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Do Precious Metals Have a Capacity to Hedge against Inflation

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Abstract

This study examines the inflation-hedging capacity of four precious metals: gold, silver, platinum and palladium. The ability to hedge is assessed using nominal spot returns of precious metals and the CPI inflation rate. The inflation-hedging potential is measured by the Pearson correlation coefficient as well as three alternative hedging measures. Moreover, the hedging capacity is analyzed across different investment horizons and two sample periods (1974/2013 and 1990/2013). The evidence from this research shows that individual precious metals should not be considered as substitutes in reducing the inflation risk. This paper established that gold and platinum have the most significant and reliable inflation-hedging capacity among the investigated precious metals. On the whole, all analyzed assets consistently exhibit the inflation-hedging property, particularly during the episodes of economic and financial turmoil.

Keywords: precious metals; inflation hedging; spot price; investment horizon

INTRODUCTION

In the last couple of years, there has been an increasing interest in the impact of quantitative easing practices and fiscal policies of the world's major central banks in the United States and Japan. As a result, very topical questions have arisen about the role of precious metals, particularly gold and silver, in the inflationary economic environment, which is focused on keeping the interest rates low at the expense of price stability. The aim of this research is to evaluate an individual potential of different precious metals to hedge against the US originated inflation, namely: gold, silver, platinum and palladium, during the years 1974-2013 and 1990-2013. This study examines general hedging capacity of precious metals using a simple "quick scan" for measuring the hedging potential in form of the Pearson correlation coefficient (Spierdijk & Umar, 2013a).

Over the past decade, the precious metals market has seen a remarkable increase in nominal prices, what has attracted the interest of public opinion and caused spreading misconceptions about the nature of long term investments. As explained by Bialkowski et al. (2011), the recent gold price boom is not a speculative bubble and its value is fundamentally sound. There is, however, a variety of controversial opinions as to what factors have driven the recent changes in the metals' prices. For instance, the Nobel prize laureate in Economics in 2008, Paul Krugman (2011), remarked:

"So what determines the price of gold at any given point in time? Hotelling models say that people are willing to hold onto an exhaustible resources because they are rewarded with a rising price. Abstracting from storage costs, this says that the real price must rise at a rate equal to the real rate of interest".

The current economic crisis has revealed many weaknesses of the biggest world economies and encouraged inflationary practices. After the prices of precious metals plunged in 2008, they started to recover in the end of 2009. Over the years 2003-2012, the increasing prices of gold, silver and platinum reached the all-time high levels in 2011. For instance, the London Fix gold prices hit the historical level of almost $1900 per ounce in September 2011, whereas gold cost approximately $350 per ounce in January 2003[1].

Traditionally, people have subscribed to the belief that gold and silver are practically risk-free in long investment horizons and offer a natural hedge against inflation. This common perception is probably based on the fact that gold has historically maintained its purchasing power. During the current crisis in the Euro Area and the financial cliff in the United States, the sustainability and adequacy of the pension funds have become vocal in the public domain. With respect to the long term investment profile, the well recognized fact about pension funds is that one of their main objectives is the protection of pension outcome against inflation. In view of the Asset and Liability Management (ALM) mechanism, Amenc et al. (2009) showed that commodities have significant inflation-hedging properties and are a valuable investment for the long-term investors. Nonetheless, in the search for new ways of securing pension income, a possible use of individual precious metals to hedge the positions of institutional investors remains questionable.

In the past, "the automatic stabilizing mechanism" for the price of gold was determined by a relative value of its supply and demand, for instance: if the price level had increased, the relative price of gold to the other goods was reduced, what also was likely to reduce the incentives to produce gold and increase its price (Capie et al., 2005). The fall of the Bretton

[1] Source: the London Bullion Market Association (LBMA) and the London Platinum & Palladium Market (LPPM).

Woods system (1968-1973) marks a critical point in the history of the precious metals' prices and the detachment of gold value from the monetary system. However, it was not until the breakdown of the Smithsonian Agreement in March 1973 and the introduction of a floating exchange system by major European banks that the convertibility of dollar to gold eventually collapsed (Wang et al., 2011).

Some of the most important issues concerning metals trading is “price transparency of spot and forward markets, the ability to manage risk through hedging, and the ability to take physical possession of usable metal” (Stundza, 2000: 40B14). The end of the gold standard did not imply that gold had lost its hedging potential (see Capie et al., 2005, for a review). Although gold stopped being a medium of exchange, it has maintained the property to store value and the potential to hedge against inflation as a commodity and a financial asset. Gold can be described as a unique commodity because of its durability, acceptability and liquidity. It can also be relatively easily authenticated and transported (Worthington & Pahlavani, 2007). Nowadays, the demand for gold is determined by both industrial demand and institutional investment demand (Levin & Wright, 2006). Moreover, some authors suggest that the demand for gold can rise with the expected inflation rate (e.g. Feldstein, 1980).

Platinum and palladium could be identified as the second most important precious metals in the global markets after gold and silver. However, in the academic literature on precious metals, platinum is often analyzed separately from gold and silver. It is often assumed to represent "the other metals", like palladium (e.g. Hillier et al., 2006). The prices of palladium have been "playing catch up" with platinum and the two metals have information content to each other similar to the content between gold and silver (Sari et al., 2010). Historically, the returns for platinum and palladium show the strongest positive correlation among all precious metals but the correlation between palladium and gold is relatively weak (Hammoudeh et al., 2010).

As Hillier *et alii* (2006) remarks: "platinum is also jointly extracted with other metals (especially palladium)" (Hillier et al., 2006: 99). He also commented that platinum offers some hedging potential for stock during the time of extreme market volatility (i.e. the "safe haven" property). Besides, most of the demand for platinum and palladium is created by the autocatalyst industry while non-industrial usage dominates in the gold and silver markets (O'Connell, 2005). Platinum and palladium can be, therefore, characterized more as a commodity, rather than a traditional investment of the last resort (i.e. gold and silver) (Hillier et al., 2006). The similar factors that determine demand for platinum and palladium do not, however, imply sharing a common price behavior[2].

In spite of the different factors influencing demand for gold, silver, platinum and palladium, the prices of precious metals are related to each other. The correlation between platinum and gold has been, in general, recognized as strong and positive, except one period of structural break in the years 1996-2001 (Kearney & Lombra, 2009). Regardless of the fact that the price of platinum is often found to closely follow the price of gold, this relationship has recently been more significant for silver (Sari et al., 2010).

The long term relationship between price movements of gold and silver is also proven to be significant, although, some demand factors for gold are different than for silver. As Hammoudeh and colleagues reported: "silver outperforms gold when the market is up and does worse when the market is down. Traders know it is better to buy silver before gold when the market is booming, but to sell silver before gold when the market starts to head down" (Hammoudeh et al., 2010: 636). The demand for gold is dominated by the financial operations of central banks and jewelry industry, whereas the monetary role of silver has been phasing out. The

[2] Sari et al. (2010) commented: "palladium jewelry also competes with platinum jewelry in China" (Sari et al., 2010).

demand for silver is more commodity-driven and derives partially from its specific industrial usage (i.e. silver is an excellent conductor of heat and electricity) (Ciner, 2001). As opposed to the differences in commercial uses of the precious metals, many authors have found a long term cointegration relationship between gold and silver (e.g. Wahab et al., 1994; Escribano & Granger, 1998 and Liu & Chou, 2003).

From the perspective of long term investors, the close relationship between gold and silver would make investing in both metals unattractive[3] (Lucey & Tully, 2006). However, a recent study by Ciner (2001) on precious metals in the Tokyo Commodity Exchange, suggests that the long term relation between gold and silver prices no longer exists and the two assets should not be regarded as substitutes considering their capacity to hedge similar risks (also see Erb & Harvey, 2006; Batten et al., 2008). For this reason, it seems appropriate to separately assess the capacity of each precious metal to hedge against inflation, in order to obtain more transparent and direct hedging measures.

The aim of this study is to evaluate the inflation-hedging capacity of the spot returns for gold, silver, platinum and palladium in two sample periods from January 1974 until February 2013 and from April 1990 until February 2013. The hedging potential of the individual precious metals is estimated using the Pearson correlation coefficient. Furthermore, three alternative hedging measures are introduced to allow for a comparison between different interpretations of the hedging capacity (i.e. the Fisher coefficient (β), the hedge ratio (Δ) by Schotman & Schweitzer, 2000 and the hedge ratio (S) by Bodie, 1976). In pursuance of more universal estimations, this paper attempt to measure the hedging capacity for various investment horizons

[3] Lucey and Tully conclude: "this relationship is neither stable nor constant however and thus there may be potential at certain times to include both. In particular, as many funds, etc. are rebalanced annually, if not more frequently, and as can be seen that in most one year samples there is not a stable relationship, the case for the inclusion of both gold and silver in portfolios may still be defensible" (Lucey & Tully, 2006: 53).

ranging between one-month and ten-years. Rolling window and extending window analyses are also included to account for time-variations in the hedging capacity of precious metals.

This paper finds that the examined spot returns of precious metals show significant ability to hedge against the US CPI inflation rate, in particular considering gold and platinum. The study has been organized in the following way. The first section discusses the academic literature on properties of precious metals as an investment instrument in form of a brief review. The second chapter describes the methodology of this research in detail. The third section gives an overview of the data and sample periods which are used in this investigation. In the next part of this paper, the empirical analysis of the econometric model and hedging estimates are provided. Finally, the last two sections summarize and conclude the main results.

BRIEF LITERATURE SURVEY ON PRECIOUS METALS

Notwithstanding the vast academic literature describing possible use of gold as a financial instrument, most of available research on the hedging capacity ignores individual potential of the other commonly-traded precious metals. In addition, relatively little work has been dedicated to a quantitative research into the hedging potential of platinum and palladium. A large and growing body of literature has investigated the hedging potential of commodities (e.g. Bodie, 1983; Bird, 1984; Ankrim & Hansel, 1993; Hoevenaars et al., 2008; Gorton & Rouwenhorst, 2006) and gold has certainly been one of the most extensively analyzed commodities. In an excellent study on gold, the World Gold Council concluded:

"Gold has a unique performance profile in terms of returns, volatility and correlation, and these characteristics combine to produce in gold a very different reaction to economic and financial variables relative to other commodities in periods of expansion and recession alike" (WGC, 2011: 16).

In relation to precious metals, it has been previously suggested that gold can been considered as a commodity (Salant & Henderson, 1978; Solt & Swanson, 1981; amongst several others). From a theoretical point of view, commodities are potentially a valuable investment because they offer relatively idiosyncratic risks (e.g. weather, geopolitical, supply, and event risks), in comparison to stock or bonds (Daskalaki & Skiadopoulos, 2011). Another common perception is that commodities can provide a hedge against inflation. However, Ciner (2011) questions the causality from inflation to commodity prices and suggests the reverse casualty with respect to transmission of permanent shocks. Jaffe (1989) points out that if we classify gold as a commodity, its price is expected to rise with the supply-side driven inflation levels thus offering a hedge against domestic currency depreciation.

Nevertheless, the seemingly related precious metals show different characteristics than the other commodities. Over the last forty years, precious metals have exhibited different cycle lengths of commodity price busts than the other commodities (Jacks, 2013). The volatility of gold and silver is more persistent than in case of other commodities (e.g. copper), hence those assets can be attractive for the investors seeking short-term volatility (Hammoudeh & Yuan, 2008). Baur (2013) has recently reported that gold exhibits seasonal anomalies in September and November with statistically significant positive returns and lower volatility than in the other months.

The reminder of this chapter starts with explaining how precious metals can be utilized as investment instruments. Next, the hedging potential of precious metals is discussed. In the context of hedging properties, the literature on precious metals has covered a number of specific research areas, which could roughly be classified into two groups. One strand of the literature is focused on the relationship between returns of the metals and stock returns. Another category of studies explores the capacity of precious metals to hedge against inflation.

Investments and prices of precious metals

Popular aggregate commodity indices, which are applied in research on the hedging capacity of an asset, often suffer from aggregate bias as they can add some unrelated risks (Sari et al., 2010). It has been argued that the structure of correlations and returns differs between individual commodity indices and aggregate commodity indices (e.g. Erb & Harvey, 2006; Fulli-Lemaire, 2013). Michaud and colleagues (2006) questioned the relevance of the commodity future indices components in understanding the gold returns (e.g. insurance premium, collateral yield or roll/convenience yields). They concluded that gold is a useful tactical asset in institutional strategic asset allocation using the London Fix spot price of gold[4]. Considering the hedging potential of precious metals, the returns on individual commodities' prices can provide a more transparent and direct financial measures than future commodity indices (Michaud et al., 2006).

There are many ways to invest in precious metals. Bullion, stocks of mining companies and mutual funds (i.e. investing in the precious metals stocks and bullion) are the most common methods of exposure to precious metals' price fluctuations. They are mainly suitable for small investors, who cannot afford holding large positions in future contracts, and usually involve high transaction costs (Blose, 1996). The purpose of using the future price contracts is to partially eliminate the transaction costs and decrease the risk of spot prices' volatility, although it also implies limiting potential profits from favorable price movements (NYMEX, 2001). Fixing the price of the future contracts can limit or prevent realization of the potential inflation-hedging benefits from investing in precious metals during the time of financial and economic turmoil. For

[4] ''During times of relative stability a small positive allocation may be useful. During time periods of abnormally positive economic activity gold returns may reflect multiplier effects associated with cultural issues. During periods of fiscal or monetary mismanagement, crises of various kinds or fundamental changes in the dominant currency, gold may be a very useful asset for hedging risk'' (Michaud et al., 2006: 26).

this reason, the spot prices can be useful in assessing the time-variations in the inflation-hedging capacity of precious metals and the hedging potential of corresponding future contracts. Ultimately, a choice between focusing on spot prices or future prices of precious metals depends on the preferences[5] of different users, including speculators, arbitrageurs, "investors, traders, physical users and physical producers" (El Hedi et al., 2012).

The spot prices of precious metals include the expectations of future price movements and the value future contracts converges to spot prices at the expiration. Regarding precious metals as non-perishable physical commodities, their cost of carry should be higher than potential arbitrage opportunities[6]. Under normal market conditions and adequate supplies, the future prices of commodities should be equal the present spot prices plus the cost of carry (NYMEX, 2001). This situation leads to the contango structure of the future markets, where the spot prices are lower than corresponding future prices. As noted by NYMEX (2001): "precious metals markets are almost always contango markets which reflect carrying charges. The contango is particularly consistent in gold because of a perceived unlimited spot supply of gold in central bank holdings" (NYMEX, 2001: 6). Adequately, the physical precious metals are an attractive investment opportunity in comparison to the future contracts, if the prevailing cost of carry is lower than the contango (NYMEX, 2001).

Nonetheless, the differences between the future contracts and the spot prices "usually is not a major consideration in the precious metals markets"[7] (NYMEX, 2001: 17). Furthermore,

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[5] For a discussion of different perspectives on metals hedging see NYMEX (2001).

[6] As Fassas explains: "where storage is feasible, its costs have to be compared with the futures rollover costs. Therefore, but a new structure of ETPs has recently emerged (especially in Europe), which uses synthetic replication through derivatives" (Fassas, 2011: 139).

[7] "Gold returns tend to be consistent regardless of whether an investor chooses to use spot or futures. (…) This is a by-product of the shape of the gold futures curve, which tends to be flat for the most actively traded frontend of the

the spot prices of precious metals are relatively insensitive to the changes in their supply (i.e. inventory) and the high available inventory of precious metals is likely to preserve the contangoed markets[8] (Symeonidis et al., 2012). As a consequence, the spot prices of precious metals constitute a vital price signal for the future contracts and can be employed as a feasible proxy in the analysis of the inflation-hedging capacity of precious metals (e.g. Gosh et al., 2004; Capie et al., 2005; McMillan, 2005; El Hedi et al., 2012).

Recently, there has been an increasing interest in exchange traded fund (ETFs) investing in precious metals, which are often argued to be a more tax-friendly alternative to the traditional index mutual funds[9]. Despite their capacity to gain tax efficiencies and trading flexibility, ETFs are not a valuable investment vehicle for the defined-contributions pension plans because of the long investment horizons and the tax-deferred nature of retirement liabilities (Dellva, 2001). Besides, the brokers commissions involved in trading the ETF's securities significantly lower their attractiveness for the small investors, "who cannot afford to create country-specific ETFs in kind and are used to investing small amounts periodically" (Miffre, 2007: 114).

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curve, and the fact that most investors either trade in spot or can potentially take physical delivery of the futures contracts. However, exercising this latter option can be quite costly and is not often taken" (WGC, 2011: 15).

[8] "Metals, and gold in particular, exhibit the lowest correlation with inventory. (…). Low storage costs relative to their value and sufficiently high inventory levels relative to demand, especially for precious metals, are the main reasons for these low correlations" (Symeonidis et al., 2012: 2657).

[9] ''ETF shares are issued to and redeemed from institutional investors "in kind," meaning institutions deliver or receive baskets of stocks in exchange for ETF shares. Institutions receiving these shares are indifferent as to the cost basis of the individual shares because their cost basis is the price they paid when they created the ETF. (…) This process should reduce the realized capital gains for the ETF as a result of changes in the benchmark portfolio. Shares distributed in kind are not a taxable event for the ETF. Managers can use the in-kind redemption to change the compositions of the ETF without triggering a tax liability" (Dellva, 2001: 122).

Spierdijk and Umar (2013a: 12) mentioned exchange traded funds (ETFs) and exchange traded notes (ETNs) in the context of inflation hedging as the means of direct investment in S&P GSCI Total Return Index[10] (see also, Fulli-Lemaire, 2013, for a discussion). Similarly to the S&P GSCI index[11], the spot prices of precious metal can be separately utilized through a synthetic replication of price derivatives. The ETFs can invest in a basket of precious metals or consider the assets separately, allowing investors to get exposure to the performance of precious metals. In fact, Fassas (2011) demonstrates that the recent inflows of capital into the commodity-linked exchange traded products (ETPs) "are an important driver of the spot prices" and "have a direct effect on the spot prices of gold, silver and platinum, but rule out the case of causality" (Fassas, 2011: 127-138). Although the ETPs can be used by financial institutions to directly invest in precious metals (i.e. by a gold holding trust or tracking spot prices, future contracts and other indices of precious metals), equities of precious metals companies continue to be the most common way of investment (Conover et al., 2009).

[10] "The GSCI index uses T-bills as collateral. Currently the S&P GSCI includes 24 commodity futures contracts, classified into five groups (energy, industrial metals, precious metals, agriculture, and livestock)" (Spierdijk & Umar, 2013a: 12).

[11] The other two most popular commodity indices are the Dow Jones-AIG Commodity Index (DJ AIG) and the Reuters-CRB (Commodity Research Bureau) Index (CRB) (Michaud et al., 2006).

Precious metals and stocks

Previous studies have reported the capacity of gold to hedge against stocks (e.g. Baur & Lucey, 2010; Baur & McDermott, 2010). Coudert and Raymond-Feingold (2011) examined the hedging potential of gold to hedge against stocks applying the standard cointegration test for a long-run relationship in the years 1978-2009. Gold was found to be weakly correlated on average with stocks and offer a good long term hedging opportunity for the US investors (Coudert & Raymond-Feingold, 2011). Recently, Kolev (2013) has documented that average gold returns were less volatile and twice as large as the returns on the aggregate stock market, during the quantitative easing sub-sample period in the US from September 2008 until January 2013.

When one talks about the long term hedging capacity of precious metals, a distinction should be introduced between the speculative short-term focus on precious metals' returns and their hedging capacity. The short term focus on price and returns is also important to understand the precautionary demand for gold as well as the role of gold as a "safe haven". Chong and Miffre (2010) suggest that precious metals (i.e. gold, silver and platinum) are a valuable diversifier and a "refuge asset" for stock markets in periods of high volatility. The term "safe haven" refers to so-called "flight to quality" or "flight to safety" episodes when capital flows into the assets classes, which can offer positive returns during periods of economic and financial turmoil (e.g. Caballero & Krishnamurthy, 2008; Conover et al., 2009: Coudert & Raymond-Feingold, 2011).

Baur and Lucey (2010), argue that in the short run, despite its historically high volatility, gold may offer a "safe haven" opportunity for stocks. The "safe haven" opportunity could be defined as an uncorrelated or a negatively correlated asset during the time of economic distress[12]

[12] In their analysis of the investment potential of gold, Baur and Lucey (2010) introduce also a distinction between a hedge (i.e. an asset that is on average uncorrelated or negatively correlated with another asset) and a diversifier (i.e. an asset that is on average positively correlated with another asset).

(Baur & Lucey, 2010). Nevertheless, “in the longer run, gold is not a safe haven, that is, investors that hold gold more than 15 trading days after an extreme negative shock lose money with their gold investment” (Baur & Lucey, 2010: 228).

The literature on the relationship between precious metals and stock draws heavily from the Capital Asset Pricing Model (CAPM). On the one hand, the returns of precious metals are historically highly volatile. This finding suggests that holding an undiversified portfolio of precious metals can be very risky. On the other hand, commodities like precious metals can reduce the overall riskiness of a portfolio. In 1989, Jaffe published a paper in which he described the relationship between precious metals (i.e. gold and silver) and returns on common stocks in the years 1971-87. In this research, the standardized covariance (i.e. "beta") of the returns on physical gold with the returns on the S&P 500 proxy was identified to be near to zero. McCown and Zimmerman (2010) also pointed out that gold and silver can be characterized by the market risk close to zero in the years 1970-2006. Hillier et al. (2006) investigated the potential benefits of including gold, silver and platinum in the S&P500 index portfolio, in the years 1976-2004, and found that each of those precious metal can improve the portfolio performance. In another study of the S&P500 portfolio, Chua and colleagues (1990) conclude that gold bullion is a more reliable medium of diversification then gold stocks and has its beta indistinguishable from zero in the 1970s and 1980s.

Hedge against inflation

Considering the recognized store value of gold, the use of this commodity as a proxy for changes in inflation has been widely discussed. Feldstein (1980) shows that an increase in expected inflation is likely to increase the relative price of gold. Chua and Woodward (1982) demonstrate that gold is a good hedge against both unexpected and expected inflation. Nevertheless, the relationship between gold and the unexpected inflation has often been questioned. In a more recent study, Blose (2010) has demonstrated that the spot prices of gold do not change with the unexpected changes in inflation and gold should not be used to predict inflation expectations.

There is a large volume of published studies addressing the role of precious metals in hedging against inflation. Nevertheless, the academic literature on hedging properties of precious metals is biased towards the analysis of the hedging potential of gold. For example, Jaffe (1989) tests the inflation-hedging properties of gold by regressing the monthly nominal returns on the CPI inflation over the period 1971-87 and shows that a one per cent change in the price level was associated with a 2.95% increase in the price of gold. Much of the available research on the hedging properties of gold has been conducted employing the conventional VAR and cointegration frameworks (e.g. Kolluri, 1981; Moore, 1990; Mahdavi & Zhou, 1997; Ghosh et al., 2004 and Beckmann & Czudaj, 2013). However, the results of the research are often inconsistent.

In an investigation into the potential of gold to hedge against inflation during 1976-2005, Levin and Wright (2006) found a significant long term relation between gold and inflation following the Johansen procedure and the cointegration method. This finding confirms the common perception that gold is a good long term hedge against inflation as well as it supports the hypothesis that a one-percent increase in the US price level causes the same increase in the price of gold (Levin & Wright, 2006). However, Taylor (1998) argued that silver is the only precious metal, which vary in the long term one-to-one relation with inflation. In another study, McCown and Zimmerman (2010) provided evidence that gold and to a smaller degree silver have the capacity to hedge against inflation using the cointegration approach. The research on the long term relation between gold and inflation is not, however, entirely devoted to the US market. By way of illustration, Rubbaniy et al. (2012) examines the relationship between precious metals (i.e. gold, silver, platinum) and the German inflation over the period 1985-2010. Using the cointegration technique, he argued gold is the only precious metals which can provide long term inflation-hedge.

Despite the fact that majority of studies prove the significance of the cointegrating relation, some authors have questioned this result. For instance, according to Mahdavi and Zhou (1997), no cointegration between gold and inflation was observed in the years 1970 to 1994. Worthington and Pahlavani (2007) showed that there exists a structural break in the long-run relationship between gold and inflation in the 1970s but the cointegration is strong in the post-1970s period. Perhaps the most serious disadvantage of the cointegration method is that it relies on the assumption about the degree of integration of the US CPI (see Mahdavi & Zhou, 1997). In an investigation into the properties of inflation time series, Murray et al. (2009) concluded that only the years 1967-81 can be characterized by a unit-root and inflation is stationary in other periods. Consequently, the cointegration analysis is sensitive to the choice of sample period and stationarity test.

A variety of definitions of the capacity of an asset to hedge against inflation have been suggested. For example, an asset which offers a good hedge against inflation in short-run, can be described as significantly and positively correlated with inflation[13] (Taylor, 1998). This interpretation, however, requires taking a long position in a given asset by investors, in order to reduce the risk of liabilities (see Brealey & Myers, 1991 and Taylor, 1998). The general hedging capacity can be easily assessed by analyzing the regression coefficient (i.e. the "Fisher coefficient") in a simple OLS regression, where the returns for assets are a dependent variable and the *ex-post* inflation rates are a regressor (e.g. Jaffe & Mandelker, 1976; Boudoukh & Richardson, 1993; Taylor, 1998; Bekaert & Wang, 2010). This approach is one of the "quick scan" methods which are available for measuring the hedging potential of an asset[14].

As noted by Bruno and Chincarini (2011), relatively little academic literature has been published on what proportions of different asset classes in a portfolio are appropriate for hedging against inflation. They examined the potential of gold to hedge against inflation using mean-variance optimization of real returns and found that gold can be utilized in the mean-variance portfolio (i.e. 5-10% of the portfolio's value) "while minimizing the downside risk from inflation" (Bruno & Chincarini, 2011: 113). In his seminal paper, Bodie (1976) refers to the hedging capacity of an asset, which has the potential to reduce real return variance of a nominally risk-free portfolio. This approach is supported by the work of Spierdijk and Umar (2010, 2013a & 2013b), who show that an interpretation of the hedging measures by Bodie (1976) could be simplified to an analysis of the Pearson correlation coefficient.

Furthermore, Spierdijk and Umar (2013a) compared the four common measures of the capacity of commodities to hedge against inflation. In their studies, the authors explained that the

[13] Another approach to determine a hedge includes setting a certain limit on the downside risk of an asset and measuring a reduction in the probability of real returns to fall below the specified threshold (see Reilly et al., 1970 and Branch, 1974).

[14] Taylor (1998) performed similar analysis for platinum and palladium (i.e. 1988-1996) adopting the regression measures mentioned above, although, he found little evidence for the hedging potential the two metals.

Pearson correlation between inflation and nominal returns (see Bodie, 1982 and Hoevenaars et al., 2008) is the important link between the Fisher coefficient, the hedge ratio by Schotman and Schweitzer (2000) and the hedge ratio by Bodie (1976). In addition, they showed that the interpretation of different hedging measures depends on investors' preferences and can lead to contradictory results. Accordingly, it is advised that the correlation coefficient should be the leading indicator of inflation-hedging capacity as a "scale-free" measure (Spierdijk and Umar, 2013a).

METHODOLOGY

A variety of methods is used to assess the hedging capacity of an asset. The previous studies by Spierdijk and Umar (2013a & 2013b) have reported four common hedging capacity measures, which can be used as a "quick scan" for the hedging capacity of an asset. The calculations of the hedging measures are constructed on the "stand-alone" basis and designed to measure only the relationship between a precious metal's return and an inflation rate. Firstly, one-period hedging measures are discussed. Secondly, in order to include the multi-period perspective, a dynamic extension in form of a bivariate VAR system is explained[15]. The wild bootstrap technique is introduced to construct confidence intervals for the multi-period measures. Moreover, the rolling and extending window analysis is applied in this study to capture time variations in the correlation coefficients.

Notation

It is assumed that a simple *k*-period nominal return on an asset from time *t* until *t+k* is denoted as $R_t^{(k)}$. $\pi_t^{(k)}$ designates the inflation rate from time *t* until *t+k*.

[15] In this paper, the terms "multi-period hedging measures", "holding period" and "investment horizon" are used interchangeably. They attempt to describe a hedge opportunity from the perspectives of short-term and long-term investors.

