PREDICTING GOLD AND SILVER SPOT PRICES IN TURKEY

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ABSTRACT

PREDICTING GOLD AND SILVER SPOT PRICES IN TURKEY

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The major aim of this study is to determine the best models describing the price movements of gold and silver and generate further reliable forecasts using appropriate macroeconomic and financial indicators. In that sense, modeling and forecasting analysis is conducted under the framework of a benchmark linear model-ARIMAX and a probit model using monthly data for the period between January 2002 and November 2012. To determine the best models, a variable selection procedure is implemented through a search algorithm aimed at minimizing Akaike Information Criteria for the ARIMAX and probit models. Then, the selected ARIMAX model and the probit models are adopted to predict the directional change in gold and silver prices. The predictive power of the models is evaluated based on two goodness-of-fit measures, namely direction-of-change error and root mean square error. Model performances are further assessed by a validation exercise through a recursive one step ahead forecasting for the twelve months starting from October 2008, financial turmoil period. The results for gold suggest that linear model outperforms the probit models in predicting the negative growth of gold prices whereas the probit models provide timely predictions for the positive growth of gold prices. As regards to silver prices, it is pointed out that the best probit model is superior to the ARIMAX model considering the overall predictive performance.

Keywords: Forecasting, Probit Model, ARIMAX model, Gold, Silver

ÖZ

TÜRKİYE'DEKİ ALTIN VE GÜMÜŞ SPOT FİYATLARININ TAHMİNİ

Deveci, Duygu
Yüksek Lisans, İktisat Bölümü
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Bu tezin temel amacı, Ocak 2002-Kasım 2012 dönemine ait aylık verilerle, altın ve gümüş fiyat değişimlerini makroekonomik ve finansal göstergelerle en iyi açıklayan modelleri belirlemek ve belirlenen modellerle altın ve gümüş fiyatları için güvenilir tahminler oluşturmaktır. En iyi modelleri belirlemek amacıyla, ölçüt doğrusal-ARIMAX modeli ve probit modelleri için Akaike Bilgi kriterini asgarileştirmeyi amaçlayan bir değişken seçim algoritması oluşturulmuştur. Daha sonra, seçilen ölçüt ARIMAX modeli ve probit modelleri altın ve gümüş fiyatlarındaki değişimleri tahmin etmek amacıyla kullanılmıştır. Bu modellerin tahmin gücü, değişimin yönü hata terimleri ve kök ortalama kare hatası kullanılarak değerlendirilmiştir. Model performanslarını ayrıca değerlendirmek amacıyla, Ekim 2008'den itibaren 12 aylık bir zaman aralığı için bir adım ilerlemeli tekrarlanan tahmin yöntemi kullanılarak bir doğrulama çalışması yapılmıştır. Altın fiyatları için sonuçlar incelendiğinde, altın fiyatlarındaki daralmaların doğrusal-ARIMAX modeli tarafından daha iyi tahmin edildiği, altın fiyatlarındaki genişlemenin ise probit modelleri tarafından daha iyi tahmin edildiği gözlemlenmiştir. Gümüş fiyatlarındaki değişimlerde daralma ve genişleme durumlarının ikisinde de probit modellerin genel olarak doğrusal modele üstün geldiği sonucuna ulaşılmıştır.

Anahtar Kelimeler: Tahmin, Probit Modeli, ARIMAX Modeli, Altın, Gümüş

To my sisters;

Bilge, Özge and Ezgi

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CHAPTER 1

INTRODUCTION

Recently, commodity markets have become prominent as an alternative investment class. The rapidly rise of commodity prices is partly connected with the growing pattern of market transactions. A certain class of commodity markets contributes to this expansion, i.e. precious metal markets which consist of gold, silver, platinum and palladium. Gold and silver are especially important among these metals because of their large trading volumes along with the hedging opportunities against risk. These two metals constitute separate asset classes attributed to their distinctive economic usage. Gold serves as a monetary asset whereas silver becomes an important industrial input.

There is a considerable interest in the literature to explore the link of gold and silver with macroeconomic variables and financial indicators. While some studies including, Ciner (2001) and Erb and Harvey (2006) investigate the relationship between gold and silver, a large number of studies[1] focus on examining the effect of various macroeconomic and financial variables on gold and silver prices through vector auto regression (VAR) and GARCH models . Another focus of the literature is directed to the predictability of gold and silver prices. In this framework, while Hammoudeh, Malik and Mcaleer (2011), Khalifa, Miao and Ramchander (2011) employ GARCH-type models, Ismail, Yahya and Shabri (2009) utilize a multiple linear regression model. With respect to forecasting, the common feature of the

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[1] Ghosh, Levin, MacMillan and Wright (2004); Levin, Montagnoli and Wright (2006); Malliaris and Malliaris (2013); Sari, Hammoudeh and Soytas (2010) ; Hammoudeh and Yuan (2008), Morales and Andreosso-O'Callaghan (2012)

above studies is that they aim to generate point predictions. Unlike these, Parisi, Parisi and Díaz (2008) adopt a neural network model to predict directional change in gold and silver prices.[2]

The aim of this study is to determine the best models characterizing the price movements of gold and silver and thereafter to generate reliable forecasts using monthly macroeconomic and financial indicators. For that purpose, modeling within the framework of a benchmark linear model-ARIMAX and a probit model is carried out by applying a variable selection algorithm for each metal. The selected models are employed to predict the directional change in gold and silver prices. A comprehensive goodness-of-fit measure, namely direction-of-change error, is adopted to evaluate the predictive power of all models including ARIMAX and probit models. An additional measure, i.e. root mean square error is employed to assess the performance of the probit models. Moreover, a validation exercise is implemented using recursive forecasting with an expanding window for further evaluation of all models.

Contributions of this study are twofold. First, an alternative approach is constructed by using probit model along with a benchmark linear model-ARIMAX to forecast gold and silver prices. Second, given the absence of an available study on predicting Turkish gold and silver prices, a modeling and forecasting scheme is offered in this study.

This study is organized as follows: Chapter 1 briefly introduces the study, Chapter 2 reviews the empirical literature for the precious metal markets, Chapter 3 briefly overviews the structure of Turkish precious metal markets, Chapter 4 provides the data used in the empirical analysis, Chapter 5 describes the empirical methodology, Chapter 6 presents the empirical results with the preliminary analysis and finally Chapter 7 concludes the study.

[2] Parisi, Parisi and Díaz (2008)

CHAPTER 2

LITERATURE REVIEW

Commodities have considerable importance in the context of economics due to their capacity to influence current and upcoming production and investment decisions. Commodities also draw attention of financial investors regarding asset allocation decisions. As stated in Chan and Young (2006), inclusion of commodities yield risk reduction in portfolios through hedging strategies. Chow, Jacquier, Kritzman and Lowry (1999) also claim that commodities are more preferable in times of financial turmoil. This finding indicates that diversification benefits can be provided by incorporating key commodity contracts to broader financial trading and investment. Speaking of key commodities, the market for precious metals-gold, silver and platinum - has attracted considerable attention in the recent decade. Soytas, Sari, Hammoudeh and Hacihasanoglu (2009) relate this rising interest with their frequent tradability, large trade volumes, high liquidity and policy implications in line with interest rates and exchange rates. Central banks also contribute to this interest with their revised foreign reserve management in order to decrease the dependency in US dollar denominated assets for diversification.

The literature about precious metals centered upon gold and silver due to their specific features. Existing studies examine short-and-long run relationship of gold and silver with other commodities, macroeconomic factors and financial market variables. Forecasting is another area studied in the literature regarding these two metals. Considering the growing importance of gold and silver markets, it is crucial to identify determinants of gold and silver prices from a diverse variable pool covering commodity market, business cycle, monetary policy and financial market. Furthermore, it is also important to derive a model with a proper forecasting ability.

There is a line in the literature that investigates the relation between gold and silver. Escribano and Granger (1998), Ciner (2001), Erb and Harvey (2006) underline that gold and silver should not be considered as a single market although they move together. This is an implication of separating markets. The phenomenon of diverse classification suggests that separate analysis should be constructed for gold and silver. Batten, Ciner and Lucey (2010) support this point by finding that driving macroeconomic and financial factors of fluctuations in the metal prices are distinct. This separation is because of their different features and economic utilizations. Silver and gold are traditionally used in jewelry industry and traded as investment assets. Silver has also become an input in industrial products as a result of its unique properties. Gold, on the other hand, preserve its role as a monetary asset.

A major part of the literature about gold and silver uses time series methods like vector autoregression (VAR) and GARCH models. There are also studies utilizing a neural network model to investigate cointegration and effect of short run shocks on gold and silver. Soytas et al. (2009) find a strong inter-linkage between gold and silver in the short run. They also argue that short run factors lead to fluctuations in gold price. Their findings suggest a point as in Baffes (2007) that both metals respond positively to oil shocks in the short run. This statement is supported by other studies such as Hammoudeh and Yuan (2008), Morales and Andreosso-O'Callaghan (2012). Using GARCH type models, Hammoudeh and Yuan (2008) note that gold, silver and copper are affected by oil shocks differently and global political events push up metal prices. Morales and Andreosso-O'Callaghan (2012) also examine the relation of precious metal returns with three stock indices and oil returns within a GARCH framework. The findings suggest that shocks to oil return have a significant positive impact on precious metal prices whereas shocks to market returns seem to be impotent. In the same manner, Sari, Hammoudeh and Soytas (2010) analyze spot prices of four precious metals, US dollar/Euro exchange rate and oil price for the investigation of co-movement among variables. The results show no indication of cointegration in the long run but remarkable responses to shocks in the short run. They further argue that rise in interest rates moderate metal price volatility. Ghosh, Levin, MacMillan and Wright (2004); Levin, Montagnoli and Wright (2006) claim that gold price and inflation rate are cointegrated underlying the capacity of gold to serve as a hedge against inflation in the long run. On the contrary, through a neural network analysis, Malliaris and Malliaris (2013) conclude that each variable-gold, oil and euro- is determined by its own lag and the variables are not cointegrated.

