, for $i = 0, \ldots, m$.

The null hypothesis of TI cointegration corresponds to $\xi' = (\beta, O_{r,k.m})'$ so that $\xi' Z_{t-1}^{(m)} = \beta' Z_{t-1}$. We can estimate both (5) and its time invariant counterpart (2), which is equivalent to (5) with $m = 0$, by maximum likelihood. The likelihood ratio test for the null hypothesis of standard (TI) cointegration against the alternative TV cointegration is given by:

$$LR_T^{tvc} = -2\left[\hat{l}_T(r, m = 0) - \hat{l}_T(r, m)\right] \tag{6}$$

where $\hat{l}_T(r, \cdot)$ are the log-likelihoods computed in the estimated values of the VECM parameters. When $m = 0$, we are in a TI case, when $m > 0$, we are in a TV case. In both cases, r is the cointegration rank which we assume to be given. Bierens and Martins (2010) prove in Theorem 1 that given $m, r \geq 1$, under the null hypothesis of standard cointegration, the LR_T^{tvc} statistic defined above is asymptotically distributed as a chi-squared distribution with $r \times m \times k$ degrees of freedom.[16]

2.5 Empirical results

2.5.1 The Real Price of Gold and Silver

Jastram (1978) pointed out that the purchasing power of gold depends on the relation of commodity prices to gold prices. The author used the term "Retrieval Phenomenon" to describe the cyclical swings of the commodity price level around the level of gold. Due to this phenomenon, gold maintains its purchasing power over the

[16] Bierens and Martins (2009) compute empirical critical values via Monte Carlo simulations and show that even for T = 100 these values are very close to the asymptotic critical values.

long-run.[17]

Another way to assess how effective gold and silver have been as inflation hedges is to examine the historical fluctuations in the real (inflation-adjusted) prices (Erb and Harvey, 2013). If gold (silver) was a perfect inflation hedge, the real price of gold (silver) would be stationary. In that respect, we employ four alternative unit root tests to examine the stationarity properties of the real price of gold and silver: (i) Dickey and Fuller (1979, henceforth ADF), (ii) Phillips and Perron (1988, henceforth PP), (iii) the Zivot and Andrews (1992) unit root test with one break and (iv) the Lee and Strazicich (2003) for two breaks. The two break unit root test of Lee and Strazicich (2003) has been employed in order to counterbalance the potential loss of power of tests that ignore more than one break. Table 2 reports the results of the stationarity tests applied to the real price of gold and silver for the UK and the US. There is strong evidence at the 5% level that the real price of gold and silver is stationary. This conclusion is supported by both the Zivot and Andrews (1992), and Lee and Strazicich (2003) unit root test that allow for structural break(s).

Next, it would be interesting to examine how these variables evolved over the 200 year period, under different inflation regimes.[18] Figures 4 and 5 illustrate the real price of gold and silver on US and UK local currencies since 1791 (1792 for silver). The price of both metals is deflated by the CPI series. In Figures 4 and 5 the darker shaded areas denote the inflationary periods, while the brighter shaded areas denote the deflationary periods.

The evidence drawn from the US experience (Figure 4) reveal that in five out of

[17]Jastram (1978) used the term "golden constant" to communicate his belief that the real price of gold maintains its purchasing power over long periods and that gold's long-run average real return has been zero. Nonetheless, for Jastram (1978), the short-run was a period of few years, while the long-run refers to many decades.

[18]We have adopted the inflationary and deflationary periods proposed by Jastram and Leyland (2009). The authors defined those periods in a descriptive sense of price behavior. Inflation refers to a period of rapidly rising prices while deflation connotes an interval of swiftly falling prices. Although, the 1980-2000 period could be considered as part of Great Moderation period rather than a deflationary period, while the 2001-2010 period could be better described as 'inflation uncertainty' period rather than 'inflationary period'.

six major inflationary periods of US history since the eighteenth century, gold has lost its purchasing power while it has increased in two out of three deflationary periods. After 1971 this phenomenon has reversed, with gold to gain power in two inflationary periods and looses power in the Great Moderation period. For the US investor, silver holds its purchasing power in two out of three deflationary periods while losses its power in inflationary periods again until around 1930. In 1933 President Roosevelt took the US off the gold standard. Thereafter, the purchasing power of silver increased in inflationary periods and decreased in deflationary periods.

The UK evidence (Figure 5) demonstrates that before 1971 when the price of gold was freed, gold losses its operational power in all three inflationary periods while holds or even increases its operational power in the three deflationary periods. In the period after 1971, this phenomenon was altered, with gold to gain power in the two inflationary periods and looses power during the Great moderation period. Silver holds its purchasing power in two out of three deflationary periods while losses its power in inflationary periods until around 1930. After the decision of the British government to suspend the gold standard, the operational wealth of silver increased in inflationary periods and decreased in deflationary periods until recently.

2.5.2. Time-invariant (TI) and time-varying (TV) cointegration analysis

Having established that the nominal gold, silver prices and the alternative inflation measures are all $I(1)$ (see Table 1), we proceed to the bivariate cointegration analysis. Since cointegration tests are sensitive to the lag length, we estimate a VECM with up to 12 lags in each case and use both the Akaike (AIC) and the Schwarz (SIC) information criteria for additional robustness.[19] Another important issue is whether the deterministic component is present in the long-run relationship. Since both the price

[19]There are cases where the two information criteria indicate the same lag length. The results in these cases are identical.

of precious metals and the consumer prices may include a trend, we follow Doornik et al. (1998) notation and adopt two trend specifications for each model: the Case I model (H_c) with a constant to lie in the cointegration space and the Case II model (H_l) with unrestricted constant and restricted trend that allows for non-zero drift in any unit-root processes found in the cointegration analysis.

In the generalized Fisher effect framework, our definition of long-run inflation hedging is derived from the comovement of gold or silver nominal price with the consumers prices in the following time-series regression:

$$PM_t = a + \beta CPI_t + u_t \tag{7}$$

where PM_t and CPI_t denote the natural logarithm of precious metals (gold or silver) prices and consumers prices respectively and u_t is the error. The coefficient β is the *LR* elasticity of gold and silver prices with respect to goods prices, indicating the percentage change in precious metals prices for every 1% change in goods prices. Possible outcomes once the null of no cointegration is rejected, include $0 < \beta < 1$ (partial hedge), $\beta = 1$ (full hedge), and $\beta > 1$ (superior performance).

The results of the Johansen (1995) (TI-VECM) and the Bierens and Martins (2010) (TV-VECM) cointegration tests for the US and the UK are summarized in Table 3. The pairs of variables which did not show any evidence of time-invariant or time-varying cointegration were excluded from the subsequent analysis.[20]

[20]The numerical time-invariant and time-varying cointegration test results are available from the authors upon request.

2.5.2.1 Time-invariant cointegration analysis

The results for the Johansen's trace test determine whether a long-term relation exists between each pair of gold (silver) prices and consumer prices. The null hypothesis is that there is no cointegrating relation, and if this is rejected, we test the hypothesis that there is at most one cointegrating vector. Results in Table 3 suggest that there is one cointegrating vector between each pair of gold prices and headline inflation in both countries according to the AIC (weaker evidence was found for SIC). The evidence for silver prices and headline inflation indicates no long-run relationship for both countries. We also observe strong evidence for a cointegrating relationship for gold prices and expected CPI measures (HP, CF) for the UK. The same holds for the US (AIC), though the evidence is weaker for the SIC. A weak long-run relationship between silver prices and CF is also evident (AIC) for the UK and in Case II models for the US. Strong long-run relationship between gold price and the three core price measures is found for Case I model in the UK (moderate evidence was found for Case II model). Similar result emerges for the US (AIC). The SIC criterion supports cointegration in fewer cases for both countries. No significant cointegrating relation is present between silver prices and core price level measures.

Table 4 reports the long-run estimates for the relationship between gold and the alternative consumer price measures for the UK and the US. The Johansen trace test has not shown any significant long-run relationship between silver prices and the alternative CPI measures. The cointegration vectors have been normalized on gold and in each case the CPI coefficients have the expected sign. Turning to the magnitudes of the long-run coefficients, the estimated point coefficients for the US (Panel A in Table 4) range from 1.24 (HD) to 1.61 (CF). As can be seen most of the CPI coefficients are highly significant, indicating a positive relationship between US gold prices and the various consumer price measures. For the UK (Panel B in Table 4) the estimated point coefficients range between 1.03(*ses*) and 1.33(*d*4). It is also evident from the results that the long-run coefficient for the expected price level is higher compared to that

of headline and core price level for the US. The highest coefficient for the UK is also observed for the expected CPI measures (CF) for most cases. Overall, gold provide superior hedge of future inflation in the long-run and this ability is stronger in the US (average *LR* 1.36) compared to the UK (average *LR* 1.16).

2.5.2.2 Time-varying cointegration analysis

Over the last two centuries, the UK and the US have witnessed policy regime shifts and changes in market conditions. These events could affect the long-run relationship between precious metals and consumer prices. Furthermore, previous evidence of non-linearity for gold and silver (Frank and Stengos, 1989) reinforces the argument for the time-varying approach.[21] For this purpose, we relax the assumption that the long-run relationship has remained constant through the last two century period by employing the time-varying framework of Bierens and Martins (2010), where the cointegrating vectors fluctuate over time and the Johansen set up is considered as a special case of the model.[22] Evidence of time-varying cointegration at each significance level will be referred as the case where the null hypothesis is rejected for the Chebyshev polynomial expansion up to order four ($m = 1 \ldots 4$). For example, if the null hypothesis for Chebyshev polynomial of order one ($m = 1$) is rejected at the 10% and the rest three ($m = 2 \ldots 4$) at the 5% level, this will be referred as rejection at the 10% level. If at least in one m we cannot reject the null, then no time-varying cointegration is considered.[23]

For the pair of US gold price and headline CPI (Panel A in Table 3), strong evidence emerges of a time-varying cointegration at the 5% level in both models (AIC) and in Case I model (SIC). The evidence for the Case II model is at the 10% level. Results for

[21]Note that a linear model with time-varying coefficients is an approximation to any non-linear model (Granger, 2008)

[22]The asymptotic p-values of Bierens and Martins (2010) test, for different combinations of the order m of the Chebyshev polynomial expansion and the lag order p, are presented in Bierens and Martins (2009).

[23]Following Bierens and Martins (2010) since p-values are zero for any m larger than four we present the results until fourth order for the Chebyshev polynomial expansion.

the UK (Panel B in Table 3) are in favor of a time-varying long-run relation between gold prices and headline CPI in Case I model (AIC and SIC) at the 5% and 10% significance level respectively. For the pair of silver prices and headline CPI, a time-varying long-run relation was found at the 5% level.

A significant time-varying long-run relation is detected between US gold prices and all the expected CPI measures at the 5% level (AIC) while according to SIC a significant relationship at the 5% was found against CF in both models (Panel A, Table 3). For the pair of US silver prices and expected measures, significant time-varying relationship was found in all models for the CF measure. A significant long-run relation is found between UK gold prices and the CF at the 10% level across all models. For the HP, there is evidence in favor of time-varying cointegration (AIC). For the UK silver prices, there exists a time-varying cointegration relationship with the expected price measures (HP, CF) according to both information criteria at the 5% level.

The time-varying cointegration test between US precious metal prices and core price measures reveals a significant time-varying relationship between US gold prices and the three core measures according to both information criteria. For the US silver prices and core measures, a weak time-varying relationship was detected in Case I models for *ses* at the 10% level. Evidence provided for UK shows a time-varying long-run relationship between UK gold prices and two core measures at the 5% significance level, namely *d*4 and *la*8, for both information criteria. Evidence of time-varying cointegration also found for the UK silver prices and all core price measures except the Case II model of *d*4 (both AIC and SIC).

In general, for the US there is evidence in favor of time-varying cointegration between gold prices and headline, expected and core measures. Similar results hold for the UK's gold prices while strong time-varying cointegration emerges between the UK's silver price and all price level measures. To sum up, we get stronger evidence of TV cointegration for both countries compared to the TI case. In the UK, we observe a wider comovement of precious metals with the alternative CPI measures (more coin-

tegration pairs) whereas in the US the magnitude of the relationship is stronger within the TI framework with higher *LR* betas.