The Pearson correlation (ρ)

$$\rho = Corr_t\left[R_t^{(k)}, \pi_t^{(k)}\right] \qquad \textbf{(1)}$$

The Pearson correlation is applied in order to capture the general strength of a linear relation between inflation rate and nominal returns of an asset (see Bodie, 1982). Despite the fact that a complete characterization of the relationship can be achieved only when the normality assumption holds, this measurement is potentially meaningful for the analysis of hedging capacity. The absolute value of the correlation coefficient (ρ) in *Equation 1* determines the hedging capacity of an asset[16]. A positive value of ρ implies a long position in an asset and the negative value indicates a short position (Hoevenaars et al., 2008; Spierdijk & Umar 2010, 2013a and 2013b).

[16] The higher is the absolute value of the correlation, the better a hedging capacity is considered to be. The interpretation of the Pearson correlation (ρ) as a measure of the hedging capacity of an asset against inflation can be summarized as follows: if $-1 < \rho < 0$, then an asset is considered to be a "perverse hedge"; $0 < \rho < 1$ shows a "positive hedge"; $\rho = 0$ is a "non-hedge"; $\rho = 1$ or $\rho = -1$ determine a "perfect hedge" (i.e. in line with Hoevenaars et al., 2008; Spierdijk & Umar, 2010, 2013a and 2013b).

The Fisher coefficient (β)

This measure is based on the original Fisher hypothesis (Fisher, 1930), which describes the one-to-one relation between the expected nominal return on an asset and the expected inflation rate at a given time *t*. This paper utilizes the empirical regression approach towards the Fisher hypothesis, which have been proposed by Fama and Schwert (1977) and further developed by Boudoukh and Richardson (1993) (also see Bekaert & Wang, 2010). This paper uses the OLS regression model by Boudoukh and Richardson (1993: 1348), which estimates the relationship between the asset returns and the *ex-post* inflation rate[17]:

$$R_t^{(k)} = \mu^{(k)} + \beta^{(k)}\pi_t^{(k)} + \varepsilon_t^{(k)} \qquad \textbf{(2)}$$

i.e. $Corr_t\left[\varepsilon_t^{(k)}, \pi_t^{(k)}\right] = 0$, $E_t\left[\varepsilon_t^{(k)}\right] = 0$ and $Var_t\left[\varepsilon_t^{(k)}\right] = \sigma^2 \neq 0$

The Fisher coefficient (β) in *Equation 2* "reflects the contemporaneous impact of inflation on expected asset returns" (Spierdijk & Umar, 2013a: 5). The underlying assumption is that β=1 "is consistent with the hypothesis that real return are complete hedge against inflation", 0< β<1 implies a partial hedge, β<1 is a perverse hedge and β>1 is more than complete hedge (Spierdijk & Umar, 2010: 8).

[17] As Spierdijk and Umar remark: "since ex post inflation is equal to the ex ante inflation rate plus a prediction error (...) the OLS estimates (...) can be viewed as coming from a regression of returns on expected inflation in the presence of measurement errors. This results in the problem of errors-in-variables, inducing a bias in the estimate of" the Fisher coefficient (β) (...) usually, this bias is downward" (Spierdijk & Umar, 2010: 8).

The hedge ratio (Δ) by Schotman and Schweitzer (2000)

The concept of hedging demand, which is independent of the level of risk aversion of a mean-variance investor, comes from the work by Campbell and Viceira (2000), where the authors distinguished it from the speculative asset demand. Schotman and Schweitzer (2000) focused separately on the two kinds of the mean-variance investor's demand and described the inflation hedging demand as[18]:

$$\Delta^{(k)} = \frac{Cov_t\left[R_t^{(k)}, \pi_t^{(k)}\right]}{Var_t\left[R_t^{(k)}\right]} \qquad \textbf{(3)}$$

The higher is the magnitude of the hedge ratio in *Equation 3*, the better is an asset as a hedge against inflation (Schotman & Schweitzer, 2000; Spierdijk & Umar, 2010, 2013a and 2013b). Alternatively, this ratio can be determined by analyzing the weights of inflation-tracking portfolio by Lynch (2001) (see *Equation 4*). The hedge ratio can be interpreted as "a special case of an inflation-tracking portfolio, where the inflation rate is tracked by a single nominal return series" (Spierdijk & Umar, 2013a: 6).

$$\pi_t^{(k)} = c^{(k)} + \Delta^{(k)} R_t^{(k)} + \eta_t{}^{(k)} \qquad \textbf{(4)}$$

i.e. $Corr_t\left[\eta_t{}^{(k)}, R_t^{(k)}\right] = 0$, $E_t\left[\eta_t{}^{(k)}\right] = 0$ and $Var_t\left[\eta_t{}^{(k)}\right] = \sigma^2 \neq 0$

[18] "The hedging demand represents the fraction of the asset that has to be added to the nominal bonds in order to obtain the global minimum-variance (GMV) portfolio" (Spierdijk & Umar, 2013a: 5).

The hedge ratio (*S*) by Bodie (1976)

Bodie (1976) demonstrated an application of the global minimum variance (GMV) portfolio framework for calculating the hedge ratio and the cost of hedging. In his analysis of the inflation hedging capacity of an asset, Bodie (1976) created a nominally riskless portfolio that consists only of risk-free bonds (e.g. T-bills). He postulated that by adding a risky security to this portfolio, the associated maximum possible reduction in the real return variance can capture the hedging capacity of an asset, whereas the associated minimum reduction in the real expected return represents the cost of hedging (see Spierdijk & Umar, 2010, 2013a and 2013b).

The only risk present in this framework, which affects the real returns, is the inflation risk (i.e. nominal returns are risky). Accordingly, the hedge ratio (*S*) by Bodie (1976) is a ratio of the real return variance of the GMV portfolio (σ_{GMV}^2) to the real return variance of a nominally riskless asset (σ_b^2). The interpretation of *Equation 5* is that the lower is the value of this ratio, the better hedging opportunity against inflation is offered by a risky asset[19]. *Equation 6* shows the cost of hedging, which is expressed as a difference between the expected real return on bond and the expected real return on the GMV portfolio[20].

$$S = \frac{\sigma_{GMV}^2}{\sigma_b^2} \tag{5}$$

$$C = \mu_b - \mu_{GMV} \tag{6}$$

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[19] Spierdijk and Umar (2013a: 7) mentioned the following: "The interpretation of the hedge ratio as the reduction in real-return variance does not require normally distributed asset returns and inflation rates. However, our assumption of mean-variance utility implicitly assumes that investor preferences are fully captured by the mean and variance of portfolio returns".

[20] "Both the hedge ratio and the cost of hedging are based on the GMV portfolio. Consequently, Bodie (1976)'s hedge ratio constitutes an upper bound on the possible reduction in real return volatility. Similarly, the costs of hedging are a lower bound on the possible decrease in expected real return" (Spierdijk & Umar, 2010: 11).

This paper does not address the cost of hedging by Bodie (1976). As it is further explained in the next sub-section, the ratio by Bodie (1976) can be expressed in terms of the Pearson correlation coefficient. For the sake of parsimony, the analysis of hedging potential is limited to the behavior of the Pearson correlation (ρ).

Interdependence of the hedging measures

Spierdijk and Umar (2010 & 2013a) show that the considered measures boil down to a scaled version of the Pearson correlation (ρ). The absolute value of the correlation coefficient between the nominal asset returns and the inflation rate constitute a "scale-free" measure and can be used to interpret and "compare the hedging capacity across assets, sample periods, and investment horizons"[21] (Spierdijk & Umar, 2013a: 9).

When comparing the hedge ratio (Δ) by Schotman and Schweitzer (2000) in *Equation 3* with the Fisher coefficient (β) by Boudoukh and Richardson (1993) in *Equation 2*, it should be noticed that the two measures are reciprocally related (see *Equations 7* and *8*). For example, *Equation 7* illustrates the fact that the Fisher coefficient (β) can be also expressed in terms of the Pearson correlation coefficient (ρ) from *Equation 1*.

[21] "The other hedging measures are scale dependent and do therefore not allow for a comparison of the hedging ability across different dimensions. (...) For the square of the correlation coefficient to be interpreted as the reduction in real return variance realized by adding the asset to a portfolio of nominal bonds only, we have to use simple (instead of continuously compounded) asset returns and inflation rates. The gross multi-period asset returns and inflation rates are obtained as the product of the one-period gross returns and inflation rates. Because the multi-period returns arise as a product, they are non-linear functions of the model parameters" (Spierdijk & Umar, 2013a: 9-11).

$$\beta^{(k)} = \frac{Cov_t\left[R_t^{(k)}, \pi_t^{(k)}\right]}{Var_t\left[\pi_t^{(k)}\right]} = \rho\left(\frac{Var_t\left[R_t^{(k)}\right]}{Var_t\left[\pi_t^{(k)}\right]}\right)^{1/2} \quad \textbf{(7)}$$

$$\Delta^{(k)} = \frac{Cov_t\left[R_t^{(k)}, \pi_t^{(k)}\right]}{Var_t\left[R_t^{(k)}\right]} = \rho\left(\frac{Var_t\left[\pi_t^{(k)}\right]}{Var_t\left[R_t^{(k)}\right]}\right)^{1/2} \quad \textbf{(8)}$$

Moreover, Bodie (1982) pointed out that the hedge ratio (*S*) can be also expressed in terms of the correlation coefficient (ρ)[22] (Spierdijk & Umar, 2013a).

$$S = 1 - \rho^2 \quad \textbf{(9)}$$

Despite the fact that the approach proposed by Schotman and Schweitzer (2000) is also based on the mean-variance portfolio framework, unlike Bodie (1976), they focus only on the optimal weight of a risky asset[23]. Considering this interpretation of the Bodie's (1976) hedge ratio (*S*), if ρ=-1 or ρ=1, then the value of *S* is zero and an asset is a perfect hedge. Analogously, for ρ=0, the ratio is equal to one and an asset has no potential to hedge against inflation (Spierdijk & Umar, 2013a).

[22] "The squared correlation coefficient reflects the maximum possible decrease in the k-period real-return variance of a portfolio consisting of k-period nominally risk-free bonds, realized by adding the risky asset to the nominal bonds. This results in the following definition: An asset is a better hedge against inflation when the absolute value of the correlation between nominal asset returns and the rate of inflation is higher" (Spierdijk & Umar, 2013a: 8).

[23] This "implies that they ignore the cost of hedging" (Spierdijk & Umar, 2010: 13).

Multi-period hedging measures

This paper calculates the hedging measures for the following investment horizons: one month (i.e. **1M**), six months (i.e. **6M**), one year (i.e. **1Y**), two years (i.e. **2Y**), three years (i.e. **3Y**), four years (i.e. **4Y**), five years (i.e. **5Y**) and ten years (i.e. **10Y**). The realized returns for different investment horizons are obtained using non-overlapping holding periods and simple returns. In order to construct confidence intervals for the multi-period hedging measures, the relationship between the nominal asset returns and the inflation rate should be determined.

Many authors have demonstrated the usefulness of the vector autoregressive (VAR) model framework in specifying the asset returns and their long-term properties (e.g. Hodrick, 1992; Campbell & Viceira 1999, 2000 and 2001). Recently, several studies investigating the relation between asset returns and inflation rate have been carried out using the VAR model as the econometric specification of returns (e.g. Schotman & Schweitzer, 2000; Hoevenaars et al., 2008; Wang, 2011).

Considering the fact that there exists a very limited number of non-overlapping observations for the precious metal prices (e.g. platinum and palladium), it is difficult to construct the hedging measure for holding periods of five (5Y) and ten years (10Y). The use of VAR model is a convenient alternative for creating more meaningful and reliable hedging measures. Following the work of Spierdijk and Umar (2010, 2013a & 2013b), this paper employs the bivariate VAR approach[24] to examine the relation between a one-period return on a precious metal and a one period inflation rate.

[24] In this paper, the simple bivariate VAR models use constant terms (i.e. μ_1 and μ_2), although, time trends are not included in the framework.

Equation 10 is a general representation of the bivariate VAR(p, q) model and the specification of the dynamic relation between monthly asset returns (R_t) and inflation (π_t).

$$\pi_t = \mu_1 + \sum_{a=1}^{p} \beta_{1a} R_{t-a} + \sum_{b=1}^{q} \gamma_{1b} \pi_{t-b} + \varepsilon_{1,t} \quad \textbf{(10)}$$

$$R_t = \mu_2 + \sum_{a=1}^{p} \beta_{2a} R_{t-a} + \sum_{b=1}^{q} \gamma_{2b} \pi_{t-b} + \varepsilon_{2,t}$$

$$E_t[\varepsilon_{1,t}] = E_t[\varepsilon_{2,t}] = 0 \text{ and } E_t[\varepsilon_{1,t}, \varepsilon_{2,t}] = \Sigma_t \quad \textbf{(10.1)}$$

In this study, π_t denotes a monthly inflation rate (i.e. CPI) at time *t*. It is calculated as a simple return on the monthly US CPI. R_t represents a nominal simple return on one of the four analyzed precious metals. Each unknown VAR model is estimated employing ordinary least squares (OLS) method per each equation[25]. Due to the model estimation, it is difficult to obtain analytical confidence intervals for the hedging measures. To tackle the problem of residual risk, as it is explained in the next sub-section, the bootstrapping procedure for VAR models is adapted.

[25] "Consistent (OLS) estimation of the VAR model does not require any assumption about conditional heteroskedasticity". (...) Because we find similar results regardless of the (homoskedastic or heteroskedastic) distributional assumptions about the VAR residuals, we estimate the correlations under the assumption that the VAR errors follow the empirical distribution of the VAR residuals" (Spierdijk & Umar, 2013a: 10-11).

Confidence intervals of hedging measures

In 1988, basing on the previous studies of Wu (1986) and Beran (1986), Liu published a paper in which he proposed including the non-parametric wild bootstrap method for data generating process (DGP) in the linear models with the heteroskedasticity of unknown type (see Flachaire, 2005 and Kline & Santos, 2012). The residual-based "wild" bootstrap method was further developed by Mammen (1993), who showed the wild bootstrap performs well when "large number of regressors are present" (Kline & Santos, 2012: 54). This recursive-design bootstrap is also proven to perform well against some forms of GARCH error processes as well as independently of the assumption about i.i.d. errors or conditional heteroskedasticity (Gonçalves & Kilian, 2004; Ahlgren & Catani, 2012). In this paper, one of the most widely used two-point distribution of the wild bootstrap (i.e. u_t^{random}), which was proposed by Mammen (1993), is applied to the fitted model residuals (e.g. Flachaire, 2005; Davidson, 2007; Spierdijk & Umar 2013a).

$$u_t^{\text{random}} = \begin{cases} \dfrac{1-\sqrt{5}}{2} & \text{with prob.: } p = \dfrac{\left(1+\sqrt{5}\right)}{2\sqrt{5}} \qquad (\mathbf{11.1}) \\ \dfrac{1+\sqrt{5}}{2} & \text{with prob.: } 1-p \qquad (\mathbf{11.2}) \end{cases}$$

Equations 11.1 and *11.2* describe the two-point distribution of the random variable - u_t^{random}. This asymmetric distribution is designed to introduce the skew correcting error to the estimated model residuals. In other words, this methods takes "account of skewness of the disturbances" (Davidson & Flachaire, 2008: 168).

Considering the analysis of the "stand-alone" relation between a one-month precious metal's return and a one-month inflation rate, the bivariate VAR model is estimated for each sample period as well as for each precious metal separately. Every bivariate VAR model consists of two separate VAR models: one for the monthly inflation rate in the LHS of the regression and another for the monthly return on a precious metal in the LHS of the equation (see *Equation 10*). Consequently, every bivariate VAR model can be utilized to recursively simulate two time series: one for the inflation rate and one for the precious metal returns.

Firstly, an individual VAR model is estimated by the OLS method. Secondly, the estimated model residuals are re-sampled by the means of the random two-point distribution. Thirdly, the new bootstrap residuals replace the residuals of the originally estimated VAR model and such model is further employed to recursively simulate new bootstrap time series (also see Ahlgren & Catani, 2012). The returns for different investment horizons and the bootstrap hedging measures are calculated for every recursively simulated bootstrap time series. This bootstrap procedure is repeated many times using the original dataset, in order to find the confidence intervals (i.e. B=200 and 95% CI) of point estimates of the hedging measures (also see Spierdijk & Umar, 2013a).

Having the new bootstrap time series of the original sample size allows for calculation of the 95% confidence intervals (CI) for the bootstrap hedging measures. Nevertheless, the bootstrap estimates must be interpreted with caution because the values of the correlation between nominal returns and inflation rates can be overstated. The major problem with this method is that it is likely to deliver an overestimated correlation structure in the contemporaneous covariance matrix of multivariate VAR models[26] as we multiply the error terms (i.e. $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$) in *Equations 10* by the same white noise error term (Grobys, 2012).

Robustness check

Regarding the time series properties of the variables (i.e. asset returns and inflation rate), the inflation rate is likely to have the long term high volatility[27] whereas the returns on assets can be more volatile in short-tem (Schotman & Schweitzer, 2000; Spierdijk & Umar, 2010 and 2013a). As the result, precious metals' returns are likely do exhibit different dynamics than inflation rate and the relationship between them could vary accordingly. Pearson correlation (ρ) constitutes the vital component of the four considered hedging measures. Therefore, the correlation coefficient offers a benchmark for investigating the time-varying behavior of the hedging capacity of an asset. This study attempts to account for the changing value of correlation by analyzing the rolling window and extending window estimates as well as the historical hedge prices of precious metals.

The rolling window estimates allow for "a comparison of the hedging capacity across different time periods" as well as gaining "insight in the time-varying behavior of the hedging capacity" (Spierdijk & Umar, 2013a: 19). In this paper, the rolling window of the fixed size of 5-years is used to estimate the correlations for different holding periods. The size of the window

[26] Grobys (2012: 58) points out that "(...) using the same vector of the pick-distribution for all endogenous variables' error vectors in each sample would generate a correlation structure that is higher than the empirical one".

[27] As Schotman and Schweizer (2000: 302-303) state: "even more important is the widely recognized strong persistence of inflation, probably related to inertia of monetary policies carried out by the central banks. (...) Institutional investors like pension funds have a very long horizon. (...) It is therefore interesting to study the effects of changing correlation coefficients when the investment horizon increases".

has been chosen on the basis of "eyeballing" as the period of sixty months reveals some general patterns in time without compromising the time variations. The fixed window starts after the initial five years. Next, it is moved along a time series until the end of a given sample period.

While the rolling window could reveal significant "in-sample" variations of the correlation coefficient, the extending window estimates help to evaluate the "out-of-sample" accuracy of the bootstrap confidence intervals and are complementary to the rolling window analysis. The "out-of-sample" property refers to the forward extending window with a fixed initial sample. This approach examines the cumulative performance of the hedging capacity and offers some intuition as to how sensitive is the correlation measure through time. The initial period of 5-years is set for each holding period, in order to obtain the first observation. Subsequently, the window is extended along a time series by adding one data point (i.e. one month) forward until the end of a given sample period.

DATA DESCRIPTION

The statistical calculations and data management were conducted in Eviews (Version 7.2) as well as Gretl (Version 1.7.1; also see Baiocchi and Distaso, 2003) statistical packages. Microsoft Excel 2007 spreadsheet application was used utilizing the VBA programming language environment. This paper uses monthly data which cover two periods: from January 1974 until February 2013 (i.e. **1974/2013**) and from April 1990 until February 2013 (i.e. **1990/2013**). This structure is chosen to focus the study on the hedging potential of different precious metals.

Unlike other studies (e.g. Ang et al., 2008; Roache & Attié, 2009; Brière & Signori, 2012), this paper does not explicitly attempt to measure effects of a structural break present in the inflation time series. Following the work of Spierdijk and Umar (e.g. Spierdijk & Umar, 2013a), this work opts for using monthly data because of the relatively short sample periods.

Table 1 summarizes sources of the data included in the calculations. The average monthly spot prices for Gold (**GL**), Silver (**SL**), Platinum (**PL**) and Palladium (**PA**) come from the London Bullion Market Association (LBMA) and the London Platinum & Palladium Market (LPPM)[28]. The statistical analysis of the hedging capacity against inflation during the period 1974/2013 is restricted to gold and silver because the data available for platinum and palladium is not sufficient. The nominal monthly spot prices for platinum and palladium are available only from April 1990 because the full price fixing mechanism (i.e. "the London Fix") was established in 1989 (Kendall, 2004).

[28] The PM London Fixing spot price is determined at 3 p.m., what coincides with opening of the US markets. It is important to note that the monthly averages of spot prices does not reflect the prices at the time of a spot contract but rather show an average nominal price fixed by the market during a given month.

Sample statistics

Table 2 presents the basic sample statistics on the monthly data for the precious metal nominal returns and the CPI inflation (**CPI**). The sample analysis shows that the average monthly inflation rate is higher in the period 1974/2013 (i.e. 0.34% with SD= 0.34%) than in the period 1990/2013 (i.e. 0.22% with SD= 0.27%). This difference can be partially accounted for by the Great Moderation period in the full sample 1974/2013, regarding the structural break in inflation rate in the-mid 1980s. *Figures 1* and *2* illustrate the decreasing oscillations in the time series for the CPI inflation rate and gold returns starting in the years 1982-83.

The average monthly nominal return on gold during the period 1974/2013 (1990/2013) is 0.66% (0.6%), while silver increases on average 0.82% (0.86%) over the same interval. Despite the comparable levels of gold and silver returns between the sample periods 1974/2013 and 1990/2013, the volatilities of the two metals are consistently lower for the shorter sample. This result could be easily explained as the volatility of a risky asset is likely to increase over longer time intervals. In the years 1990/2013, the returns on platinum yield results similar to gold with respect to mean (i.e. 0.6%), however, the volatility of platinum is higher than gold (i.e. 5.2% vs. 3.62%). Regarding palladium, the average return (i.e. 1%) and the volatility (i.e. 8.31%) are the highest among the precious metals because of its relatively small supply.

Considering the samples 1974/2013 and 1990/2013, the nominal returns on precious metals and the CPI inflation rate are characterized by an excess kurtosis and departures from normality. Especially in the full-sample 1974/2013, the returns on gold and silver show a substantial skewness of observations (i.e. GL: 2.16 and SL: 1.82). In the years 1990-2013, the skewness of the nominal returns is smaller and significant only for gold and platinum (i.e. GL:

0.65 and PL: -0.33). In the sub-sample 1990/2013, the skewness of the CPI inflation rate is much larger than in the full sample (i.e. CPI: -1.5 vs. -0.03).

Time-series properties

The log of CPI in the considered samples is rejected as being I(1) by Augmented Dickey-Fuller test (ADF)[29]. This outcome was also found by Spierdijk and Umar (2013a & 2013b), where the log of CPI is analyzed in the years 1970/2011.

Table 3 presents the monthly correlations coefficients between the precious metals and CPI for the period 1990/2013. The following two pairs of the precious metals score the highest on the absolute value of the correlation: GL/ SL (i.e. 65%) and PL/PA (i.e. 65%). This finding suggests that the returns of those metals are closely related. Moreover, all the precious metals in this period are significantly correlated with the inflation rate, although the value for CPI/PA is the lowest among this group.

Figure 3 shows the simple returns on gold, silver and CPI during the period 1974/2013. The sample correlation is generally lower than in the period 1990/2013: between the CPI inflation rate and gold it is 18% (with probability |t|=.000), while the correlation with silver is 13% (with probability |t|=.003). *Figure 4* compares the prices of gold and silver over the same interval with the corresponding correlation of approximately 90% (with probability |t|=.000). This indicates that the returns for silver closely follow the returns for gold.

[29] i.e. applying Akaike information criterion as defined in Eviews 7.2 using 15 lags and an intercept. This result preliminarily rejects the use of VEC specification instead of VAR models. The Johansen cointegration test (Johansen, 1991 and 1995) can be additionally conducted to validate this choice of the econometric model (Spierdijk & Umar, 2013a). However, this paper focuses on the inflation-hedging capacity of precious metals as well as the time-varying behavior of the Pearson correlation and the cointegration analysis is beyond the scope of this study.

Figure 5 illustrates the spot prices of all four precious metal using monthly data from April 1990 until February 2013. As can be seen from *Figures 4* and *5*, a remarkably increasing trend in the prices of precious metals has been present in the data, since the beginning of the 1990s. The unprecedented rise in the nominal prices started in the mid-2000s.

EMPIRICAL ANALYSIS

This section defines the initial estimations of the bivariate VAR models. Furthermore, the bootstrap procedure for VAR models is explained and applied to the time series. Those two chapters are followed by the analysis of hedging measures. In the next sections, the results of hedging measures and bootstrap estimates are discussed using different investment horizons and sample periods. Finally, a robustness check is performed in form of the rolling window and extending window analyses.

VAR models

Considering the results of the Akaike criterion and the Portmanteau test for residual autocorrelation, the lag structure should be determined individually for each precious metal[30]. The analysis of deterministic residual covariance for each VAR model, along with the tests mentioned above, support including twelve lags for gold and silver for the period 1974/2013. For the sample 1990/2013, it can be generalized that palladium, gold and silver should include two lags, whereas the results for platinum suggest twelve-lag structure. However, in their analysis of commodity indices, Spierdijk and Umar (2013a) used a four-lag structure in the general VAR model using monthly data and noticed that varying the lag structure does not significantly change the results[31].

[30] The initial 12 lags (i.e. one year) were set to calculate the test for an optimal lag selection for the VAR model.

[31] The potential consequences of changing the lag-structure have been investigated examining the VAR models for the CPI inflation (i.e. CPI as the dependent variable - LHS of *Equation 10*). Each considered VAR model for CPI has been further modified, in order to remove the insignificant lag-terms from the regression. Moreover, the time trend was added in the general analysis of *Equation 10*. After removing each insignificant term of the regression, the VAR models were re-estimated to check for the changes in model significance. The final "clean" models represented the

$$\pi_{t+1} = \mu_1 + \sum_{i=1}^{12} \beta_{1i} R_{t-i} + \sum_{j=1}^{12} \gamma_{1j} \pi_{t-j} + \varepsilon_{1,t+1} \qquad \textbf{(13)}$$

$$R_{t+1} = \mu_2 + \sum_{i=1}^{12} \beta_{2i} R_{t-i} + \sum_{j=1}^{12} \gamma_{2j} \pi_{t-j} + \varepsilon_{2,t+1}$$

i.e. $E_t[\varepsilon_{1,t}] = E_t[\varepsilon_{2,t}] = 0$ and $E_t[\varepsilon_{1,t}, \varepsilon_{2,t}] = \Sigma_t$

In this paper, an important simplifying assumption is made by setting the twelve-lag structure for all analyzed VAR models (see *Equation 13*). The reason for this simplification is that the bootstrap procedures, which are written in VBA programming language, would need to be adjusted for each individual VAR model separately. This work includes four precious metals in the period 1990/2013, what implies eight individual VAR models (i.e. 4x2). Moreover, in the sample 1974/2013, the two bivariate models for GL and SL indicate a need for another four individual VAR models (i.e. 2x2). With the total of 12 separate VAR models, adjusting the bootstrap procedure for each model is cumbersome, therefore, the 12-lag structure is adapted in the analysis to facilitate calculations. Additionally, the 12-lag structure can be useful in detecting relationships in a twelve months cycle between the inflation rate and the precious metals' returns.

Tables 4-7 show the four estimated VAR models (i.e. two bivariate VAR models) for GL and SL in the sample period 1974/3013. *Tables 8-15* present the estimated VAR models for GL, SL, PL and PA in the sample period 1990/2013. In general, all VAR models, which describe CPI as the dependent variable (i.e. CPI in the LHS of *Equation 10*), have higher determination coefficient (i.e. Adj. R^2= 28-50%) than the models for precious metals (i.e. Adj. R^2= 11-18%). Considering these differences between the VAR models in the values of adjusted R^2, this study produced results which corroborate the findings of a great deal of the previous studies (e.g. Spierdijk & Umar 2010 & 2013a).

statistically more significant estimates of this VAR formulation of the returns. Nevertheless, the improvements in adj. R^2 of the models were rather insignificant (i.e. 1-2% an average).

The innovations in the VAR models show significant departures from normality, although the skewness of observations depends of the sample size. In general, the skewness of the nominal returns is positive and reflects a relatively fat right tail of the residual distribution. The precious metals are characterized by lower skewness in the shorter sample period, what largely corroborates the results of the sample statistics analysis[32]. For example, the residuals in the bivariate model for gold have skewness of 0.65 in the sub-sample (i.e. 1990/2013) and 1.8 in the full-sample (i.e. 1974/2013). Similarly, the returns of silver have the skewness of 0.14 in the years 1990-2013, while this value is 1.5 in the full-sample. The skewness of the CPI inflation rate is negative in both sample periods, except the model for platinum, ranging from -0.3 to -0.45 in the sub-sample and from -0.5 to -0.6 in the full-sample.