Beside these, there are studies exploring predictability of gold and silver prices or returns through different models. A series of forecasting analysis are constructed under neural network, GARCH and ARIMA frameworks. Studies like Hammoudeh, Malik and Mcaleer (2011) along with Khalifa, Miao and Ramchander (2011) adopt GARCH-type models to forecast different volatility measures. Hammoudeh, Malik and Mcaleer (2011) argue that GARCH-t model is better in terms of forecasting the return volatility of precious metals through Value-at-Risk. Khalifa, Miao and Ramchander (2011) analyze the predictive power of a GARCH model employing four types of volatility measures for gold, silver and copper. The results suggest that the forecasting performance of integrated volatility via Fourier transformation (IVFT) and realized volatility outperform the others. Dooley and Lenihan (2005) compare the forecasting ability of a lagged forward price model and an ARIMA model for future zinc and lead prices. ARIMA model shows greater performance in forecasting. Studies like Parisi, Parisi and Díaz (2008); Ismail, Yahya and Shabri (2009) focus on gold price forecasting with a different approach. Parisi, Parisi and Díaz (2008) develop a dynamic neural network model to forecast direction of change in gold prices. They claim that such networks can substitute for time series methods like ARIMA considering the predictive performance. Ismail, Yahya and Shabri (2009) predict monthly gold prices with a linear regression model using financial and monetary variables like Commodity Research Bureau future index, US Dollar/Euro exchange rate, S&P 500 Index, NYSE Index, US Dollar index and inflation, money supply, treasury bill rate to predict gold prices. Two models are proposed. The first model is fitted using all possible variables and the other one considering lagged values of Commodity Research Bureau future index, US Dollar/Euro exchange rate, inflation and money supply. The latter provide better forecasting accuracy.

Regarding gold and silver markets in Turkey, the literature is limited to the study of Soytas et al. (2009) to the extent of our knowledge. They investigate information transfer between spot gold and silver prices in Turkish market, world oil price, Turkish interest rate, Turkish lira/US dollar exchange rate through a VAR model. They find evidence of a positive short-run relationship between oil price and both metal prices.

This study aims to determine the best models describing the price movements of gold and silver and then to obtain reliable forecasts using monthly macroeconomic and financial indicators. Probit models and a linear-ARIMAX model are established to forecast the directional change in gold and silver prices. The major contributions of this study are twofold. First, probit model structure is introduced to forecast the sign of change in the metal prices and this approach has not been used before for gold and silver to the extent of our knowledge. Second, given the absence of an available study on predicting Turkish gold and silver prices a potential framework is constructed for modeling and forecasting purposes in this study.

CHAPTER 3

A BRIEF OVERVIEW OF PRECIOUS METALS MARKET IN TURKEY

The structure of Turkish precious metals market is briefly explained in order to highlight the importance of the metals-gold and silver- in Turkey, which is our starting point for this study. Gold has become the key metal in the formation of a sound precious metal market in Turkey. Gold export and import have been liberalized in 1993, which brought a sudden upsurge in the gold sector. These developments have raised the necessity to restructure the sector and as a consequence of this concern, Istanbul Gold Exchange (IGE) was established in 1995. Its members -along with the Central Bank have been granted to import gold. In addition to gold, the trading of silver and platinum has been initiated under the IGE in 1999. Thereby, the trading of precious metals has been extended. Gold, silver and platinum have been the listed metals to trade under the IGE. Almost no transaction for platinum has occurred since the onset of its trading, so we concentrate on gold and silver in this study.

The Borsa Istanbul was established with the merger of Istanbul Stock Exchange and Istanbul Gold Exchange in 2013. Currently, precious metals transactions are operated in the related division of Borsa Istanbul. The division has two submarkets concerning the defined metals. Precious Metals Market includes spot trading and Precious Metal Lending Market deals with the lending and certificate transactions.

The major advancement with the launch of Istanbul Gold Exchange is the constitution of an organized market for the precious metals trading. Istanbul Gold Exchange has paved the way for channeling the metals into the financial system and for the integration of Turkish precious metals market with the international market.

Besides, it has provided the development of financial instruments based on gold and silver.

The transactions of gold with an amount less than 100 tonnes in 1995 has risen to 300 tonnes in 2012 and silver transactions with an amount less than 100 tonnes in 1999 have exceeded 400 tonnes in 2012.[3] With respect to the amount of transactions, silver reveals an upward trend with slight variations although the amount of gold follows a fluctuating pattern.[4]

[3] [4] Source: IGE

CHAPTER 4

DATA

This study aims to evaluate the predictive performance of leading indicators for gold and silver prices. The empirical analysis of modeling and forecasting is carried out using monthly observations covering the period from January 2002 to November 2012. The data is started from 2002 in order to avoid the influences of the 2000-2001 financial crisis in Turkey.

The spot prices of gold (lngold) and silver (lnsilver) are originally taken from Istanbul Gold Exchange (IGE) in a daily frequency. To generate monthly spot prices, the following formula is applied

$$P_t^{\alpha} = \frac{\sum_{i=0}^{n} \omega * \mu}{\sum_{i=0}^{n} \omega}, \qquad \mathrm{t} = 1,2,3, \ldots, T$$

where α is the metal- gold or silver respectively, ω is amount of daily transactions , μ is average daily spot price, n is the number of trading days in the month, t is month index, T is sample size. In this way, the daily series is transformed to monthly values. Standardization is also required for different measurement units as Turkish Lira per gram between 2002-2005 and Turkish Lira per kilogram from 2005 onward. Besides, six zeros have been removed from Turkish Lira in 2005 resulting in disparity of the prices before and after 2005. Prices, thus, have been transformed into uniform values[5].

[5] 1999-2005 range is multiplied by 1000 to find price per kg, in that way all data is expressed in terms of Turkish Lira per kilogram. In 2005, six zeros were deleted from lira, so the prices until January 2005 are divided by 1 million for adjustment.

In this study, various leading indicators are considered as explanatory variables to predict gold and silver prices. The leading indicator variables consist of Turkish money supply-M2, Turkish benchmark bond rate, brent oil price, Turkish Lira/US Dollar exchange rate, Turkish industrial production, Borsa Istanbul 100 Index[6], Turkish consumer price index, world consumer price index and credit risk default premium. In Table 1, all indicators are grouped in two main categories with regard to their economic motive to be embodied in modeling and forecasting spot prices of gold and silver.

Table 1: Leading Indicator Series

Category	Leading Indicator
Macroeconomic indicators	Turkish money supply (M2), Turkish Lira/US Dollar exchange rate, Turkish industrial production, Turkish consumer price index, World consumer price index
Financial indicators	Brent oil price, Borsa İstanbul 100 Index, Turkish benchmark bond rate, Credit risk default premium

Given the utilization of gold as a monetary asset and silver usage in industrial production, some macroeconomic variables can be useful in modeling and forecasting the prices of these metals. As mentioned before, we employ Turkish money supply (lnm2), Turkish Lira/ US Dollar exchange rate (lnex) and the seasonally adjusted series of Turkish industrial production (lnindpro), Turkish

[6] Formerly known as Istanbul Stock Exchange 100 Index.

consumer price index (lnturkey_cpi) and world consumer price index (lnworld_cpi) obtained from International Financial Statistics (IFS) database. Price indices are included considering inflation hedging capability of the metals in both domestic and global markets in accordance with the arguments in Levin et al. (2006) and Gosh et al. (2004). Following Batten et al. (2010), we further add some macroeconomic variables into our analysis. Firstly, seasonally adjusted series of industrial production is used to capture possible connections of silver and gold prices to business cycles. Second variable involved is Turkish money supply which is potentially important for predicting gold and silver prices. Given gold and silver are traded commonly in terms of US dollar, monthly Turkish Lira/US Dollar exchange rate may contribute to volatility in gold and silver prices denominated in TL.

A domestic benchmark bond rate (lnbond), retrieved from Borsa İstanbul, is also employed as a leading indicator in this study. It is highly liquid and it sets a standard for performance evaluation in the bond market. The series is generated with the rate of the *Government Domestic Debt Security* (GDDS) having the highest volume on the last day of each month.

Credit risk default premium (lncrdp) is another leading indicator sourced from Economic Research -Federal Reserve Bank of Saint Louis, signaling for default risk specifically financial credit risk. Regarding the roles of gold and silver in times of financial crisis, default risk is linked to financial conditions and structural effects of the international economy. It is computed as the difference between Moody's Seasoned Aaa Corporate Bond Yield and Moody's Seasoned Baa Corporate Bond Yield as stated in Levin et al. (2006).

Monthly data of Europe Brent spot price (lnbrent) expressed as US dollar per barrel obtained from US Energy Information Administration is included in forecasting equations for spot prices of gold and silver. Oil price seems to be a good candidate to forecast gold and silver prices. A part of the literature investigates the link of gold and silver market to oil market with a hypothesis of co-movement among these essential commodities. Oil together with precious metals-primarily gold and silver- are important commodities for investors, policy makers and producers. Because they are all traded very commonly and priced in terms of US dollar, the prices of these commodities are fundamental particularly for a developing country like Turkey (Soytas et al., 2009).

The Borsa Istanbul 100 (lnise100) Index is a broad- term capitalization weighted index based on national market companies. This index has potential importance to feature sensitivity of gold and silver spot prices to stock market. Besides, inclusion of the index allows us to conclude about the hedging benefits in portfolios in case of a significant negative relationship. The daily index series taken from Borsa Istanbul are transformed into monthly frequency data by calculating average closing value of the trading days for each month[7].