Since strong evidence is found in favor of time-varying cointegration, we present the plots of the time-varying coefficients for the cases that significant time-varying relationship has been detected at the 5% significance level. The time-varying coefficients β_{1t} and β_{2t} correspond to the cointegrating relationship $\beta_t^{'}Z_t = \beta_{1t}PM_t + \beta_{2t}CPI_t$ or $\beta_t^{'}Z_t = e_t$ where the process e_t represents the short-run deviations from equilibrium (real shocks or change in monetary regime).[24] Then β_t's will be approximated by $\beta_t(m) = \sum_{i=0}^{m} \xi_i P_{i,T}(t)$, where the ξ_i's indicate the Fourier coefficient.[25]

The plots of the various CPI betas (β2t) for the US are presented in Figure 6. We observe time variation in gold-HD (g_HD) relation. The headline inflation beta moves above its mean value after the early 2000 period, a finding in line with Batten et al. (2014), who also report an increase in comovement between the two variables since 2002. Increased volatility is observed for gold-HP (gold-d4) up to (after) the 1930s. For the silver and CF pair, we observe relative instability up to the beginning of the 20th century and stability after that. The UK results are plotted in Figure 7. A decrease in long term comovement between gold and HD is observed from the late 1990s until 2008. For the same period the core CPI beta (g_d4) increases, while the gold-HP beta moves towards zero. Silver betas after 1990s deviate from their average value. The silver- HD long term comovement follows an upward trend after the 1930s. For the most recent period, the HD and HP betas move between zero and unity indicating a partial hedging ability of silver prices in the UK.

In general, we observe instability in the time-varying beta coefficients. The time-varying betas of gold are on average above unity for both countries, providing a

[24]The Chebyshev polynomial ($P_{i,T}(t)$) order m and the VECM order p have been chosen according to the AIC. We thank Luis F. Martins for making the GAUSS code available.

[25]The components of time varying beta coefficients are rescaled to a maximum absolute value across variables and time of one. As Martins and Gabriel (2013) indicate, imposing the usual normalization in order to achieve linear dependence has consequences for time consistency of cointegration spaces. The authors conclude that this anomaly should be considered if there is evidence of structural breaks in the cointegrating relation.

superior hedging ability for gold. The long-run elasticity of gold is more stable against expected inflation (HP) after 1930. Strong instability for silver-CPI betas is observed before the 1950s for both countries. The average time-varying beta coefficients of gold against the alternative CPI measures are lower for the UK compared to the US, confirming the evidence found in the time-invariant case.

2.6 Conclusions

This study has examined the long-run hedging properties of gold and silver against alternative measures of consumers price level for the UK and the US. A sample that spans for more than two centuries is employed. We consider a time-invariant and a time-varying approach in which the long-run cointegrating relation varies smoothly over time, allowing for non-linear adjustment in the long term dynamics.

First, we assess the two precious metal hedging effectiveness by examining the historical fluctuations in their real prices. If the real price of gold (silver) is mean reverting, then it follows that the series will return to its mean value. We show that the real price of gold and silver is stationary in both countries, after accounting for structural break(s).

Second, we found evidence that gold performance is superior against headline, expected and core CPI in the long-run. Within the time-invariant approach, the inflation hedging ability of gold is found on average higher in the US compared to the UK. In particular, the average gold's *LR* beta was found 1.36 for the former and 1.16 for the later. This finding is further confirmed by the time-varying approach. For gold, the time-varying betas against headline and expected inflation are higher than unity, affirming gold's superior hedging ability in both countries. Moreover, we display that the long-run relationship of gold against expected inflation became more stable over the last decades.

Finally, within the time-invariant approach, there is no long-run relationship be-

tween silver and all the price measures. The time-varying approach, where the adjustment is allowed to be nonlinear, overthrows this result: we found that there is strong evidence for time-varying long-run relation between silver prices and the alternative inflation measures for the UK while weaker evidence (if any) was found for the US. Overall, for both countries, there is stronger evidence in favor of time-varying long-run relationship between gold and silver prices and the alternative price level measures, relative to the time-invariant approach.

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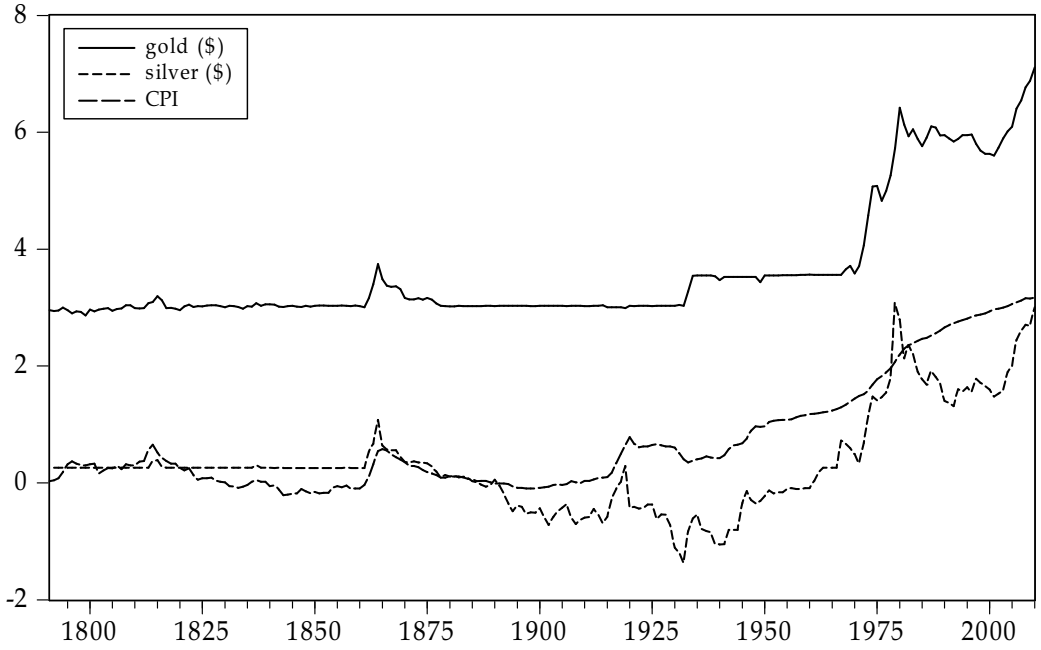

Fig. 1. US gold prices, silver prices and consumer price level (in logarithms)

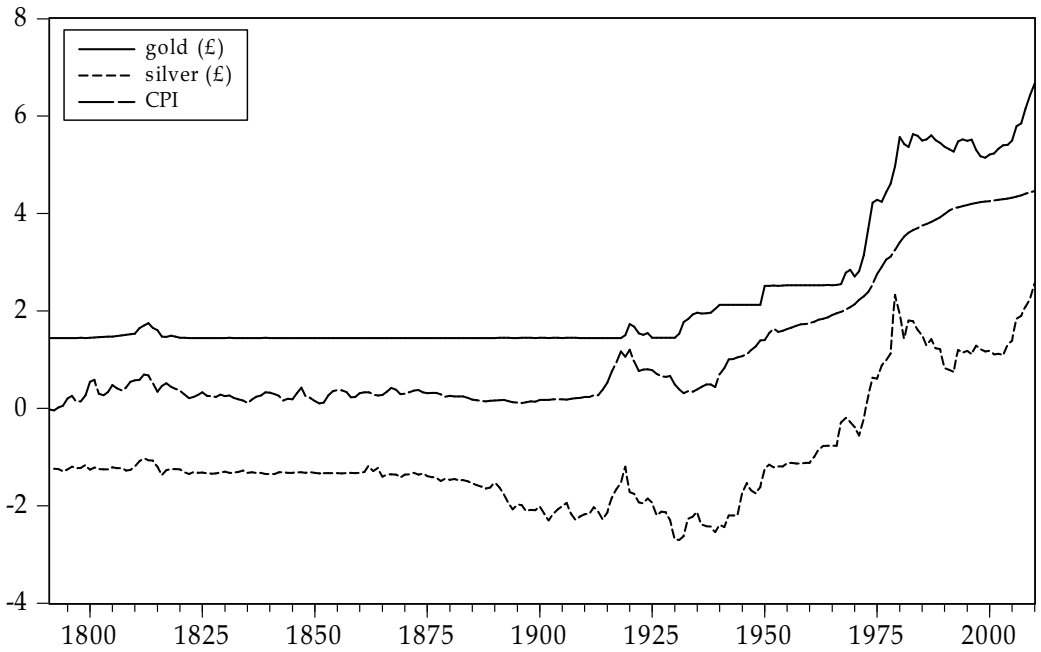

Fig. 2. UK gold prices, silver prices and consumer price level (in logarithms)