The skewness of models' residuals is substantial especially in the full-sample period. As a result, the skewness of the analyzed data should be accounted for in this study, when constructing the confidence intervals of the simulated hedging measures estimations. In this paper, the residual-based wild bootstrap technique is proposed in the next sub-section as a popular method which takes account for skewness of the disturbances (see *Confidence intervals of the hedging measures*).

Analyzing the structure of coefficients of the lagged variables more regularities can be observed. The constant terms in the VAR regressions for CPI (i.e. LHS) are significant. Additionally, one and two years lags as well as eleven and twelve years lags are also significant for CPI. This fact indicates some cyclical behavior of the inflation rates within the 12-months period. In period 1974/2013, despite the low predictive power of the VAR models, the absolute

[32] In sample period 1990/2013, the residuals in the bivariate VAR models were characterized by following values for skewness of distributions: GL/CPI: -0.4/0.65; SL/CPI: -0.45/0.14; PL/CPI: 0.3/0.52 and PA/CPI: -0.3/0.18. Considering the full-sample 1974/2013, the corresponding value for the VAR models were: GL/CPI: -0.6/1.8 and SL/CPI: -0.5/1.5.

values for persistence of inflation rate[33] are consistently higher than persistence of GL (i.e. 0.82 vs. 0.4) and SL (i.e. 0.83 vs. 0.13). In period 1990/2013, the differences in persistence for the precious metals and CPI are smaller and more erratic.

The shorter sample (i.e. 1990/2013) focuses on the period of the unprecedented increases in the prices of gold and silver, what have made the precious metals an attractive hedge opportunity in the inflationary economic environment the recent years. The lag structure of the model coefficients of the precious metals also reveals some annual patterns. The most common significant results for the lagged coefficients of the nominal returns were the 1st, 2nd, 10th, 11th and 12th lag, although, the outcomes vary more between the metals than in case of the CPI models. In period 1974/2013, the VAR models describing SL and GL as the dependent variable (i.e. LHS) have somehow lower predictive power than the corresponding models for period 1990/2013[34]. The most significant coefficients are produced in the bivariate VAR model for platinum and the CPI inflation (i.e. 1990/2013), with the model adjusted R^2= 18% and 40% respectively.

[33] A simple method to gain some knowledge about the persistence is to calculate an absolute value of a sum of the VAR coefficients (i.e. for a given lagged dependent variable). For example, regarding the models for CPI in LHS of *Equation 10*, some insights about the inflation persistence can be gained by adding up all 12 coefficients of lagged CPI. This result can be further compared with the absolute value of the sum calculated for a precious metal return. However, the very low significance of the VAR model of the precious metals can undermine the importance of these findings.

[34] This finding should be interpreted with caution because it can also indicate a higher level of volatility aggregated over the longer sample period (i.e. 1973/2013).

Bootstrap procedure

The values for simple returns (i.e. CPI, GL, SL, PL and PA) were imported to Microsoft Excel 2007 worksheets and then transformed according to the residual-based wild bootstrap procedure for VAR models. The macro-scripts for the bootstrap procedures, which have been written in the VBA language compatible with Excel, are available in *Appendices A* and *B*.

In order to facilitate servicing of the VBA macros, two versions of the bootstrap scripts were prepared (i.e. one for each considered sample period). *Appendix A* displays the macro-script for the sample 1990/2013. The script in *Appendix B* is designed to work with data in the sample 1974/2013. In addition, the macro-scripts include short comments describing the calculations step by step. The OLS estimates of the VAR models as well as the simulated bootstrap time series (i.e. B=200) were stored and processed in separate Excel worksheets after each bootstrap iteration.

Care needs to be taken, when interpreting the results of the bootstrap hedging measures. As stressed before, the wild bootstrap is likely to offer the average bootstrap estimates, which are higher than empirical values. Moreover, the low significance of the VAR models, which describe the precious metals' returns, can cause the bootstrap to deliver some undesired statistical properties of the simulated time series. Consequently, the significance of hedging estimates should be tested through time.

HEDGING MEASURES ANALYSIS

As a rule of thumb, Spierdijk & Umar (2013a) advised using the Pearson correlation coefficients (ρ) when choosing between contradictory results of the hedging measures (see *Interdependence of the hedging measures*). In this paper, the inflation-hedging measures will be analyzed as scaled versions of the correlation coefficient. The confidence intervals of the correlation coefficients were constructed using the percentile method. The 2.5% and 97.5% percentiles were calculated to obtain the 95% CI[35]. Moreover, wide range as well as high volatility of the bootstrap estimates could indicate some additional parameter uncertainty. As it is mentioned before, using multiple hedging measures instead of the Pearson correlation coefficient (ρ) is not necessarily a valuable extension for a study of the hedging potential. The four hedging measures can lead to possibly contradictory results. As it is explained by Spierdijk & Umar (2013a: 9):

"It is possible that an asset is a complete hedge against inflation according to the Fisher coefficient, although its correlation with inflation is low. Hence, adding such an asset to a portfolio of nominal bonds will not lead to a large reduction in the real-return variance. Similarly, the hedging demand for an asset that is strongly correlated with inflation may be low. Such an asset is able to realize a substantial reduction in the portfolio's real-return variance, although the hedging demand for the asset is low".

[35] "For example, if 0 lies in the confidence interval, then the hedging measure does not significantly differ from 0 at a 5% significance level" (Spierdijk & Umar , 2013a: 14).

The comparison of the hedging measures can lead to some contradictive conclusions. The hedge ratio (Δ) by Schotman and Schweitzer (2000) and the Fisher coefficient (β) are reciprocally related hedging measures. By their construct, the hedge ratio (Δ) determines the highest hedging potential for the precious metals with the lowest volatility, whereas the Fisher coefficient indicates the assets with the highest volatility. The values for Fisher coefficient may seem to be overestimated, although, the absolute values of this measure depend on the relative differences in scales of volatility for the nominal returns and inflation rate (i.e. nominal assets returns tend to have higher volatility than inflation over a longer time horizon). Analogously, the reciprocal hedge ratio (Δ) by Schotman and Schweitzer (2000) is noticeably lower than the values for the correlation coefficient (ρ).

The analysis of the hedging capacity of precious metals can be confined to examination of the correlation coefficient between nominal returns and inflation rate in the two sample periods. Adequately, the results which are discussed in this research are based on the estimated values of the Pearson correlation coefficient (ρ). Using the example of gold in the full sample period 1974/2013, the first part of this section compares the calculated hedging measures utilizing different investment horizons and bootstrap estimates. In the second part, the estimated inflation-hedging ability of precious metals is analyzed in the two sample periods.

Comparison of the hedging measures

As highlighted in the previous paragraphs, employing different hedging measures may lead to contradictive conclusions. This can be illustrated by looking at gold in the longer sample period (see *Table 16*). On the whole, the comparison of hedging measures shows that the estimates of the Fisher coefficient (β) are consistent with the values of the Pearson correlation. The hedging capacity increases with the holding period and reaches remarkable hedging properties for the long investment horizons above two years. The value of the Fisher coefficient is bigger than one for all investment periods and increases monotonically, what suggests that gold is more than a complete hedge against inflation. However, the rise in value of these measures is not identical. The correlation coefficient experiences sharper increases than the Fisher coefficient for one-year and four-year investment horizons.

Even more evident discrepancies are present between the outcomes of the Pearson correlation and the hedge ratio (Δ) by Schotman and Schweitzer (2000). Unlike the correlation coefficient and the Fisher coefficient, the interpretation of the hedge ratio by Schotman and Schweitzer (2000) is consistent for the preferences of a mean-variance investor. Considering different investment horizons, the hedge ratio (Δ) indicates a relatively stable hedging ability with the holding periods above three years being marginally more significant. It is important to note, that no extreme values are observed for the long investment horizons, which is caused by the high volatility of the gold returns aggregated over time. Lastly, the hedge ratio (*S*) by Bodie (1976), conveys essentially the same information about the hedging performance as the Pearson correlation. Nevertheless, including the hedge ratio (*S*) in the analysis allows to interpret the square of the correlation coefficient as “the reduction in real return variance realized by adding the asset to a portfolio of nominal bonds” (Spierdijk & Umar, 2013a: 8).

Gold and silver

In this paper, aside from analyzing the inflation-hedging ability of individual precious metals, the sample design has been selected to capture possible differences in the hedging capacity between two sample periods: 1974/2013 (i.e. *Tables 4* and *5*) and 1990/2013 (i.e. *Tables 6* and *7*). The considered spot prices of platinum and palladium are available only in the shorter sub-sample. Therefore, the comparative sub-sample analysis is restricted to gold and silver.

Table 16 (i.e. gold) and *Table 17* (i.e. silver) examine the hedging capacity of precious metals in the full sample 1974-2013. The four measures of inflation-hedging properties are expressed as mean values of the bootstrap estimates along with the volatility of the estimates measured by standard deviation. For the sub-sample 1990-2013, the estimations of the hedging measures for gold and silver are reported in *Table 18*. A considerable amount of studies have investigated the inflation-hedging capacity of various assets using the Fisher correlation coefficient (e.g. Jaffe & Mandelker, 1976; Irwin & Brorsen, 1985; Irwin & Landa, 1987; Bodie, 1983; Boudoukh & Richardson, 1993; Taylor, 1998 and Bekaert & Wang, 2010). In order present the estimates in a more accessible way, the Pearson correlation coefficient as well as the Fisher coefficient are presented in *Table 18* (i.e. gold and silver) and *Table 19* (i.e. platinum and palladium).

In the full sample, the impact of the nominal returns volatility on the hedge ratio (Δ) of silver (i.e. Δ: 2%-11%) is more evident than for gold (i.e. Δ: 8%-17%). According to the other hedging measures in *Table 17*, silver shows higher possible hedging ability than gold, although, the volatility of silver observations (i.e. *SD*) is consistently larger, particularly for the longest investment horizons. When comparing the hedging capacity of different precious metals, there exists a tradeoff between the absolute value of the correlation coefficient (i.e. the general strength of the relationship) and the reliability of hedging instruments.

In the period 1974/2013, the estimates for gold are significant in all investment horizons excluding the shortest holding period of one month. On the contrary, in the previous study on the hedging capacity of commodity futures (i.e. over the years 1970-2011), Spierdijk and Umar (2013a) have found no significant results for precious metals using the aggregate S&P GSCI Total Return Index. This finding suggests that there is a difference between the hedging ability of the aggregate precious metals indices and the nominal spot prices of precious metals[36]. For this reason, in future investigations it might be possible to focus on the individual inflation-hedging capacity of different precious metals.

Basing on the estimated correlation coefficient for gold, the investment horizons of 3-years (i.e. ρ= 76%) and to a smaller extent 2-years (i.e. ρ= 73%) and 4-years (i.e. ρ= 91%) achieve the best hedging capacity in terms of the tradeoff between the instrument stability (i.e. *SD*: 6-8%) and the average hedging opportunity. For example, adding gold in the 3-year investment horizon to portfolio of nominal bonds can reduced the real-return variance by at most 58%. The empirical estimates of the correlation coefficient for the holding periods from 2-years to 4-years further demonstrate substantial and relatively constant hedging capacity (i.e. ρ: 43-54%) across the investment horizons. The most extreme values of the hedging capacity were recorded for holding periods of 4-years, 5-years and 10-years. The positive correlation between returns on gold and inflation rate for the longest investment horizons is close to one. In case of the 10-year investment period, the correlation of 98% would imply that in maximum 96% of the real-return variance can be eliminated by adding gold to the nominally riskless portfolio.

[36] The hedging capacity of silver in the sample period 1974/2013 is even more significant and increases with the length of the investment period (see *Table 17*).

Similar conclusions can be drawn from the analysis conducted for silver in the full sample period. The estimates for silver are positive and significant for all investment periods. As argued before, silver offer slightly stronger correlation with inflation than gold but it is also characterized by higher parameter uncertainty, especially for the longer investment horizons. The values of the correlation between the nominal silver return and inflation rate increase monotonically and signal almost “perfect hedge” opportunities for the long investment horizons from 4-years to 10-years (i.e. ρ= 94-95%).

Such high values of the correlation coefficient are useful only as a historical reference. The hedging capacity of gold and silver, which is described in the longer sample period (i.e. 1974/2013), does not fully apply to the modern price conditions. Over the years 1973-2013 gold has performed better as the hedge against inflation than silver because it has offered comparable levels of the correlation coefficient in all investment horizons, while remaining relatively stable in the long investment periods. Nevertheless, the values of the bootstrap estimates of the hedging measures should not be taken at their face value. By their construct, the bootstrap hedging estimates ought to be analyzed as an upper bound on the hedging capacity of precious metals. In order to obtain more robust estimates the hedging potential for the long investment horizons, future research my attempt to extend the length of a sample period.

Turning to the analysis of the sub-sample analysis of gold and silver, the period 1990/2013 reveals striking differences in the hedging capacity of precious metals when compared with the performance in the full sample period (see *Table 18* vs. *Tables 16 & 17*). In general, the estimates for gold and silver are similar for all investment horizons. Considering the length of investment period, the variations in the hedging capacity of precious metals are more pronounced in the shorter sample period. In reviewing the volatility of the bootstrap estimations, the years 1990-2013 have been characterized by lower parameter uncertainty measured by the standard deviation. However, the bootstrap confidence intervals of the estimates for gold reject 2-year and 3-year investment horizons, whereas silver is not significant in 2-year, 4-year and 5-year holding periods.

The spot returns of gold and silver are found to be reliable inflation-hedging instruments in the short investment horizons, except the 1-year investment period for gold. For the holding periods shorter than one year the correlation coefficient oscillates between 34-40% for gold and 31-42% for silver. These values of the correlation result in a maximal possible reduction in real-return variance of 12-16% and 10%-18%, respectively. This outcome seems to be a reasonable approximation for the short-term hedging capacity of gold and silver. The more surprising correlations can be observed for gold in the holding periods of 4-years and 5-years[37]. In the long investment horizon, the hedging capacity of gold is strong but negative with the potential to eliminate at most 45-49% of the real-return variance. These findings show that an investor could benefit from taking a short position in gold regarding the long-term investment focus (i.e. "perverse hedge"), while buying gold and silver is likely to be a better short-term hedging strategy.

[37] The long investment horizons offer the maximum absolute values of the correlation coefficient (i.e. ρ= -67% for the 4-years period and ρ= -70% for the 5-years period).

Platinum and palladium

The results of the inflation-hedging measures for platinum and palladium, which are displayed in *Table 19*, are not significant for the 4-year investment period. In most cases, the correlation coefficient for the two metals is positive, although, the 2-year and 5-year investment horizons for palladium present the negative relationship between the spot returns and inflation rate. The volatility of the bootstrap estimates increases with the length of investment period for both precious metals. Moreover, the standard deviation of the Pearson correlation is equal for palladium and platinum regarding short investment horizon. Above all, the hedging capacity of platinum is substantially higher than the inflation-hedging ability of palladium excluding the longest holding period.

The spot prices of platinum perform well as the medium-run hedge against inflation, considering the holding periods from 1-year to 3-years (i.e. ρ= 41-42%). In the sample period 1990/2013, platinum offers the highest possible reduction in the real-return variance (i.e. 53%) among the considered precious metals for the longest examined investment horizon of 5-years. Unlike the other precious metals the correlation coefficient for platinum is significant and positive for the longer investment horizons. As a consequence, this research shows that platinum has the highest ability to hedge against inflation in the longer investment horizons. In relation to the other precious metals, palladium is characterized by the lowest hedging capacity in the sample period 1990/2013. The only exception is the investment horizon of 5-years, when the correlation coefficient is strong and negative (i.e. ρ= -72%).

Even though the results presented in this chapter are quite encouraging, the time-variations in the hedging estimates should be further tested in the next section of the work.

PARAMETER STABILITY

The parameter stability analysis for the correlation coefficient (ρ) is conducted for different investment horizons and performed over time using the original monthly data. This paper adapts rolling window and extending window calculations as the complementary techniques to test for robustness of the hedging estimates. In addition, a historical perspective on the hedge price of precious metals is provided, to facilitate the interpretation of results.

The hedge price of precious metal

The time-varying nature of the relationship between precious metals and inflation can be pictured by "inflation hedge price", which is the monthly dollar price that a given precious metal would have to be in order to maintain its purchasing power through time (Gosh et al., 2004). This exercise presents the store value of the assets in real terms adopting a buy-and-hold strategy (i.e. the initial sample price holding constant its purchasing power). In theory, if the nominal price is equal to the hedge price, the precious metals co-move with the value of US CPI index, what implies a perfect short-term hedge against inflation.

Figures 6 and *7* depict the inflation monthly hedge prices for gold and silver. Gold (silver) prices remarkably exceeded the average inflation rate in 2006 (2010), what provides a tentative but tantalizing argument supporting the hedging capacity of precious metals. Yet, during the sample 1974/2013, gold was not a reliable hedge instrument. *Figure 6* exhibits an erratic pattern of the price of gold from February 1974. The nominal price of gold was a good hedge against inflation only during a few short episodes in the 1970s and 1980s. Moreover, the nominal price of gold fell below the hedge price over the years 1990-2005. With respect to the price of silver, the period 1974/2013 was characterized by even larger deviations from the hedge price. Besides, *Figure 7* shows that the nominal value of silver was below the hedge price from the early 1980s until 2010. *Figures 8* and *9* plot the nominal prices for platinum and palladium as well as the corresponding values for gold from May 1990. Platinum closely follows the price of gold in the period 1990-2000. The nominal price of platinum has been greater than the hedge price only from 2003. Despite the fact that the price of platinum have been considerably increasing for over a decade, this metal has performed worse in maintaining purchasing power than gold as it has remained more volatile after 2001. In contrast to the other precious metals, the prices of palladium seem more stable. Besides, palladium could be identified as at the most reliable store of value among the precious metals because its nominal price has virtually never fallen below the hedge price.

Selection of sample period

The two techniques which are employed to test the parameter stability are interrelated. On the one hand, the rolling window analysis offers some insight into the time-varying nature of the contemporaneous correlation between precious metals and inflation during the examined samples. The fixed window (i.e. 5-years) starts after the initial five years. Next, it is moved along a time series until the end of a given sample period. On the other hand, the extending window approach considers a cumulative performance of the correlation coefficient through time. The initial values of correlation are obtained utilizing a sample of the first sixty months (i.e. five years). Subsequently, the window is extended along a time series by adding one data point (i.e. one month) forward until the end of a given sample.

Before analyzing the robustness of hedging estimates, it should be noticed that the hedging capacity of precious metals can exhibit different hedging properties depending on the chosen sample. *Figures 10*, *11* and *13* plot the correlation coefficients for gold using the extending window for the periods 1974/2013 and 1990/2013. As shown in *Figure 10*, if we consider the longer period of almost 40 years, the cumulative value of correlation between gold and inflation rate is positive and relatively stable for all investment horizons. However, it can be seen from the extending window estimates in *Figures 11* and *13* that the hedging capacity of gold changes significantly regarding the shorter sample (i.e. 1990/2013), which is focused on the most recent economic shocks. These differences are most elaborate for the long investment horizons of 1Y-5Y, what also corroborates the significance of the bootstrap hedging estimates (see *Hedging measures analysis*). Regardless of the short investment horizons being more volatile in the sample 1990/2013, the holding periods of 1M-6M exhibit comparable levels of the hedging potential with the values for the longer sample (i.e. 1974/2013). A similar pattern was found for the extending window approach in the relationship between silver and inflation (see *Figures 15*, *16* and *18*).

As it was mentioned in the methodology section, the returns on precious metals and inflation rate are likely to have different time-series properties. Even though increasing the length of a sample period can reduce parameter uncertainty, it also implies the higher risk of including structural change in the observations. Spierdijk and Umar (2013a: 21) concluded that capturing the time-varying relation between inflation rate and asset returns is crucial "to accurately assess the hedging capacity of an asset". The sample period ought to reflect the relevant price conditions, hence increasing the number of observations may not be always preferable. In this paper, the rolling and extending window analyses are introduced as a simple method to illustrate the time variations. Future research could attempt to describe and quantify the time-varying relationship between precious metals' returns and inflation rate.

The rolling and extending window estimates

Figures 10-14 examine the changes in inflation-hedging properties of gold over the years 1974-2013 with a specific focus on the sub-sample of 1990-2013. In the environment, where the inflation expectations are low, the returns of precious metals are likely to be smaller than during inflationary shocks resulting in positive correlation (Spierdijk & Umar, 2013a: 20). Over the longer sample period, the positive values for the cumulative correlation between gold returns and inflation rate can be explained by stabilization of inflation during the Great Moderation (see *Figure 10*). The initial observations of the extending window, which start in January 1979, are volatile because they include the price shocks from the first and second oil crises (i.e. 1973-74 and 1979). Regarding the extending window calculations for the sub-sample 1990/2013 in *Figures 11* and *13*, the very short investment horizons of 1M-4M provide a reliable and positive inflation-hedge, with the correlation for 2M being the most effective over time (i.e. the correlation ranges from 15% to 30%). In *Figure 11*, the hedging capacity of gold in the long investment horizons (i.e. 2Y-5Y) is diminishing as the start date of the extending window moves forward in time and eventually reaches the values for a "non-hedge".

Looking from the perspective of the last 38 years, the rolling window estimates in *Figures 12* and *14* demonstrate the negative values of the correlation coefficient for gold in the late 1980s until the mid-2000s. As it was described before, the nominal price of gold was below the hedge price of gold in the years 1990-2005, what largely coincides with the values of correlation suggesting short positions of investors. During this period, there is only one point when exceptionally positive estimations were recorded, in the years leading up to and just after the financial crisis of 2001. Moreover, the hedging capacity of gold increases also during the recent economic crisis. The fall of Lehman Brothers in September 2008 marks high and positive correlation for the long holding periods of 2Y-5Y. These findings further support the idea that precious metals perform better as an inflation-hedge during the time of economic distress. During the time of crisis, the significant hedging capacity of gold pertains to all investment horizons.

The pattern of the rolling window variations of gold in *Figure 14* is consistent for 2M-6M. The values for 1Y are characterized by the largest hedging capacity (i.e. approximated range from -70% to 90%). From 1990, the values for two-months hedge are positive and grow over time. The amplitude of the variations seems to narrow from 1999 onwards. The years 1979-85 show remarkably positive correlation, while the hedging capacity shifts its values from negative to positive in 1985-98.

Figures 15, *16* and *18* help to assess the overall inflation-hedge potential of silver. On average, the cumulative value of the correlation coefficient is lower than the results for gold, considering all investment horizons (see *Figure 15* vs. *Figure 10*). The extending window estimates in *Figure 15* indicate that the initial observations in the 1974/2013 sample capture the volatility of the energy crises (i.e. 1973-74 and 1979). The positive hedging capacity of silver decreases after the inflation rate stabilized in 1980 and remains relatively constant until the recent financial crisis. In addition, after the bankruptcy of Lehman Brothers, the inflation-hedging capacity of silver has started to diminish for the long investment horizons of 2Y-5Y. The extending window for the sub-sample 1990/2013 in *Figures 16* and *18* largely corroborates the results of the full sample 1974/2013, although, it shows higher volatility of the Pearson correlation. *Figure 16* suggests that silver has offered an exceptional hedge against inflation for the investment horizons of four and five years. However, the holding periods of two and three years act relatively poorly as the inflation-hedge. It is somehow surprising that the extending window estimates of silver for the short investment horizons (i.e. 1M-6M) in *Figure 18* presents a significant increasing trend over time. Except the one-month holding period, the cumulative correlation coefficient has stabilized and turned positive since the financial shock of 2008.

Figures 17 and *19* refer to the rolling estimates for silver, in the years 1974-2013. Noticeably, the variations in correlation coefficient over time are less dispersed than gold for the holding periods from two months to one year (see *Figure 14*). The time after the fall of Lehman Brothers in 2008 is characterized by a sharp increase in hedging capacity of silver, although, this effect diminishes for the long investment horizons (i.e. *Figure 17*). In the mid-1990s, silver experiences the largest negative values of the correlation with inflation for the holding periods longer than six months. The time variations for the long-term periods is different for each investment horizons and a general trend is not as visible as in case of gold. Despite the fact that the outcomes for investment horizons of 4Y and 5Y show large absolute values of the correlation they are also unstable. This result is similar to gold.

The nominal price of silver was below the hedge price over the years 1980-2010, what could imply losing the short term hedging capacity. *Figure 19* confirms this finding as from 1980 the correlation coefficient starts to decrease. Notwithstanding the episodes of positive correlation in the beginning of the sample and in the years 1988-91, the hedging capacity was negative until 2010. On the contrary, the short investment horizons exhibit relatively good but negative hedging opportunities (e.g. 1993-97).

Figures 20-22 demonstrate the rolling window and extending window estimates for platinum, in the years 1990-2013. In 2001, the prices of commodities began to soar and the volatility of inflation increased in 2005. From 2000 until 2005/2006, the correlation between platinum returns and inflation rate has been negative and weak for the holding periods of 3Y-5Y. It can be also seen from the graphs in *Figure 20* that, apart from the long investment horizons of 3Y-5Y, the cumulative correlation estimates for all holding periods has started to converge in the mid-2000s. The rise in inflation uncertainty is exemplified by a clear the hedging capacity of platinum, which has become a reliable hedging instrument after the year 2005. This finding is even more significant for the period after the collapse of Lehman Brothers in 2008 with the correlating coefficient ranging from 20% to 40%.

The results for the rolling window estimates (see *Figures 21* and *22*) generally confirm the findings from the extending window analysis concerning the sign and trend of time-variations. However, the values of correlation coefficient for platinum are more positive and volatile then in the extending window approach. Further, the hedging capacity of platinum for the short investment horizons is the highest among the considered precious metals (see *Figure 22*). From the year 2000, the correlation estimates have become positive and started to oscillate between 20% and 80%. Apparently, the only time after this year, when the correlation coefficient turns negative for 1Y and 2Y, is the period of recent economic turmoil in 2007 and 2008. The maximal absolute values for the long-term holding periods are comparable with results for gold and silver, albeit less volatile and more reliable. The longest examined period of five years maintains a growing positive trend within the whole sample. Nevertheless, the holding periods of three and five years offer the highest absolute values of the correlation coefficient.

Figures 23-26 display the rolling window and extending window estimates for palladium, in the years 1990-2013. In contrast with the previous results on hedge prices, palladium is a worse hedging instrument than platinum. The longer (i.e. 2Y-5Y, *Figures 23* and *24*) and the shorter (i.e. 1M-1Y, *Figures 25* and *26*) investment horizons exhibit different time characteristics and should be investigated separately. In the extending window approach, the initially negative estimates in *Figure 23* weight heavily on the values of the correlation coefficient. As a result, the estimates for holding periods 2Y-5Y decrease to the “non-hedge” value of zero correlation in the end of the sample. The fixed window method in *Figure 24* yields similar results with respect to the long holding periods. Over the years 2005-2009, the hedging capacity of palladium for the investment horizons of 2Y-4Y is large and positive. In the perspective of five years, this metal is more volatile than the rest of long investment horizons.

In *Figure 25*, the time-variations for the extending window estimates of palladium resemble the results for platinum. However, the values of correlation coefficient are lower than in the case of palladium’s wealthy cousin (see *Figure 20*). During the years 2002-2013, the hedging capacity for the short investment horizons has been ranging from 10% to 20% and remained stable for 1M, 2M and 1Y. In *Figure 21*, the rolling window correlation coefficients move together in all short holding periods. Moreover, the fixed window estimates show similar results with the one obtained using the extending window technique. Palladium has been less reliable as the inflation-hedge and more volatile through time than platinum.

SUMMARY AND DISCUSSION

The evidence from this study suggests that gold, silver, platinum and palladium have different time-series properties. In order to adequately measure the inflation-hedging capacity of precious metals, the hedging ability of those assets should be determined separately.

The results rolling window and extending analyses largely confirm the main findings for the hedging measures' estimates. Gold performs better than silver as a hedge against inflation in both long and short investment horizons. Furthermore, gold (and to some extent silver) is a reliable inflation-hedging instrument for the holding periods shorter than one year. However, considering the short-term hedging focus, gold and platinum offer the most stable and positive values of the Pearson correlation coefficient. Palladium is characterized by the least significant hedging capacity among the examined precious metals. In addition, it was illustrated that platinum has provided most effective hedge against inflation for all investment horizons in the years 1990-2013.