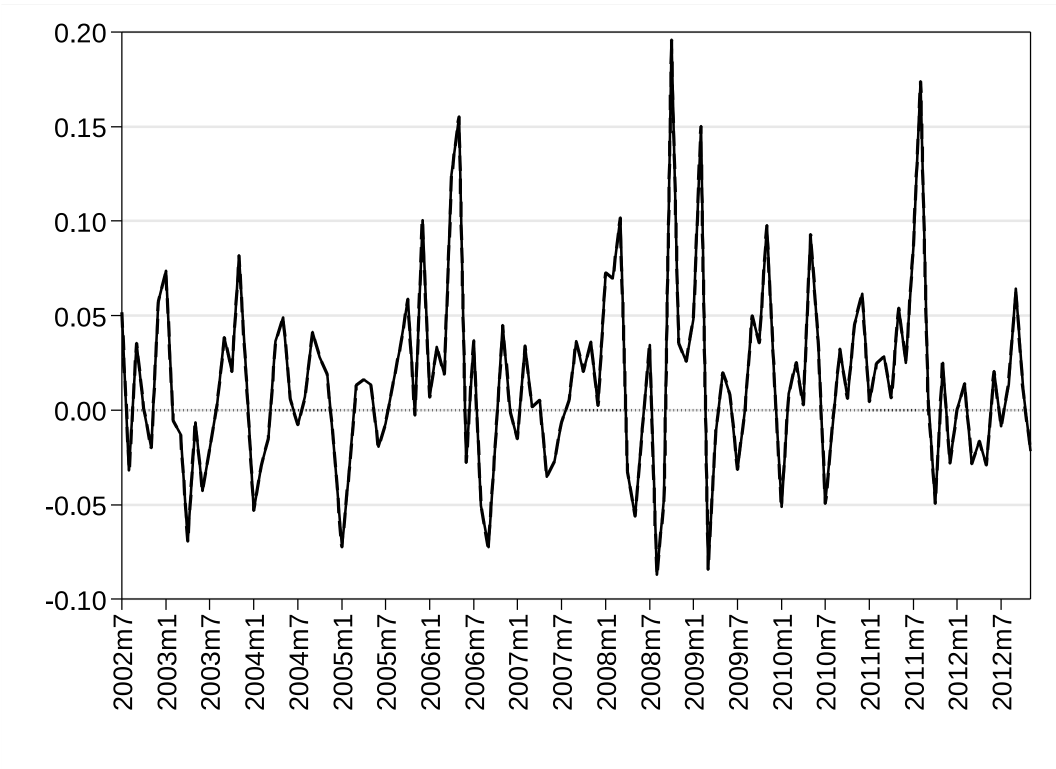

Figure 1: Gold prices, logarithmic first difference (Source: IGE)

[7] Second session, if any, is also taken into account.

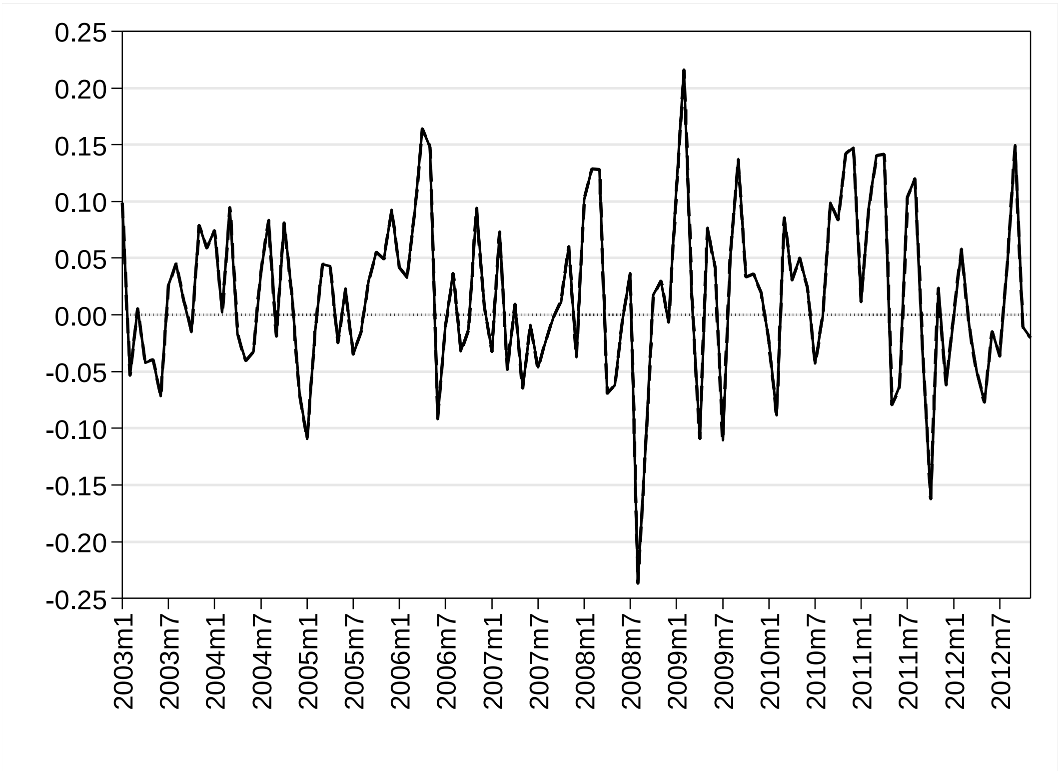

Figure 2: Silver prices, logarithmic first difference (Source: IGE)

The logarithmic first differences of monthly gold and silver prices are shown in Figure 1 and Figure 2, respectively. The available data covers the period from July 2002 to November 2012 for gold and from January 2003 to November 2012 for silver. The gold series consist of 79 periods of expansion and 46 periods of contraction. As for silver, the data exhibits 67 periods of positive growth and 52 periods of negative growth. A couple of inferences can be made from the figures. First, both metal prices have gone through a dramatic expansion followed by a significant contraction during 2008 global financial crisis. Second the global political events of 2006 push up gold and silver prices.

CHAPTER 5

METHODOLOGY

Our aim is to determine the best models which characterize the price movements of gold and silver and then to explore the predictive capacity of leading indicators through the selected models for each precious metal. To this end, initially, separate modeling exercises in the context of a linear model and a probit model are conducted for gold and silver. Then, the forecasting performances of the selected models are evaluated analogously. We focus on forecasting the sign of change in gold and silver prices in this study, since directional forecasting of price movements is found to be more useful and accurate in comparison to point price level forecasting as asserted by Leung, Daouk and Chen (2000).

5.1 Models

5.1.1. Benchmark Linear Model

In the literature, it is a common practice to use linear models for forecasting purposes in the metal markets. Moreover, a number of studies employing leading indicators approach utilize linear models for prediction. Hence, we develop a linear model to replicate the existing forecasting practice following the guidelines in studies such as Dooley and Lenihan (2005), Ismail et al. (2009), Poon and Granger (2003) and Njegovan (2005). Thereby, the predictive capacity of the probit model is evaluated with that of the linear one to explore the usefulness of the method applied in this study.

The linear leading indicator model is of the form:

$$\Delta_d {y_t}^{\alpha} = \lambda + \mathbf{X_{t-k}} + \psi\ (L)\ \Delta_d y_t + \eta\ (L)\varepsilon_t$$

where $\Delta_d y_t$ is the logarithmic d^{th} order difference of respective metal price, α stands for the metal-gold or silver, λ is intercept term, $\boldsymbol{X_{t-k}}$ is a matrix consisting of (stationarized) leading indicator series, ε_t is normally distributed error term and $\psi(L) = \psi L^1 + \psi L^2 + \cdots + \psi L^p$, $\eta\ (L) = \eta L^1 + \eta L^2 + \cdots + \eta L^q$ are polynomials in the lag operator L.

To be more specific, linear estimation is conducted within an ARIMAX(p,d,q) model framework with p being the order of autoregressive component, d being the order of integration and q being the order of moving average component.

5.1.2. Probit Model

The use of probit model is proposed by the fact that the response variable takes on only two possible values, either expansion or contraction in the prices of gold and silver. The initial process of building such a model is designating positive and negative growths in gold and silver prices. As noted before, data for response variables are expressed as first differences in the logarithm of metal prices. Taking these values, the binary variable, Υ_t , is generated in such a way that ones represent positive growth and zeros represent negative growth as:

$$\Upsilon_{t,\alpha} = \begin{cases} 1 & \text{if } \Delta_1 y_t > 0 \\ 0 & \text{otherwise} \end{cases} \qquad (1)$$

where $\Delta_1 y_t$ is monthly rate of change in the respective metal price and α stands for the metal- gold or silver.

Parallel with the propositions in Estralla and Mishkin (1998) and more recently Njegovan (2005), we adopt a probit model based on a linear link such that

$$\Upsilon_{t,\alpha} = \lambda + \boldsymbol{X'_{t-k}}\boldsymbol{\beta} + \varepsilon_t$$

where $\Upsilon_{t,\alpha}$ is the binary variable in (1), $\boldsymbol{\beta}$ is a coefficient vector, λ is the intercept term, $\boldsymbol{X_{t-k}}$ is a matrix of leading indicators, and ε_t is the normally distributed error term. Then, the equation to be estimated becomes:

$$P\left(\left(\Upsilon_{t,\alpha} = 1 \middle| \boldsymbol{X_{t-k}}\right)\right) = F(\boldsymbol{X'_{t-k}\beta})$$

where F representing the cumulative normal distribution function and $\boldsymbol{X_{t-k}}$ is a conditioning matrix of macroeconomic and financial indicators. The probit model is estimated by maximum likelihood, with the likelihood function L, described as

$$L = \prod_{i=1}^{T} F(\boldsymbol{X'_{t-k}}\boldsymbol{\beta})^{Y_i}(1 - F(\boldsymbol{X'_{t-k}}\boldsymbol{\beta}))^{(1-Y_i)} .$$

Then, the log-likelihood function is

$$\log(\mathrm{L}) = \sum_{i=1}^{T}\left[Y_i \log F(\boldsymbol{X'_{t-k}}\boldsymbol{\beta}) + (1 - Y_i)\log\left(1 - F(\boldsymbol{X'_{t-k}}\boldsymbol{\beta})\right)\right]$$

which is equivalent to total of all contraction and expansion periods

5.2. Variable Selection Procedures

Modeling is a fundamental practice prior to forecasting. Choosing the most influential explanatory variables is of particular interest in modeling. In our case, it is critical to determine a subset of leading indicators holding potential information in modeling and forecasting positive and negative growth in gold and silver prices.[8]

In the variable selection procedure, lags of the leading indicators are also considered given their potential predictive contribution in the models. A process with the following details is applied to provide computational feasibility in the search procedure. A correlation matrix between the first difference of logarithmic metal price and stationarized leading indicator series taken at lags zero to twelve is constructed and the only lag having the highest correlation with the response variable series is chosen for each leading indicator. This method is separately implemented for gold and silver. Thus, the variable set which contains each leading indicator at the lag determined with this method is considered in the variable selection procedure for the relevant metal.