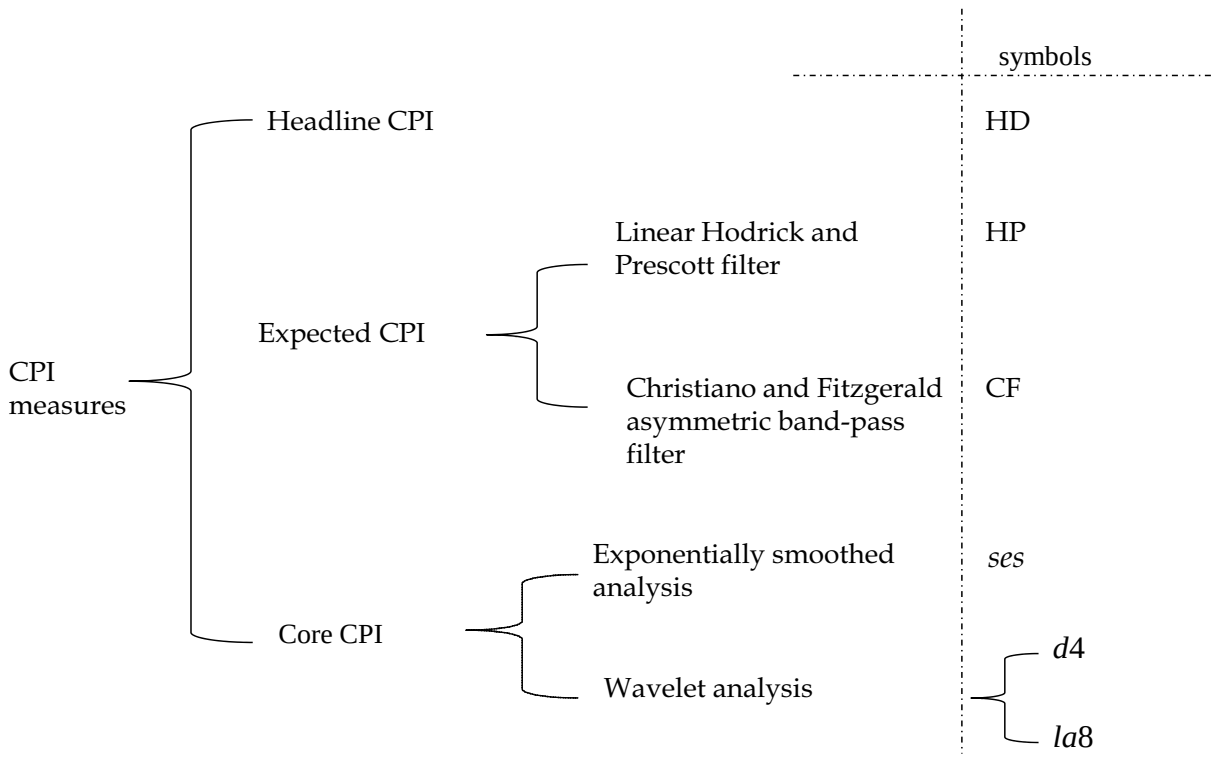

Fig. 3. Alternative inflation measures

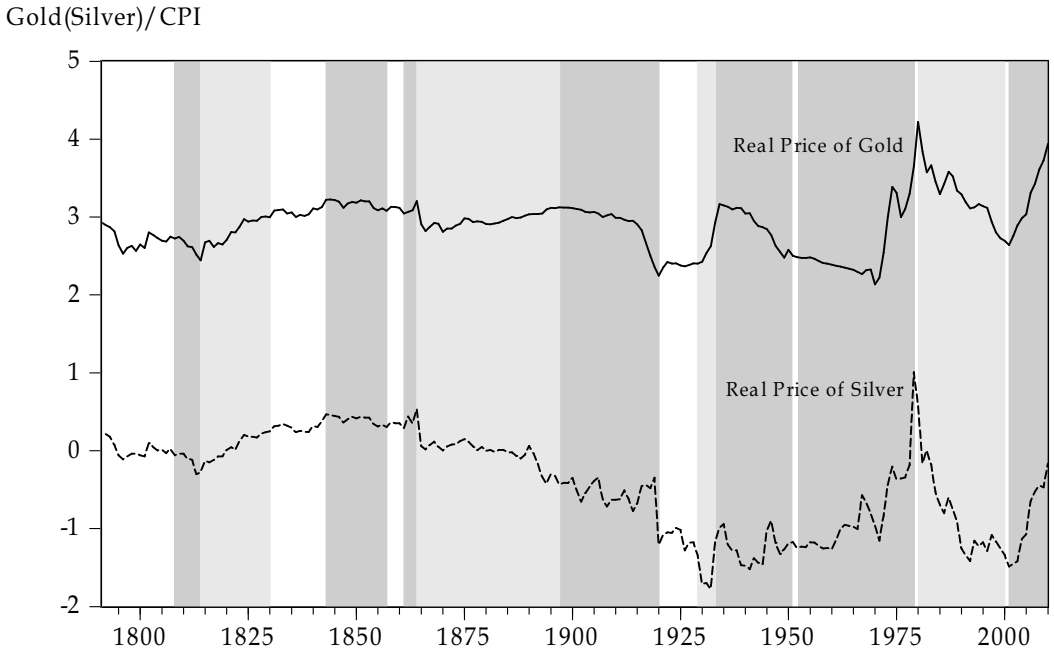

Fig. 4. The Real Price of Gold and Silver in US, 1791-2012

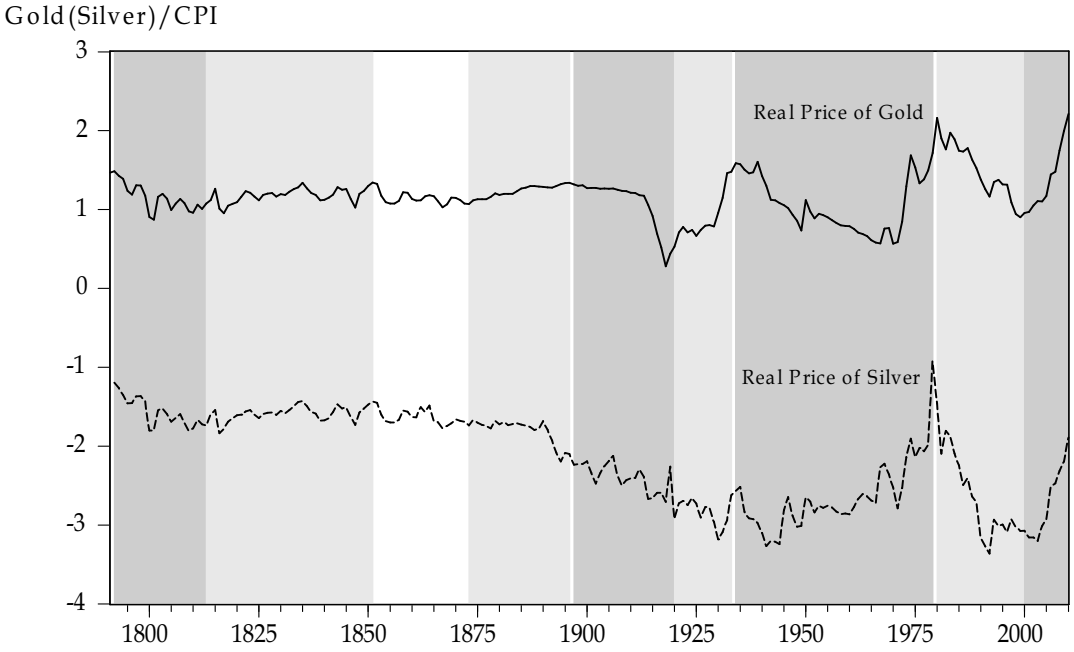

Fig. 5. The Real Price of Gold and Silver in UK, 1791-2012

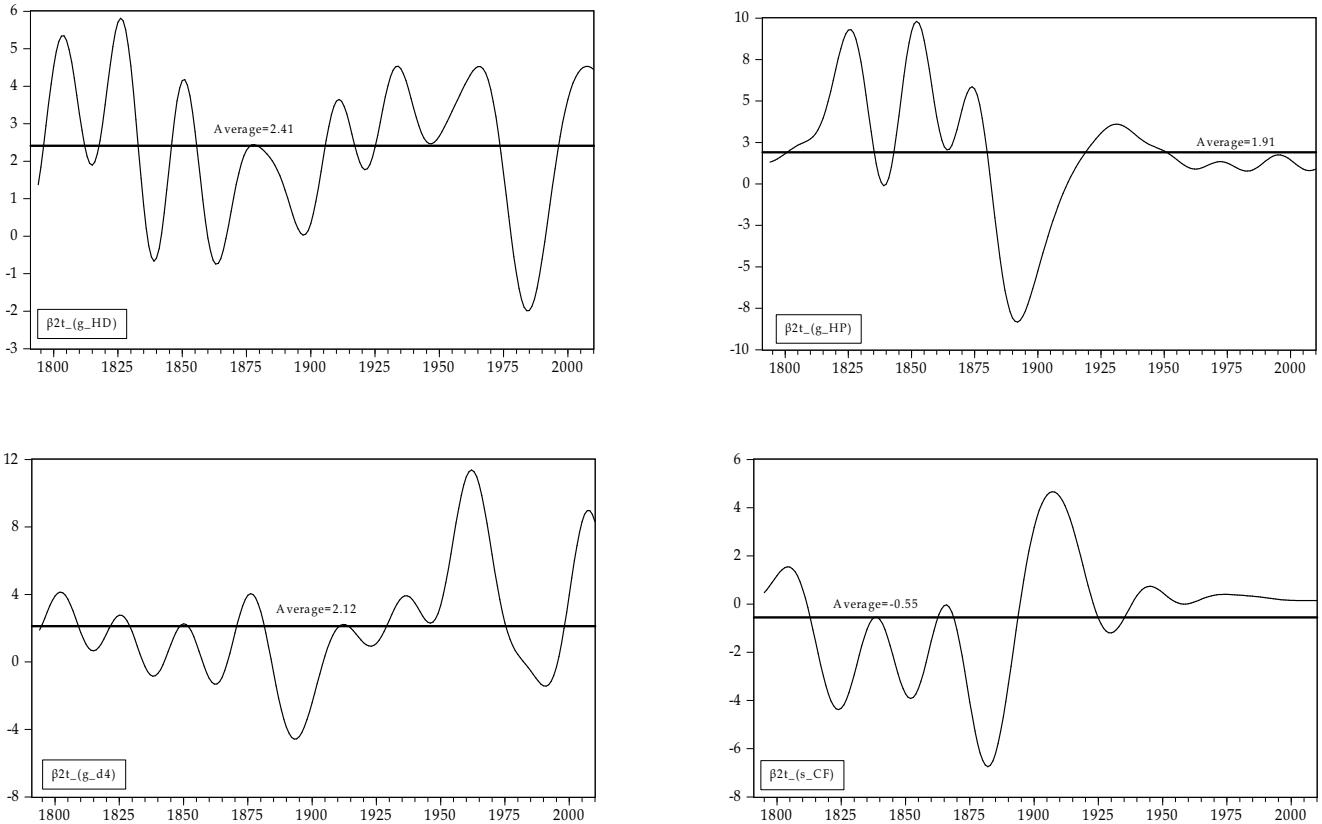

Figure 6. US Time varying Cointegrating Vectors

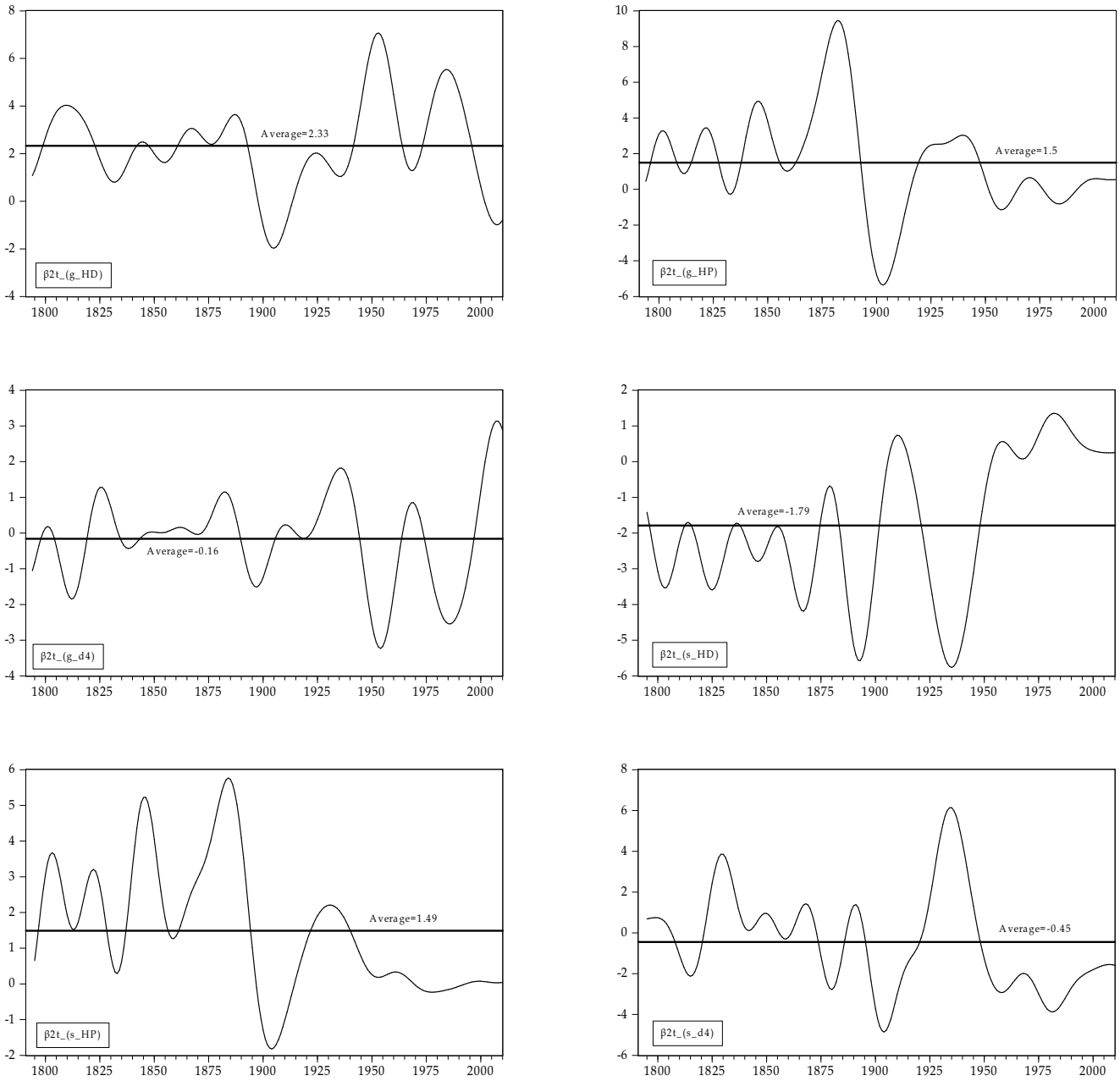

Figure 7. UK Time varying Cointegrating Vectors

Table 1. Unit root and stationarity tests

	US						UK					
	ADF		PP		NP		ADF		PP		NP	
Series	c	c,t	c	c,t	c	c,t	c	c,t	c	c,t	c	c,t
Log levels												
gold	0.99	0.99	0.99	0.99	4.60	0.08	0.99	0.99	0.99	0.99	4.33	0.61
silver	0.96	0.98	0.97	0.98	0.51	-1.79	0.99	0.99	0.99	0.99	2.81	-0.33
HD	0.99	0.97	0.99	0.99	3.20	-0.09	0.99	0.98	0.99	0.99	3.07	-0.03
HP	0.99	0.97	0.99	0.99	3.22	-0.09	0.99	0.97	0.99	0.99	3.01	-0.19
CF	0.99	0.10	0.99	0.99	3.21	-0.11	0.33	0.12	0.99	0.99	3.01	-0.16
*d*4	0.98	0.92	0.94	0.74	0.38	-2.48	0.99	0.96	0.92	0.76	0.37	-2.77
*la*8	0.85	0.61	0.94	0.64	0.18	-2.42	0.73	0.53	0.92	0.67	0.10	-2.70
ses	0.99	0.98	0.99	0.99	3.43	0.22	0.99	0.98	0.99	0.98	3.20	0.22
Returns (First differences)												
gold	0.00	0.00	0.00	0.00	-90.3***	-79.5***	0.14	0.00	0.00	0.00	-81.66***	-88.29***
silver	0.00	0.00	0.00	0.00	-90.3***	-78.7***	0.00	0.00	0.00	0.00	-107.86***	-98.64***
HD	0.00	0.00	0.00	0.00	-79.6***	-72.8***	0.00	0.00	0.00	0.00	-80.96***	-96.29***
HP	0.02	0.01	0.00	0.00	-13.0**	-17.9***	0.00	0.00	0.01	0.02	-19.94***	-21.17***
CF	0.72	0.00	0.01	0.03	-19.0***	-19.1***	0.76	0.00	0.02	0.05	-19.27***	-20.43***
*d*4	0.00	0.00	0.00	0.00	-81.4***	-36.7***	0.00	0.00	0.00	0.00	-54.63***	-28.79***
*la*8	0.04	0.13	0.00	0.00	-5.91*	-9.58**	0.14	0.41	0.00	0.00	-4.63	-6.40**
ses	0.00	0.00	0.00	0.00	-16.39***	-34.2***	0.00	0.00	0.00	0.00	-6.49**	-25.14***

Notes: The unit root tests are applied with (c,t) or without (c) a time trend. We report *p*-values for the Dickey and Fuller (1979) and the Phillips and Perron (1988) tests, while MZ_a is reported for the Ng and Perron's (2001). The lag length for the Dickey and Fuller (1979) test is selected via the Schwarz information criterion. The Phillips and Perron (1988) and the Ng and Perron's (2001) tests are based on the Bartlett kernel with bandwidth selected from the Newey–West method. ***, **, * denote rejection of the null-unit root hypothesis at the 1, 5 and 10% level respectively.

Table 2. Unit root tests for Real Price (RP) series

		ADF	PP	ZA		LS		
		t-stat.	t-stat.	t-stat.	TB		t-stat.	TB
RP_g_{us}	c	-3.12[6]**	-1.93	-4.67[6]**	1972	Model A	-3.80[8]*	1916, 1972
	c,t	-3.17[6]*	-2.03	-4.68[6]**	1972	Model C	-6.14[8]***	1835, 1953
RP_g_{uk}	c	-3.12[1]**	-1.88	-5.46[7]**	1972	Model A	-4.88[9]***	1915, 1979
	c,t	-3.18[1]*	-1.97	-5.5[7]**	1972	Model C	-6.15[11]***	1828, 1953
RP_s_{us}	c	-2.19[0]	-2.06	-3.25[2]**	1891	Model A	-4.09[13]**	1919, 1978
	c,t	-2.55[0]	-2.47	-3.7[2]**	1920	Model C	-5.30[13]**	1918, 1978
RP_s_{uk}	c	-2.46[0]	-2.31	-3.69[6]**	1891	Model A	-4.11[11]**	1919, 1978
	c,t	-2.91[0]	-2.61	-3.87[6]**	1920	Model C	-5.03[11]*	1919, 1978

Notes: ***, **, * indicate rejection of the null-unit root hypothesis at the 1, 5 and 10% level respectively. The number in the bracket shows the number of lagged difference terms in the corresponding unit root test. It was chosen by the Schwarz Criterion for ADF and ZA while for LS was chosen by the 't-sig' approach suggested by Perron (1997). We set an upper bound of fifteen for the lag length and test downwards until a significant (at the 10% level) lag is found. The Phillips and Perron (1988) test is based on the Bartlett kernel with bandwidth selected from the Newey–West method. In LS test, Model A allows for two shifts in the level, while Model C allows for two shifts in the level and the trend. TB denotes the time break date.

Table 3. Time-invariant (TI) and time-varying (TV) cointegration tests

	Case I: H_c^{AIC}		Case II: H_l^{AIC}		Case I: H_c^{SIC}		Case II: H_l^{SIC}	
	TI-VECM	TV-VECM	TI-VECM	TV-VECM	TI-VECM	TV-VECM	TI-VECM	TV-VECM
Panel A: United States								
Headline inflation								
(g_{us}, HD)	**	**	**	**	*	**	×	*
(s_{us}, HD)	×	*	×	×	×	*	×	×
Expected inflation measures								
(g_{us}, HP)	**	**	×	**	×	*	×	×
(g_{us}, CF)	**	**	**	**	**	**	**	**
(s_{us}, HP)	×	×	×	×	×	×	×	×
(s_{us}, CF)	×	**	*	**	×	**	*	**
Core inflation measures								
(g_{us}, $d4$)	×	**	×	**	×	**	×	**
(g_{us}, $la8$)	**	**	**	**	*	**	×	**
(g_{us}, ses)	**	**	**	**	**	**	×	×
(s_{us}, $d4$)	×	×	×	×	×	×	×	×
(s_{us}, $la8$)	×	×	×	×	×	×	×	×
(s_{us}, ses)	×	*	×	×	×	*	×	×
# of CI pairs	5/12	9/12	5/12	7/12	4/12	9/12	2/12	5/12
Panel B: United Kingdom								
Headline inflation								
(g_{uk}, HD)	**	**	**	×	×	*	*	×
(s_{uk}, HD)	×	**	×	**	×	**	×	**
Expected inflation measures								
(g_{uk}, HP)	**	**	**	*	**	×	×	×
(g_{uk}, CF)	**	*	**	*	**	*	**	*
(s_{uk}, HP)	×	**	×	**	×	**	×	**
(s_{uk}, CF)	×	**	*	**	×	**	*	**
Core inflation measures								
(g_{uk}, $d4$)	**	**	*	**	**	**	×	**
(g_{uk}, $la8$)	**	**	*	**	**	**	*	**