The extending window analysis supports the relevance of the bootstrap estimates. In the full sample 1974/2013, gold and silver were found to exhibit positive values of the correlation for all investment horizons. Yet, the sub-sample analysis shows that the inflation-hedging capacity of precious metals is sensitive to the length of sample period. Therefore, the choice of sample data could be a major factor, if not the only one, causing inconsistencies in the academic discussion of inflation-hedging properties of individual precious metals.

The rolling window estimates has revealed large the time-variations in the hedging capacity. Precious metals have performed exceptionally well during the recent financial crisis. The hedging capacity of precious metals has increased and stabilized after the bankruptcy of Lehman Brothers in September 2008, especially for the short investment horizons.

CONCLUSION

This study set out to assess the potential of precious metals' spot returns to hedge against the US CPI inflation rate. The generalizability of much of the published studies on precious metals is difficult to achieve because there exists a gap in the literature regarding specific focus on various types of precious metals. The evidence from this research shows that individual precious metals should not be considered as substitutes in reducing the inflation risk of a portfolio. On the whole, all analyzed assets consistently show the inflation-hedging ability, what opens the possibilities to further their interpret individual hedging potential.

The precious metals have proved to offer the most effective hedge against inflation during the periods of high uncertainty in the international markets. This paper shows that the spot prices of precious metals are sensitive to the episodes of economic and financial turmoil. However, this study does not offer a corresponding comparison with the performance of future contracts and was not designed to analyze the relative advantages of using the spot prices of precious metals. The hedging measures indicate that gold and platinum have a statisticaly significant hedging capacity, which is also characterized by relatively small time-variations. Consequently, gold and platinum might be preferred as the most reliable instruments for hedging against inflation.

There is abundant room for progress in examining the hedging potential of platinum. So far, however, far too little attention has been paid to studying the inflation-hedging capacity of precious metals other than gold or silver. Despite the similarities between the demand and price factors of platinum and palladium, the first commodity cannot be regarded as a good proxy for the non-traditional precious metals like palladium.

It is important to stress that an interpretation of the hedging capacity of precious metals can be sensitive to idiosyncrasies of different time intervals. When analyzing the hedging potential of assets, the relevance of selected sample periods with the current price conditions is crucial to conduct a meaningful research. The findings of the current study are consistent with those of Spierdijk and Umar (2010, 2013a & 2013b) who concluded that establishing the time-varying relation between the assets returns and inflation rate will help to better understand the nature of inflation-hedging capacity.

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Table 1: summaries the notation and data sources as well as it provides a short description of the main variables that are considered in this paper.

Name	Type	Source/Database	Description
Gold (GL) Silver (SL) Platinum (PL) Palladium (PA)	monthly data; nominal price (spot contract)	The London Bullion Market Association (LBMA) The London Platinum & Palladium Market (LPPM)	i.e. monthly averages for the PM London Fix Spot Price ($)
Inflation rate	monthly data; price index	Datastream: Thomson Reuters (Code: USCONPRCE)	i.e. a return on the consumer price index (i.e. seasonally corrected US CPI - all urban index)

Table 2: provides the basic sample statistics on the variables' monthly data, which are included in the analysis. The sample statistics cover the two sample periods: from January 1974 until February 2013 (i.e. **1974/2013** - the upper panel) and from April 1990 until February 2013 (i.e. **1990/2013** - the lower panel).

The upper panel displays the statistics on gold and silver nominal returns (i.e. simple returns) as well as the CPI inflation rate, which is expressed as a simple return on the US CPI. The lower panel shows nominal returns on the spot prices of Gold (**GL**), Silver (**SL**), Platinum (**PL**), Palladium (**PA**) and inflation (**CPI**).

	Gold	**Silver**	**CPI**
	1974/2013		
Mean [%]	0.66	0.82	0.34
Median [%]	0.07	0.00	0.29
Maximum [%]	48.39	75.44	1.43
Minimum [%]	-16.79	-39.45	-1.77
Volatility [%]	5.08	8.83	0.34
Skewness	2.16	1.89	-0.03
Kurtosis	20.29	17.82	7.18
Observ. [#]	469	469	469

	Gold	**Silver**	**Platinum**	**Palladium**	**CPI**
		1990/2013			
Mean [%]	0.60	0.86	0.60	1.00	0.22
Median [%]	0.11	0.00	0.75	0.62	0.21
Maximum [%]	18.10	21.48	26.50	40.40	1.38
Minimum [%]	-11.74	-19.70	-25.39	-27.44	-1.77
Volatility [%]	3.62	6.43	5.20	8.31	0.27
Skewness	0.65	0.15	-0.33	0.03	-1.50
Kurtosis	5.37	4.15	8.65	5.61	15.87
Observ. [#]	274	274	274	274	274

Figure 1: graphs the inflation rate (i.e. CPI), using monthly from January 1974 until May 1990.

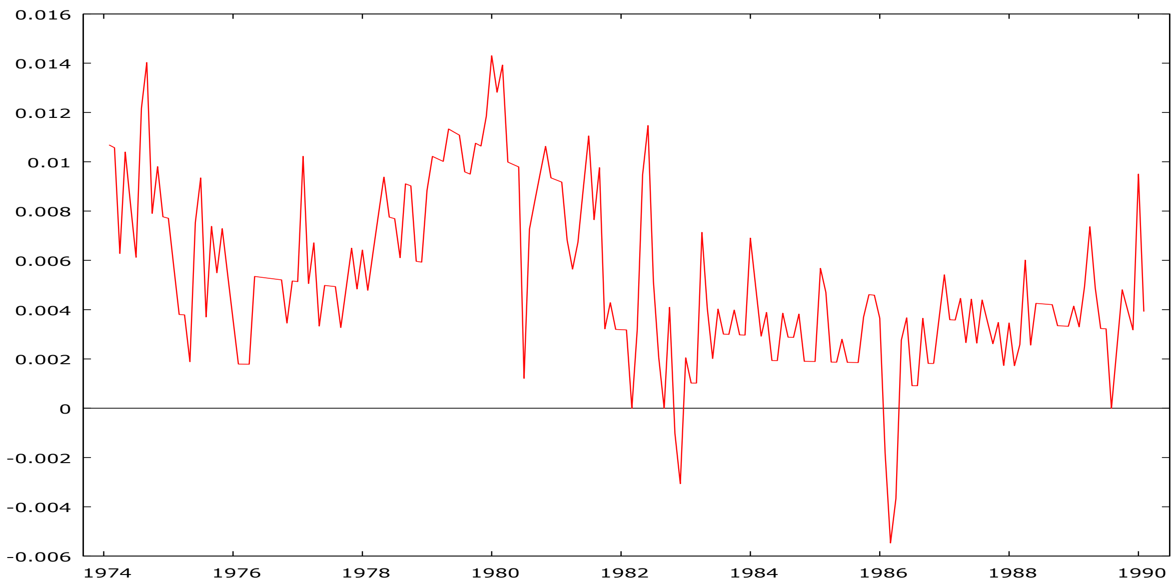


Figure 2: the monthly returns on Gold (i.e. GL), using monthly from January 1974 until May 1990.

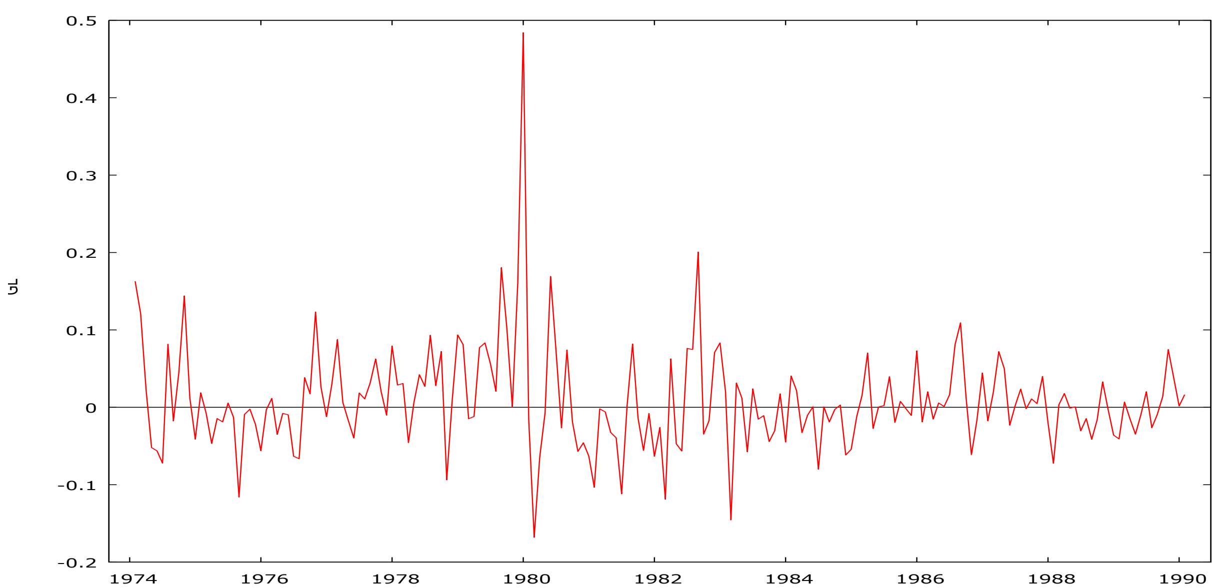


Table 3: shows the Pearson correlation coefficient (ρ) for the sample period 1990/2013 between CPI, GL, SL, PL and PA.

		CPI	GL	SL	PL
GL	ρ	0.24			
	Prob.	0.00			
	Obs.	274			
SL	ρ	0.20	0.65		
	Prob.	0.00	0.00		
	Obs.	274	274		
PL	ρ	0.26	0.54	0.54	
	Prob.	0.00	0.00	0.00	
	Obs.	274	274	274	
PA	ρ	0.15	0.31	0.42	0.65
	Prob.	0.01	0.00	0.00	0.00
	Obs.	274	274	274	274

Figure 3: graphs the inflation rate (i.e. CPI - right y-axis) and the simple nominal returns on Gold (GL) and Silver (SL), using monthly from January 1974 until February 2013.

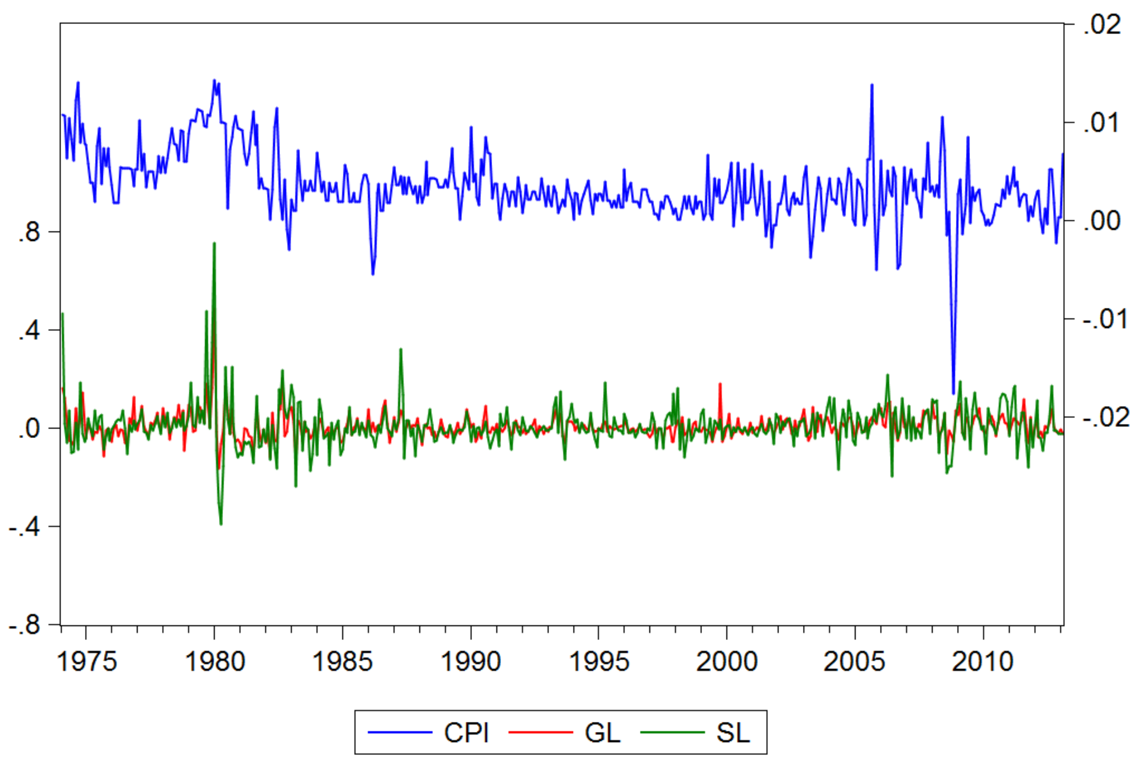


Figure 4: shows nominal spot prices of gold and silver (i.e. right y-axis), using monthly data from 1974/01 until 2013/02.

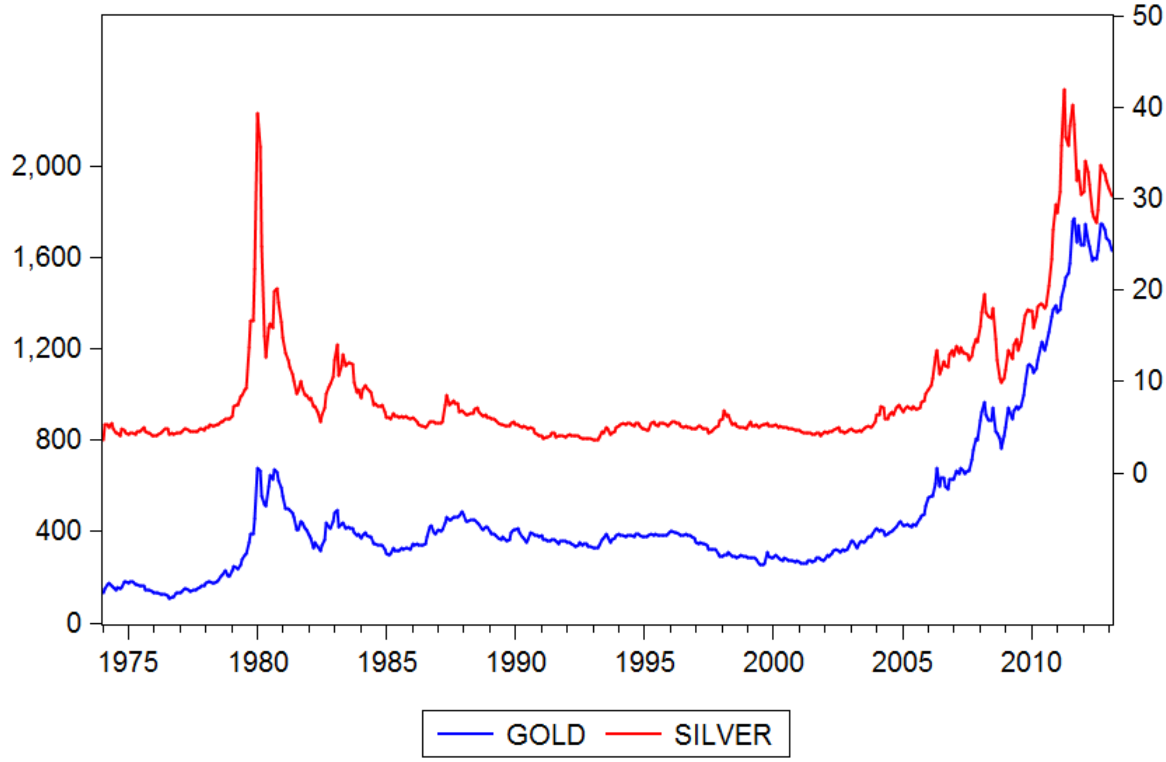


Figure 5: illustrates the spot prices for gold, silver (i.e. right y-axis), platinum and palladium using monthly data from 1990/03 until 2013/02.

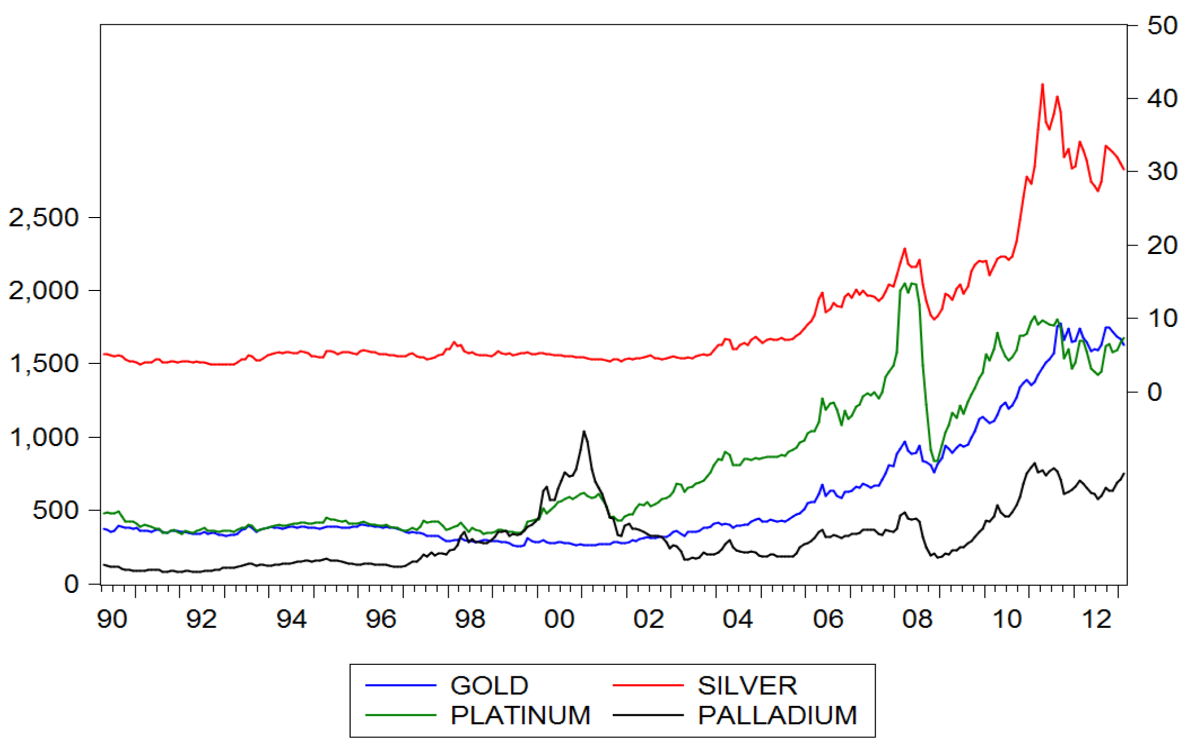


Table 4: displays one of two individual models (i.e. **CPI** in the LHS of *Equation 13*), which jointly constitute the bivariate VAR model from *Equation 13*. This table shows the initial estimation of the VAR model during the sample period 1974/2013. The estimated results are calculated for the single VAR model describing gold returns (i.e. GL) and the CPI inflation rate (i.e. CPI) using 12 lags and a constant term. The estimates are based on the OLS method per equation. The analogously estimated individual VAR model for GL (i.e. GL in the LHS of *Equation 13*) is presented in *Table 5*.

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	0.000490561	0.000195073	2.5148	0.01227	**
CPI_1	0.542461	0.0481186	11.2734	<0.00001	***
CPI_2	-0.0782036	0.0546533	-1.4309	0.15318	
CPI_3	0.0350896	0.0550344	0.6376	0.52408	
CPI_4	0.0593015	0.0549032	1.0801	0.28070	
CPI_5	-0.0172249	0.0546434	-0.3152	0.75274	
CPI_6	0.0825925	0.0545433	1.5143	0.13069	
CPI_7	0.00905473	0.0545481	0.1660	0.86824	
CPI_8	0.0128442	0.0546592	0.2350	0.81433	
CPI_9	0.096072	0.0545071	1.7626	0.07868	*
CPI_10	0.0698771	0.0544899	1.2824	0.20040	
CPI_11	0.15769	0.0545367	2.8914	0.00403	***
CPI_12	-0.154716	0.0480725	-3.2184	0.00139	***
GL	0.0067864	0.00238337	2.8474	0.00462	***
GL_1	-0.000155301	0.00245289	-0.0633	0.94955	
GL_2	0.000950044	0.00244547	0.3885	0.69784	
GL_3	0.000800488	0.00242864	0.3296	0.74186	
GL_4	0.003562	0.00242325	1.4699	0.14231	
GL_5	0.000269763	0.00243184	0.1109	0.91172	
GL_6	-0.00231426	0.00242606	-0.9539	0.34066	
GL_7	0.00275043	0.00241638	1.1382	0.25565	
GL_8	0.000695128	0.00240926	0.2885	0.77308	
GL_9	0.000780878	0.00240262	0.3250	0.74533	
GL_10	-0.00166954	0.00239491	-0.6971	0.48610	
GL_11	0.000113507	0.00236912	0.0479	0.96181	
GL_12	0.00017604	0.00229744	0.0766	0.93896	

Marks. *** : significance 0.01 ; **: significance 0.05 ; *: significance 0.1

Adj. R^2= 0.483765

Table 5: displays one of two individual models (i.e. **GL** in the LHS of *Equation 13*), which jointly constitute the bivariate VAR model from *Equation 13*. This table shows the initial estimation of the VAR model during the sample period 1974/2013. The estimated results are calculated for the single VAR model describing gold returns (i.e. GL) and the CPI inflation rate (i.e. CPI) using 12 lags and a constant term. The estimates are based on the OLS method per equation. The analogously estimated individual VAR model for CPI (i.e. CPI in the LHS of *Equation 13*) is presented in *Table 4*.

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	0.0030379	0.00393171	0.7727	0.44014	
GL_1	0.203528	0.0481253	4.2291	0.00003	***
GL_2	-0.140271	0.0485052	-2.8919	0.00402	***
GL_3	0.03356	0.0486071	0.6904	0.49029	
GL_4	0.0375147	0.0486079	0.7718	0.44067	
GL_5	0.102426	0.0484421	2.1144	0.03506	**
GL_6	-0.0230657	0.0486149	-0.4745	0.63541	
GL_7	0.0375037	0.0484215	0.7745	0.43904	
GL_8	0.0445838	0.0481966	0.9250	0.35546	
GL_9	0.0182092	0.0481049	0.3785	0.70522	
GL_10	-0.0482985	0.0479231	-1.0078	0.31410	
GL_11	0.11562	0.0471082	2.4544	0.01451	**
GL_12	0.0142797	0.0459961	0.3105	0.75636	
CPI	2.72072	0.955514	2.8474	0.00462	***
CPI_1	0.0386642	1.09635	0.0353	0.97188	
CPI_2	-2.05083	1.09245	-1.8773	0.06115	*
CPI_3	2.73466	1.09456	2.4984	0.01285	**
CPI_4	-0.522419	1.10051	-0.4747	0.63524	
CPI_5	-1.12113	1.0929	-1.0258	0.30555	
CPI_6	0.575138	1.09465	0.5254	0.59957	
CPI_7	1.40356	1.09014	1.2875	0.19861	
CPI_8	-0.212607	1.09445	-0.1943	0.84606	
CPI_9	-0.937432	1.09437	-0.8566	0.39215	
CPI_10	0.858577	1.09233	0.7860	0.43230	
CPI_11	-2.18497	1.09748	-1.9909	0.04712	**
CPI_12	-1.00976	0.972824	-1.0380	0.29987	

Marks. *** : significance 0,01 ; **: significance 0,05 ; *: significance 0,1

Adj. R^2= 0.117424

Table 6: displays one of two individual models (i.e. **CPI** in the LHS of *Equation 13*), which jointly constitute the bivariate VAR model from *Equation 13*. This table shows the initial estimation of the VAR model during the sample period 1974/2013. The estimated results are calculated for the single VAR model describing silver returns (i.e. SL) and the CPI inflation rate (i.e. CPI) using 12 lags and a constant term. The estimates are based on the OLS method per equation. The analogously estimated individual VAR model for SL (i.e. SL in the LHS of *Equation 13*) is presented in *Table 7*.

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	0.000458627	0.000192718	2.3798	0.01776	**
CPI_1	0.532262	0.0479713	11.0954	<0.00001	***
CPI_2	-0.0954187	0.0542445	-1.7590	0.07928	*
CPI_3	0.0420674	0.0540248	0.7787	0.43660	
CPI_4	0.071792	0.0538738	1.3326	0.18337	
CPI_5	-0.0131331	0.0537962	-0.2441	0.80725	
CPI_6	0.0797691	0.0536848	1.4859	0.13804	
CPI_7	0.0331629	0.0538478	0.6159	0.53831	
CPI_8	0.0145915	0.0539919	0.2703	0.78709	
CPI_9	0.0855277	0.0540651	1.5819	0.11440	
CPI_10	0.0840371	0.0537929	1.5622	0.11897	
CPI_11	0.1509	0.0537515	2.8074	0.00522	***
CPI_12	-0.159711	0.0474082	-3.3688	0.00082	***
SL	0.00399865	0.00135515	2.9507	0.00334	***
SL_1	-0.000233695	0.00141941	-0.1646	0.86930	
SL_2	0.00260441	0.0014293	1.8222	0.06912	*
SL_3	0.00174003	0.00143618	1.2116	0.22634	
SL_4	0.00169255	0.00142021	1.1918	0.23401	
SL_5	0.0015825	0.00140616	1.1254	0.26104	
SL_6	-0.000897237	0.00141073	-0.6360	0.52511	
SL_7	0.000530518	0.0014081	0.3768	0.70654	
SL_8	0.000117098	0.00140138	0.0836	0.93345	
SL_9	0.000355883	0.00140022	0.2542	0.79949	
SL_10	-0.00317774	0.0013985	-2.2723	0.02356	**
SL_11	0.00174852	0.00137813	1.2688	0.20521	
SL_12	-0.000742294	0.00130273	-0.5698	0.56911	

Marks. *** : significance 0,01 ; **: significance 0,05 ; *: significance 0,1

Adj. R^2= 0.494633

Table 7: displays one of two individual models (i.e. **SL** in the LHS of *Equation 13*), which jointly constitute the bivariate VAR model from *Equation 13*. This table shows the initial estimation of the VAR model during the sample period 1974/2013. The estimated results are calculated for the single VAR model describing silver returns (i.e. SL) and the CPI inflation rate (i.e. CPI) using 12 lags and a constant term. The estimates are based on the OLS method per equation. The analogously estimated individual VAR model for CPI (i.e. CPI in the LHS of *Equation 13*) is presented in *Table 6*.

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	0.00428809	0.00682324	0.6285	0.53004	
SL_1	0.274282	0.0481733	5.6937	<0.00001	***
SL_2	-0.140932	0.0500335	-2.8168	0.00507	***
SL_3	0.0463827	0.0505771	0.9171	0.35962	
SL_4	0.0059103	0.05006	0.1181	0.90607	
SL_5	-0.0074899	0.0495555	-0.1511	0.87993	
SL_6	-0.0545349	0.0495989	-1.0995	0.27216	
SL_7	0.00122207	0.0495606	0.0247	0.98034	
SL_8	0.0487209	0.0492603	0.9890	0.32319	
SL_9	0.00141396	0.0492786	0.0287	0.97712	
SL_10	0.0100087	0.049506	0.2022	0.83988	
SL_11	0.0247365	0.0485734	0.5093	0.61083	
SL_12	-0.0190126	0.0458523	-0.4146	0.67861	
CPI	4.95194	1.67822	2.9507	0.00334	***
CPI_1	-0.516653	1.91397	-0.2699	0.78734	
CPI_2	-3.55385	1.90809	-1.8625	0.06321	*
CPI_3	2.6651	1.89819	1.4040	0.16103	
CPI_4	-0.00194008	1.89977	-0.0010	0.99919	
CPI_5	-2.67418	1.88888	-1.4157	0.15757	
CPI_6	1.02309	1.89341	0.5403	0.58924	
CPI_7	3.39447	1.88872	1.7972	0.07300	*
CPI_8	0.541658	1.90001	0.2851	0.77572	
CPI_9	-3.84743	1.8991	-2.0259	0.04339	**
CPI_10	0.184497	1.89835	0.0972	0.92262	
CPI_11	-1.29873	1.90776	-0.6808	0.49639	
CPI_12	-0.102185	1.69016	-0.0605	0.95182	

Marks. *** : significance 0,01 ; **: significance 0,05 ; *: significance 0,1

Adj. R^2= 0.104931

Table 8: displays one of two individual models (i.e. **CPI** in the LHS of *Equation 13*), which jointly constitute the bivariate VAR model from *Equation 13*. This table shows the initial estimation of the VAR model during the sample period 1990/2013. The estimated results are calculated for the single VAR model describing gold returns (i.e. GL) and the CPI inflation rate (i.e. CPI) using 12 lags and a constant term. The estimates are based on the OLS method per equation. The analogously estimated individual VAR model for GL (i.e. GL in the LHS of *Equation 13*) is presented in *Table 9*.