Variable selection for linear and probit models is conducted through distinct search procedures based on the minimization of the Akaike Information Criterion (AIC) defined as

$$\mathrm{AIC}_i = -2\mathrm{MLL_i} + 2\pi_i$$

where $\mathrm{MLL_i}$ is the maximum log likelihood and π_i is the number of parameters of model i.

To begin with the ARIMAX (p,d,q) model, variable selection procedure consists of two phases. The first phase involves identification of optimal AR and MA orders, p and q. In this context, an automated algorithm for stepwise search is employed

[8] All procedures described in this section are implemented for each metal individually.

following Hyndman and Kahandakar (2008).[9] [10] The algorithm starts by choosing the base model which give the minimum AIC among the following four: ARIMAX (0,d,0), ARIMAX (1,d,0), ARIMAX (0,d,1) and ARIMAX (2,d,2). To examine different alternatives, p and q values of the base model are changed by ±1 and AIC value is computed for all variations. Next, considering all models developed so far, the algorithm assigns the model with the minimum AIC as the new base model. This procedure continues until it is not possible to reach a lower value of AIC. In the second phase, using the model obtained from the automated search, the optimal leading indicators are selected through a stepwise backward elimination procedure on the basis of minimizing AIC.

For the probit model, the optimal leading indicators are chosen through an exhaustive search algorithm aimed at minimizing AIC.[11] The algorithm computes AIC for the model which includes all m leading indicators at first. Next, AIC is calculated considering all possible subsets of m-1 leading indicators. This procedure is repeated sequentially until one leading indicator remains, yielding m possible subsets. The subset with minimum AIC is selected out of all models.

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[9] The order of integration- d is formerly specified as a result of the preliminary analysis, so the related step which explores d using unit root tests in the algorithm is not applied. It is important to determine the order of autoregressive component, p, and the order of moving average component, q for this model (Box and Jenkins,1970). Considering the frequency of the data, maximum values of p and q are set to 12.

[10] The algorithm uses all leading indicators.

[11] Given the number of all leading indicators, m, when m≤15, a subset can be chosen out of all possible combinations. (Knuth,2005)

5.3. Predictive Performance Evaluation

The models chosen as a result of the variable selection procedures described in Section 5.2., are adopted to predict the directional change in gold and silver prices separately. Regarding the amount of output in a study such as this, some tools can be used to make the results more compact and more comparable. To that end, we have exploited two of widely-used goodness-of-fit criteria. The general criterion is the direction of change error which is used to assess the forecasting performance of all models-probit models and ARIMAX model. Additionally, the predictive performance of probit models is evaluated based on root mean square error. To begin with, the direction-of-change error basically refers to directional difference between actual and predicted values. For probit models, it is calculated after transforming the estimated probabilities into binary variables applying the 0.5 rule in line with the model building process. In more details, positive growth is predicted if an estimated probability exceeds 0.5; otherwise negative growth is predicted. For ARIMAX model, the direction-of-change error is calculated by comparing the signs of estimated and actual growth. This measure is expressed as the number of incorrect forecasts and the percentage error counts.

Probit models are evaluated with an additional measure of predictive performance, i.e. root-mean-square error. The root-mean-square error for the binary variable is

$$\mathrm{RMSE}= \sqrt[2]{\frac{\sum_{t=1}^{T}\left(Y_t-\widehat{Y_t}\right)^2}{T}} \qquad (2)$$

where Y_t denote the binary variable in (1), $\widehat{Y}_t$ is the estimated probability at time t and T is the sample size.

CHAPTER 6

EMPIRICAL RESULTS

As mentioned before, our aim is to determine the best models describing the price movements of gold and silver and then to explore the predictive capacity of leading indicators for each precious metal using monthly data between January 2002 and November 2012. In this respect, a preliminary analysis given in Section 6.1 starts with the implementation of unit root tests for the whole data set. Next, lag selection procedure is carried out prior to the variable selection process.

6.1. Preliminary analysis

Our analysis commences with a preliminary unit root test, the Augmented Dickey Fuller (ADF) test. The lag length for the test is determined through a general to specific approach. More specifically, the maximum lag length is set to 12 and insignificant lags are sequentially dropped until the last lag becomes significant. Unit root test results for all variables are documented in Table 2. According to the results, the null hypothesis of a unit root is not rejected in all series at the 5% significance level. The only exception to this is lnworld_cpi, which appears to be borderline stationary.

Table 2: Augmented Dickey Fuller Unit Root Test (in Levels)

Variables	With Intercept	With Intercept and Trend	None
lngold	-0.26	-2.70	2.76*
lnsilver	0.01	-2.62	2.26*
lnbond	-1.43	-2.30	-2.45*
lnbrent	-1.73	-2.69	1.28
lncrdp	-2.64	-2.75	-2.60*
lnise100	-1.44	-2.37	1.34
lnindpro	-1.45	-2.38	2.02
lnm2	-2.02	-0.59	4.87*
lnworld_cpi	-0.14	-3.49*	3.99*
lnturkey_cpi	-1.82	-2.73	5.42*
lnex	-2.14	-2.53	-0.17
Test Critical Values (5%)	***-2.88***	***-3.44***	***-1.94***

Note: * indicates rejection of the null hypothesis at 5 % significance level

6.2. Estimation Results

A detailed procedure is outlined for modeling gold and silver prices in Section 5.2. Through this method, we specify an ARIMAX model as a benchmark model and select outstanding probit models for each metal.[12] In this section, both the benchmark linear model and the selected probit models are estimated to qualify their ability to predict directional price changes. The fitted values are checked further against the actual contraction and expansion periods.

[12] For each metal, the selected probit models minimize AICs with very close values.

6.2.1 Estimation Results for Gold

Variable selection procedure for gold ends up with an ARIMAX (0,1,0) model as a benchmark and three probit models. First linear model and then probit models are elaborated in this section. To begin with, the estimation results for ARIMAX (0,1,0) model is presented in Table 3 and the fitted values are depicted in Figure 3.

ARIMAX model estimation results exhibit that all leading indicators are significant and the signs of the parameter estimates are consistent with economic theory. Considering the frequent inclusion of gold, bond and oil in investment portfolios, the negative parameter estimates for lnbond at lag three and lnbrent at lag two can be ascribed to the potential substitution effect between gold and these assets. The positive estimate for lnex highlights the hedging capacity of gold against exchange rate risk. Moreover, the positive relationship between lngold and lnm2 indicates that an increase in money supply leads to a rise in gold price with fixed supply of gold. Looking at the direction-of-change error measure, the linear model reveals false signals for 12 out of 79 (15.2%) positive growth periods and 31 out of 46 (67.4%) negative growth periods.

Table 3: Estimation Results of Benchmark Linear Model for Gold

Parameter Estimates	
Intercept	0.01** [0.01]
lnbond(-3)	-0.10*** [0.00]
lnbrent(-2)	-0.09** [0.02]
lnex	0.50*** [0.00]
lnm2	0.17** [0.02]
Summary Statistics	
Max value of log-likelihood	225.74
R^2	0.33
χ^2 (AR12)[13]	9.13 [0.69]
Direction-of-Change Error Counts	
Positive growth	15.2% (12/79)
Negative growth	67.4% (31/46)

Note: p values are in square brackets, *** significance at 1 %, **significance at 5 % and *significance at 10 %

From Figure 3, further details can be observed about the performance of the linear model. The model correctly signals for the uninterrupted expansion in the gold price during the period from the last quarter of 2008 to early 2009 which correspond to the financial crisis. But it fails to capture the negative growth occurred just before this expansion. Moreover, it generates accurate signals for the expansions caused by the political environment in the first half of 2006.