(g_{uk}, ses)	**	×	**	×	×	*	*	×
(s_{uk}, $d4$)	×	**	×	×	×	**	×	×
(s_{uk}, $la8$)	×	**	×	*	×	**	×	**
(s_{uk}, ses)	×	**	×	**	×	**	×	**
# of CI pairs	6/12	11/12	7/12	9/12	4/12	11/12	5/12	8/12

Notes: **, * indicate rejection of the null-unit root hypothesis at the 5% and 10% level of significance, respectively. TI-VECM and TV-VECM refer to the. Johansen (1995) and the Bierens and Martins (2010) cointegration tests, respectively. The critical values as well as the p-values of all the Johansen trace tests are obtained by computing the respective response surface according to Doornik (1998). $g_{us}(s_{us})$ denotes gold (silver) prices for the US. $g_{uk}(s_{uk})$ denotes gold (silver) prices for the UK. $H_c^{AIC}(H_l^{AIC})$ and H_c^{SIC} (H_l^{SIC}) denote the Case I (Case II) model, with the exponents AIC and SIC indicating the Akaike and Schwarz information criteria employed for lag length selection.

Table 4. Long-run relationship between gold prices and consumer prices

	Cointegrating vectors	Loading	Cointegrating vectors	Loading
Panel A: United States		H_c^{AIC}		H_l^{AIC}
(g_{us}, HD)	$g_{us} = 2.58^{***}_{(-28.42)} + 1.24^{***}_{(-12.26)} CPI_{HD}$	$\alpha_{g_{us},HD} = 0.004_{(0.42)}$	$g_{us} = -0.002_{(0,77)} t + 1.28^{***}_{(-9.27)} CPI_{HD}$	$\alpha_{g_{us},HD} = 0.012_{(1.31)}$
(g_{us}, HP)	$g_{us} = 2.86^{***}_{(-30.5)} + 1.29^{***}_{(-12.3)} CPI_{HP}$	$\alpha_{g_{us},HP} = -0.0006_{(-1.01)}$		
(g_{us}, CF)	$g_{us} = 2.8^{***}_{(-30.24)} + 1.37^{***}_{(-12.84)} CPI_{CF}$	$\alpha_{g_{us},CF} = 0.0002^{*}_{(1.77)}$	$g_{us} = -0.004^{**}_{(2.2)} t + 1.61^{***}_{(-11.17)} CPI_{CF}$	$\alpha_{g_{us},CF} = 0.00002^{***}_{(3.03)}$
$(g_{us}, la8)$	$g_{us} = 2.85^{***}_{(-31.49)} + 1.27^{***}_{(-13.42)} CPI_{la8}$	$\alpha_{g_{us},la8} = 0.018_{(1.2)}$	$g_{us} = -0.002_{(0.96)} t + 1.35^{***}_{(-10.38)} CPI_{la8}$	$\alpha_{g_{us},la8} = 0.029^{*}_{(1.93)}$
(g_{us}, ses)	$g_{us} = 2.85^{***}_{(-28.77)} + 1.3^{***}_{(-12.08)} CPI_{ses}$	$\alpha_{g_{us},ses} = 0.005_{(1.14)}$	$g_{us} = -0.001_{(0.5)} t + 1.32^{***}_{(-9.2)} CPI_{ses}$	$\alpha_{g_{us},ses} = 0.008^{*}_{(1.74)}$
		H_c^{SIC}		H_l^{SIC}
(g_{us}, HD)	$g_{us} = 2.89^{***}_{(-15.85)} + 1.39^{***}_{(-8.63)} CPI_{HD}$	$\alpha_{g_{us},HD} = -0.004_{(-0.69)}$		
(g_{us}, CF)	$g_{us} = 2.8^{***}_{(-30.24)} + 1.37^{***}_{(-12.84)} CPI_{CF}$	$\alpha_{g_{us},CF} = 0.0002^{*}_{(1.77)}$	$g_{us} = -0.004^{**}_{(2.2)} t + 1.61^{***}_{(-11.17)} CPI_{CF}$	$\alpha_{g_{us},CF} = 0.00002^{***}_{(3.03)}$
(g_{us}, ses)	$g_{us} = 2.82^{***}_{(-21.57)} + 1.3^{***}_{(-10.5)} CPI_{ses}$	$\alpha_{g_{us},ses} = 0.007^{*}_{(1.69)}$		
LR beta	*min* 1.24	*max* 1.61	*Average* 1.36	
Panel B: United Kingdom		H_c^{AIC}		H_l^{AIC}
(g_{uk}, HD)	$g_{uk} = 1.09^{***}_{(-16.19)} + 1.12^{***}_{(-25.05)} CPI_{HD}$	$\alpha_{g_{uk},HD} = 0.018_{(0.99)}$	$g_{uk} = -0.001_{(0.92)} t + 1.15^{***}_{(-18.61)} CPI_{HD}$	$\alpha_{g_{uk},HD} = 0.03^{*}_{(1.74)}$
(g_{uk}, HP)	$g_{uk} = 1.09^{***}_{(-16.43)} + 1.15^{***}_{(-25.07)} CPI_{HP}$	$\alpha_{g_{uk},HP} = -0.0006_{(-0.52)}$	$g_{uk} = -0.001_{(1.11)} t + 1.19^{***}_{(-19.03)} CPI_{HP}$	$\alpha_{g_{uk},HP} = 0.0004_{(0.31)}$
(g_{uk}, CF)	$g_{uk} = 1.08^{***}_{(-18.32)} + 1.17^{***}_{(-25.43)} CPI_{CF}$	$\alpha_{g_{uk},CF} = 0.00001_{(0.03)}$	$g_{uk} = -0.021^{*}_{(1.66)} t + 1.24^{***}_{(-20.95)} CPI_{CF}$	$\alpha_{g_{uk},CF} = 0.00001_{(0.91)}$
$(g_{uk}, d4)$	$g_{uk} = 1.09^{***}_{(-15.44)} + 1.11^{***}_{(-23.49)} CPI_{d4}$	$\alpha_{g_{uk},d4} = 0.043_{(1.09)}$	$g_{uk} = -0.001_{(0.54)} t + 1.13^{***}_{(-16.96)} CPI_{d4}$	$\alpha_{g_{uk},d4} = 0.065_{(1.6)}$
$(g_{uk}, la8)$	$g_{uk} = 1.09^{***}_{(-16.39)} + 1.16^{***}_{(-24.66)} CPI_{la8}$	$\alpha_{g_{uk},la8} = 0.01_{(0.38)}$	$g_{uk} = -0.001_{(0.37)} t + 1.17^{***}_{(-17.96)} CPI_{la8}$	$\alpha_{g_{uk},la8} = 0.024_{(0.84)}$
(g_{uk}, ses)	$g_{uk} = 1.09^{***}_{(-16.73)} + 1.15^{***}_{(-25.23)} CPI_{ses}$	$\alpha_{g_{uk},ses} = 0.011_{(1.29)}$	$g_{uk} = -0.001_{(0.63)} t + 1.17^{***}_{(-18.79)} CPI_{ses}$	$\alpha_{g_{uk},ses} = 0.017^{\star}_{(1.92)}$
		H_c^{SIC}		H_l^{SIC}
(g_{uk}, HD)			$g_{uk} = -0.002_{(1.05)} t + 1.15^{***}_{(-13.06)} CPI_{HD}$	$\alpha_{g_{uk},HD} = 0.045^{**}_{(2.72)}$
(g_{uk}, HP)	$g_{uk} = 1.09^{***}_{(-8.57)} + 1.24^{***}_{(-14.67)} CPI_{HP}$	$\alpha_{g_{uk},HP} = -0.0008^{*}_{(-1.63)}$		
(g_{uk}, CF)	$g_{uk} = 1.08^{***}_{(-18.32)} + 1.17^{***}_{(-25.43)} CPI_{CF}$	$\alpha_{g_{uk},CF} = 0.00001_{(0.03)}$	$g_{uk} = -0.021^{*}_{(1.66)} t + 1.24^{***}_{(-20.95)} CPI_{CF}$	$\alpha_{g_{uk},CF} = 0.00001_{(0.91)}$
$(g_{uk}, d4)$	$g_{uk} = 1.2^{***}_{(-6.19)} + 1.33^{***}_{(-11.18)} CPI_{d4}$	$\alpha_{g_{uk},d4} = -0.026_{(-1.44)}$		
$(g_{uk}, la8)$	$g_{uk} = 1.09^{***}_{(-15.05)} + 1.14^{***}_{(-23.23)} CPI_{la8}$	$\alpha_{g_{uk},la8} = 0.013_{(0.46)}$	$g_{uk} = -0.0003_{(0.16)} t + 1.15^{***}_{(-16.28)} CPI_{la8}$	$\alpha_{g_{us},la8} = 0.025_{(0.87)}$
(g_{uk}, ses)			$g_{uk} = -0.003_{(1.47)} t + 1.03^{***}_{(-13.91)} CPI_{ses}$	$\alpha_{g_{uk},ses} = 0.033^{***}_{(3.93)}$
LR beta	*min* 1.03	*max* 1.33	*Average* 1.16	