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	0.0017368	0.0003696	4.6994	<0.00001	***
CPI_1	0.476848	0.0633928	7.5221	<0.00001	***
CPI_2	-0.158354	0.071688	-2.2089	0.02814	**
CPI_3	-0.0506089	0.0721537	-0.7014	0.48374	
CPI_4	0.0492706	0.072298	0.6815	0.49623	
CPI_5	-0.113424	0.0725283	-1.5639	0.11919	
CPI_6	0.0838278	0.0726246	1.1543	0.24956	
CPI_7	-0.0806539	0.0724971	-1.1125	0.26705	
CPI_8	-0.0203207	0.0724707	-0.2804	0.77942	
CPI_9	0.0449267	0.0720414	0.6236	0.53348	
CPI_10	-0.0239341	0.0723196	-0.3309	0.74098	
CPI_11	0.205079	0.0714384	2.8707	0.00447	***
CPI_12	-0.268794	0.064286	-4.1812	0.00004	***
GL	0.0158866	0.0042261	3.7592	0.00021	***
GL_1	-0.0035045	0.0043602	-0.8037	0.42236	
GL_2	-0.0009701	0.0042077	-0.2306	0.81785	
GL_3	0.0037932	0.0041921	0.9048	0.36648	
GL_4	0.0048362	0.0041978	1.1521	0.25046	
GL_5	8.80E-05	0.0041926	0.021	0.98328	
GL_6	0.0034862	0.004216	0.8269	0.40913	
GL_7	0.0070533	0.0042053	1.6772	0.09482	*
GL_8	-0.0018815	0.0042233	-0.4455	0.65637	
GL_9	-0.0030358	0.0041811	-0.7261	0.46852	
GL_10	-0.0083255	0.0041922	-1.986	0.0482	**
GL_11	-0.0049478	0.0041851	-1.1823	0.23829	
GL_12	-0.00293	0.0041591	-0.7045	0.48182	

Marks. *** : significance 0,01 ; **: significance 0,05 ; *: significance 0,1 .

Adj. R^2= 0.282658

Table 9: displays one of two individual models (i.e. **GL** in the LHS of *Equation 13*), which jointly constitute the bivariate VAR model from *Equation 13*. This table shows the initial estimation of the VAR model during the sample period 1990/2013. The estimated results are calculated for the single VAR model describing gold returns (i.e. GL) and the CPI inflation rate (i.e. CPI) using 12 lags and a constant term. The estimates are based on the OLS method per equation. The analogously estimated individual VAR model for CPI (i.e. CPI in the LHS of *Equation 13*) is presented in *Table 8*.

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	0.00950954	0.00574911	1.6541	0.09944	*
GL_1	0.0601456	0.0652074	0.9224	0.35728	
GL_2	-0.0455268	0.0628908	-0.7239	0.46984	
GL_3	0.0376356	0.0627818	0.5995	0.54944	
GL_4	0.0312712	0.0629494	0.4968	0.61982	
GL_5	0.0166858	0.0627184	0.2660	0.79044	
GL_6	0.0319924	0.0631343	0.5067	0.61281	
GL_7	-0.00685581	0.0632908	-0.1083	0.91383	
GL_8	0.00494085	0.0632125	0.0782	0.93777	
GL_9	0.0190892	0.0626137	0.3049	0.76073	
GL_10	0.0161767	0.0632347	0.2558	0.79831	
GL_11	0.185194	0.0616324	3.0048	0.00294	***
GL_12	0.00217915	0.0622923	0.0350	0.97212	
CPI	3.55622	0.946007	3.7592	0.00021	***
CPI_1	-0.578987	1.05538	-0.5486	0.58380	
CPI_2	-2.93803	1.06659	-2.7546	0.00633	***
CPI_3	0.755925	1.07954	0.7002	0.48447	
CPI_4	-0.479039	1.08231	-0.4426	0.65845	
CPI_5	-0.928043	1.08908	-0.8521	0.39500	
CPI_6	0.753334	1.08854	0.6921	0.48958	
CPI_7	-0.402073	1.0872	-0.3698	0.71185	
CPI_8	1.33779	1.08096	1.2376	0.21710	
CPI_9	-1.29137	1.07546	-1.2008	0.23105	
CPI_10	1.32738	1.07881	1.2304	0.21977	
CPI_11	-3.34474	1.06531	-3.1397	0.00191	***
CPI_12	-0.201744	0.996725	-0.2024	0.83977	

Marks. *** : significance 0,01 ; **: significance 0,05 ; *: significance 0,1

Adj. R^2= 0.127894

Table 10: displays one of two individual models (i.e. **CPI** in the LHS of *Equation 13*), which jointly constitute the bivariate VAR model from *Equation 13*. This table shows the initial estimation of the VAR model during the sample period 1990/2013. The estimated results are calculated for the single VAR model describing silver returns (i.e. SL) and the CPI inflation rate (i.e. CPI) using 12 lags and a constant term. The estimates are based on the OLS method per equation. The analogously estimated individual VAR model for SL (i.e. SL in the LHS of *Equation 13*) is presented in *Table 11*.

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	0.00157052	0.000382239	4.1087	0.00005	***
CPI_1	0.457991	0.0635565	7.2061	<0.00001	***
CPI_2	-0.208943	0.0706429	-2.9577	0.00341	***
CPI_3	-0.0169956	0.0715523	-0.2375	0.81245	
CPI_4	0.0521037	0.0717419	0.7263	0.46840	
CPI_5	-0.11631	0.0721704	-1.6116	0.10839	
CPI_6	0.112558	0.0722399	1.5581	0.12054	
CPI_7	-0.0575707	0.071989	-0.7997	0.42468	
CPI_8	0.00330823	0.0717518	0.0461	0.96326	
CPI_9	0.0405565	0.0712612	0.5691	0.56981	
CPI_10	0.0169895	0.0712542	0.2384	0.81175	
CPI_11	0.165461	0.0701008	2.3603	0.01907	**
CPI_12	-0.253103	0.0635134	-3.9850	0.00009	***
SL	0.00734354	0.00237047	3.0979	0.00218	***
SL_1	-0.000289083	0.00244511	-0.1182	0.90599	
SL_2	0.00212523	0.00243284	0.8736	0.38325	
SL_3	0.00364682	0.00241924	1.5074	0.13304	
SL_4	0.00115376	0.00242754	0.4753	0.63503	
SL_5	0.00309905	0.00242744	1.2767	0.20297	
SL_6	0.00139752	0.00244129	0.5725	0.56756	
SL_7	0.00303419	0.00244463	1.2412	0.21578	
SL_8	-0.0019454	0.00245489	-0.7925	0.42889	
SL_9	-0.00220075	0.00244535	-0.9000	0.36905	
SL_10	-0.00510618	0.00245818	-2.0772	0.03886	**
SL_11	-0.000299268	0.00243254	-0.1230	0.90219	
SL_12	-0.00127206	0.00238901	-0.5325	0.59491	

Marks. *** : significance 0,01 ; **: significance 0,05 ; *: significance 0,1

Adj. R^2= 0.278893

Table 11: displays one of two individual models (i.e. **SL** in the LHS of *Equation 13*), which jointly constitute the bivariate VAR model from *Equation 13*. This table shows the initial estimation of the VAR model during the sample period 1990/2013. The estimated results are calculated for the single VAR model describing silver returns (i.e. SL) and the CPI inflation rate (i.e. CPI) using 12 lags and a constant term. The estimates are based on the OLS method per equation. The analogously estimated individual VAR model for CPI (i.e. CPI in the LHS of *Equation 13*) is presented in *Table 10*.

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	0.0253774	0.0105222	2.4118	0.01664	**
SL_1	0.145722	0.0651339	2.2373	0.02620	**
SL_2	-0.0764712	0.0654055	-1.1692	0.24351	
SL_3	-0.0225307	0.0654192	-0.3444	0.73085	
SL_4	0.0774806	0.0651826	1.1887	0.23576	
SL_5	-0.0652238	0.065431	-0.9968	0.31987	
SL_6	-0.00765367	0.0657599	-0.1164	0.90744	
SL_7	0.0804093	0.0658128	1.2218	0.22301	
SL_8	-0.106031	0.0658093	-1.6112	0.10848	
SL_9	-0.0427982	0.0658795	-0.6496	0.51655	
SL_10	0.0327017	0.0667392	0.4900	0.62459	
SL_11	0.020984	0.0654685	0.3205	0.74886	
SL_12	-0.0408153	0.0642927	-0.6348	0.52615	
CPI	5.32124	1.71768	3.0979	0.00218	***
CPI_1	-1.37959	1.88759	-0.7309	0.46558	
CPI_2	-3.37921	1.924	-1.7563	0.08033	*
CPI_3	-0.81423	1.92559	-0.4228	0.67279	
CPI_4	-0.342411	1.93322	-0.1771	0.85957	
CPI_5	-3.14023	1.94267	-1.6165	0.10733	
CPI_6	0.436669	1.95437	0.2234	0.82339	
CPI_7	0.656157	1.94	0.3382	0.73549	
CPI_8	1.36398	1.92943	0.7069	0.48031	
CPI_9	-2.60938	1.91204	-1.3647	0.17365	
CPI_10	-1.38112	1.91619	-0.7208	0.47177	
CPI_11	-3.18137	1.8979	-1.6763	0.09501	*
CPI_12	1.18805	1.76459	0.6733	0.50143	

Marks. *** : significance 0,01 ; **: significance 0,05 ; *: significance 0,1

Adj. R^2= 0.118790

Table 12: displays one of two individual models (i.e. **CPI** in the LHS of *Equation 13*), which jointly constitute the bivariate VAR model from *Equation 13*. This table shows the initial estimation of the VAR model during the sample period 1990/2013. The estimated results are calculated for the single VAR model describing platinum returns (i.e. PL) and the CPI inflation rate (i.e. CPI) using 12 lags and a constant term. The estimates are based on the OLS method per equation. The analogously estimated individual VAR model for PL (i.e. PL in the LHS of *Equation 13*) is presented in *Table 13*.

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	0.00128759	0.000366642	3.5119	0.00053	***
CPI_1	0.370502	0.063459	5.8384	<0.00001	***
CPI_2	-0.231064	0.0682519	-3.3855	0.00083	***
CPI_3	-0.0222685	0.0695	-0.3204	0.74894	
CPI_4	0.06948	0.0695441	0.9991	0.31878	
CPI_5	-0.124043	0.0691618	-1.7935	0.07417	*
CPI_6	0.169539	0.0682632	2.4836	0.01370	**
CPI_7	-0.0452115	0.0675345	-0.6695	0.50386	
CPI_8	0.0649901	0.0672045	0.9671	0.33451	
CPI_9	0.0867508	0.0661577	1.3113	0.19104	
CPI_10	0.0250091	0.0665703	0.3757	0.70749	
CPI_11	0.171627	0.0653018	2.6282	0.00915	***
CPI_12	-0.239796	0.0588415	-4.0753	0.00006	***
PL	0.0104104	0.00275072	3.7846	0.00020	***
PL_1	0.00642824	0.00287448	2.2363	0.02627	**
PL_2	0.00442489	0.00288511	1.5337	0.12644	
PL_3	0.00404569	0.00288936	1.4002	0.16277	
PL_4	0.00533904	0.00289012	1.8473	0.06595	*
PL_5	0.00321531	0.00290174	1.1081	0.26896	
PL_6	-0.000443047	0.00292933	-0.1512	0.87991	
PL_7	0.0100175	0.002915	3.4365	0.00070	***
PL_8	-0.00497046	0.00300496	-1.6541	0.09944	*
PL_9	-0.00436444	0.00300272	-1.4535	0.14741	
PL_10	-0.00856181	0.00299318	-2.8604	0.00461	***
PL_11	-0.00337394	0.0030058	-1.1225	0.26280	
PL_12	0.00308092	0.00298069	1.0336	0.30237	

Marks. *** : significance 0,01 ; **: significance 0,05 ; *: significance 0,1

Adj. R^2= 0.394606

Table 13: displays one of two individual models (i.e. **PL** in the LHS of *Equation 13*), which jointly constitute the bivariate VAR model from *Equation 13*. This table shows the initial estimation of the VAR model during the sample period 1990/2013. The estimated results are calculated for the single VAR model describing platinum returns (i.e. PL) and the CPI inflation rate (i.e. CPI) using 12 lags and a constant term. The estimates are based on the OLS method per equation. The analogously estimated individual VAR model for CPI (i.e. CPI in the LHS of *Equation 13*) is presented in *Table 12*.

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	0.0197198	0.00854598	2.3075	0.02189	**
PL_1	0.150119	0.0660255	2.2736	0.02389	**
PL_2	0.0698758	0.0664669	1.0513	0.29420	
PL_3	0.0465458	0.0665968	0.6989	0.48529	
PL_4	-0.00535365	0.0668854	-0.0800	0.93627	
PL_5	-0.0554624	0.0667505	-0.8309	0.40688	
PL_6	-0.0703688	0.0671559	-1.0478	0.29578	
PL_7	0.00188511	0.0686348	0.0275	0.97811	
PL_8	-0.13151	0.068916	-1.9083	0.05757	*
PL_9	0.0586021	0.0691981	0.8469	0.39792	
PL_10	0.0883461	0.0697212	1.2671	0.20636	
PL_11	0.0761877	0.0690722	1.1030	0.27114	
PL_12	-0.0852269	0.0684193	-1.2457	0.21413	
CPI	5.49635	1.45229	3.7846	0.00020	***
CPI_1	-2.07063	1.55405	-1.3324	0.18401	
CPI_2	-2.24578	1.59922	-1.4043	0.16155	
CPI_3	-1.27424	1.59513	-0.7988	0.42519	
CPI_4	-0.76662	1.60055	-0.4790	0.63240	
CPI_5	-0.551688	1.59956	-0.3449	0.73048	
CPI_6	-1.19293	1.58699	-0.7517	0.45298	
CPI_7	1.84172	1.54861	1.1893	0.23553	
CPI_8	-0.973061	1.54595	-0.6294	0.52968	
CPI_9	-2.87804	1.51412	-1.9008	0.05855	*
CPI_10	1.16312	1.5282	0.7611	0.44736	
CPI_11	-3.71885	1.5029	-2.4744	0.01405	**
CPI_12	0.680676	1.39809	0.4869	0.62681	

Marks. *** : significance 0,01 ; **: significance 0,05 ; *: significance 0,1

Adj. R^2= 0.175361

Table 14: displays one of two individual models (i.e. **CPI** in the LHS of *Equation 13*), which jointly constitute the bivariate VAR model from *Equation 13*. This table shows the initial estimation of the VAR model during the sample period 1990/2013. The estimated results are calculated for the single VAR model describing palladium returns (i.e. PA) and the CPI inflation rate (i.e. CPI) using 12 lags and a constant term. The estimates are based on the OLS method per equation. The analogously estimated individual VAR model for PA (i.e. PA in the LHS of *Equation 13*) is presented in *Table 15*.

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	0.00159651	0.000374241	4.2660	0.00003	***
CPI_1	0.475438	0.0640084	7.4278	<0.00001	***
CPI_2	-0.24845	0.0709327	-3.5026	0.00055	***
CPI_3	0.00848122	0.0719174	0.1179	0.90622	
CPI_4	0.041856	0.0718617	0.5825	0.56082	
CPI_5	-0.119047	0.0709145	-1.6787	0.09453	*
CPI_6	0.137325	0.0703843	1.9511	0.05223	*
CPI_7	-0.0726161	0.0705438	-1.0294	0.30436	
CPI_8	0.0231245	0.0703534	0.3287	0.74268	
CPI_9	0.0319899	0.069725	0.4588	0.64680	
CPI_10	0.00364046	0.0698876	0.0521	0.95850	
CPI_11	0.14942	0.0690042	2.1654	0.03136	**
CPI_12	-0.22901	0.0616226	-3.7163	0.00025	***
PA	0.00406705	0.00180924	2.2479	0.02550	**
PA_1	0.00104021	0.00189022	0.5503	0.58263	
PA_2	0.000292747	0.00187368	0.1562	0.87598	
PA_3	0.00370563	0.00187864	1.9725	0.04972	**
PA_4	0.00100525	0.00188887	0.5322	0.59509	
PA_5	0.00185735	0.00189033	0.9826	0.32683	
PA_6	-0.000690974	0.00188513	-0.3665	0.71429	
PA_7	0.00482539	0.00188188	2.5641	0.01096	**
PA_8	-0.00460648	0.00189842	-2.4265	0.01600	**
PA_9	-0.00111073	0.00192316	-0.5776	0.56411	
PA_10	-0.0053701	0.00191372	-2.8061	0.00543	***
PA_11	0.00134471	0.00193964	0.6933	0.48882	
PA_12	-0.000364842	0.00186379	-0.1958	0.84497	

Marks. *** : significance 0,01 ; **: significance 0,05 ; *: significance 0,1

Adj. R^2= 0.306380

Table 15: displays one of two individual models (i.e. **PA** in the LHS of *Equation 13*), which jointly constitute the bivariate VAR model from *Equation 13*. This table shows the initial estimation of the VAR model during the sample period 1990/2013. The estimated results are calculated for the single VAR model describing palladium returns (i.e. PA) and the CPI inflation rate (i.e. CPI) using 12 lags and a constant term. The estimates are based on the OLS method per equation. The analogously estimated individual VAR model for CPI (i.e. CPI in the LHS of *Equation 13*) is presented in *Table 14*.

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	0.034859	0.0136396	2.5557	0.01122	**
PA_1	0.269679	0.0650061	4.1485	0.00005	***
PA_2	-0.0525325	0.0666183	-0.7886	0.43116	
PA_3	0.0449341	0.0673646	0.6670	0.50541	
PA_4	0.0528364	0.0671958	0.7863	0.43248	
PA_5	0.0711858	0.0672736	1.0582	0.29107	
PA_6	-0.0449595	0.0670656	-0.6704	0.50327	
PA_7	-0.0222471	0.067906	-0.3276	0.74349	
PA_8	-0.0303282	0.0683929	-0.4434	0.65785	
PA_9	0.0324267	0.0684799	0.4735	0.63628	
PA_10	0.000204286	0.0692551	0.0029	0.99765	
PA_11	0.0828002	0.0689105	1.2016	0.23074	
PA_12	0.00805532	0.0663537	0.1214	0.90348	
CPI	5.15436	2.29293	2.2479	0.02550	**
CPI_1	-4.44964	2.51443	-1.7696	0.07808	*
CPI_2	0.160444	2.58997	0.0619	0.95066	
CPI_3	-2.93838	2.55316	-1.1509	0.25095	
CPI_4	-0.298436	2.56003	-0.1166	0.90730	
CPI_5	-1.96823	2.53634	-0.7760	0.43852	
CPI_6	-2.50925	2.52051	-0.9955	0.32050	
CPI_7	4.13313	2.50256	1.6516	0.09995	*
CPI_8	-3.28886	2.49598	-1.3177	0.18889	
CPI_9	-4.85264	2.46313	-1.9701	0.04999	**
CPI_10	2.76266	2.48149	1.1133	0.26671	
CPI_11	-5.64684	2.45344	-2.3016	0.02223	**
CPI_12	0.542839	2.25675	0.2405	0.81012	

Marks. *** : significance 0,01 ; **: significance 0,05 ; *: significance 0,1

Adj. R^2= 0.112680

Table 16: displays the four common inflation-hedging measures for gold in period 1974/2013, namely: the Pearson correlation coefficient (ρ), the Fisher coefficient (β), the hedge ratio (Δ) by Schotman and Schweitzer (2000) and the hedge ratio (S) by Bodie (1976). These measures are calculated for different holding periods (i.e. 1M-10Y). "*L*" and "*U*" represent the 95% bootstrap confidence intervals (i.e. *B*=200). "*SD*" designates the values for standard deviation of the bootstrap hedging measures. The last column of each measures shows the empirical (i.e. "*Emp.*") values of the hedging measures' estimates. The insignificant results are written in italics.

	ρ	SD	*Emp.* ρ	β	SD	*Emp.* β	Δ	SD	*Emp.* Δ	S	SD	*Emp.* S
1M	*0.34*	0.12	0.18	*2.59*	0.84	2.71	*0.04*	0.02	0.01	*0.87*	0.05	0.97
L	*-0.06*			*-0.67*			*0.00*			*0.85*		
U	*0.39*			*3.05*			*0.05*			*1.00*		
2M	0.49	0.13	0.22	3.01	0.78	3.08	0.08	0.02	0.02	0.74	0.08	0.95
L	0.01			0.12			0.00			0.71		
U	0.54			3.28			0.09			1.00		
4M	0.63	0.13	0.23	3.36	0.68	2.77	0.12	0.03	0.02	0.59	0.12	0.95
L	0.12			0.98			0.03			0.54		
U	0.68			3.63			0.13			0.99		
6M	0.65	0.12	0.30	3.62	0.61	3.56	0.12	0.02	0.03	0.57	0.11	0.91
L	0.23			1.90			0.04			0.53		
U	0.69			3.91			0.12			0.95		
1Y	0.70	0.09	0.43	4.17	0.58	5.08	0.12	0.02	0.04	0.51	0.10	0.81
L	0.39			2.22			0.06			0.47		
U	0.73			4.51			0.12			0.85		
2Y	0.73	0.08	0.43	5.34	0.71	4.90	0.10	0.01	0.04	0.46	0.08	0.81
L	0.49			3.31			0.07			0.43		
U	0.75			5.76			0.11			0.76		
3Y	0.76	0.06	0.54	6.72	0.88	7.32	0.09	0.01	0.04	0.41	0.07	0.71
L	0.60			4.55			0.06			0.37		
U	0.79			7.23			0.11			0.65		
4Y	0.91	0.08	0.45	5.64	0.76	1.82	0.15	0.02	0.11	0.16	0.10	0.79
L	0.77			3.85			0.10			0.13		
U	0.93			6.26			0.19			0.41		
5Y	0.88	0.12	0.38	4.64	0.86	1.14	0.17	0.03	0.13	0.21	0.13	0.86
L	0.58			2.46			0.08			0.16		
U	0.92			5.14			0.19			0.67		
10Y	0.98	0.14	0.98	7.38	1.87	2.13	0.14	0.08	0.46	0.02	0.03	0.03
L	0.96			3.62			0.11			0.00		
U	1.00			8.57			0.26			0.07		

Table 17: displays the four common inflation-hedging measures for silver in period 1974/2013, namely: the Pearson correlation coefficient (ρ), the Fisher coefficient (β), the hedge ratio (Δ) by Schotman and Schweitzer (2000) and the hedge ratio (*S*) by Bodie (1976). These measures are calculated for different holding periods (i.e. 1M-10Y). "*L*" and "*U*" represent the 95% bootstrap confidence intervals (i.e. *B*=200). "*SD*" designates the values for standard deviation of the bootstrap hedging measures. The last column of each measures shows the empirical (i.e. "*Emp.*") values of the hedging measures' estimates. The insignificant results are written in italics.

	ρ	SD	*Emp.* ρ	β	SD	*Emp.* β	Δ	SD	*Emp.* Δ	*S*	SD	*Emp. S*
1M	0.31	0.06	0.13	3.94	0.98	3.32	0.02	0.01	0.00	0.90	0.03	0.98
L	0.11			1.14			0.01			0.86		
U	0.37			4.94			0.03			0.99		
2M	0.42	0.08	0.16	4.02	0.86	4.00	0.04	0.01	0.01	0.82	0.04	0.97
L	0.21			2.01			0.01			0.80		
U	0.45			5.17			0.05			0.96		
4M	0.59	0.10	0.20	4.88	0.74	4.54	0.07	0.02	0.01	0.64	0.08	0.96
L	0.34			2.97			0.02			0.60		
U	0.63			5.64			0.08			0.89		
6M	0.62	0.09	0.26	5.51	0.67	7.02	0.07	0.01	0.01	0.60	0.09	0.93
L	0.30			3.55			0.02			0.57		
U	0.66			6.16			0.08			0.91		
1Y	0.73	0.09	0.42	6.21	0.74	12.17	0.09	0.01	0.01	0.46	0.10	0.82
L	0.41			4.26			0.04			0.42		
U	0.76			7.82			0.09			0.83		
2Y	0.78	0.10	0.52	7.85	1.13	13.60	0.08	0.01	0.02	0.38	0.09	0.73
L	0.57			5.40			0.04			0.34		
U	0.81			8.95			0.09			0.68		
3Y	0.85	0.10	0.59	9.43	1.38	15.38	0.08	0.01	0.02	0.27	0.10	0.65
L	0.63			6.54			0.05			0.20		
U	0.89			10.76			0.10			0.60		
4Y	0.94	0.11	0.18	9.16	1.80	0.65	0.10	0.02	0.05	0.11	0.12	0.97
L	0.72			4.62			0.05			0.05		
U	0.97			11.38			0.13			0.48		
5Y	0.95	0.16	0.36	8.34	2.25	0.93	0.11	0.02	0.14	0.08	0.15	0.87
L	0.56			3.59			0.03			0.03		
U	0.99			10.27			0.14			0.53		
10Y	0.95	0.26	0.86	15.79	6.35	1.48	0.06	0.10	0.50	0.03	0.06	0.26
L	0.94			3.77			0.01			0.01		
U	0.99			20.74			0.11			0.11		

Table 18: displays average bootstrap estimates of the Pearson correlation coefficients (ρ) and the Fisher coefficient (β) for gold and silver in period 1990/2013. "*L*" and "*U*" represent the 95% bootstrap confidence intervals (i.e. *B*=200). "*SD*" designates the values for standard deviation of the bootstrap hedging measures. The last column of each measures shows the empirical (i.e. "*Emp.*") values of the hedging measures' estimates. The insignificant results are written in italics.

	Gold - 1990/2013						Silver - 1990/2013					
	ρ	SD	*Emp.* ρ	β	SD	*Emp.* β	ρ	SD	*Emp.* ρ	β	SD	*Emp.* β
1M	0.36	0.05	0.24	3.06	0.35	3.22	0.31	0.05	0.18	5.15	0.66	4.37
L	0.16			1.90			0.12			2.78		
U	0.38			3.24			0.33			5.60		
2M	0.34	0.05	0.18	3.10	0.46	2.20	0.38	0.06	0.14	6.44	0.99	3.21
L	0.13			1.57			0.19			4.28		
U	0.36			3.51			0.40			7.18		
4M	0.40	0.06	0.17	3.62	0.48	1.76	0.39	0.08	0.23	6.76	1.39	4.97
L	0.22			2.35			0.22			4.61		
U	0.42			3.95			0.42			7.40		
6M	0.35	0.06	-0.03	4.83	0.85	-0.34	0.42	0.08	-0.06	9.50	1.93	-1.57
L	0.15			2.10			0.22			6.08		
U	0.39			5.60			0.46			10.94		
1Y	0.24	0.06	0.18	3.72	1.06	2.66	0.43	0.09	0.13	13.76	2.76	4.73
L	0.05			0.84			0.13			5.71		
U	0.32			5.22			0.48			15.47		
2Y	*0.03*	0.08	0.06	*0.62*	1.96	0.87	*0.39*	0.14	0.10	*9.51*	4.27	1.84
L	*-0.23*			*-4.79*			*-0.10*			*-2.47*		
U	*0.17*			*3.33*			*0.48*			*12.40*		
3Y	*-0.01*	0.09	0.07	*-0.08*	2.89	1.47	0.32	0.11	-0.24	9.43	3.85	-7.15
L	*-0.30*			*-5.52*			0.03			1.72		
U	*0.15*			*3.53*			0.41			12.10		
4Y	-0.67	0.08	-0.27	-14.67	1.85	-6.80	*-0.09*	0.15	0.08	*-3.09*	6.86	2.71
L	-0.75			-18.41			*-0.52*			*-17.93*		
U	-0.44			-7.60			*0.14*			*3.83*		
5Y	-0.70	0.10	-0.42	-18.55	3.61	-13.90	*0.16*	0.18	-0.46	*2.99*	4.61	-12.92
L	-0.79			-22.30			*-0.45*			*-11.13*		
U	-0.39			-9.54			*0.40*			*11.24*		

Table 19: displays average bootstrap estimates of the Pearson correlation coefficients (ρ) and the Fisher coefficient (β) for platinum and palladium in period 1990/2013. "*L*" and "*U*" represent the 95% bootstrap confidence intervals (i.e. *B*=200). "*SD*" designates the values for standard deviation of the bootstrap hedging measures. The last column of each measures shows the empirical (i.e. "*Emp.*") values of the hedging measures' estimates. The insignificant results are written in italics.