[13] Breusch Godfrey LM test for serial correlation

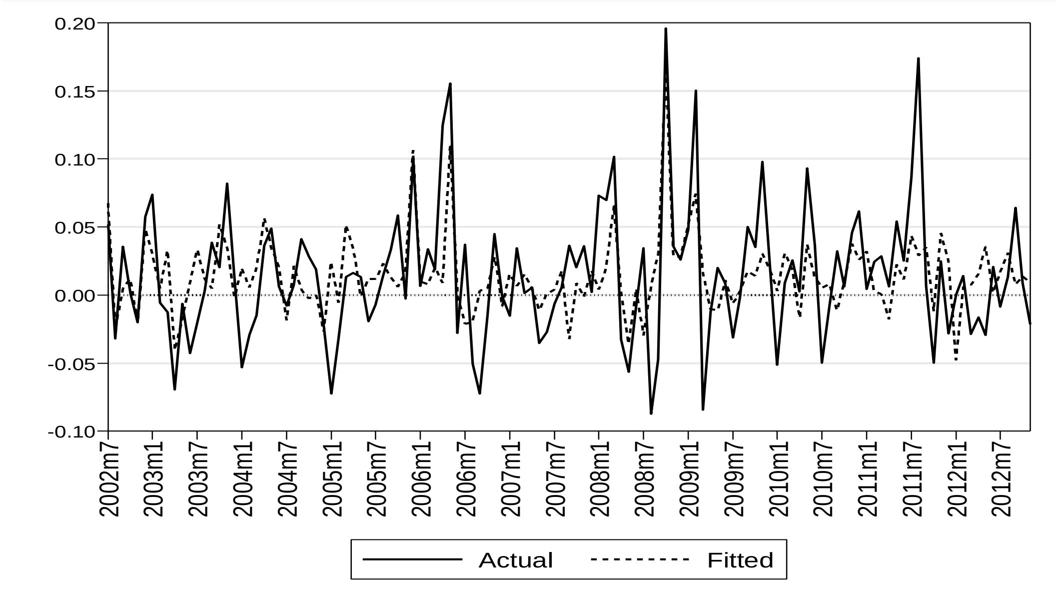


Figure 3: Gold Price, Logarithmic First Difference, Fitted Values

As regards to probit models, the estimation results are reported in Table 4. Parameter estimates for the same variable are numerically close with consistent signs in all models. An extensive inspection of the models suggests a couple of remarks. First, lnturkey_cpi at lag one and lnex are the most consistent indicators by taking part in all three models. Moreover, lnturkey_cpi at lag one seems to be negatively related to lngold. An explanation for this result might be the investment shift from gold to interest-bearing assets fueled by inflationary expectations during times of increasing inflation. Second, lnindpro at lag five appears only in Model 2 with an insignificant estimate implying that investment component of gold dominates its usage as an industrial input. Third, the signs of lnbond at lag three and lnex prop up the respective arguments of substitution and hedging above.

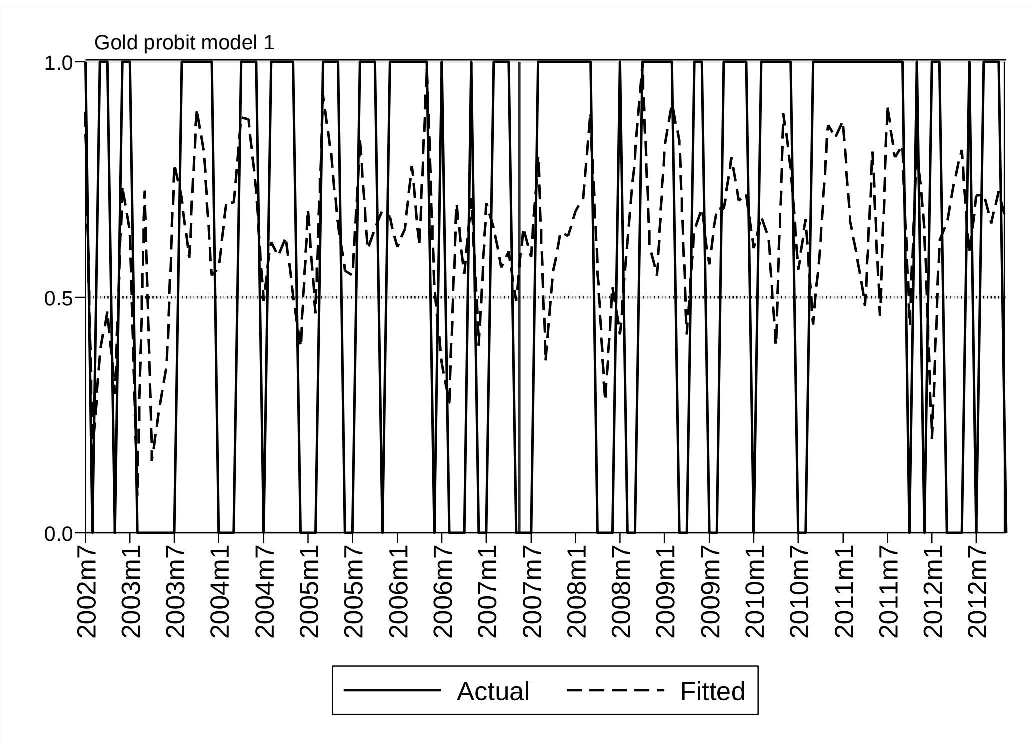
Table 4: Gold Selected Probit Models and Summary Statistics

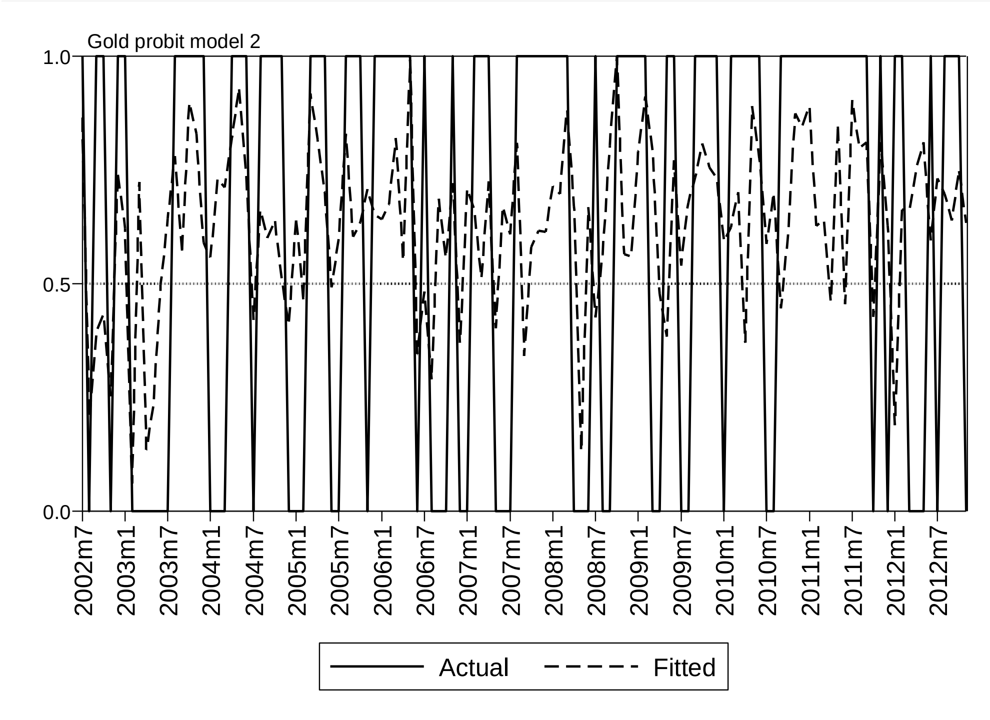
Variable and lag	Probit Models		
	1	2	3
Intercept	0.60***	0.62***	0.65***
	[0.00]	[0.00]	[0.00]
lnbond(-3)	-2.10*	-2.14*	
	[0.10]	[0.10]	
lnindpro(-5)		2.91	
		[0.21]	
lnturkey_cpi(-1)	-31.48*	-34.49*	-34.22*
	[0.08]	[0.06]	[0.07]
lnex	11.39***	11.35***	10.73***
	[0.00]	[0.00]	[0.00]
Summary Statistics			
Max value of log-likelihood	-73.20	-72.42	-74.51
AIC	154.40	154.85	155.01
RMSE	0.451	0.449	0.455
Direction-of-Change Errors			
Positive growth	12.6% (10/79)	13.9% (11/79)	11.4% (9/79)
Negative growth	67.3% (31/46)	63.0% (29/46)	71.7% (33/46)

Note: p values are in square brackets, *** significance at 1 %, **significance at 5 % and *significance at 10 %.

Model 1, which includes lnbond at lag three, lnturkey_cpi at lag one and lnex is the best model according to AIC. However, Model 2 consisting of lnbond at lag three, lnindpro at lag five, lnturkey_cpi at lag one along with lnex is superior to others regarding RMSE. Using “0.5 rule” described earlier, the model performances are evaluated with direction-of-change errors considering 79 positive and 46 negative growth periods. Model 1 fails to capture 10 (12.6%) positive growth periods as well as giving 31 (67.3%) false signals for the negative growth periods. Regarding Model 2, it fails to predict 11 (13.9%) positive and 29 (63.0%) negative growth periods. As regards to Model 3, it gives false signals for 9 (11.4%) positive growth and 33 (71.7%) negative growth periods. The direction-of-change error measure reveals that the benchmark linear model exhibits weaker performance relative to the best probit model, i.e. Model 1. It fails to predict 12 (15.2%) periods of positive growth, which is two more errors than the probit Model 1 and giving 31 (67.4%) false signals of negative growth, which is the same with probit Model 1. Consequently, positive growth is best predicted by Probit Model 3, whereas negative growth can be best captured by Probit Model 2. The probit models perform marginally better than the linear model.

Figure 4 enables further evaluation of the three probit models. All models correctly signal for the jumps in gold prices observed during the period from the last quarter of 2008 to early 2009, which corresponds to the times of global financial crisis. But, the models fail to detect the downward movement seen just before the jump by giving false signals for the two months before the last quarter of 2008. Additionally, the models predict the increase in gold prices triggered by the global political events of 2006 timely. As for linear model, it provides timely predictions for the periods under investigation except for the two months of contraction before the jump in 2008.