Notes: *,**,*** denote significance at the 10%, 5% and 1% level respectively. Numbers in parentheses are the values of the *t*-statistic. $H_c^{AIC}(H_l^{AIC})$ and H_c^{SIC} (H_l^{SIC}) denote the Case I (Case II) model, with the exponents AIC and SIC indicating the Akaike and Schwarz information criteria employed for lag length selection.

Appendix

Data description

Reinhart and Rogoff (2011) used as measures of inflation the consumer price indices or their close relative, cost-of-living indices. Since their analysis spans several earlier centuries, they rely on the meticulous work of a number of economic historians who have constructed such price indices item by item, most often by city rather than by country, from primary sources. When more than one city index is available for a country, they work with the simple average across cities (or regions) for the same country, such as in much of the pre-1800s data. [26]

The entire exchange-rate series is distinctive in two respects.[27] First, with rare exception (fourth quarter of 1833 and all of 1834), the data refer to actual and large-scale transactions rather than advertised, posted, or otherwise hypothetical exchange rates (the latter commonly recorded until the late nineteenth century). Second, the data are annual averages, covering as much of each year as possible, rather than pertaining to a specific day or month of the year. For 1870-1914, the data are annual averages of daily rates. For 1791-1869, the data are annual averages of quarterly values, these values derived as averages of all available intra-quarterly observations. For 1791-1912 the exchange-rate data pertain to what was called a "sight" (or "demand") bill of exchange. This meant that the buyer of British pounds paid in dollars immediately, but received the pounds after shipping the bill across the Atlantic and "presenting" it in London. Until 1879, in fact, "time" bills were the basis of exchange transactions. For example, a 60-day bill would involve an additional 63-day lag before receiving pounds-60 days inherent in the bill itself plus three "days of grace". The time-bill data (1791-1878) are converted to a sight-bill basis by eliminating the interest-component associated with

[26] The complete references by author and period to this body of work are provided in Carmen Reinhart's webpage. Available at: http://www.carmenreinhart.com/data/browse-by-topic/topics/2/

[27] For further details on the exchange-rate series, the interested reader may consult Lawrence H. Officer, Between the Dollar-Sterling Gold Points (Cambridge University Press, 1996) and Lawrence H. Officer, "Exchange Rates," in Susan B. Carter, Scott S. Gartner, Michael Haines, Alan Olmstead, Richard Sutch, and Gavin Wright, eds. Historical Statistics of the United States: Millennial Edition, vol. 5 (Cambridge University Press, 2006).

the additional lag beyond that for a hypothetical sight bill. For 1913 and later years the exchange-rate data are for "cable transfers," whereby pounds are received on the same day that dollar payment is made. By the year 1913, the difference between the sight and cable rate is so small as to be unimportant for most purposes.[28] Officer (p. 13-19), provides a comprehensive description of the London market price of gold.[29]

[28]Source: Lawrence H. Officer, "Dollar-Pound Exchange Rate From 1791," MeasuringWorth, 2011 URL: http://www.measuringworth.com/exchangepound/

[29]Available at: http://www.measuringworth.com/docs/GoldBackground.pdf

CHAPTER 3

ON THE RELATIONSHIP BETWEEN OIL AND GOLD BEFORE AND AFTER FINANCIAL CRISIS: LINEAR, NONLINEAR AND TIME-VARYING CAUSALITY TESTING

ABSTRACT

We examine the causal relationship between crude oil and gold spot prices before and after the recent financial crisis. In the pre-crisis period, causality is linear and unidirectional, running from oil to gold. In the post-crisis period, a bidirectional nonlinear causality relationship emerges. Volatility spillover transpires as the source of nonlinearity during this period. The time path of the causal linkages both for the returns and the levels (cointegration) was assessed via dynamic bootstrap causality analysis. We find that the causal linkage from gold to oil is time dependent and that the non-Granger causality null hypothesis rejection rate increased considerably in the post-financial crisis period. The probability of gold Granger causing oil in the short-run increases by more than 30% during the recent financial and euro crisis.

Keywords: gold prices, oil prices, linear and nonlinear Granger causality, financial crisis, volatility spillovers, rolling window causality.

3.1 Introduction

The increasing global market integration alongside with the financialization process of commodity markets, has made commodity prices more sensitive to extreme market conditions and unforeseen events. While financial crises are not a new phenomenon (see e.g., Reinhart and Rogoff, 2009), the 2007/2008 crisis differs from previous in that it is both severe and global. As a consequence, investors have been questioning previously held beliefs about the risk of equity investing and the benefits of global diversification. Intimately, the shortage of liquid financial assets in the world economy triggered a partial recreation of the interest in precious metals and energy markets (Caballero et al., 2008). Commodity markets have attracted international investor's attention not only as 'safe haven' to avoid financial risk but also as a fundamental investment strategy (Baur and McDermott, 2010).

Oil and gold are the most widely traded commodities and among the most popular economic indicators. During the recent global financial crisis, major commodity prices descend simultaneously at the aftermath of the economic downturn. In the second half of 2008, the West Texas Intermediate (WTI) crude oil price fell from a record high of $147 to $30 per barrel while the extent of the reduction exceeded 70% over a period of 6 months. The bankruptcy of Lehman Brothers saw the price of gold soar over 20% within a few weeks, as global risk appetite dramatically deteriorated and precipitated a 'flight to quality' across markets. The gold spot price, which is often used as a measure of storage of value, started its increase in early August 2007 from $660 per ounce and reached its peak of over $1000 around March 2008, after which it dropped 10% in a short time. However, ever since 2009, with the emergence of recovery expectations, the demand for commodities began to rise again and both the crude oil and gold prices started a new upward course (Figure 1).

Melvin and Sultan (1990) contend that oil price changes and political unrest are significant determinants of volatility in gold prices. Beahm (2008) supports that the price relationship between gold and oil is one of the five fundamentals that drive the

prices of precious metals, particularly gold. Narayan et al. (2010) examine the long-run relationship between gold and oil spot and future prices of different maturities through the inflation channel. They conclude that the oil market can be used to predict gold prices and vice versa. Zhang and Wei (2010) tested the linear and nonlinear (in the sense of Hiemstra and Jones, 1994) relationship between the crude oil and gold markets from January 2000 to March 2008. They provide evidence of a linear interaction between the two commodities and find a significant unilateral linear Granger causality running from crude oil to gold.

Although the two markets tend to be influenced by common factors, their prices were not completely driven by demand and supply fundamentals but rather by the financial futures and the interactions of international commodity markets. Consistent with this notion, Tang and Xiong (2010) find that as a result of the financialization process, futures prices of non energy commodities became increasingly correlated with oil after 2004. This trend intensified after the financial crisis that was triggered by the US sub-prime crisis. Since then, the importance of the interactions between the financial markets and commodity markets has risen, while the increased presence of index investors led to higher volatility in commodity prices.[1] Ciner (2001) relies on Hiemstra and Jones (1994) nonlinear causality test and provides evidence of a bidirectional feedback relation between stock index returns and oil futures markets, that was more pronounced in the 1990s. Bekiros and Diks (2008a), employ alternative econometric approaches (linear and nonlinear) and find evidence of a bidirectional causality relationship between crude oil spot and futures prices. Their empirical results show that these leads and lags patterns might change over time depending on the different methods or periods employed. Investors' decisions and portfolio rebalancing could also act as a channel to spillover shocks from other markets and across different commodities (Kyle and Xiong, 2001).

[1]Tang and Xiong (2010) document that the total value of commodity exchanges via index funds for institutional investors soared from $15 billion in 2003 to $200 billion in mid-2008.

One puzzling question is how the relationship between oil and gold has evolved and how the recent crisis has affected them. In contrast to the existing literature, our causality analysis allows for linear, nonlinear and time-varying perspective.[2] Our contribution to the literature is twofold. First, we assess how the recent financial crisis has affected the relationship between the two most important commodities. Second, we employ linear, nonlinear and time-varying techniques to examine the causal relationship between oil and gold. In a related study, Zhang and Wei (2010) investigated the nonlinear causality relationship between crude oil and gold spot prices. They employed the nonparametric test proposed by Hiemstra and Jones (1994), which is a modified version of the test by Baek and Brock (1992). The Hiemstra and Jones test relaxes the strict *i.i.d* hypothesis, allowing for the existence of short-term autocorrelations in time series. However, Diks and Panchenko (2005, 2006) point out that the relationship tested by the Hiemstra and Jones (1994)'s approach is not generally compatible with the definition of Granger causality and it may lead to spurious rejections of the null hypothesis of no Granger causality. Consequently, our attention shifts to the nonlinear procedure proposed by Diks and Panchenko (2006, D&P henceforth).

Full sample and subsample analysis reveals that the bidirectional linear price transmission mechanism detected in pre-crisis period became nonlinear in the post-crisis period. Volatility spillover effects are considered as a potential source of nonlinear causal linkages. Given that linear and nonlinear causal linkages are found to be sample dependent, a dynamic rolling window causality framework is also adopted. We employ the fixed length rolling window bivariate causality test proposed by Hill (2007). Bootstrap rolling causality analysis reveals that the non-causality (gold$\nrightarrow$oil) null hypothesis rejection frequency has increased after the financial crisis. For the opposite direction, the non-causality null (oil$\nrightarrow$gold) has a rejection rate close to 90%, roughly stable throughout the subsamples. Gold emerges as more significant during the period

[2]Baek and Brock (1992) noted that the standard causality testing procedure that relies on linearity assumptions is inappropriate to detect nonlinear relationships.

of crisis, as confirmed by the probit analysis that is employed.