	Platinum - 1990/2013						Palladium - 1990/2013					
	ρ	SD	*Emp. ρ*	**β**	SD	*Emp. β*	**ρ**	SD	*Emp. ρ*	**β**	SD	*Emp. β*
1M	0.28	0.05	0.24	5.07	0.84	4.76	0.14	0.02	0.14	3.64	0.59	4.43
L	0.16			3.23			0.06			2.22		
U	0.30			5.58			0.15			4.73		
2M	0.36	0.04	0.25	7.52	0.91	4.68	0.21	0.04	0.10	6.22	1.21	3.23
L	0.26			5.23			0.11			3.74		
U	0.39			8.32			0.23			7.13		
4M	0.35	0.04	0.34	7.07	0.89	6.43	0.17	0.04	0.13	5.64	1.55	4.11
L	0.26			5.27			0.03			1.60		
U	0.38			8.05			0.21			7.24		
6M	0.33	0.06	-0.12	10.21	1.87	-2.50	0.24	0.06	-0.15	10.52	2.93	-5.49
L	0.14			4.05			0.08			4.09		
U	0.37			11.41			0.32			14.57		
1Y	0.42	0.07	0.34	12.54	2.18	7.50	0.21	0.07	0.08	10.42	3.57	3.67
L	0.23			6.29			0.05			2.70		
U	0.48			14.15			0.30			16.13		
2Y	0.41	0.08	0.11	10.90	2.61	2.03	-0.25	0.07	-0.29	-10.06	3.46	-8.56
L	0.20			5.43			-0.40			-16.02		
U	0.48			12.54			-0.06			-3.17		
3Y	0.41	0.11	0.33	16.16	4.40	7.74	0.33	0.09	-0.30	16.90	6.28	-9.80
L	0.27			10.07			0.13			8.99		
U	0.52			19.63			0.47			29.57		
4Y	*-0.06*	0.13	-0.32	*-1.34*	4.04	-6.81	*0.27*	0.18	-0.48	*15.41*	12.90	-13.06
L	*-0.22*			*-4.92*			*-0.40*			*-25.67*		
U	*0.13*			*3.88*			*0.50*			*36.93*		
5Y	0.73	0.21	-0.68	8.49	3.41	-13.07	-0.72	0.12	-0.44	-47.75	11.28	-23.22
L	0.17			1.97			-0.83			-68.95		
U	0.90			14.31			-0.31			-19.71		

Figure 6: plots the monthly hedge-price of gold (i.e. the initial price of $129) and the nominal price of gold from February 1974 until January 2013. Moreover, the US CPI index is included.

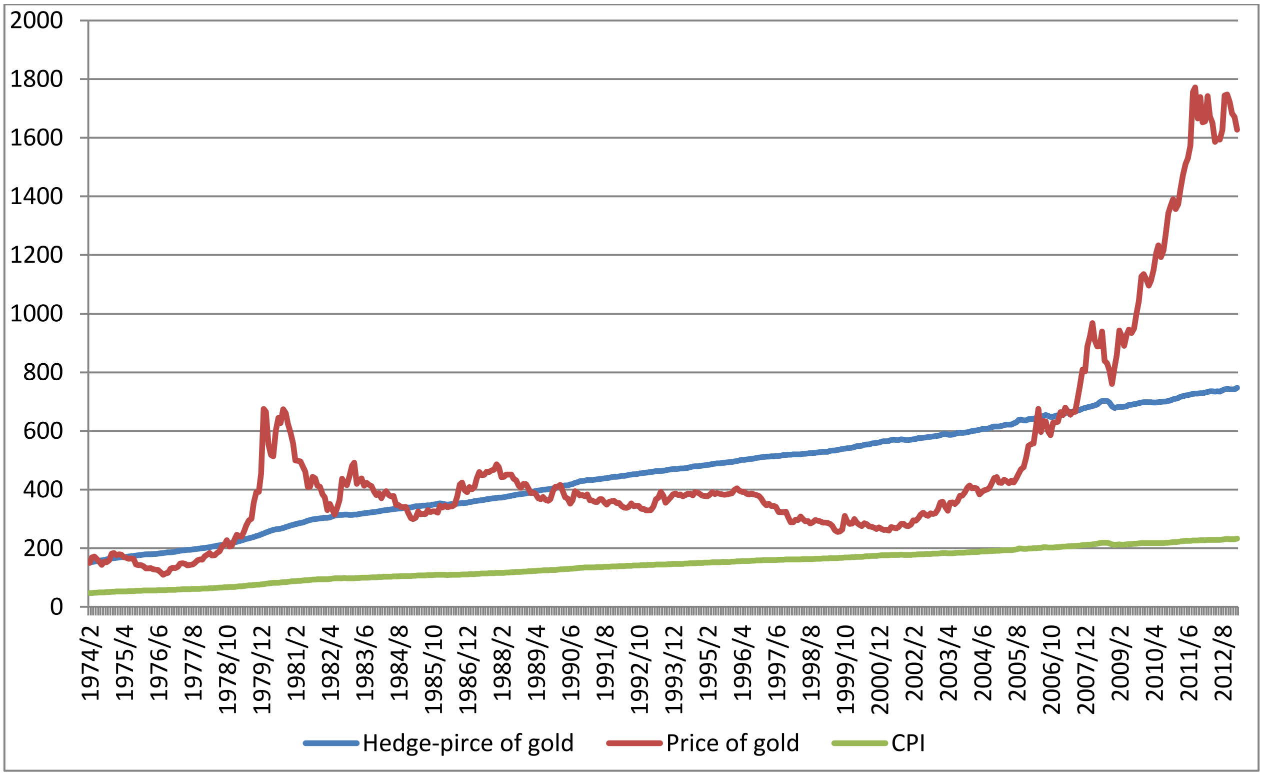


Figure 7: plots the monthly hedge-price of silver (i.e. the initial price of $3.6) and the nominal price of silver from February 1974 until January 2013.

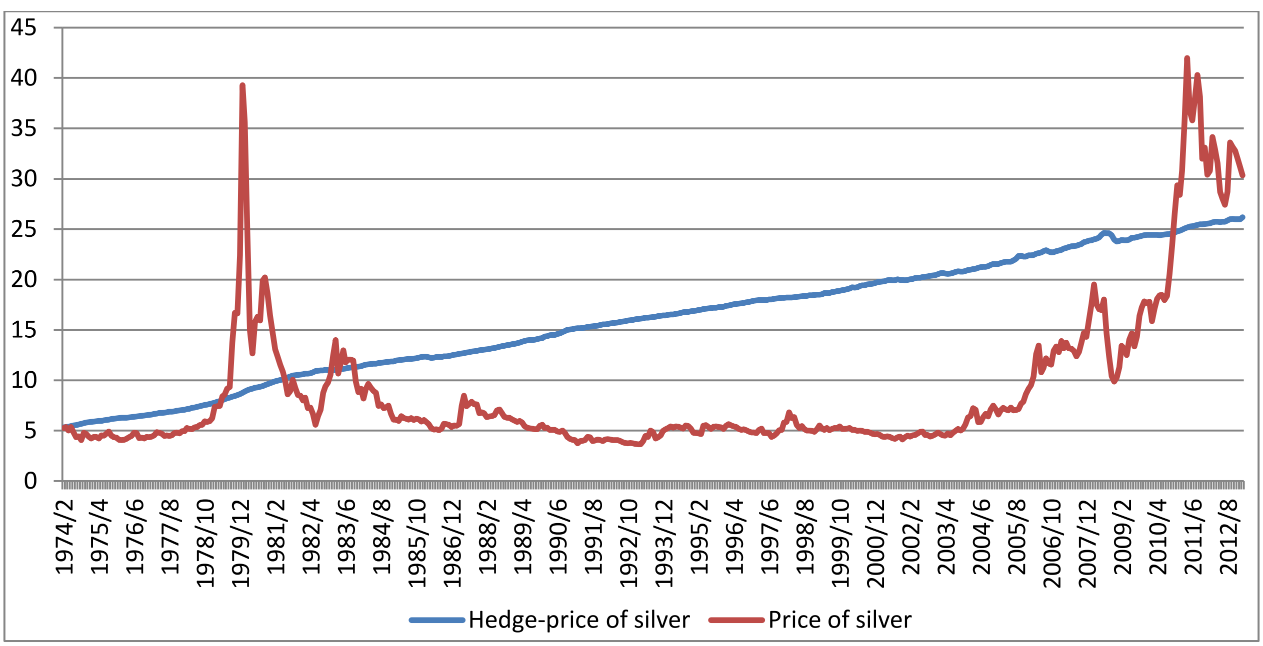


Figure 8: compares the monthly platinum hedge-price (i.e. the initial price of $488) and the nominal price of platinum with the monthly gold hedge-price (i.e. the initial price of $369) and the nominal price of gold from May 1990 - January 2013.

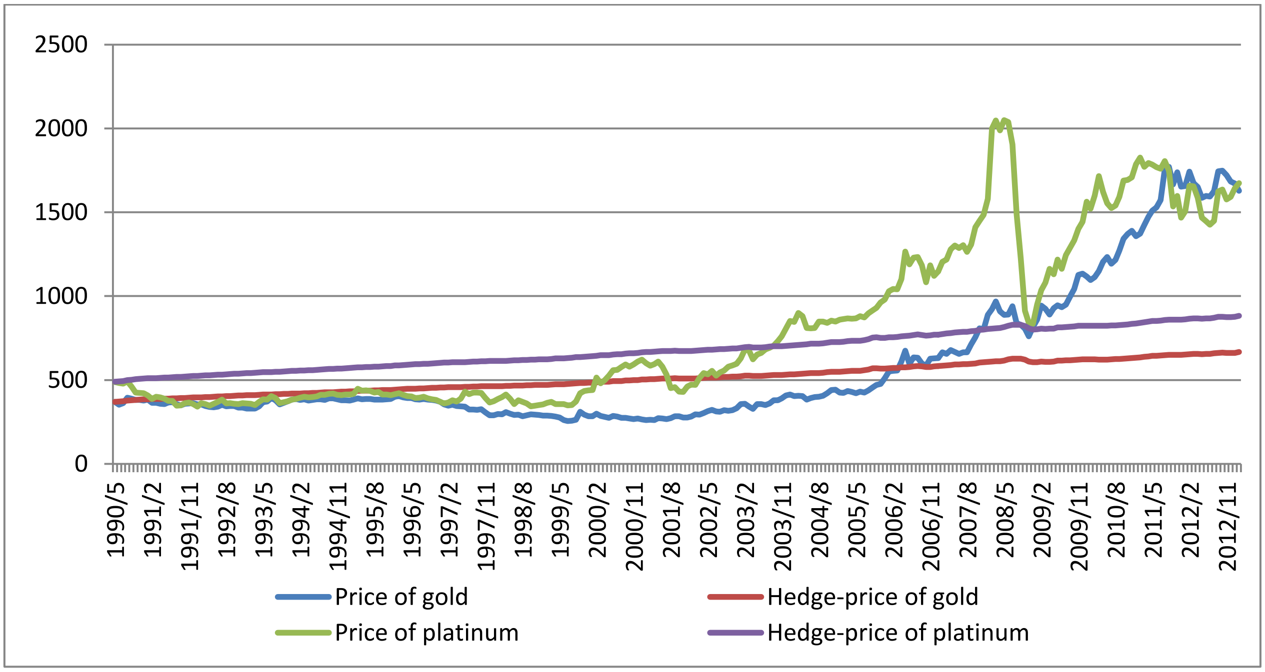


Figure 9: compares the monthly palladium hedge-price (i.e. the initial price of $120) and the nominal price of palladium with the monthly gold hedge-price (i.e. the initial price of $369) and the nominal price of gold from May 1990 - January 2013.

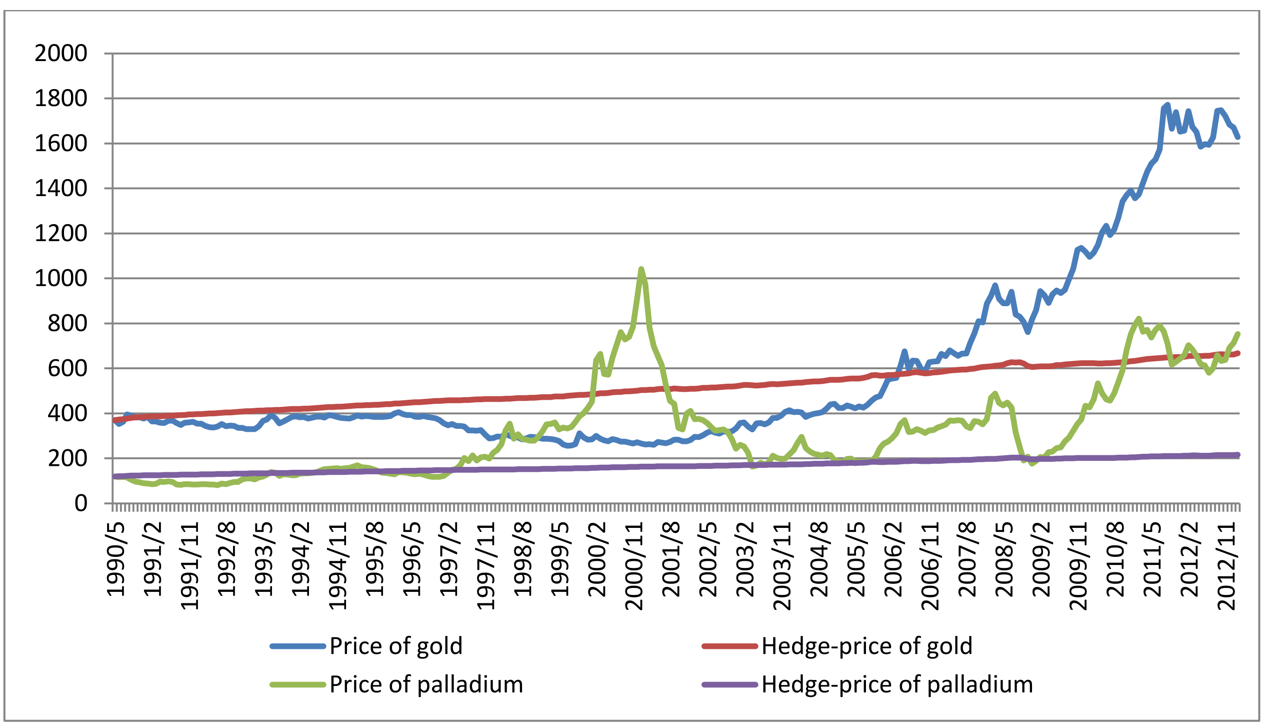


Figure 10: The extending window estimates of correlation between GL and CPI - 1974/2013 (i.e. 1M-5Y). The initial sample length is 5-years thus the observations start in January 1979.

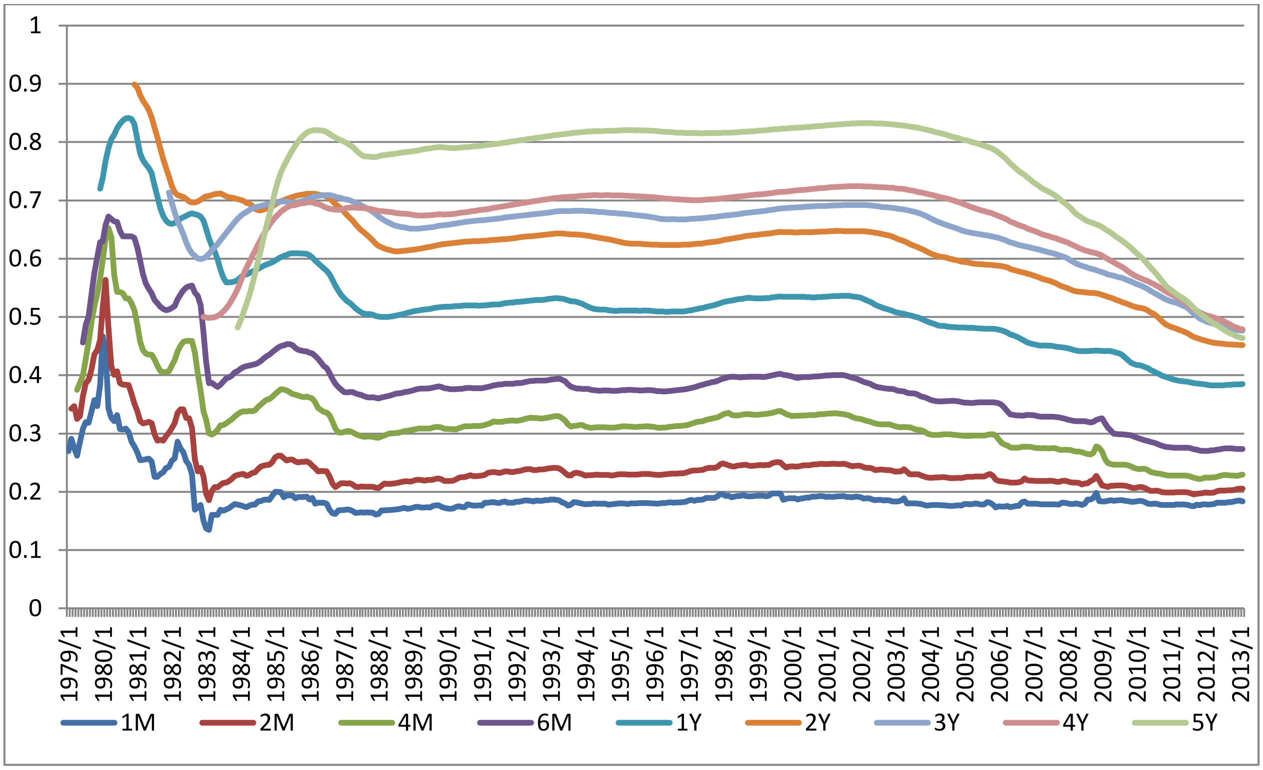


Figure 11: The extending window estimates of correlation between GL and CPI - 1990/2013 (i.e. 1Y-5Y). The initial sample length is 5-years. The observations start in April 1995 for all investment horizons.

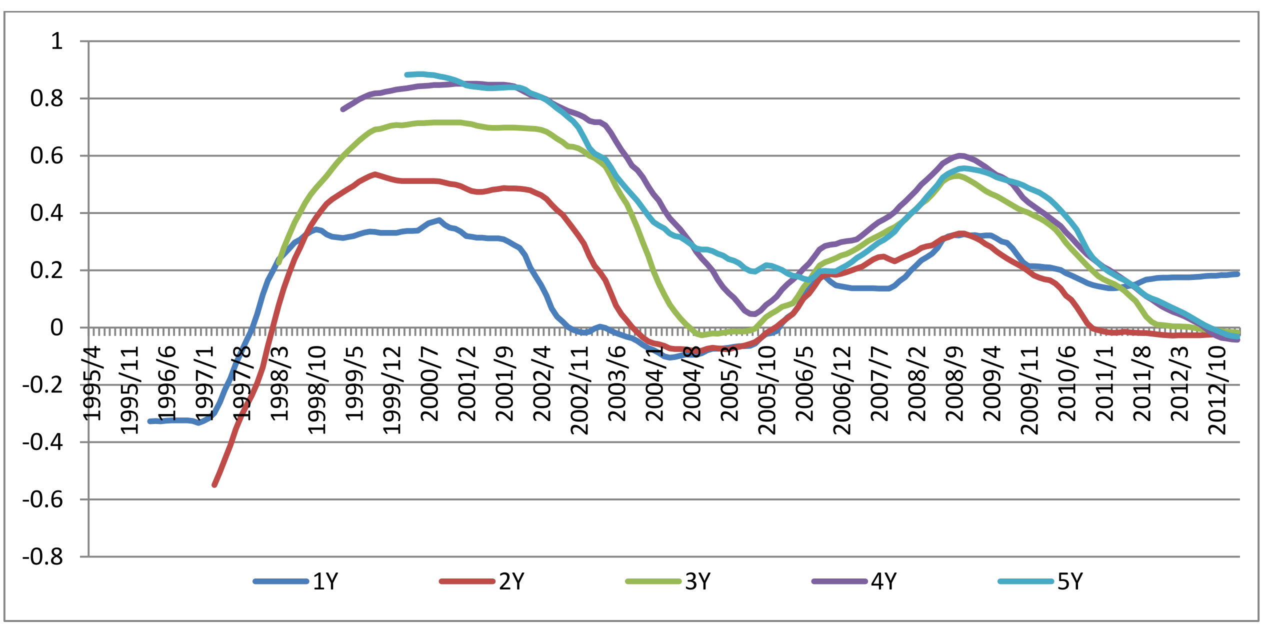


Figure 12: The rolling window estimates of correlation between GL and CPI - 1974/2013 (i.e. 2Y-5Y). The fixed window of 5-years is set in the beginning of the sample period, therefore, the observations start in February 1979 for all investment horizons (i.e. 5 years after the start of sample period 1974/2013).

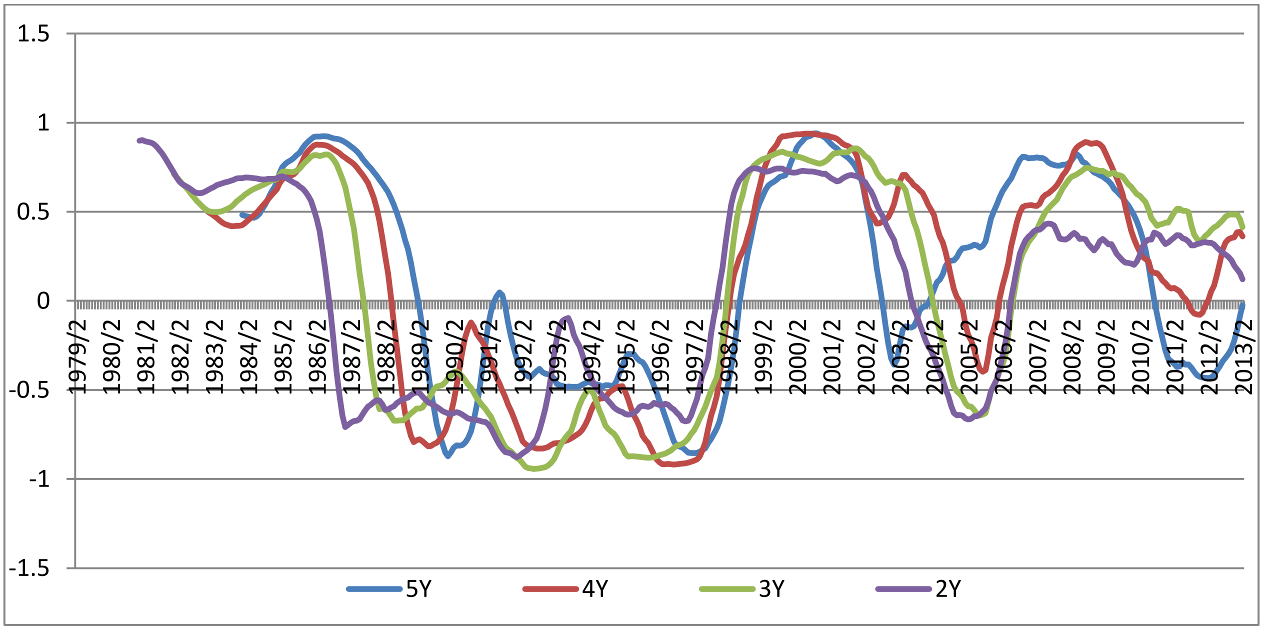


Figure 13: The extending window estimates of correlation between GL and CPI - 1990/2013 (i.e. 1M-6M). The initial sample length is 5-years. The observations start in April 1995 for all investment horizons.

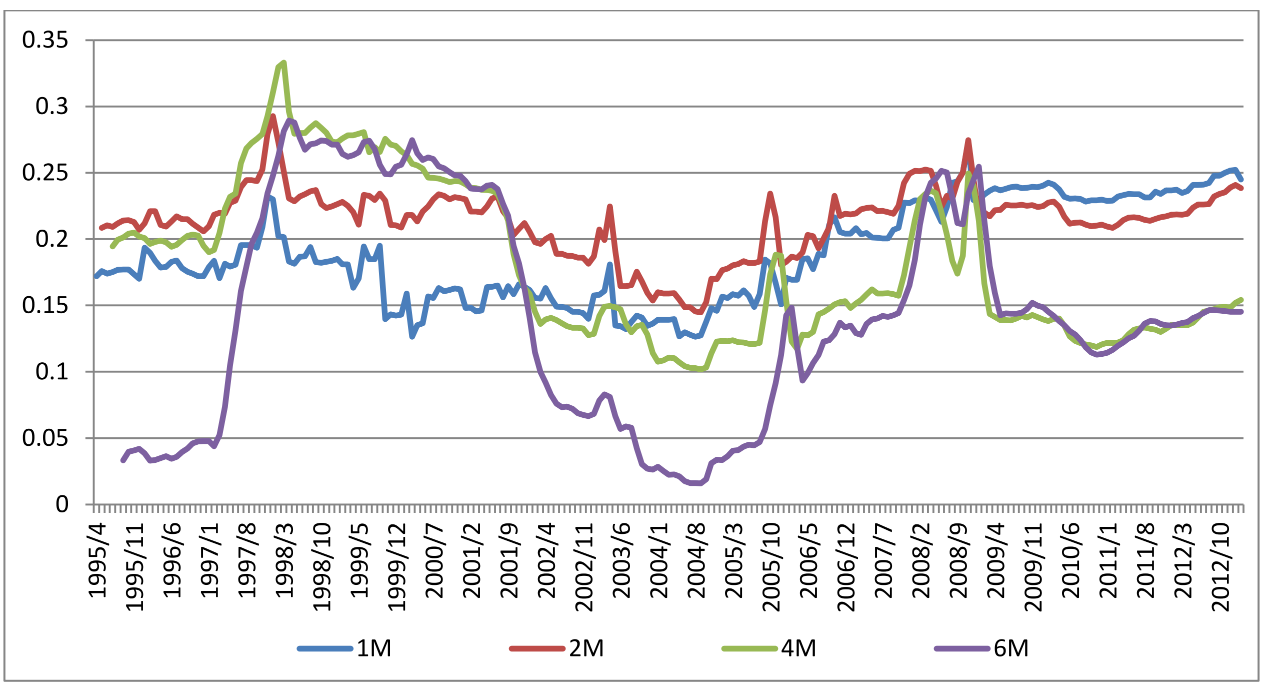


Figure 14: The rolling window estimates of correlation between GL and CPI - 1974/2013 (i.e. 2M-1Y). The fixed window of 5-years is set in the beginning of the sample period, therefore, the observations start in February 1979 for all investment horizons (i.e. 5 years after the start of sample period 1974/2013).