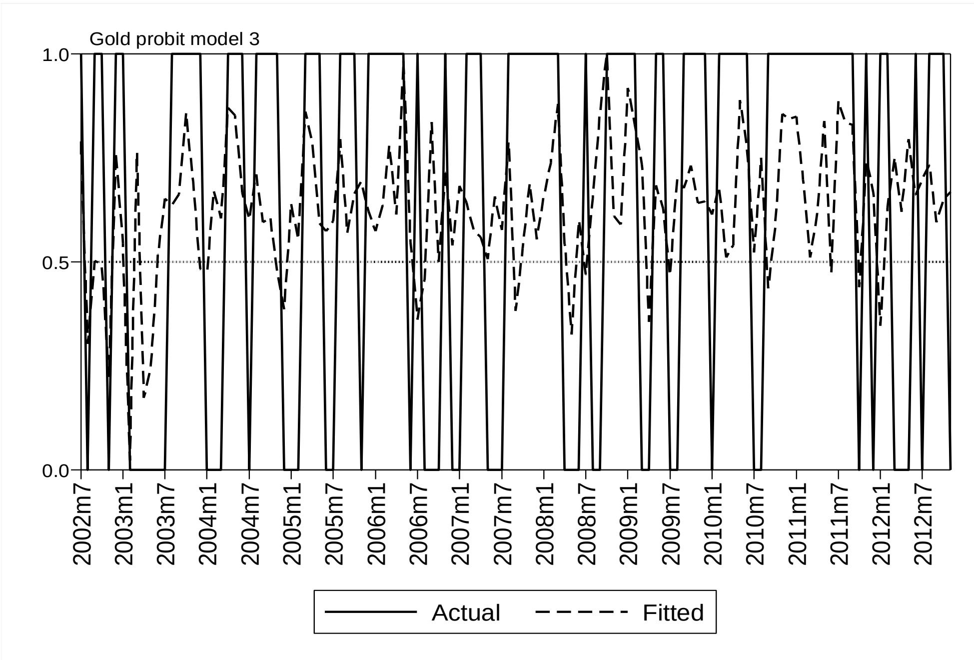


Figure 4: Fitted probabilities of gold probit models

6.2.2. Estimation Results for Silver

For silver, the search procedure point out an ARIMAX (2,1,2) model as a benchmark and four probit models. This section discusses first the benchmark linear model and then the selected probit models. Table 5 shows the estimation results for ARIMAX (2,1,2) model and Figure 5 depicts the fitted values for further evaluation.

Table 5: Estimation Results of Benchmark Linear Model for Silver

Parameter Estimates	
Intercept	0.03*** [0.00]
lnbrent(-3)	-0.11 [0.12]
lnturkey_cpi(-1)	-2.01** [0.04]
lnm2	0.26* [0.07]
lnex	0.20 [0.17]
AR(1)	-0.75*** [0.00]
AR(2)	-0.67*** [0.00]
MA(1)	1.08*** [0.00]
MA(2)	0.81*** [0.00]
Summary Statistics	
Max value of log-likelihood	161.70
AIC	-303.41
χ^2(AR12)	5.25 [0.94]
Direction-of-Change Error Counts	
Positive growth	17.9% (12/67)
Negative growth	53.8% (28/52)

Notes: p-values in square brackets; *significance at 10 %, **significance at 5 %, *** significance at 10 %

The estimation results show that lnbrent at lag three and lnex are found to be insignificant to predict the growth of silver prices. Second, lnturkey_cpi at lag one seems to influence silver prices negatively. Also, the positive sign of lnm2 can be associated with the pattern desribed for gold. Regarding predictive power, direction-of-change error criterion shows that the linear model fails to predict 12 out of 67 (17.9%) periods of expansion and 28 out of 52 (53.8%) periods of contraction in silver prices.

Figure 5 illustrates the performance of the linear model in depth. The model correctly signals the growth in silver prices, which is triggered by the financial crisis, during the first quarter of 2009. In addition, it captures the period of expansion in silver prices for the first half of 2006, which corresponds to the times of global political conflict,

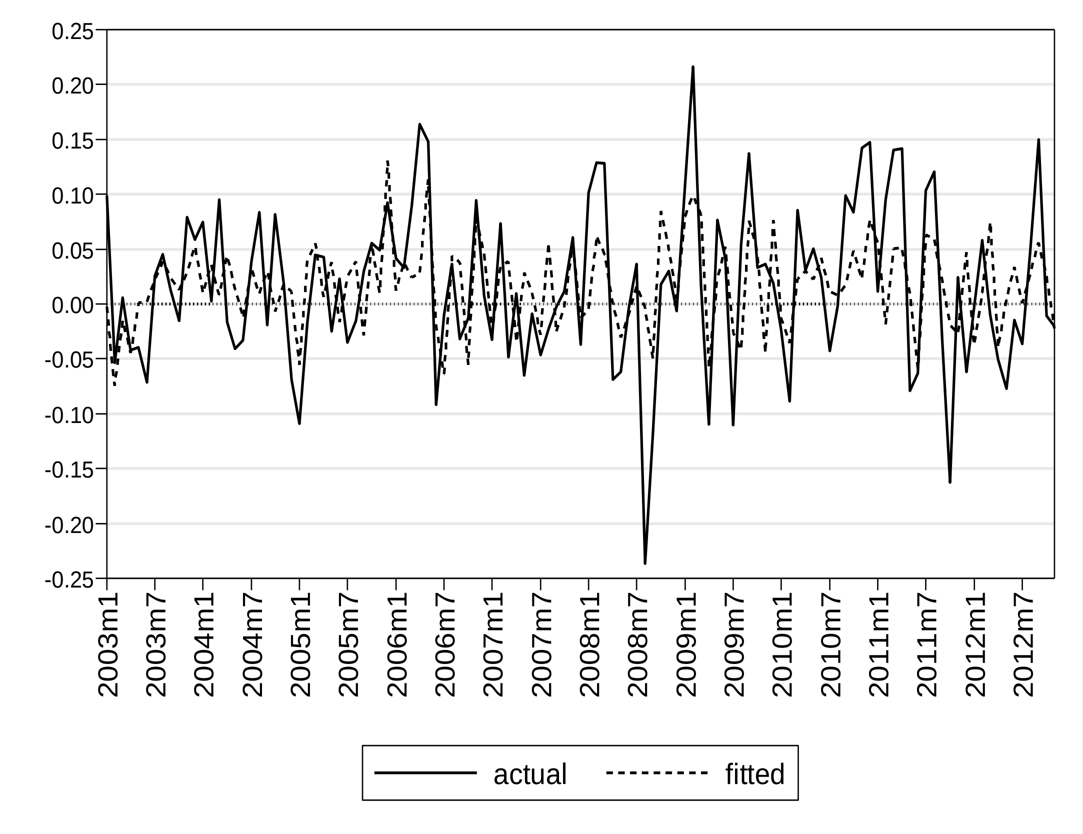


Figure 5: Silver Price, Logarithmic First Difference, Fitted Values

The estimation results for the selected probit models are provided in Table 6. Some inferences can be made from the results given. Firstly, similar parameter estimates are produced with consistent signs for the same variable across the four model specifications. Besides, lnworld_cpi at lag twelve appearing only in Model 2 is insignificant. Likewise, lnbrent at lag three is included only in Model 3 and it turns out to be insignificant. Moreover, lnturkey_cpi at lag one and lnex are the most notable performers because they are both present in all of the four models. Lnindpro appears in the best three models and its positive sign can be attributed to the industrial usage of silver.

Table 6: Silver Selected Probit Models and Summary Statistics

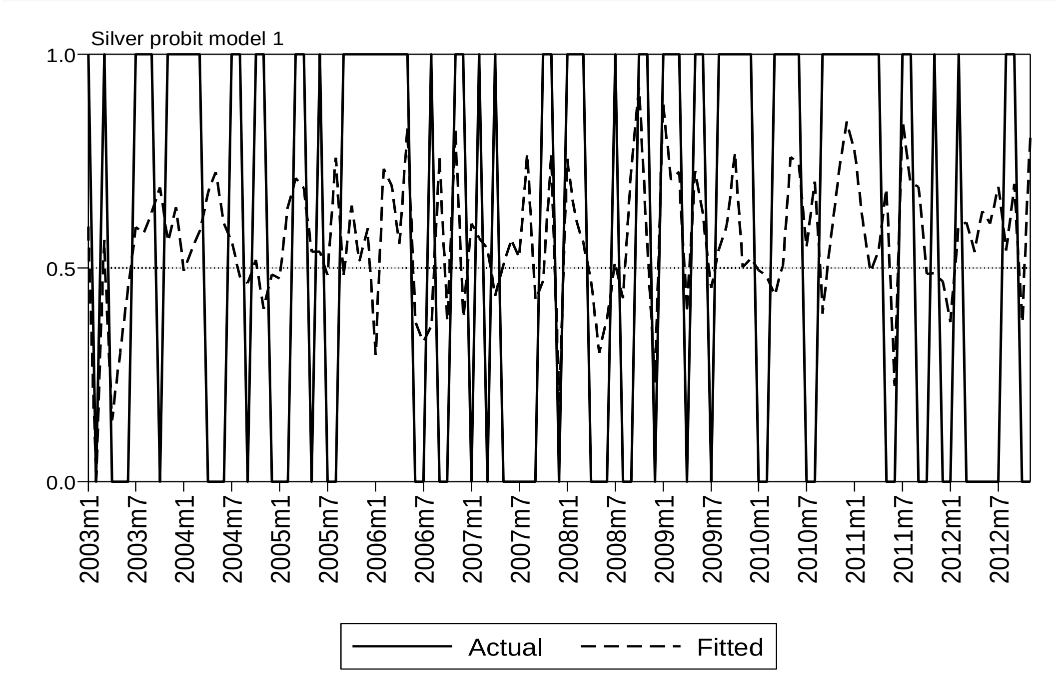
Variable and lag	Probit Models			
	1	2	3	4
Intercept	0.52**	6.6	0.50**	0.54***
	[0.01]	[0.21]	[0.01]	[0.00]
lnbrent(-3)			-1.59	
			[0.27]	
lnindpro	3.81*	3.76*	3.70*	
	[0.09]	[0.10]	[0.10]	
lnturkey_cpi(-1)	-52.03**	-56.27**	-46.58	-51.88**
	[0.03]	[0.02]	[0.06]	[0.04]
lnworld_cpi(-12)		-1.3		
		[0.25]		
lnex	5.37*	5.61*	5.12*	5.57*
	[0.08]	[0.07]	[0.10]	[0.07]
Summary Statistics				
Max value of log-likelihood	-74.97	-74.32	-74.35	-76.44
AIC	157.94	158.64	158.71	158.88
RMSE	0.470	0.467	0.469	0.477
Direction-of-Change Error Counts				
Positive growth	19.4 % (13/67)	23.9 % (16/67)	28.3 % (19/67)	22.4 % (15/67)
Negative growth	48.1% (25/52)	55.8 % (29/52)	50.0 % (26/52)	55.8% (29/52)

Notes: p-values in square brackets; *significance at 10 %, **significance at 5 %, *** significance at 10 %

Negative sign of lnturkey_cpi at lag one points out the investment part of silver, investment flow from silver to assets with interest payments might be the reason for this relationship. The positive sign of lnex implies an increase in demand for silver through expectations of devaluation in the domestic currency.