The remaining of the paper is organized as follows: Section 2 presents the data and methodology, Section 3 discusses the empirical results and Section 4 concludes.

3.2 Data and methodology

3.2.1 Data description

This study employs daily time series data on crude oil and gold spot prices, over the period 2003:01 to 2012:12.[3] The crude oil price data are obtained from the US Energy Information Agency,[4] quoted in US dollars per barrel, while the gold price data come from the World Gold Council,[5] quoted in US dollars per ounce (Figure 1).

3.2.2 Methodology

3.2.2.1 Linear Granger causality tests

Assume that $\{S_t, R_t, t \geq 1\}$ are two scalar-valued strictly stationary time series (i.e. $I(0)$). We can state that $\{S_t\}$ Granger causes $\{R_t\}$ if past and current values of S contain additional information on future values of R that is not contained in the past and current R_t values. If $F_{S,t}$ and $F_{R,t}$ denote the information sets consisting of past observations of S_t and R_t up to and including time t, and if '$\sim$' denote equivalence in distribution, then $\{S_t\}$ Granger causes $\{R_t\}$ if, for $p \geq 1$:

$$\left(R_{t+1}, \ldots, R_{t+p}\right) \mid \left(F_{S,t}, F_{R,t}\right) \sim \left(R_{t+1}, \ldots, R_{t+p}\right) \mid F_{S,t} \tag{1}$$

The value of $p = 1$ is often used, i.e. testing for Granger non-causality comes down

[3]Following the notation of Bekiros and Diks (2008b), we have denoted the pre-financial crisis period as PI (2003:01 till 2007:07), the post-financial crisis period as PII (2007:08 till 2012:12) and the entire sample period as PIII.

[4]Available at: http://www.eia.gov.

[5]Available at: http://www.gold.org/.

to comparing the one-step-ahead conditional distribution of $\{R_t\}$ with and without past and current observed values of $\{S_t\}$. A conventional approach of testing for Granger causality is to assume a linear and parametric time series model for the conditional mean $E\left(R_{t+1} \mid \left(F_{S,t}, F_{R,t}\right)\right)$. In this case, causality can be tested by comparing the residuals of a fitted autoregressive model of R_t with those obtained by regressing R_t on (infinite) past values of both $\{S_t\}$ and $\{R_t\}$ (Granger, 1969). The approach developed by Toda and Yamamoto (1995, T&Y henceforth) employs a modified Wald test restricting the parameters of the VAR (p) model in levels, where p is the lag length of the VAR. The optimal order of the VAR(p) is augmented by the maximal order of integration (d_{max}). Then one could test only the first $p - d_{max}$ coefficient matrices.[6]

3.2.2.2 Nonlinear Granger causality test

There is no evidence to suggest that economic relationships are linear. Therefore, it would make sense to consider the case of nonlinearity (for a review on nonlinear models see Ramsey, 1996). For two strictly stationary and weakly dependent variables, R_t and S_t, let $\mathbf{Z}_t^{\kappa}$ be the κ- length lead vector of R_t, $S_t^{l_s}$ the l_s- length lag vector of S_t and finally, $R_t^{l_r}$ the l_r- length lag vector of R_t (l_s, $l_r \geq 1$). Assuming that the null hypothesis of no causality is a proposition about the invariant distribution of the (l_s+l_r+κ)- dimensional vector $\mathbf{X}_t = \left(\mathbf{S}_t^{l_s}, \mathbf{R}_t^{l_r}, \mathbf{Z}_t^{\kappa}\right)$, the time subscript can be dropped.[7] The joint probability density function $f_{S,R,Z}(s,r,z)$ along with its marginals, under the null should ensure:

$$\frac{f_{S,R,Z}(s,r,z)}{f_{S,R}(s,r)} = \frac{f_{R,Z}(r,z)}{f_R(r)} \tag{2}$$

The latter states that R and Z are independent conditionally on $S = s$ for each fixed

[6]The novelty of this approach lies on the fact that it does not require pretesting to determine the cointegrating properties of the system hence overcoming the potential unit root and cointegration test bias.

[7]As a common practice, it is assumed that κ is equal to 1 and for presentation purposes we set l_s=l_r= 1.

value of s. D&P demonstrate that this reformulated null hypothesis implies:

$$q \equiv E\left[f_{S,R,Z}(S,R,Z)\, f_R(R) - f_{S,R}(S,R) f_{R,Z}(R,Z)\right] = 0 \tag{3}$$

where the proposed estimator for q is:

$$T_n(\vartheta_n) = \frac{(2\vartheta_n)^{-d_S-2d_R-d_Z}}{n(n-1)(n-2)} \sum_i \left[\sum_{k,k\neq ij} \sum_{j\neq i} \left(I_{ik}^{SRZ} I_{ij}^{R} - I_{ik}^{SR} I_{ij}^{RZ}\right)\right] \tag{4}$$

where, $\mathrm{I}_{ij}^{X}=\mathrm{I}\left(\| \mathbf{X}_i - \mathbf{X}_j \| \leq \vartheta_n\right)$, with $\mathrm{I}(\cdot)$ to be the indicator function and ϑ_n the bandwidth which depends on the sample size. Hence, if we denote $\hat{f}_X(\mathbf{X}_i)$ as the local density estimator of the vector $\mathbf{X}$ at $\mathbf{X}_i$, then:

$$\hat{f}_X(\mathbf{X}_i) = (2\vartheta_n)^{-d_X}(n-1)^{-1} \sum_{j,j\neq i} I_{ij}^{X} \tag{5}$$

The $T_n(\vartheta_n)$ statistic could be written as:

$$T_n(\vartheta_n) = \frac{(n-1)}{n(n-2)} \sum_i \left(\hat{f}_{S,R,Z}(S_i,R_i,Z_i)\, \hat{f}_R(R_i) - \hat{f}_{S,R}(S_i,R_i)\, \hat{f}_{R,Z}(R_i,Z_i)\right) \tag{6}$$

D&P demonstrate that if $\vartheta_n = \mathrm{C}n^{-\beta}$ with $(C > 0, 1/4 < \beta < 1/3)$, then $T_n(\vartheta_n)$ converges in distribution to the standard normal distribution:

$$\sqrt{n}\frac{(T_n(\vartheta_n) - q)}{S_n} \xrightarrow{d} N(0,1) \tag{7}$$

where S_n is the estimated standard error of $T_n(\cdot)$. Overall, the risk of over rejecting the null is reduced substantially with the D&P test relative to the Hiemstra and Jones (1994) nonparametric approach.

3.2.2.3 Hill (2007) causality test

Hill (2007) establishes a sequential multi-horizon non-causality test strategy, which can be employed to characterize nonlinear causality chains for a trivariate process in terms of linear parametric restrictions. Hill's (2007) efficient causality test is based on Wald type test statistics under joint null hypothesis of zero parameter linear restrictions. It relies on a vector autoregression (VAR) framework of order p at horizon h, named (p,h)-autoregression, as the following:

$$W_{t+h} = \alpha + \sum_{k=1}^{p} \pi_k^{(h)} W_{t+1-k} + u_{t+h} \tag{8}$$

where W_t is a m-vector stationary process, $m \geq 2$, $\pi_k^{(h)}$ are matrix-valued coefficients, u_t is a zero mean $m \times 1$ vector white noise process with non singular covariance matrix Ω=E$[u_t u_t^{'}]$ and α is the constant term. In this study we consider the bivariate case. Causality occurs at any horizon if and only if it occurs at horizon 1 (see Hill 2007, Theorem 2.1). We assume W_t as a 2-vector stationary process, $W_t = \left(S_t^{'}, R_t^{'}\right)$. R does not linearly causes S at 1-step ahead if and only if the RS-block $\pi_{\text{RS},1}^{(h)} = 0$ for $k = 1$. In the case of nonstationarity for some or all variables in the VAR model, the (p,h)-autoregression Eq. (8) is extended in the Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996) model by adding d extra lags to the VAR models (discussed in 2.2.1). A straightforward Wald test of linear zero restrictions is performed in order to test for 1-step ahead non-causality. Due to possible inferior performance of the χ^2 distribution in small sample distributions, a parametric bootstrap method for simulating small sample p-values is proposed by Hill (2007, see Appendix B.2).[8]

[8]The rolling window regressions adopted in our empirical analysis are based on 5000 bootstrap replications. The GAUSS code is available at: http://www.unc.edu/~jbhill/software.htm

3.3 Empirical results

We start our analysis by examining the stationarity properties of the series. The augmented Dickey and Fuller (1979) and the Phillips and Perron (1988) unit root tests together with the Kwiatkowski et al. (1992) stationarity test all indicate that the (log) variables are integrated of order one. Furthermore, the unit root tests allowing for one and two endogenous structural breaks of Lee and Strazicich (2003, 2004) were also conducted but no significant breaks were detected in our series for the three periods under investigation (see Tables 5, 6 and 7 in the Appendix). Therefore, (log) levels of the variables will be used in the T&Y procedure (long-run) and their first differences in the short-run Granger causality test and the D&P test. For Hill's (2007) causality test, VAR models of differences and levels (excess-lag technique following T&Y and Dolado and Lütkepohl, 1996) are both employed in order to control for cointegration of unknown form.[9]

Table 1 presents the linear Granger causality test for the two subperiods and the full sample for both the returns (short-run) and the log prices (long-run, T&Y). The evidence in returns reveals a unidirectional causality running from crude oil to gold spot returns in the pre-financial crisis period. Evidence in favor of bidirectional causality is found in the post-financial crisis period and the entire sample period. These results are further reinforced by the T&Y long-run approach (log prices).

Papana et al. (2013) perform a simulation study of different direct causality measures and stress the importance of investigating linear as well as nonlinear linkages, in order to confirm the existence of causal effects. Accordingly, our next step would be to relax the assumption of linearity. The D&P testing procedure that allows for nonlinearity is carried out for three cases. First, the test is implemented to the stationary (returns) series for nonlinear causality. In the second step, the D&P test is applied

[9]Johansen (1995) cointegration test indicates that the crude oil and the gold prices do not cointegrate over the full sample as well as the two subperiods (see Table 8 in the Appendix).

on the delinearized series.[10] Lastly, the procedure is re-applied in the GARCH-BEKK filtered VAR residuals in order to examine volatility spillover effects.[11] In a similar vein with Bekiros and Diks (2008a, b) the bandwith value for the D&P test is set equal to one.

Table 2 presents the D&P test results. In the pre-crisis period, the results fail to reject the null of the nonlinear causality relationship between oil and gold returns (PI in Panel A and B). We cannot reject the non-causality null neither on the raw data nor on the VAR residual series. Given that no evidence of nonlinear dependence emerges in the pre-crisis period (Table 2), we can argue that in PI there is a significant and persistent linear unidirectional causality running from oil to gold (Table 1). In PII (post-crisis period), unfiltered (raw) returns indicate a bidirectional nonlinear causality between oil and gold. The nonlinear causality for the filtered VAR-residuals confirms the results for the raw returns and offers support for the existence of a nonlinear price transmission. The results presented in Table 2 (Panel A and B) reveal a significant two-way nonlinear causal relationship for both the raw data and the VAR residuals, in the post-financial crisis period. In PIII (full sample), the results for raw data indicate a (rather weak) one-way nonlinear causality running from gold to oil returns. This causal linkage seems to be nonlinear in nature since it tends to be stronger in the case of the VAR residuals. Generally, weak evidence is found for the nonlinear causal linkages running from gold to oil returns in PIII (both raw and filtered data).

Next, we employ second moment filtering in the three periods under investigation.[12] Once GARCH-BEKK(1,1) filtering is employed, the nonlinear causality evidence

[10]By removing linear predictive power with a VAR model, any causal linkage from one residual series of the VAR model to another can be considered as nonlinear predictive power (Hiemstra and Jones 1994, p. 1648). The lag length of the VAR specification was based on the Akaike and Schwartz information criteria.

[11]Following Bekiros and Diks (2008a, b), the second-moment filtering has been conducted on the data through a bivariate GARCH-BEKK (1, 1) model.

[12]Pavlidis et al. (2013) highlight the perils of neglecting multivariate conditionally heteroskedasticity when testing for nonlinear causality in mean. The authors examine the stock return-volume causal relationship for the US, UK and Japan and find that in several cases the test statistics become insignificant when heteroskedasticity robust tests are employed.

disappears (Table 2). The bidirectional causal relationship has vanished in PII period and the same applies for the unidirectional linkage (gold$\nrightarrow$ oil) in PIII. The latter indicates that the nonlinear causality is due to volatility effects. Overall, it seems that the additional explanatory power of volatility spillover is important for the oil and gold markets, especially after the financial crisis period.

The evidence from the previous section highlights the different behavior in the vicinity of recent crisis. However, the dating of the subsamples was imposed and the actual effect could have started before or after these dates. Therefore, one needs to study the evolving patterns of causality over rolling fixed length sample periods. In order to control for any apparent trend, we pass the series through a linear filter. The window length is set equal to 522 days (close to 2 years of daily data), generating a total of 2086 windows. We employ VAR models in differences (returns) and log levels (with excess lags) where the optimal order is selected by minimizing the AIC ($p = 1, \ldots, 30$ is considered). We perform bootstrap tests of non-causality for each window and count the non-causality null hypothesis rejection rate for both VAR models in differences and levels. Tests of the null hypothesis that oil does not cause gold and vice versa, are performed at the 5% level. The upper bound of the size tests of (Δ)oil$\nrightarrow$(Δ)gold and (Δ)gold$\nrightarrow$(Δ)oil is 0.1 ($0.1\times h$). Table 3 presents the rolling windows bootstrap p-values.[13]

Allowing the fixed window to move through our sample, we find evidence of (strong) causality running from oil to gold spot returns for all the sample periods under consideration (Panel A in Table 3). The latter is not valid in the opposite causality direction (gold$\nrightarrow$oil). The most prominent characteristic is the significant increase in the number of windows providing evidence of causality from gold to oil in the post-financial crisis period. Causality from gold to oil that takes place in pre-crisis period almost doubled in post-crisis period, from 22.5% to 39%. Profound causality running from oil to gold (99%) is found during the NBER recession period. Oil and gold rolling

[13]The results in Table 3 assume $k = 1$. For $k = 2$ up to 6 the results are also available upon request.

window bootstrap p-values are presented in Figure 2. More close inspection of Figure 2, though, reveals an interesting pattern. The gray line (gold$\nrightarrow$oil) decreases substantially in 2007 compared to 2006. The next two years 2008 and 2009 are characterized by increased volatility in the p-values. The euro crisis that evolved from 2009 to mid-2012 has again increased the significance of gold, with numerous p-values (gray line) laying under the 5% line. Overall, the rejection rates of the gold$\nrightarrow$oil null are clustered around 2007 (financial crisis, Lehman Brothers bankruptcy) and after 2009 when the euro crisis emerged (sovereign debt crisis). The black line (oil $\nrightarrow$gold) remains below the 5% line for the whole period with only few exceptions.

Once we control for cointegration a slightly different picture emerges (Panel B in Table 3). In this case, we examine the non-causality null hypothesis in the levels (log prices) of the variables. The strong causality running from oil to gold found in the short-run (PI in Panel A), decreases to 50.52% in the long-run (PI in Panel B). This causal linkage remained strong in PII (94.34%) and also during the NBER recession period (100%). The causal relationship running from gold to oil increased only marginally in the post-crisis period, compared to the pre-crisis period (26.3% and 25.4% respectively). The rejection rate of the null hypothesis that gold$\nrightarrow$oil for PI, PII and PIII appears stable around 26%. Figure 3 plots the p-values for the VAR in levels. Again, we observe that the gray line (gold$\nrightarrow$oil) falls bellow the 5% line in 2007 (around financial crisis) and in 2011 (euro debt crisis). The black line remains below the 5% line from 2007 to the end of the sample period with few exceptions in 2010 and 2012. The overall conclusion from the bootstrap rolling causality analysis is that for both cases (returns in Figure 2 and levels in Figure 3) the significance of gold emerges in the specific crisis periods.

The rejection rates differ in periods close to financial crisis of 2007 and after 2009 when the euro crisis emerged. The visual inspection of Figures 2 and 3 is informative but insufficient to draw conclusions. Therefore, we explore how the recent turbulent and crises periods (financial turmoil, financial crisis and the sovereign debt-euro crisis) affect the causal linkage from gold to oil, by employing a probit regression model:

$$P_i = p(y_i = 1) = \beta_0 + \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_3 + u_i, \quad i = 1, \ldots N \tag{9}$$

The dependent variable, y_i takes the value of 0 if we cannot reject the non-causality null hypothesis (gold$\nrightarrow$oil) and 1 otherwise. D_1 takes the value of 1 during the period from the peak of the credit boom (second quarter of 2007) until the collapse of Lehman Brothers in September 2008, D_2 takes the value of 1 in the peak of financial crisis (fourth quarter of 2008) and D_3 takes the value of 1 on specific dates related to the euro crisis.[14] The goal is to quantify the relationship between the different crises periods and the probability of rejecting the gold$\nrightarrow$oil null hypothesis. Table 4 presents the marginal effects for Eq. (9).[15] When the causal linkage is examined in returns (Panel A), we observe that a unit change in financial crisis and the euro crisis dummy variables, increase the probability of rejecting the gold$\nrightarrow$oil null hypothesis by 0.35 and 0.30 respectively. Similarly, being in the financial turmoil period decreases the probability of rejecting the null hypothesis (gold$\nrightarrow$oil) by 0.26. When cointegration is taken into account (Panel B), the probability of rejecting the null hypothesis increases in the financial turmoil and euro debt crisis periods by 0.12 and 0.06 respectively. In the peak of the recent financial crisis this probability decreases by 0.16.

In general, the marginal effects are higher in Panel A reflecting the fact that the crisis dummy variables affect the short-run more than the long-run. In the short-run, both the financial crisis and the euro crisis increase the probability of no rejection (gold$\nrightarrow$oil). The latter confirms the increased role of gold during these turbulent periods. In the long-run, the effect of financial crisis is not significant at the 1% level. Conversely, the financial turmoil and the euro crisis increase the probability of gold$\nrightarrow$oil rejection count.

[14]We construct a timeline of the Euro crisis by combining two external sources: the Financial Times (Interactive Timeline: Greek Debt Crisis), the Wall Street Journal (Europe's Debt Crisis - Timeline), in conjunction with specific events (e.g. increase in sovereign CDS spreads, bailout agreements, political turmoil) occurred in the GIIPS (Greece, Ireland, Italy, Portugal, Spain). The compiled joint timeline covers a period starting October 2009 (Greek elections) and ending July 2012.

[15]Logit models provide qualitatively similar results and are available from the authors upon request.

3.4 Conclusions

Oil and gold are the most important commodities. This study examines the causal relationship between the two during the recent financial crisis. The linear and non-linear Granger causality tests suggest that crude oil and gold markets have become more interrelated after the 2007 turbulence in the financial markets. The linear causal relationship detected on returns disappears after linear filtering. Nonlinear causal linkages in post-financial crisis period are revealed but vanished after GARCH filtering both for the post-financial crisis and the entire sample period. Evidence emerges that the nonlinear linkages between the oil and gold markets can be attributed to volatility spillover effects.

The dynamic analysis enlightens us further on how this relationship evolved. Significant changes in the causality test for the two commodities at the turn of the recent financial crisis demonstrate that their interdependence evolves as economic conditions change. A stable relationship is evident for crude oil which consistently influences gold during all fixed rolling subsamples. The reverse does not hold, as it appears that gold did cause oil mostly during the crisis. The latter justifies the rising importance of gold during volatile periods. This is further confirmed in the case where we allow for cointegration. Probit analysis revealed that during the crisis the probability of rejecting the non-Granger causality null (gold$\nrightarrow$oil) increased more than 30% in the short-run and more than 6% in the long-run.

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Figures

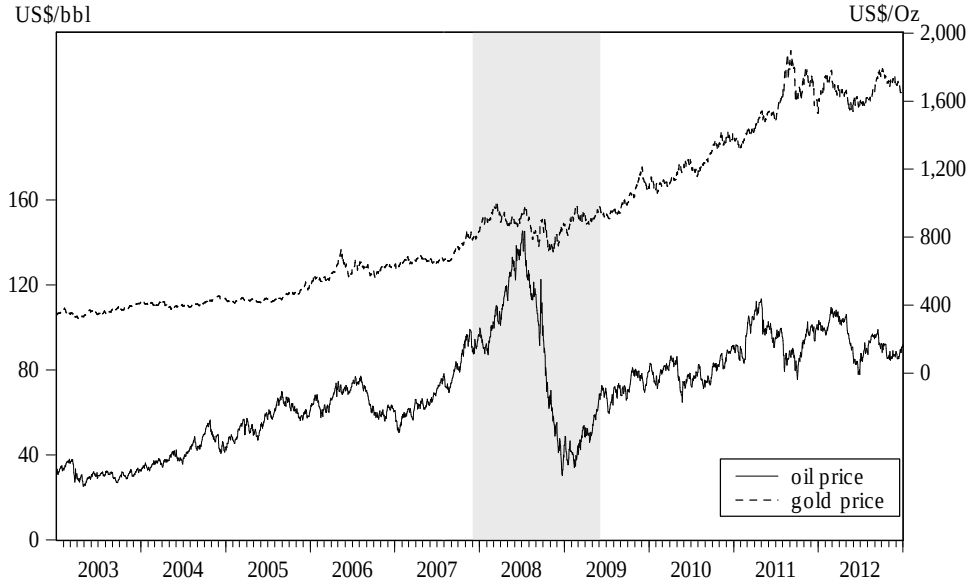

Fig.1. Crude oil and gold spot prices (shaded areas represent NBER recession dates)

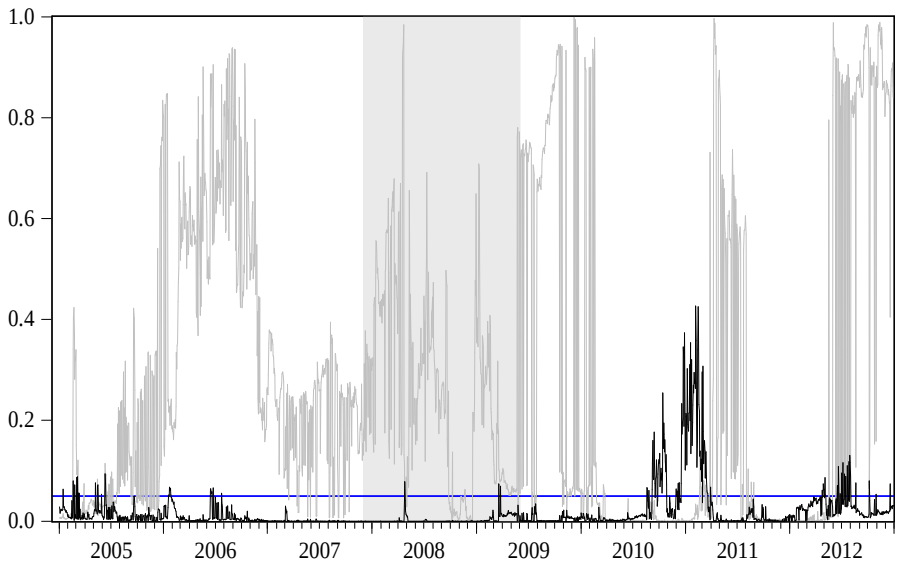

Fig.2. *Oil* $\nrightarrow$ *Gold* (black line) and *Gold* $\nrightarrow$ *Oil* (gray line) bootstrap *p*-values for VAR in first differences (shaded areas represent NBER recession dates). The blue horizontal line denotes the 5% significance level.

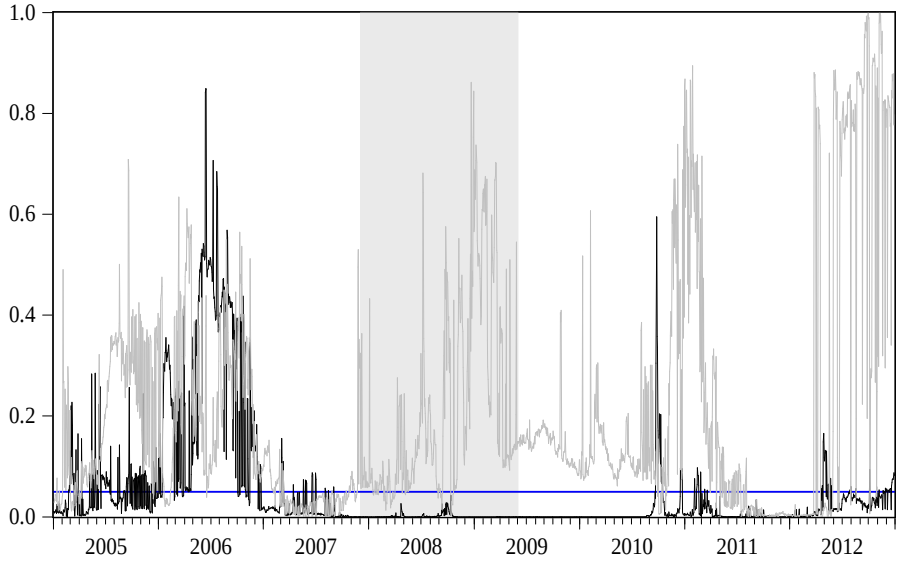

Fig.3. *Oil* $\nrightarrow$ *Gold* (black line) and *Gold* $\nrightarrow$ *Oil* (gray line) bootstrap *p*-values for VAR in levels (shaded areas represent NBER recession dates). The blue horizontal line denotes the 5% significance level.

Table 1. Linear Causality tests

	Linear Granger Causality (returns)			T&Y (log prices)		
	PI	PII	PIII	PI	PII	PIII
Oil↛Gold	20.68[a]	43.25[a]	71.06[a]	20.08[a]	53.94[a]	71.29[a]
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Gold↛Oil	0.918	29.88[a]	26.67[a]	7.03[c]	38.11[a]	25.44[b]
	(0.33)	(0.00)	(0.02)	(0.07)	(0.00)	(0.04)

Notes: ↛ denotes the non-causality null hypothesis. T&Y denotes the Toda and Yamamoto (1995) approach. The AIC was used to determine the optimal lag lengths for VAR(p) models. Numbers in parenthesis are the corresponding p-values. [c], [b], and [a] represent significance at 10%, 5%, and 1% level, respectively. We denote the pre-financial crisis period as PI (2003:01 till 2007:07), the post-financial crisis period as PII (2007:08 till 2012:12) and the entire sample period as PIII.

Table 2. Nonlinear Granger causality test

Lag	Raw data (returns)			VAR filtered series			GARCH-BEKK filtered data		
	PI	PII	PIII	PI	PII	PIII	PI	PII	PIII
Panel A: Oil↛Gold									
1	2.6[a]	4.12[a]	4.2[a]	1.67[b]	3.98[a]	3.36[a]	1.46[c]	1.12	1.52[c]
	(0.00)	(0.00)	(0.00)	(0.04)	(0.00)	(0.00)	(0.07)	(0.13)	(0.06)
2	0.29	2.48[a]	1.21	-0.13	3.06[a]	1.39[c]	-0.31	0.51	0.23
	(0.38)	(0.00)	(0.11)	(0.55)	(0.00)	(0.08)	(0.62)	(0.3)	(0.4)
3	-0.64	2.27[a]	0.33	-0.73	1.74[b]	0.02	-1.08	-0.74	-1.11
	(0.74)	(0.01)	(0.36)	(0.76)	(0.04)	(0.49)	(0.86)	(0.77)	(0.86)
4	-0.57	1.59[b]	0.24	-0.28	1.24[c]	0.05	-0.17	0.93	-0.66
	(0.71)	(0.05)	(0.40)	(0.61)	(0.1)	(0.47)	(0.57)	(0.17)	(0.74)
Panel B: Gold↛Oil									
1	-0.72	2.9[a]	1.94[b]	-1.15	2.49[a]	1.44[c]	-0.43	-0.04	0.07
	(0.76)	(0.00)	(0.02)	(0.87)	(0.00)	(0.07)	(0.66)	(0.51)	(0.47)
2	-0.43	2.07[a]	1.18	-0.48	2.08[a]	1.33[c]	-0.54	-0.3	0.08
	(0.66)	(0.01)	(0.11)	(0.68)	(0.01)	(0.09)	(0.29)	(0.61)	(0.46)
3	0.30	1.77[b]	1.52[c]	0.51	1.47[c]	2.03[b]	1.05	-0.54	0.84
	(0.38)	(0.03)	(0.06)	(0.3)	(0.07)	(0.02)	(0.14)	(0.7)	(0.19)
4	0.28	1.43[c]	1.27[c]	0.30	1.96[b]	2.06[a]	1.17	0.76	0.45
	(0.38)	(0.07)	(0.1)	(0.37)	(0.02)	(0.01)	(0.11)	(0.22)	(0.32)

Notes: This table reports the results of nonlinear causality test between oil and gold returns. ↛ denotes the non-causality null hypothesis. We set the lag length l^S=l^R=1 to 4. Numbers in parenthesis are the corresponding p-values. [c], [b], and [a] represent significance at 10%, 5%, and 1% level, respectively. PI: 01/2003-07/2007, PII: 08/2007-12/2012, PIII:01/2003-12/2012.

Table 3. Rolling windows rejection rates

	PI	PII	PIII	NBER recession
Date	12:2004-7:2007	8:2007-12:2012	12:2004-12:2012	12:2007-06:2009
Panel A: Returns (log differences)				
Oil↛Gold	95%(638)	89%(1258)	91%(1896)	99%(389)
Gold↛Oil	22.5%(153)	39%(555)	34%(708)	15%(58)
Total Obs.	672	1414	2086	390
Panel B: Levels (log prices)				
Oil↛Gold	50.52%(340)	94.34%(1334)	80.21%(1674)	100%(390)
Gold↛Oil	25.4%(171)	26.3%(372)	26.01%(543)	11.79%(46)
Total Obs.	673	1414	2087	390

Notes: ↛ denotes the non-causality null hypothesis. NBER recession denotes the US business cycle contraction period. Rejection counts at the 5% level are in parenthesis. PI: 01/2003-07/2007, PII: 08/2007-12/2012, PIII:01/2003-12/2012.

Table 4. Probit regression coefficients marginal effects

	Marginal Effect	Std. Error	z	P>|z|
Panel A: Returns (log differences)				
financial turmoil (D_1)	-0.26^a	0.03	-6.88	0.00
financial crisis(D_2)	0.35^a	0.04	7.91	0.00
euro crisis(D_3)	0.30^a	0.01	19.05	0.00
Panel B: Levels (log prices)				
financial turmoil (D_1)	0.12^a	0.02	4.58	0.00
financial crisis(D_2)	-0.16^b	0.06	-2.56	0.01
euro crisis(D_3)	0.06^a	0.02	3.10	0.00

Notes: ^{c}, ^{b}, and ^{a} represent significance at 10%, 5%, and 1% level, respectively. The dependent variable takes the value of 0 if we cannot reject the non-causality null (gold↛oil) and 1 otherwise.

Appendix

Table 5. Unit root and stationarity tests

Variables		ADF			PP			KPSS		
		PI	PII	PIII	PI	PII	PIII	PI	PII	PIII
		t-stat.			*t*-stat.			*t*-stat.		
Level										
Oil	c	-0.93	-1.76	-1.83	-1.02	-1.86	-1.93	4.04[a]	0.57[b]	3.97[a]
	c, t	-2.77	-1.78	-2.25	-2.86	-1.91	-2.49	0.6[a]	0.35[a]	0.53[a]
Gold	c	-0.63	-1.56	-0.37	-0.66	-1.55	-0.67	4.21[a]	4.49[a]	6.23[a]
	c, t	-2.99	-2.99	-3.89[b]	-2.75	-2.96	-3.96[a]	0.5[a]	0.29[a]	0.18[b]
1st differences										
Oil	c	-38.11[a]	-15.82[a]	-20.09[a]	-38.05[a]	-37.95[a]	-53.38[a]	0.03	0.07	0.06
	c, t	-38.09[a]	-15.81[a]	-20.1[a]	-38.04[a]	-37.93[a]	-53.38[a]	0.03	0.07	0.03
Gold	c	-10.98[a]	-37.64[a]	-11.79[a]	-33.61[a]	-37.69[a]	-50.7[a]	0.04	0.08	0.03
	c, t	-10.98[a]	-37.64[a]	-11.79[a]	-33.6[a]	-37.70[a]	-50.69[a]	0.03	0.03	0.02

Notes: The unit root and stationarity tests are applied with (c,t) and without (c) a time trend. Null hypothesis for the KPSS test is stationarity. The critical values for ADF and Philllips-Perron (PP) statistics are taken from MacKinnon (1996). Superscripts [c], [b], and [a] represent significance at 10%, 5%, and 1% level, respectively. Lag lengths are determined via AIC. PP was conducted using Bartlett Kernel (Newey-West Automatic). PI: 01/2003-07/2007, PII: 08/2007-12/2012, PIII:01/2003-12/2012.

Table 6. Lee and Strazicich (2004) unit root test with one break

		PI		PII		PIII	
		t-stat	T_B	*t*-stat	T_B	*t*-stat	T_B
Oil	Model A	-2.89[5]	5/21/04	-2.01[12]	1/6/09	-2.5[7]	1/6/09
	Model C	-3.75[1]	8/30/05	-2.64[12]	11/12/08	-2.85[7]	3/31/05
Gold	Model A	-2.95[9]	2/16/06	-3.17[11]	9/10/08	-3.05[11]	3/18/09
	Model C	-4.24[9][c]	12/27/05	-3.29[11]	9/10/08	-4.43[11][c]	11/14/05

Notes: The tests critical values are obtained from Lee and Strazicich, (2004, table 1). T_B denotes the endogenously determined break points. Numbers in brackets denote the optimal number of lagged first-differenced terms included to correct for serial correlation. PI: 01/2003-07/2007, PII: 08/2007-12/2012, PIII:01/2003-12/2012.

Table 7. Lee and Strazicich (2003) unit root test with two breaks

		PI			PII			PIII		
		t-stat	1st T_B	2nd T_B	t-stat	1st T_B	2nd T_B	t-stat	1st T_B	2nd T_B
Oil	Model A	-3.12[5]	5/21/04	3/25/05	-2.08[12]	1/6/09	5/25/10	-2.6[7]	3/23/05	9/26/08
	Model C	-4.91[1]	12/4/03	9/7/06	-4.00[12]	10/2/08	6/2/09	-3.87[7]	9/26/08	10/19/09
Gold	Model A	-3.09[9]	1/2/06	7/26/06	-3.38[11]	9/10/08	4/3/12	-3.21[9]	5/29/06	8/23/11
	Model C	-5.23[9]	11/4/05	6/8/06	-5.57[9][c]	7/30/08	8/23/11	-4.78[9]	7/30/08	8/23/09

Notes: The tests critical values are obtained from Lee and Strazicich (2003, table 2). T_B denotes the endogenously determined break points. Numbers in brackets denote the optimal number of lagged first-differenced terms. PI: 01/2003-07/2007, PII: 08/2007-12/2012, PIII:01/2003-12/2012.

Table 8. Johansen trace test

r	Model 2			Model 3			Model 4		
	PI	PII	PIII	PI	PII	PIII	PI	PII	PIII
0	9.04	10.6	13.40	5.2	7.14	6.51	17.19	23.05	23.60
	(0.73)	(0.58)	(0.33)	(0.78)	(0.56)	(0.63)	(0.4)	(0.1)	(0.09)
1	4.02	3.52	4.91	0.27	2.5	0.27	4.81	4.35	5.85
	(0.4)	(0.48)	(0.29)	(0.6)	(0.11)	(0.59)	(0.62)	(0.69)	(0.47)

Notes: Figures in the parenthesis are p-values. The AIC was used to determine the optimal lag length. Model 2 includes intercept in the cointegration relation, Model 3 includes deterministic trends in level and Model 4 allows for trend in the cointegrating space. PI: 01/2003-07/2007, PII: 08/2007-12/2012, PIII:01/2003-12/2012.