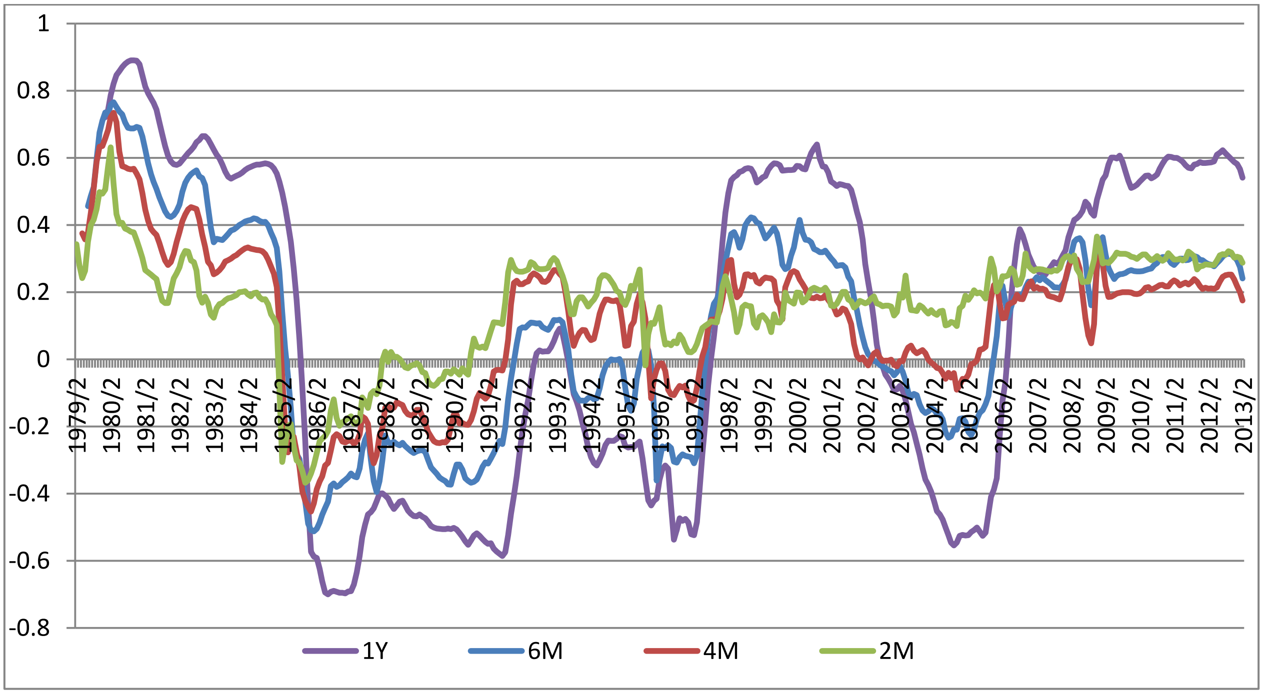


Figure 15: The extending window estimates of correlation between SL and CPI - 1974/2013 (i.e. 1M-5Y). The initial sample length is 5-years thus the observations start in January 1979.

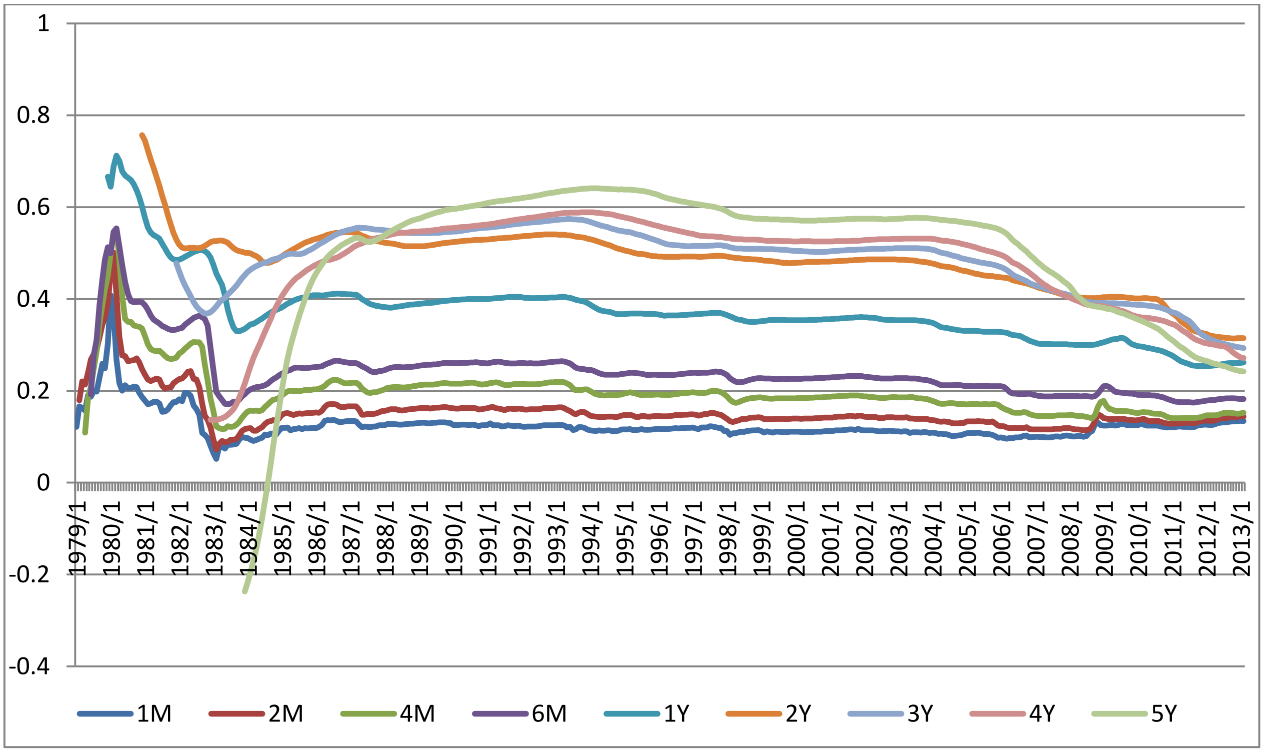


Figure 16: The extending window estimates of correlation between SL and CPI - 1990/2013 (i.e. 1Y-5Y). The initial sample length is 5-years. The observations start in April 1995 for all investment horizons.

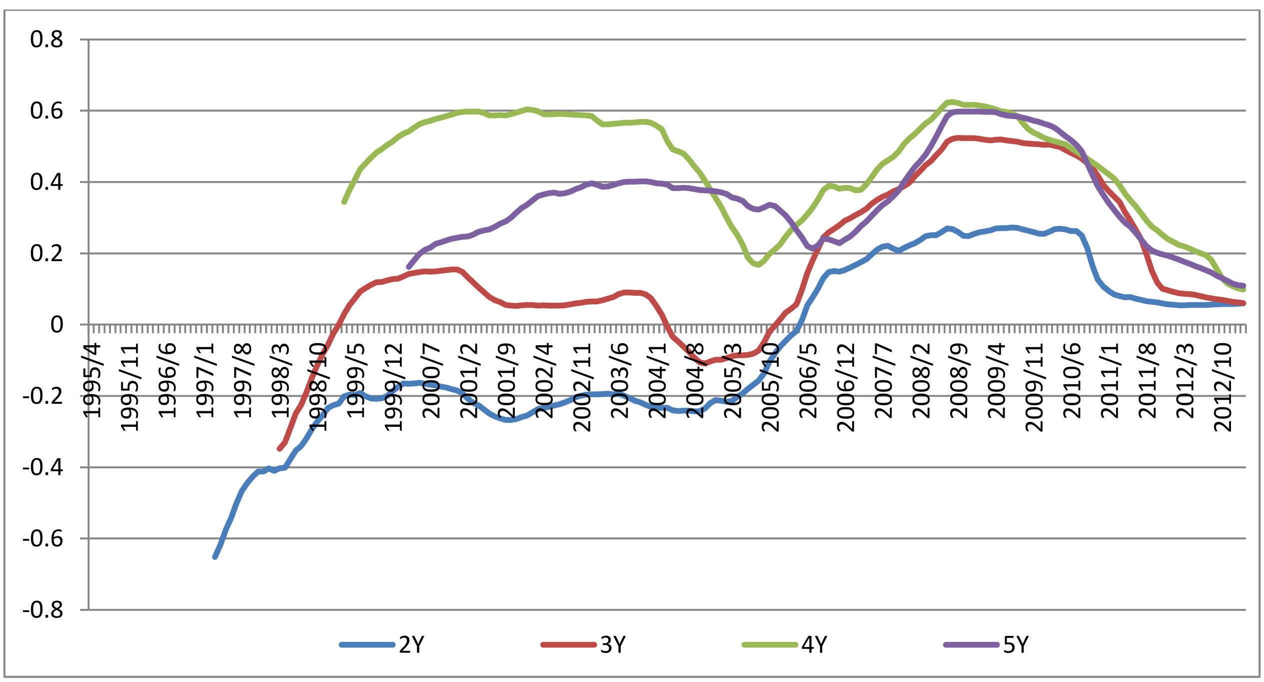


Figure 17: The rolling window estimates of correlation between SL and CPI - 1974/2013 (i.e. 2Y-5Y). The fixed window of 5-years is set in the beginning of the sample period, therefore, the observations start in February 1979 for all investment horizons (i.e. 5 years after the start of sample period 1974/2013).

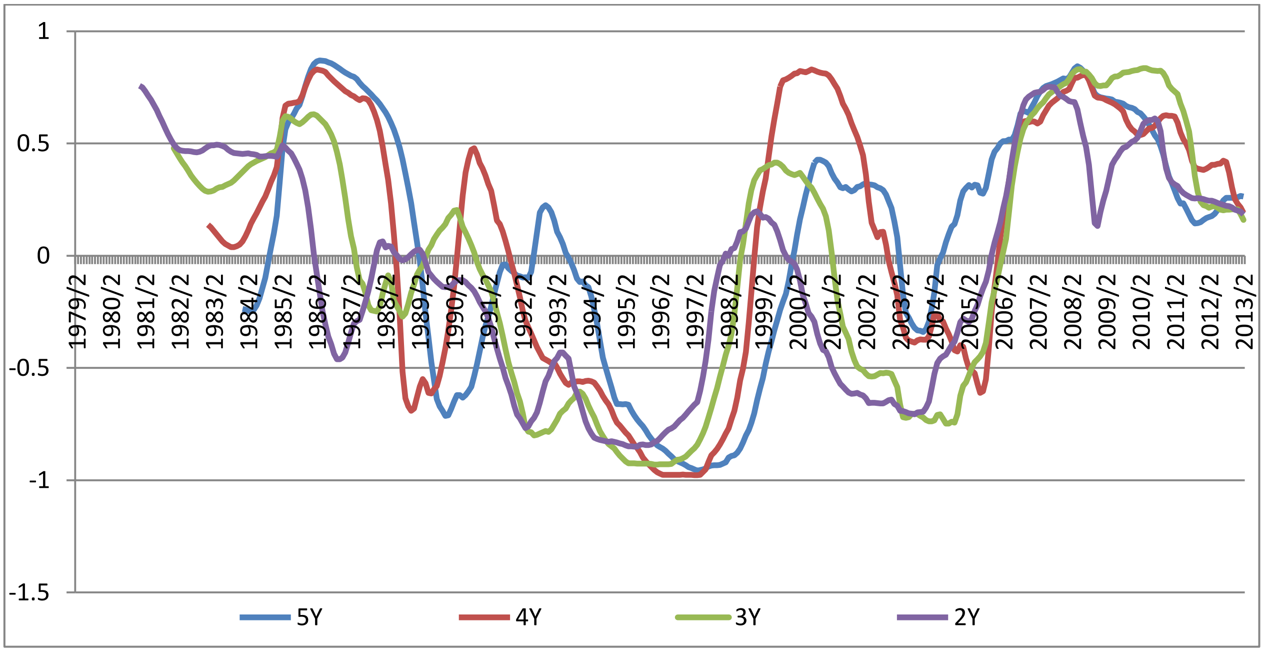


Figure 18: The extending window estimates of correlation between SL and CPI - 1990/2013 (i.e. 1M-6M). The initial sample length is 5-years. The observations start in April 1995 for all investment horizons.

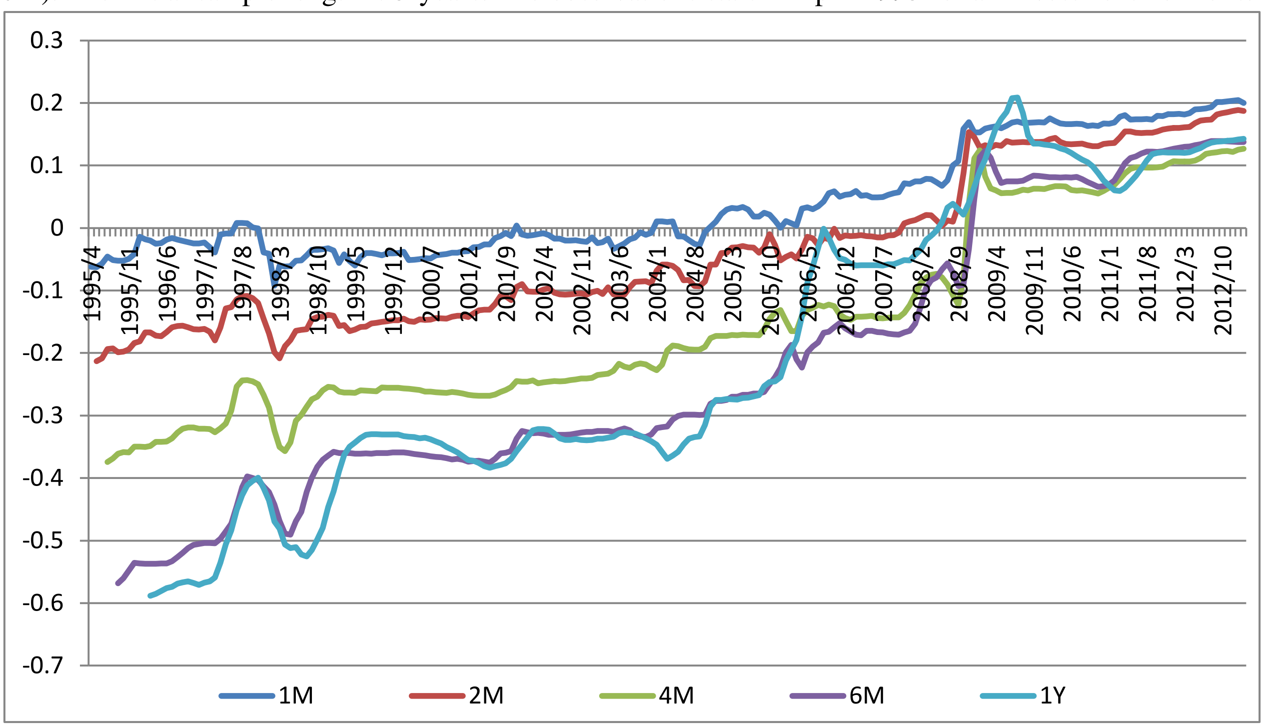


Figure 19: The rolling window estimates of correlation between SL and CPI - 1974/2013 (i.e. 2M-1Y). The fixed window of 5-years is set in the beginning of the sample period, therefore, the observations start in February 1979 for all investment horizons (i.e. 5 years after the start of sample period 1974/2013).

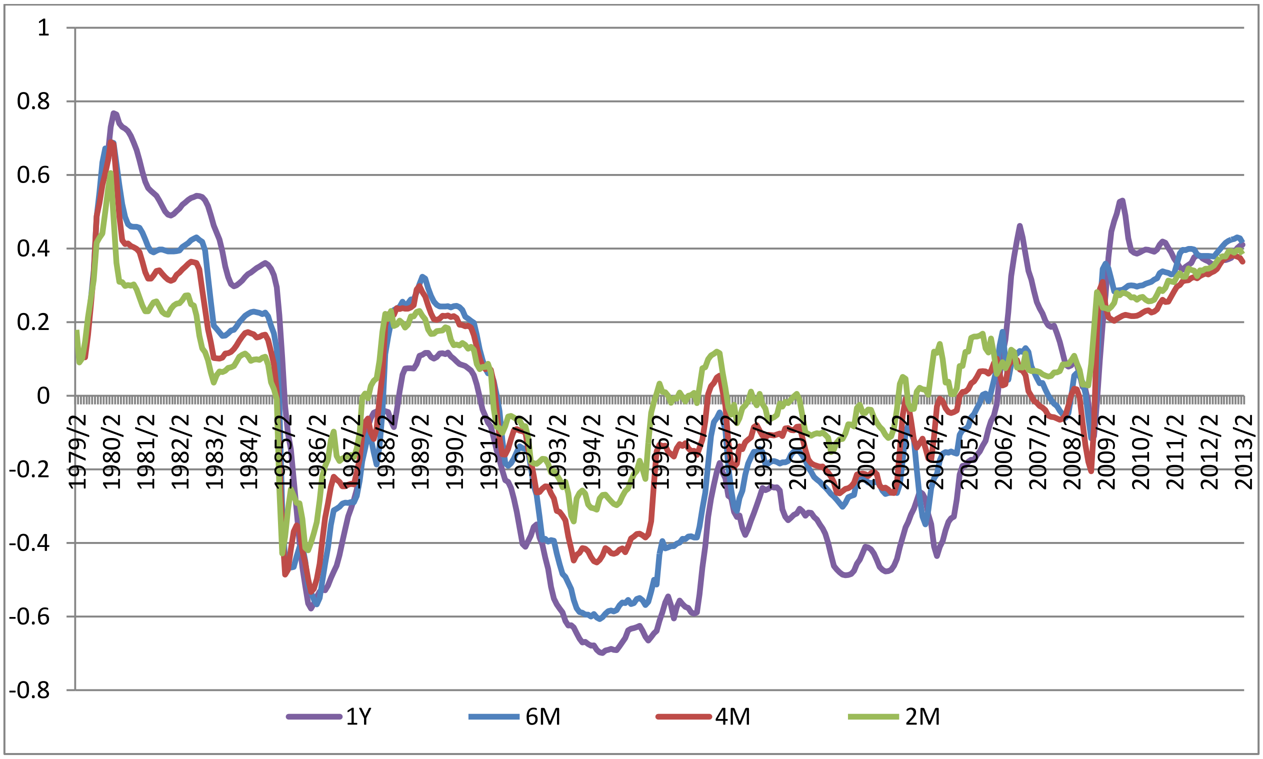


Figure 20: The extending window estimates of correlation between PL and CPI - 1990/2013 (i.e. 1M-5Y). The initial sample length is 5-years. The observations start in April 1995 for all investment horizons.

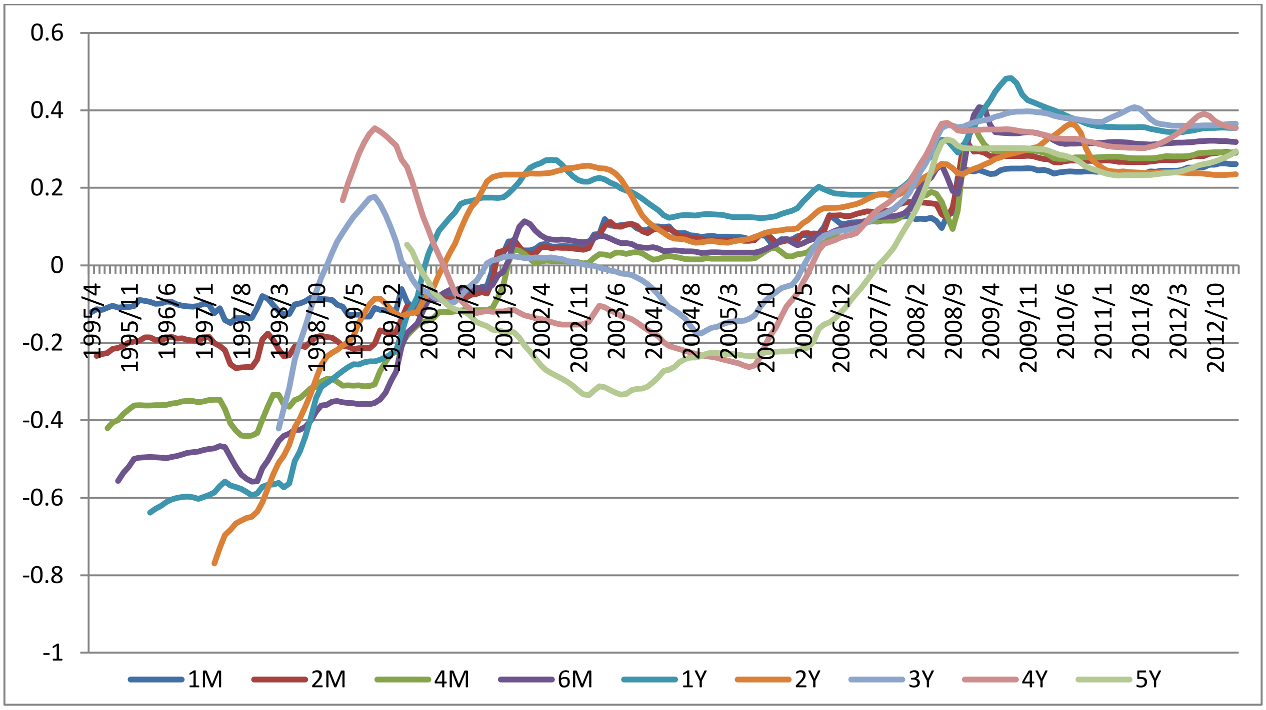


Figure 21: The rolling window estimates of correlation between PL and CPI - 1990/2013 (i.e. 1Y-5Y). The fixed window of 5-years is set in the beginning of the sample period, therefore, the observations start in May 1990 for all investment horizons (i.e. 5 years after the start of sample period 1990/2013).

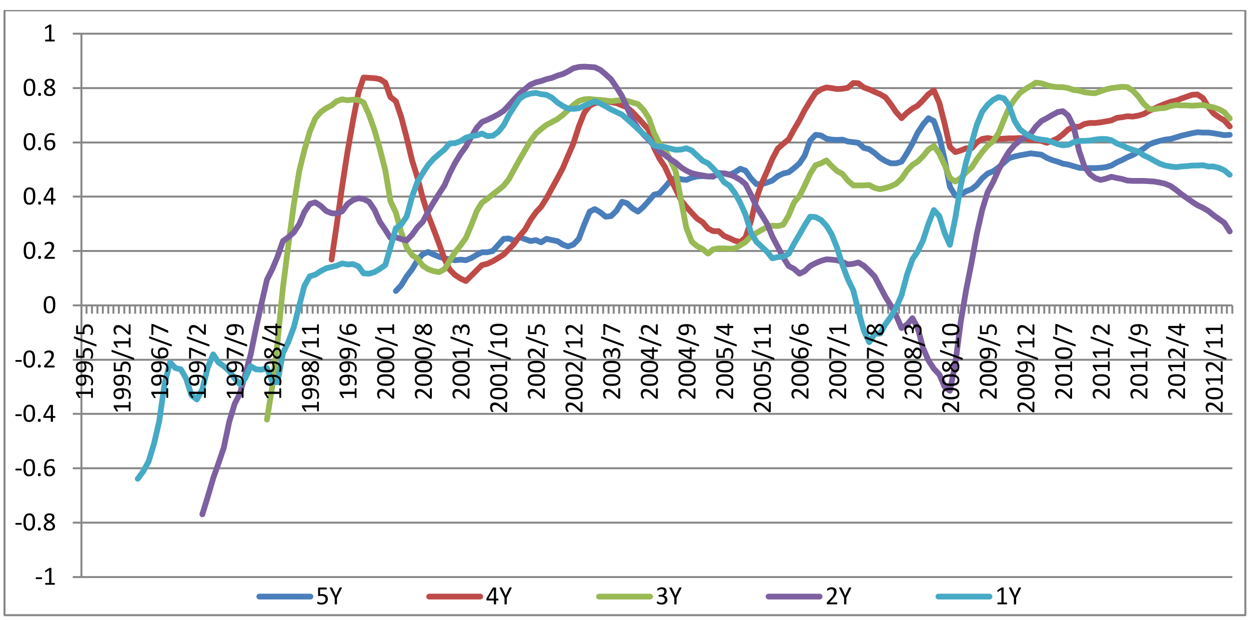


Figure 22: The rolling window estimates of correlation between PL and CPI - 1990/2013 (i.e. 2M-6M). The fixed window of 5-years is set in the beginning of the sample period, therefore, the observations start in May 1990 for all investment horizons (i.e. 5 years after the start of sample period 1990/2013).

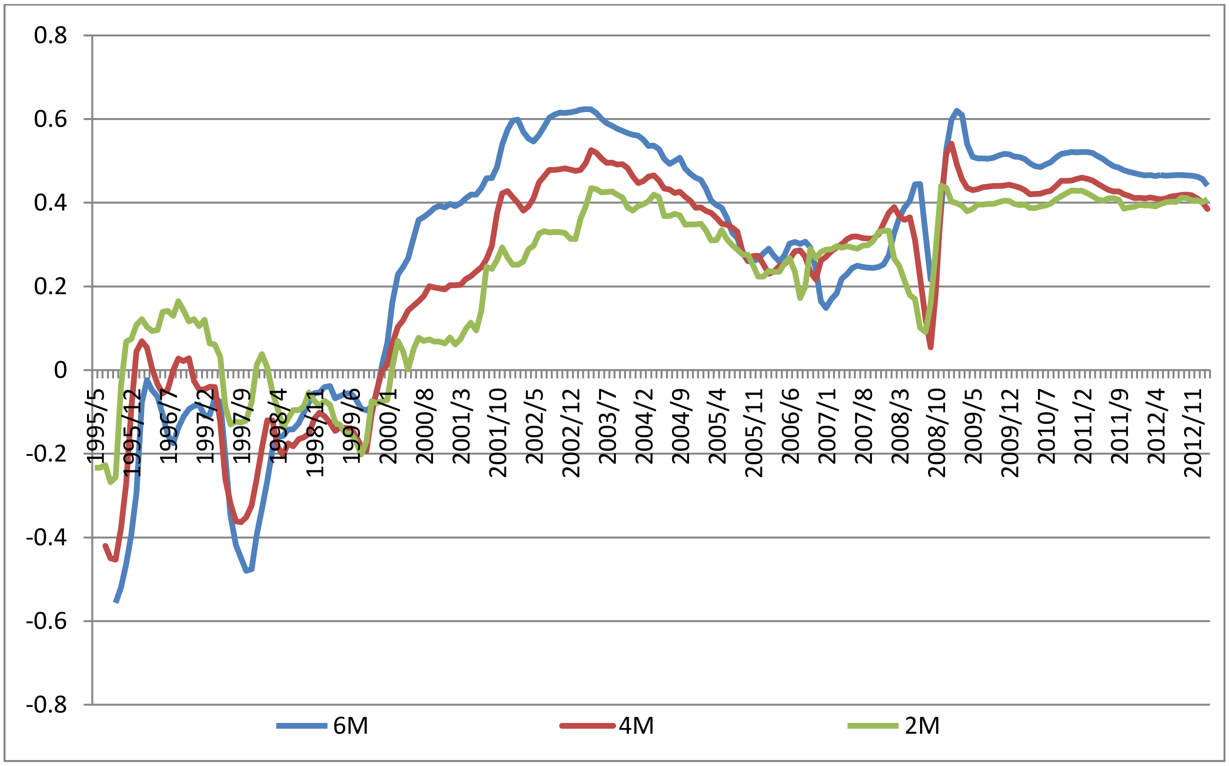


Figure 23: The extending window estimates of correlation between PA and CPI - 1990/2013 (i.e. 2Y-5Y). The initial sample length is 5-years. The observations start in April 1995 for all investment horizons.

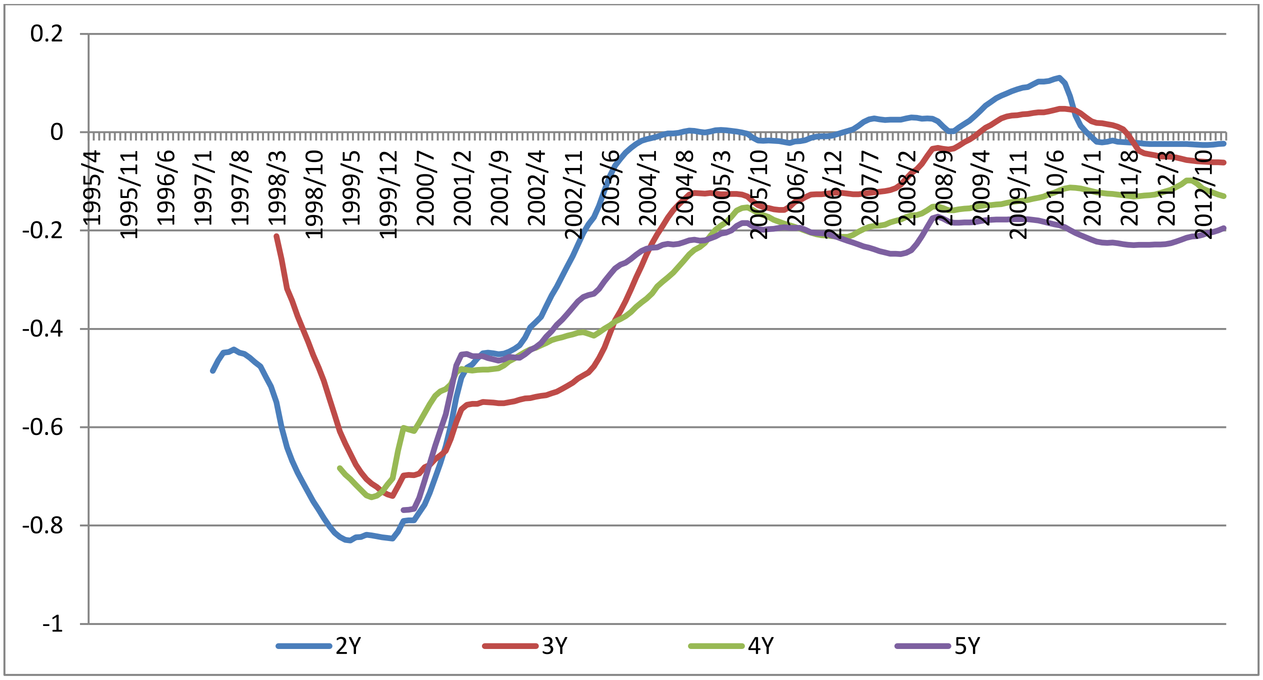


Figure 24: The rolling window estimates of correlation between PA and CPI - 1990/2013 (i.e. 2Y-5Y). The fixed window of 5-years is set in the beginning of the sample period, therefore, the observations start in May 1990 for all investment horizons (i.e. 5 years after the start of sample period 1990/2013).

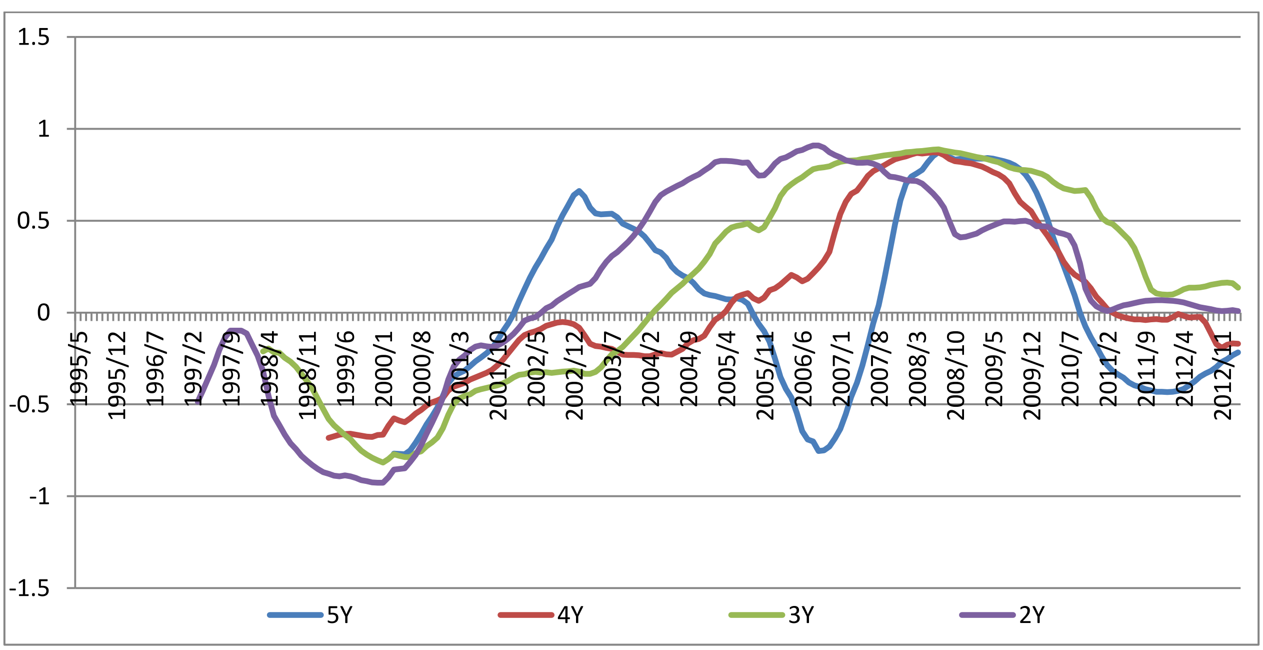


Figure 25: The extending window estimates of correlation between PA and CPI - 1990/2013 (i.e. 1M-1Y). The initial sample length is 5-years. The observations start in April 1995 for all investment horizons.

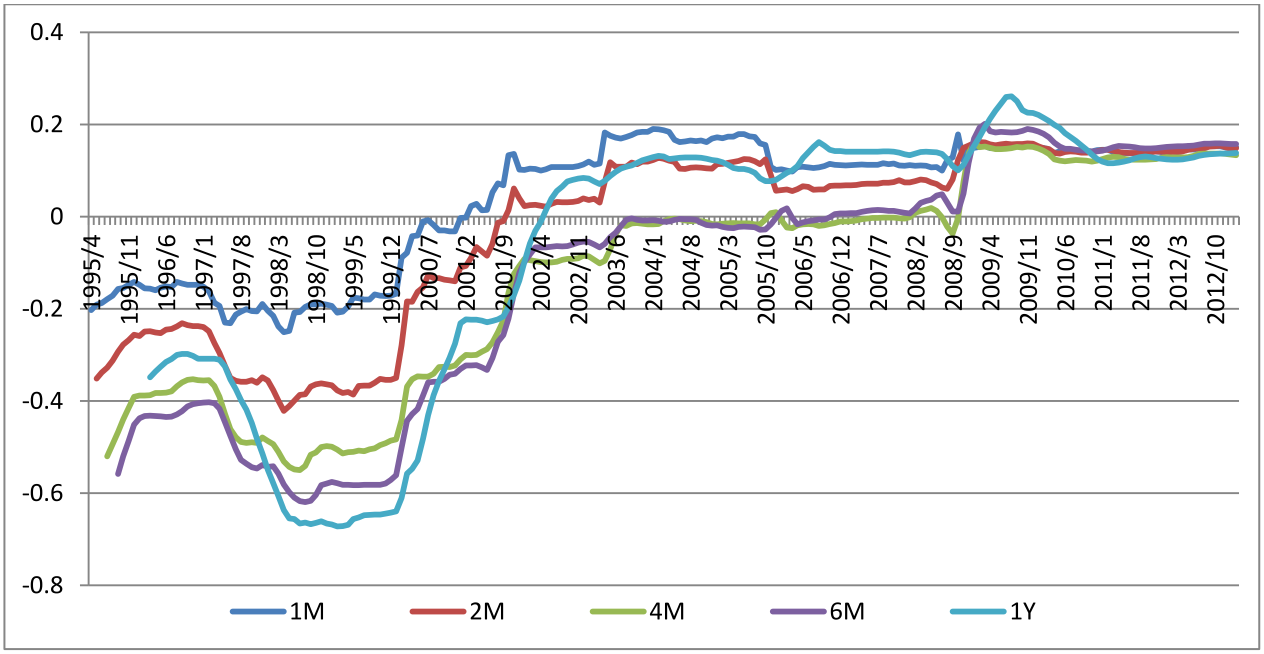
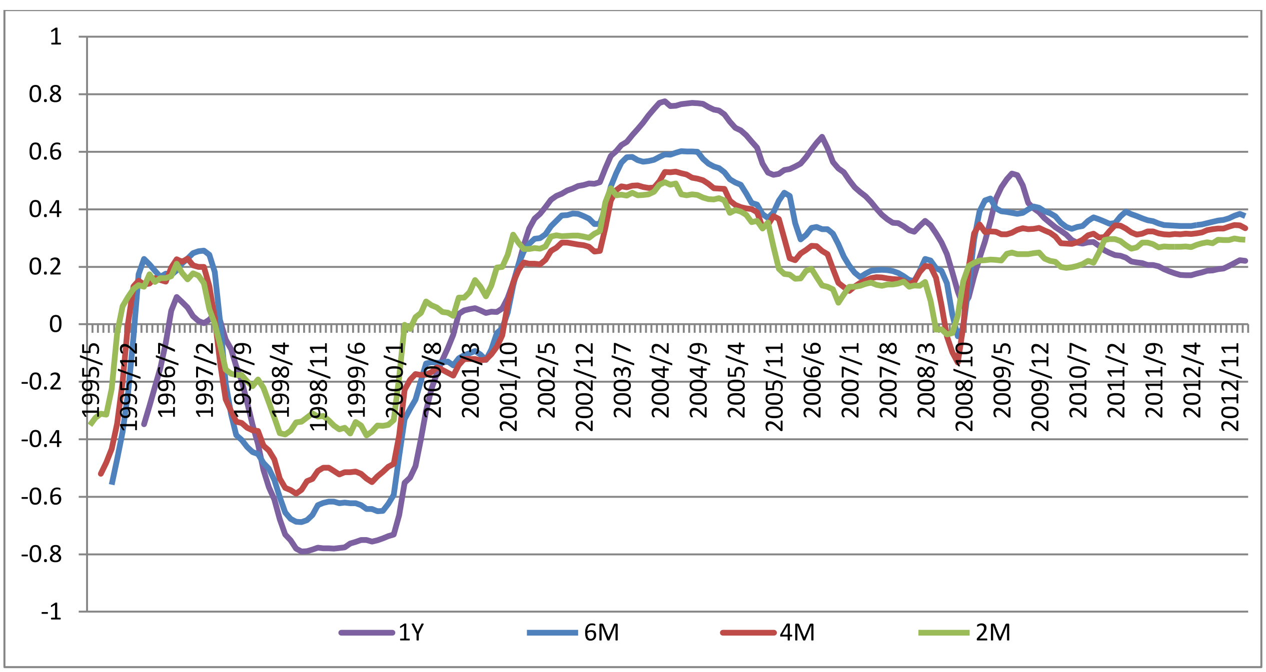


Figure 26: The rolling window estimates of correlation between PA and CPI - 1990/2013 (i.e. 2M-1Y). The fixed window of 5-years is set in the beginning of the sample period, therefore, the observations start in May 1990 for all investment horizons (i.e. 5 years after the start of sample period 1990/2013).



Appendix A

```
' Array notation
' Indices declarations: i-current, j- bootstrap loop, k-nof loops, n-sample size
Dim i, j, k As Integer
Dim n As Long
' Setting loops number k, default 1
k = 1
k = InputBox("Set loops number from 1 to 500 range, rerun after your mistake", "k", 1)
'ending exe after mistake if k<1 or k>500 or non-integer
i = Int(k)
If (k - i < 0) Or (k - i > 0) Then End
Worksheets("Calc").Cells(8, 80) = k

'Start time
Worksheets("Calc").Cells(2, 80) = Time$
'Clearing old estimations of YB and AB
Worksheets("Yboot").Range("B2:SH263").ClearContents
Worksheets("Aboot").Range("B2:AA502").ClearContents

'Declarations of auxiliary variables V1,V2,V3,et,sumet=sum of et,sumesq=sum squares of et
Dim V1, V2, V3, et As Double
'Declarations of arrays: Y0-dep.var, YOF-prognosis, YB-for bootstrap j, A0-initial coefficients
'Declarations of arrays: A0T-transposed A0, AB- for bootstrap j,ABT-transposed AB
'Declarations of arrays: UB-residuals of bootstrap j, YBF-prognosis of YB
Dim Y0(1, 1 To 262) As Double
Dim Y0F(1, 1 To 262) As Double
Dim YB(1, 1 To 262) As Double
Dim YBF(1, 1 To 262) As Double
Dim A0(1, 1 To 26) As Double
Dim A0T(1 To 26, 1) As Double
Dim AB(1, 1 To 26) As Double
Dim ABT(1 To 26, 1) As Double
Dim UB(1, 1 To 262) As Double
'Time after declarations
Worksheets("Calc").Cells(3, 80) = Time$

'Constant and initial OLS arrays
'XT*X
 Worksheets("Calc").Range("AL30:BK55").Select
   Selection.FormulaArray = _
      "=MMULT((F280:JG305),(F2:AE263))"
 '(XT*X)^(-1)
   Worksheets("Calc").Range("AL59:BK84").Select
   Selection.FormulaArray = "=MINVERSE(AL30:BK55)"
 'XT*Y
   Worksheets("Calc").Range("AJ30:AJ55").Select
   Selection.FormulaArray = _
      "=MMULT((F280:JG305),(AG2:AG263))"
 'A=A0=(XT*X)^(-1)*XT*Y
   Worksheets("Calc").Range("AK2:AK27").Select
   Selection.FormulaArray = "=MMULT((AL59:BK84),(AJ30:AJ55))"
'Time after initial OLS arrays
Worksheets("Calc").Cells(4, 80) = Time$
```

```
  'Creating A0T and loading A0, A0T into worksheets Aboot and Calc
  For i = 1 To 26
  V1 = Worksheets("Calc").Cells(1 + i, 37)
  A0(1, i) = V1
  A0T(i, 1) = V1
  Worksheets("Calc").Cells(2, 37 + i) = V1
  Worksheets("Aboot").Cells(2, 1 + i) = V1
  Next i
 'Y^=Y0^=Y0F=X*A
  Worksheets("Calc").Range("AH2:AH263").Select
  Selection.FormulaArray = "=MMULT((F2:AE263),(AK2:AK27))"
'Loading Y0^ into YB^(j-1)column
 Worksheets("Calc").Range("AH2:AH263").Select
  Selection.Copy
  Worksheets("Calc").Range("BS2").Select
  Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
     :=False, Transpose:=False
  Application.CutCopyMode = False
'Rewriting Y0 i Y0F from Calc into Y0 i Y0F and Y0 i Y0F into columns YB(j) BT
'and YB^(j-1) BS in Calc
'Rewriting initial residuals (j=0)from Calc into UB and from UB into column UB(j-1)in Calc
 For i = 1 To 262
'Loading from Calc into Y0,Y0F,UB
 Y0(1, i) = Worksheets("Calc").Cells(1 + i, 33)
 Y0F(1, i) = Worksheets("Calc").Cells(1 + i, 34)
 'Control columns
 Worksheets("Calc").Cells(1 + i, 76) = Y0F(1, i)
 UB(1, i) = Worksheets("Calc").Cells(1 + i, 35)
'Rewriting Y0, Y0F i UB into columns YB(j) BT, YB^(j-1) BS i UB(j-1) in Calc and Y0 w Yboot
Worksheets("Calc").Cells(1 + i, 72) = Y0(1, i)
Worksheets("Yboot").Cells(1 + i, 2) = Y0(1, i)
Worksheets("Calc").Cells(1 + i, 73) = UB(1, i)
 Next i
'Time before bootstrap loop j=1 and resetting sums
Worksheets("Calc").Cells(5, 80) = Time$
sumet = 0
sumesq = 0


 'Bootstrap loops j from j=1 to k
 For j = 1 To k
'Displaying the number of current loop in Calc
Worksheets("Calc").Cells(1, 69) = j
'Calculations of YB(j)
 For i = 1 To 262
'Drowing random binomial values et and rewriting data from Calc into YB and column YB(j)BT
 V1 = Y0F(1, i)
 'System random numbers generator of uniform distribution in (0;1) interval
 V3 = Rnd
 'Selecting values of et in accordance with Fibonacci binomial distribution
 If V3 <= (1 / 2) * (1 + 1 / Sqr(5)) Then et = (1 - Sqr(5)) / 2
 If V3 > (1 / 2) * (1 + 1 / Sqr(5)) Then et = (1 + Sqr(5)) / 2
 'New residual calculation, accumulation of et and squares of et
 V2 = et * UB(1, i)
 sumet = sumet + et
 sumesq = sumesq + et * et
```

```
  'calculation of bootstrapped values of dependent variable for loop j
  YB(1, i) = V1 + V2
  Worksheets("Calc").Cells(1 + i, 72) = YB(1, i)
  'Control columns
  Worksheets("Calc").Cells(1 + i, 75) = et
  Worksheets("Calc").Cells(1 + i, 76) = YB(1, i)
  Worksheets("Calc").Cells(1 + i, 77) = V2
  Worksheets("Calc").Cells(1 + i, 78) = V1
  Next i

'Estimation of bootstrapped OLS coefficients AB(j)
 'XT*YB
    Worksheets("Calc").Range("BM30:BM55").Select
    Selection.FormulaArray = _
        "=MMULT((F280:JG305),(BT2:BT263))"
 'AB=(XT*X)^(-1)*XT*YB
    Worksheets("Calc").Range("BN2:BN27").Select
    Selection.FormulaArray = "=MMULT((AL59:BK84),(BM30:BM55))"
    'Rewriting data from Calc into Ab i ABT and ABT into Aboot
    For i = 1 To 26
    V1 = Worksheets("Calc").Cells(1 + i, 66)
    AB(1, i) = V1
    ABT(i, 1) = V1
    Worksheets("Calc").Cells(3, 37 + i) = V1
    Worksheets("Aboot").Cells(2 + j, 1 + i) = V1
    Next i
 'YB^=YBF=X*AB
    Worksheets("Calc").Range("BS2:BS263").Select
    Selection.FormulaArray = "=MMULT((F2:AE263),(BN2:BN27))"
'Time after OLS for bootstrap loop j
Worksheets("Calc").Cells(6, 80) = Time$

 'Calculating residuals array UB(j)and loading UB(j)into column UB(j-1) in Calc
  For i = 1 To 262
'Actualizing prognosis YBF from column BS2
YBF(1, i) = Worksheets("Calc").Cells(1 + i, 71)
'Calculating residuals UB
  UB(1, i) = YB(1, i) - YBF(1, i)
'Loading UB(j)into column UB(j-1) in Calc
Worksheets("Calc").Cells(1 + i, 73) = UB(1, i)
  Next i

 'Loading YB(j)from Calc into YB and YB into column j in Yboot
  For i = 1 To 262
'loading from Calc into YB
  YB(1, i) = Worksheets("Calc").Cells(1 + i, 72)
'Loading YB into cell (1+j,i) in Yboot
Worksheets("Yboot").Cells(1 + i, 2 + j) = YB(1, i)
  Next i

 'MsgBox "EOF loop:" & j
 Next j

 'Time of program executing, mean V1 and variance V2 of et loading into Calc
Worksheets("Calc").Cells(7, 80) = Time$
n = CLng(262) * k
```

```
Worksheets("Calc").Cells(9, 83) = n
V1 = sumet / n
Worksheets("Calc").Cells(11, 81) = V1
V2 = sumesq / n - V1 ^ 2
Worksheets("Calc").Cells(12, 81) = V2
'99% Confidence interval for sample mean of et
Worksheets("Calc").Cells(11, 82) = ((V2 / n) ^ (1 / 2)) * WorksheetFunction.NormInv(0.005, 0, 1)
Worksheets("Calc").Cells(11, 83) = ((V2 / n) ^ (1 / 2)) * WorksheetFunction.NormInv(0.995, 0, 1)
'99% Confidence interval for sample variance of et
Worksheets("Calc").Cells(12, 82) = n * V2 / (n * (1 - 2 / 9 / n + (2 / 9 / n) ^ (1 / 2) *
WorksheetFunction.NormInv(0.995, 0, 1)) ^ 3)
Worksheets("Calc").Cells(12, 83) = n * V2 / (n * (1 - 2 / 9 / n + (2 / 9 / n) ^ (1 / 2) *
WorksheetFunction.NormInv(0.005, 0, 1)) ^ 3)
Worksheets("Calc").Range("CD1").Select
'Display of current loop reset
Worksheets("Calc").Cells(1, 69) = 0
'Saving workbook
ActiveWorkbook.Save

End Sub
'End of bootstrap VBA program
```

Appendix B

```
' Array notation
' Indices declarations: i-current, j- bootstrap loop, k-nof loops, n-sample size
Dim i, j, k As Integer
Dim n As Long
' Setting loops number k, default 1
k = 1
k = InputBox("Set loops number from 1 to 500 range, rerun after your mistake", "k", 1)
'ending exe after mistake if k<1 or k>500 or non-integer
i = Int(k)
If (k - i < 0) Or (k - i > 0) Then End
Worksheets("Calc").Cells(8, 80) = k

'Start time
Worksheets("Calc").Cells(2, 80) = Time$
'Clearing old estimations of YB and AB
Worksheets("Yboot").Range("B2:SH458").ClearContents
Worksheets("Aboot").Range("B2:AA502").ClearContents

'Declarations of auxiliary variables V1,V2,V3,et,sumet=sum of et,sumesq=sum squares of et
Dim V1, V2, V3, et As Double
'Declarations of arrays: Y0-dep.var, YOF-prognosis, YB-for bootstrap j, A0-initial coefficients
'Declarations of arrays: A0T-transposed A0, AB- for bootstrap j,ABT-transposed AB
'Declarations of arrays: UB-residuals of bootstrap j, YBF-prognosis of YB
Dim Y0(1, 1 To 457) As Double
Dim Y0F(1, 1 To 457) As Double
Dim YB(1, 1 To 457) As Double
Dim YBF(1, 1 To 457) As Double
Dim A0(1, 1 To 26) As Double
Dim A0T(1 To 26, 1) As Double
Dim AB(1, 1 To 26) As Double
Dim ABT(1 To 26, 1) As Double
Dim UB(1, 1 To 457) As Double
'Time after declarations
Worksheets("Calc").Cells(3, 80) = Time$

'Constant and initial OLS arrays
'XT*X
Worksheets("Calc").Range("AL30:BK55").Select
   Selection.FormulaArray = _
       "=MMULT((F475:QT500),(F2:AE458))"
 '(XT*X)^(-1)
   Worksheets("Calc").Range("AL59:BK84").Select
   Selection.FormulaArray = "=MINVERSE(AL30:BK55)"
 'XT*Y
   Worksheets("Calc").Range("AJ30:AJ55").Select
   Selection.FormulaArray = _
       "=MMULT((F475:QT500),(AG2:AG458))"
 'A=A0=(XT*X)^(-1)*XT*Y
   Worksheets("Calc").Range("AK2:AK27").Select
   Selection.FormulaArray = "=MMULT((AL59:BK84),(AJ30:AJ55))"
'Time after initial OLS arrays
Worksheets("Calc").Cells(4, 80) = Time$
```

```
    'Creating A0T and loading A0, A0T into worksheets Aboot and Calc
    For i = 1 To 26
    V1 = Worksheets("Calc").Cells(1 + i, 37)
    A0(1, i) = V1
    A0T(i, 1) = V1
    Worksheets("Calc").Cells(2, 37 + i) = V1
    Worksheets("Aboot").Cells(2, 1 + i) = V1
    Next i
 'Y^=Y0^=Y0F=X*A
    Worksheets("Calc").Range("AH2:AH458").Select
    Selection.FormulaArray = "=MMULT((F2:AE458),(AK2:AK27))"
'Loading Y0^ into YB^(j-1)column
  Worksheets("Calc").Range("AH2:AH458").Select
    Selection.Copy
    Worksheets("Calc").Range("BS2").Select
    Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
        :=False, Transpose:=False
    Application.CutCopyMode = False
'Rewriting Y0 i Y0F from Calc into Y0 i Y0F and Y0 i Y0F into columns YB(j) BT
'and YB^(j-1) BS in Calc
'Rewriting initial residuals (j=0)from Calc into UB and from UB into column UB(j-1)in Calc
  For i = 1 To 457
'Loading from Calc into Y0,Y0F,UB
  Y0(1, i) = Worksheets("Calc").Cells(1 + i, 33)
  Y0F(1, i) = Worksheets("Calc").Cells(1 + i, 34)
  'Control columns
  Worksheets("Calc").Cells(1 + i, 76) = Y0F(1, i)
  UB(1, i) = Worksheets("Calc").Cells(1 + i, 35)
'Rewriting Y0, Y0F i UB into columns YB(j) BT, YB^(j-1) BS i UB(j-1) in Calc and Y0 w Yboot
Worksheets("Calc").Cells(1 + i, 72) = Y0(1, i)
Worksheets("Yboot").Cells(1 + i, 2) = Y0(1, i)
Worksheets("Calc").Cells(1 + i, 73) = UB(1, i)
  Next i
'Time before bootstrap loop j=1 and resetting sums
Worksheets("Calc").Cells(5, 80) = Time$
sumet = 0
sumesq = 0

 'Bootstrap loops j from j=1 to k
 For j = 1 To k
'Displaying the number of current loop in Calc
Worksheets("Calc").Cells(1, 69) = j
'Calculations of YB(j)
 For i = 1 To 457
'Drawing random binomial values et and rewriting data from Calc into YB and column YB(j)BT
  V1 = Y0F(1, i)
  'System random numbers generator of uniform distribution in (0;1) interval
  V3 = Rnd
  'Selecting values of et in accordance with Fibonacci binomial distribution
  If V3 <= (1 / 2) * (1 + 1 / Sqr(5)) Then et = (1 - Sqr(5)) / 2
  If V3 > (1 / 2) * (1 + 1 / Sqr(5)) Then et = (1 + Sqr(5)) / 2
  'New residual calculation, accumulation of et and squares of et
  V2 = et * UB(1, i)
  sumet = sumet + et
  sumesq = sumesq + et * et
  'calculation of bootstrapped values of dependent variable for loop j
```

```
  YB(1, i) = V1 + V2
  Worksheets("Calc").Cells(1 + i, 72) = YB(1, i)
  'Control columns
  Worksheets("Calc").Cells(1 + i, 75) = et
  Worksheets("Calc").Cells(1 + i, 76) = YB(1, i)
  Worksheets("Calc").Cells(1 + i, 77) = V2
  Worksheets("Calc").Cells(1 + i, 78) = V1
  Next i

'Estimation of bootstrapped OLS coefficients AB(j)
 'XT*YB
   Worksheets("Calc").Range("BM30:BM55").Select
    Selection.FormulaArray = _
        "=MMULT((F475:QT500),(BT2:BT458))"
 'AB=(XT*X)^(-1)*XT*YB
    Worksheets("Calc").Range("BN2:BN27").Select
    Selection.FormulaArray = "=MMULT((AL59:BK84),(BM30:BM55))"
    'Rewriting data from Calc into Ab i ABT and ABT into Aboot
    For i = 1 To 26
    V1 = Worksheets("Calc").Cells(1 + i, 66)
    AB(1, i) = V1
    ABT(i, 1) = V1
    Worksheets("Calc").Cells(3, 37 + i) = V1
    Worksheets("Aboot").Cells(2 + j, 1 + i) = V1
    Next i
 'YB^=YBF=X*AB
    Worksheets("Calc").Range("BS2:BS458").Select
    Selection.FormulaArray = "=MMULT((F2:AE458),(BN2:BN27))"
'Time after OLS for bootstrap loop j
Worksheets("Calc").Cells(6, 80) = Time$

 'Calculating residuals array UB(j)and loading UB(j)into column UB(j-1) in Calc
  For i = 1 To 457
'Actualizing prognosis YBF from column BS2
YBF(1, i) = Worksheets("Calc").Cells(1 + i, 71)
'Calculating residuals UB
  UB(1, i) = YB(1, i) - YBF(1, i)
'Loading UB(j)into column UB(j-1) in Calc
Worksheets("Calc").Cells(1 + i, 73) = UB(1, i)
  Next i

 'Loading YB(j)from Calc into YB and YB into column j in Yboot
  For i = 1 To 457
'loading from Calc into YB
  YB(1, i) = Worksheets("Calc").Cells(1 + i, 72)
'Loading YB into cell (1+j,i) in Yboot
Worksheets("Yboot").Cells(1 + i, 2 + j) = YB(1, i)
  Next i

 'MsgBox "EOF loop:" & j
 Next j

 'Time of program executing, mean V1 and variance V2 of et loading into Calc
Worksheets("Calc").Cells(7, 80) = Time$
n = CLng(457) * k
Worksheets("Calc").Cells(9, 83) = n
```

```
V1 = sumet / n
Worksheets("Calc").Cells(11, 81) = V1
V2 = sumesq / n - V1 ^ 2
Worksheets("Calc").Cells(12, 81) = V2
'99% Confidence interval for sample mean of et
Worksheets("Calc").Cells(11, 82) = ((V2 / n) ^ (1 / 2)) * WorksheetFunction.NormInv(0.005, 0, 1)
Worksheets("Calc").Cells(11, 83) = ((V2 / n) ^ (1 / 2)) * WorksheetFunction.NormInv(0.995, 0, 1)
'99% Confidence interval for sample variance of et
Worksheets("Calc").Cells(12, 82) = n * V2 / (n * (1 - 2 / 9 / n + (2 / 9 / n) ^ (1 / 2) *
WorksheetFunction.NormInv(0.995, 0, 1)) ^ 3)
Worksheets("Calc").Cells(12, 83) = n * V2 / (n * (1 - 2 / 9 / n + (2 / 9 / n) ^ (1 / 2) *
WorksheetFunction.NormInv(0.005, 0, 1)) ^ 3)
Worksheets("Calc").Range("CD1").Select
'Display of current loop reset
Worksheets("Calc").Cells(1, 69) = 0
'Saving workbook
ActiveWorkbook.Save

End Sub
'End of bootstrap VBA program
```