Model 1 is selected as the best specification according to AIC and it consists of lnindpro, lnturkey_cpi at lag one and lnex. However, Model 2 outperforms the others in terms of RMSE. Direction-of-change error measures are also constructed taking 67 positive growth and 52 negative growth periods into account. Model 1 provides false signals for 13 (19.4%) positive and 25 (48.1%) negative growth periods. As regards to Model 2, it fails to predict 16 (23.9%) periods of positive growth and 29 (55.8%) periods of negative growth. Model 3 gives false signals for 19 (28.3%) positive and 26 (50.0%) negative growth periods. Model 4 fails to capture 15 (22.4%) positive growth and 29 (55.8%) negative growth periods. As for the benchmark linear model, it produces false signals for 12 (17.9%) positive and 28 (53.8%) negative growth periods. To sum up, negative growth is best predicted by Probit Model 1, whereas positive growth can best be signaled by the linear model.

Figure 6 illustrates further details for the evaluation of the models. All probit models correctly predict the rise in silver prices during the first quarter of 2009, global financial crisis period. Moreover, only Probit Model 4 produces fully accurate predictions for the rise in silver prices caused by the political conflicts during the first half of 2006. Regarding the linear leading indicator model, it correctly predicts the rise in silver prices both for the first half of 2006 and for the first quarter of 2009.


Silver probit model 1
1.0
0.5
0.0
2003m1
2003m7
2004m1
2004m7
2005m1
2005m7
2006m1
2006m7
2007m1
2007m7
2008m1
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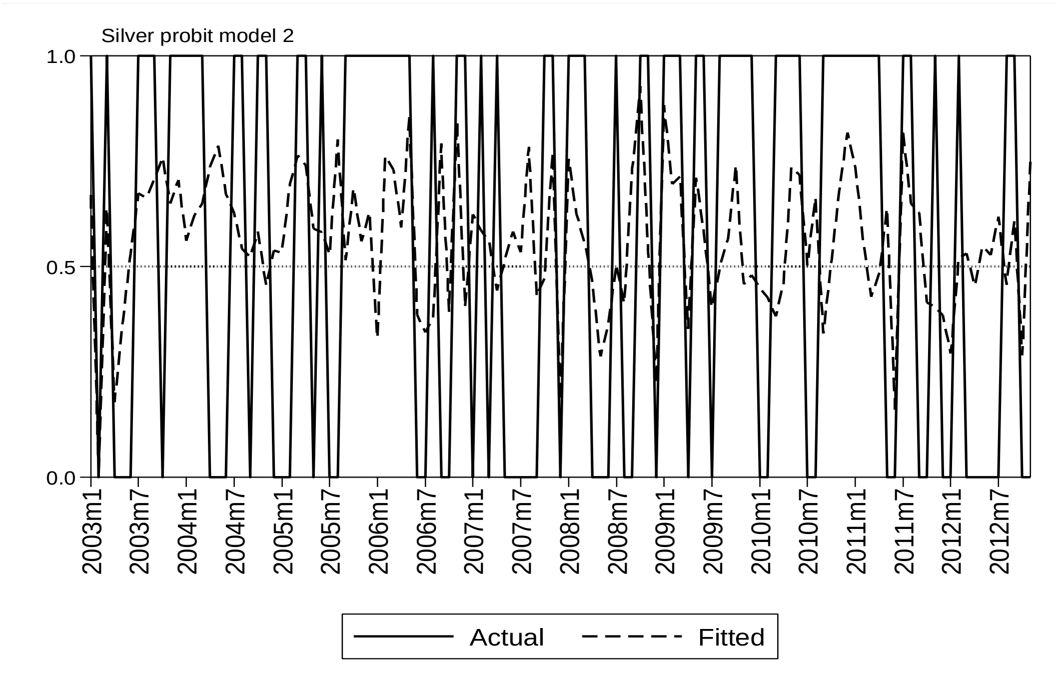
2012m1
2012m7
Actual
Fitted


Silver probit model 2
1.0
0.5
0.0
2003m1
2003m7
2004m1
2004m7
2005m1
2005m7
2006m1
2006m7
2007m1
2007m7
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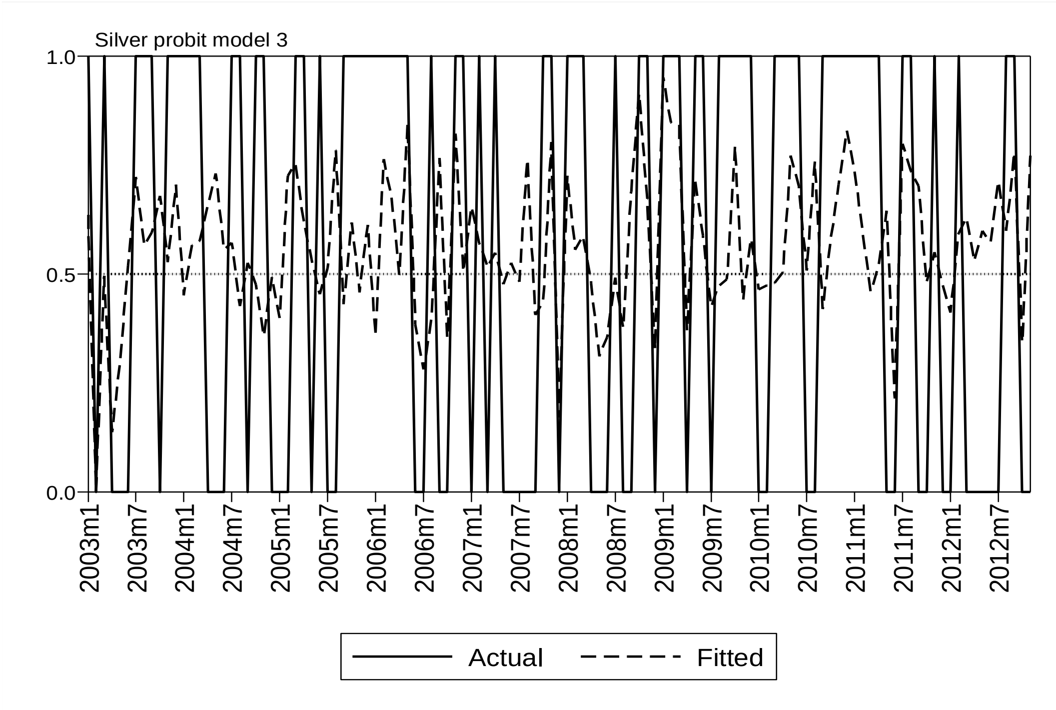
2012m7
Actual
Fitted



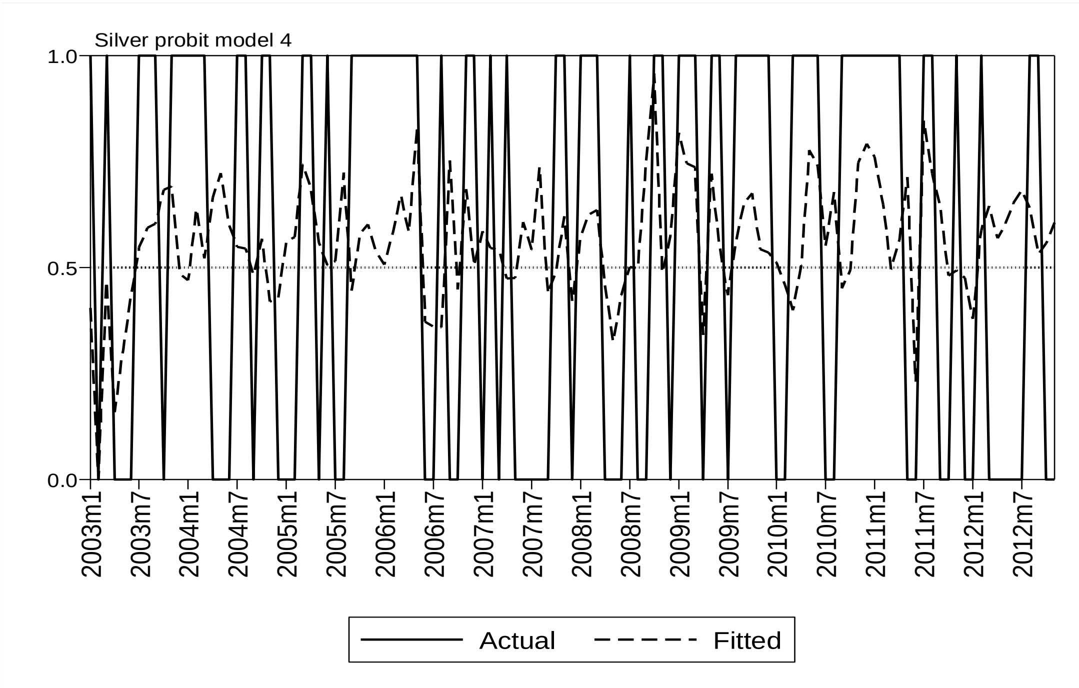


Figure 6: Fitted probabilities of silver probit models

6.3. Validation: Forecasting Exercise

In this section, a forecasting analysis is performed to further examine the capacity of the models to predict directional price movements in gold and silver. This procedure is formed as recursive forecasting with an expanding window. The process starts with the estimation of parameters with an initial data up to time t to obtain forecast at time t+1. Afterwards, the sample is increased one month and the models are re-estimated to make a new one-period-ahead forecast at time t+2. Repeating this procedure along the forecast horizon, h-step ahead forecasts are produced. In our case, the parameters are initially estimated using data from the beginning[14] of the sample up to September 2008 to obtain one-month-ahead predictions and forecasts are produced for the following twelve periods. Therefore, the forecasting horizon covers the twelve-month-period between October 2008 and September 2009. This range is especially selected to observe the prediction power of the models in gold and silver directional price changes during financial crisis.

6.3.1. Validation Exercise for Gold

The results of the validation exercises for gold prices are reported in Table 7. The Probit Model 3 seems to outperform its competitors in prediction of the impacts of 2008 financial turmoil on gold prices. It is superior based on RMSE and direction-of-change error criteria. It predicts all the positive growth periods correctly but gives 50% false signals for negative growth periods. All three models and the linear model fail to predict the contraction in gold prices in March 2009. However, except Probit Model 2, all the models timely signal the contraction in April 2009. In addition, the contraction in July 2009 is only predicted by Probit Model 3.

[14] July 2002 for gold; January 2003 for silver

The linear model performs better than Probit Model 1 and Probit Model 2 on the basis of direction-of-change error criterion. It also dominates Probit Model 3 in predictions of negative growth periods. Further, the industry recession in August 2009 is captured only by the linear model. Briefly, positive growth is best signaled by Probit Model 3 while negative growth is best captured by the linear model.

Table 7: Fitted Probabilities- Gold

	Y	**Probit Model 1**		**Probit Model 2**		**Probit Model 3**		**Linear Model**	
		$\mathbf{Y^f}$	$\mathbf{Y^P}$	$\mathbf{Y^f}$	$\mathbf{Y^P}$	$\mathbf{Y^f}$	$\mathbf{Y^P}$	$\mathbf{Y^f}$	$\mathbf{Y^P}$
2008M10	1	0.999	1	0.999	1	0.999	1	0.138	1
2008M11	1	0.569	1	0.494	0	0.573	1	0.020	1
2008M12	1	0.470	0	0.474	0	0.565	1	0.016	1
2009M01	1	0.684	1	0.575	1	0.923	1	0.033	1
2009M02	1	0.964	1	0.969	1	0.837	1	0.072	1
2009M03	0	0.912	1	0.874	1	0.753	1	0.023	1
2009M04	0	0.407	0	0.513	1	0.313	0	-0.009	0
2009M05	1	0.571	1	0.170	0	0.648	1	-0.016	0
2009M06	1	0.693	1	0.773	1	0.603	1	0.010	1
2009M07	0	0.578	1	0.555	1	0.427	0	-0.007	0
2009M08	0	0.675	1	0.668	1	0.685	1	-0.004	0
2009M09	1	0.664	1	0.718	1	0.657	1	0.017	1
RMSE		0.4785		0.5255		0.4202		N/A	
Direction-of-change error counts									
Positive growth		12.5% (1/8)		37.5% (3/8)		0% (0/8)		12.5% (1/8)	
Negative growth		75% (3/4)		100% (4/4)		50% (2/4)		25% (1/4)	

Notes: Y^P: Predicted Probabilities, Y^f: Fitted Probabilities, Y: Actual Probabilities

6.3.2. Validation Exercise for Silver

As for the silver, the results of the analysis are presented in Table 8. Probit Model 1 is the best among the probit models based on RMSE. Furthermore, it outperforms all its competitors including linear and probit models. It captures all the contraction and expansion periods correctly without failure. In addition, the negative growth of silver prices in December 2008 is signaled accurately by all probit models except Probit Model 4. Further, all probit models are successful in predicting the contraction of silver prices in April 2009 and July 2009.

Direction-of-change error measure underlines that the linear model is more successful in signaling the positive growth periods than Probit Model 2 and 3. Nevertheless, it is worst together with Probit Model 4 in predicting negative growth periods.

Table 8: Fitted Probabilities- Silver

	Y	**Probit Model 1**		**Probit Model 2**		**Probit Model 3**		**Probit Model 4**		**Linear Model**	
		Y^f	**Y^P**	**Y^f**	**Y^P**	**Y^f**	**Y^P**	**Y^f**	**Y^P**	**Y^f**	**Y^P**
2008M10	1	0.841	1	0.764	1	0.842	1	0.919	1	0.109	1
2008M11	1	0.611	1	0.450	0	0.648	1	0.514	1	0.012	1
2008M12	0	0.141	0	0.099	0	0.192	0	0.550	1	0.028	1
2009M01	1	0.871	1	0.795	1	0.911	1	0.765	1	0.041	1
2009M02	1	0.628	1	0.530	1	0.726	1	0.699	1	0.048	1
2009M03	1	0.631	1	0.551	1	0.747	1	0.661	1	0.058	1
2009M04	0	0.461	0	0.376	0	0.433	0	0.370	0	-0.017	0
2009M05	1	0.663	1	0.577	1	0.640	1	0.658	1	0.029	1
2009M06	1	0.657	1	0.568	1	0.620	1	0.556	1	0.006	1
2009M07	0	0.477	0	0.416	0	0.450	0	0.447	0	-0.008	0
2009M08	1	0.561	1	0.472	0	0.491	0	0.583	1	-0.001	0
2009M09	1	0.569	1	0.522	1	0.465	0	0.641	1	0.006	1
RMSE		0.3580		0.4102		0.3585		0.3828		N/A	
Direction-of-change error counts											
Positive growth		0% (0/9)		22.2% (2/9)		22.2% (2/9)		0% (0/9)		11.1% (1/9)	
Negative growth		0% (0/3)		0% (0/3)		0% (0/3)		33.3%(1/3)		33.3% (1/3)	

Notes: Y^P: Predicted Probabilities, Y^f: Fitted Probabilities, Y: Actual Probabilities

CHAPTER 7

CONCLUSION

This study aims to select the best models describing the directional price movements of gold and silver and thereafter to generate reliable forecasts with macroeconomic and financial leading indicators. Modeling and forecasting analysis are conducted under a benchmark linear model-ARIMAX- and a probit model using monthly data from January 2002 to November 2012. To this end, a preliminary analysis consisting of two processes is initially conducted. Firstly, ADF unit root test is implemented on the logarithmic transformation of all variables. In this way, all non-stationary series are transformed into stationary variables. Then, all dependent variables and also their lags from one to twelve are examined through cross correlation analysis and only one lag which has the highest correlation with the response variable is considered in the subsequent analysis.

The best models are determined on the basis of minimizing AIC through an exhaustive and a stepwise search procedure for probit model and ARIMAX model respectively. The results point out ARIMAX (0,1,0) model and three probit models for gold. As for silver, ARIMAX (2,1,2) model and four probit models are selected. A remarkable point of the selected models is that exchange rate and inflation are the prominent determinants of the price movements of gold and silver.

Predictions of the best ARIMAX model and the best probit models are generated for each metal. The predictive power of all models- both ARIMAX and probit- are evaluated with direction-of-change error criterion. Also, another measure, root mean square error, is used to evaluate the predictive performance of the probit models.

A validation exercise is implemented through recursive forecasting with an expanding window for the twelve-month-period beginning from October 2008 which incorporates the effects of the global financial crisis. Results of this analysis indicate that one of the probit models for gold achieved to forecast all the positive growth periods correctly. As for silver, three of the probit models outpace the benchmark model and one of the probit models give accurate signals for all the positive growth and negative growth periods. For both of the metals, the probit models generate more accurate predictions for the positive growth periods in comparison to the negative growth periods. The underlying reason might be the failure of probit model to capture downward movements when an upward trend is observed in the metal prices. Besides, the previous point about the probit model is more remarkable for gold, which can be associated with the higher proportion of the positive growth periods for gold relative to that of silver.

In conclusion, this study underlines the potential use of a probit model along with a benchmark linear model-ARIMAX for modeling and forecasting the price changes of precious metals with a focus on direction of change in prices rather than level of prices. This approach is alternative to the common practice of the literature about precious metals. Our analysis highlight that the probit models are at least as successful as the linear model in terms of forecasting for gold prices. It is also founded that the probit models generally outperform the linear model for the prediction of silver prices. As a future research agenda, a forecast combination approach can be followed to improve the forecasts of models considered for precious metal prices.

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APPENDIX

TEZ FOTOKOPİSİ İZİN FORMU

ENSTİTÜ

Fen Bilimleri Enstitüsü

Sosyal Bilimler Enstitüsü

Uygulamalı Matematik Enstitüsü

Enformatik Enstitüsü

Deniz Bilimleri Enstitüsü

YAZARIN

Soyadı : Deveci
Adı : Duygu
Bölümü : İktisat

TEZİN ADI (İngilizce) : Predicting Gold and Silver Spot Prices in Turkey

TEZİN TÜRÜ : Yüksek Lisans Doktora

1. Tezimin tamamından kaynak gösterilmek şartıyla fotokopi alınabilir.
2. Tezimin içindekiler sayfası, özet, indeks sayfalarından ve/veya bir bölümünden kaynak gösterilmek şartıyla fotokopi alınabilir.
3. Tezimden bir bir (1) yıl süreyle fotokopi alınamaz.

TEZİN KÜTÜPHANEYE TESLİM TARİHİ: