

Gold, currencies and market efficiency

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Abstract

Gold and currency markets form a unique pair with specific interactions and dynamics. We focus on the efficiency ranking of gold markets with respect to the currency of purchase. By utilizing the Efficiency Index (EI) based on fractal dimension, approximate entropy and long-term memory on a wide portfolio of 142 gold price series for different currencies, we construct the efficiency ranking based on the extended EI methodology we provide. Rather unexpected results are uncovered as the gold prices in major currencies lay among the least efficient ones whereas very minor currencies are among the most efficient ones. We argue that such counterintuitive results can be partly attributed to a unique period of examination (2011-2014) characteristic by quantitative easing and rather unorthodox monetary policies together with the investigated illegal collusion of major foreign exchange market participants, as well as some other factors discussed in some detail.

Keywords: efficient market hypothesis, gold, currencies, fractal dimension, entropy, long-term memory

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1. Introduction

For decades, the efficient market hypothesis (EMH) has been a building block of financial economics. In his fundamental paper, Fama (1970) summarizes the then-current empirical findings following the theoretical papers of Fama (1965) and Samuelson (1965). Fama (1991) then recalls various issues of the hypothesis and reviews the newer literature on the topic. The capital market efficiency is standardly parallelized with the informational efficiency so that the markets are efficient as long as all the available information is fully reflected into market prices (Fama, 1970). Depending on the level of information availability, the EMH is usually separated into three forms – weak (historical prices), semi-strong (public information), and strong (all information, even private) (Fama, 1991). The theory has been challenged on both theoretical (Malkiel, 2003) and empirical (Cont, 2001) grounds regularly, yet still it remains a popular and fruitful topic of financial research.

The empirical testing of capital markets efficiency has a long history across various assets. The already-mentioned review study of Fama (1970) focuses mainly on stock markets. In commodity markets, Roll (1972) and Danthine (1977) are among the first ones to study their efficiency arriving at contradicting results. In the same timeline, foreign exchange rates are investigated as well (Frenkel, 1976; Cornell and Dietrich, 1978). The termination of the Bretton Woods system in 1971 made the detachment of gold and currency prices interesting for research of the separate phenomena (Booth and Kaen, 1979). Nonetheless, the two still remain tightly connected. Koutsoyiannis (1983) focuses on the efficiency of gold prices and argues that the market efficiency cannot be refuted. Nevertheless, the author finds a tight connection between gold prices and the strength of the US dollar as well as the inflation, interest rates and a general state of the US economy. The gold prices and foreign exchange rates are thus found to be firmly interconnected, which is supported by another early study of Ho (1985). Frank and Stengos (1989) further suggest that simple linear testing of the gold (and silver) market efficiency need not be sufficient.

The efficiency studies of foreign exchange rates are quite unique compared to the mentioned stocks and commodities as the foreign exchange rates pricing has solid macroeconomic foundations such as the balance of payment theory, the purchasing power parity, the interest rate parity, the Fisher effect and others (Dunn Jr. and Mutti, 2004; Levi, 2005; Feenstra, 2008). These theories lead to different ways of efficiency treatment and testing.

Charles et al. (2012) examine the return predictability of major foreign exchange rates between 1975 and 2009. Using various tests, the authors show that the exchange rates are unpredictable most of the time. Short-term inefficiencies are attributed to major events such as coordinated central bank interventions and financial crises. The crises perspective is further studied by Ahmad et al. (2012) who focus on the Asia-Pacific region. They argue that the 1997-1998 Asian crisis was more disturbing compared to the 2008-2009 global financial crisis. In addition, the floating currency markets are found to be more resilient than the countries with managed currencies. Al-Khazali et al. (2012) further examine the Asia-Pacific region using the random walk and martingale definitions of the market efficiency. Out of 8 studied currencies, only three (Australian dollar, Korean won and Malaysian ringgit) are found to be efficient while the other exchange rates offer profitable

trading opportunities.

Olmo and Pilbeam (2011) review the literature on the foreign exchange rate efficiency testing based on the uncovered interest rate parity. They suggest that the rejection of efficiency in this area of research may be due to significant differences in volatilities of the logarithmic changes of exchange rates and the forward premium, in addition to conditional heteroskedasticity of the data. The authors introduce a set of profitability-based tests of market efficiency based on the uncovered interest rate parity and they show that the foreign exchange rates are much closer to market efficiency than usually claimed. Chen and Tsang (2013) inspect whether interest rates structure (yield curve) can be used for foreign exchange rate forecasting. They show that it is the case on time horizons between one month and two years. They also argue that these results can help explaining the uncovered interest rate parity puzzle by relating currency risk premium to inflation and business cycle risks. Bianco et al. (2012) further discuss the potential of using economic fundamentals for foreign exchange rates forecasting. Their fundamentals-based econometric model for weekly euro-dollar rates is shown to beat the random walk model for time horizons between one week and one month. Engel et al. (2015) construct factors from exchange rates and they use their idiosyncratic deviations for forecasting. Combining these with the Taylor rule, and monetary and purchasing power parity models, they improve the forecasting power of the model compared to the random walk benchmark for the periods between 1999 and 2007 but not for earlier periods down to 1987.

Chaboud et al. (2014) inspect the effect of algorithmic trading on efficiency of the foreign exchange markets in the high-frequency domain. They show that algorithmic trading improves market efficiency in two aspects – triangular arbitrage opportunities and auto-correlation of high-frequency returns. On the contrary, they argue that this may impose higher adverse selection costs on slower traders.

Studies of the foreign exchange rates efficiency, in the same way as of the other assets, primarily focus on testing whether a given currency or a set of currencies may or may not be considered efficient. To reflect this point, Kristoufek and Vosvrda (2013) introduce the Efficiency Index (EI) which can be used to rank assets according to their efficiency. In addition, the index is very flexible and it can incorporate various measures of the market efficiency. In the original study, Kristoufek and Vosvrda (2013) study 41 stock indices and find the Japanese NIKKEI to be the most efficient one. From a geographic perspective, the most efficient indices are localized in Europe and the least efficient ones in Asia and Latin America. Kristoufek and Vosvrda (2014b) further focus on the index specification and show that approximate entropy adds a significant informative value to the index. Kristoufek and Vosvrda (2014a) then study efficiency across various commodity futures and uncover that energy commodities are the most efficient ones whereas the livestock commodities such as cattle and hogs are the least efficient ones. Here we focus on efficiency ranking of the gold market with respect to a currency used for the purchase, and we also contribute to the discussion on statistical properties of the Efficiency Index.

2. Methods

Coming back to the roots of the efficient market hypothesis in 1965, the treatment has been split into two main branches – based on the random random walk hypothesis (Fama, 1965) and following the martingale specification (Samuelson, 1965). We follow the latter approach as it is less restrictive and it assumes the returns of the efficient market to be only serially uncorrelated and with finite variance. This straightforward treatment enables us to use various measures of market efficiency and use them to construct the Efficiency Index, which allows to rank financial assets according to their efficiency. In this section, we briefly describe the Efficiency Index, its components and its statistical treatment. Introducing a procedure to assess statistical features of the Efficiency Index is an important and novel contribution to this line of research.

2.1. Capital market efficiency measure

Kristoufek and Vosvrda (2013, 2014a,b) define the Efficiency Index (EI) as

$$EI = \sqrt{\sum_{i=1}^n \left(\frac{\widehat{M}_i - M_i^*}{R_i} \right)^2}, \quad (1)$$

where M_i is the i th measure of efficiency, \widehat{M}_i is an estimate of the i th measure, M_i^* is an expected value of the i th measure for the efficient market and R_i is a range of the i th measure. EI is thus a distance from the efficient market situation. The index can include various efficiency measures but these need to be bounded, which turns out to be rather restrictive. We utilize three efficiency measures, which meet such criterion and which are frequently used in market efficiency studies (Cajueiro and Tabak, 2004, 2005; Di Matteo et al., 2005; Di Matteo, 2007; Zunino et al., 2010, 2011; Ortiz-Cruz et al., 2012) – Hurst exponent H with an expected value of 0.5 for the efficient market ($M_H^* = 0.5$), fractal dimension D with an expected value of 1.5 ($M_D^* = 1.5$), and the approximate entropy with an expected value of 1 ($M_{AE}^* = 1$). As discussed later in this section, Hurst exponent and fractal dimension share their range for stationary processes whereas approximate entropy does not. For this point, we need to rescale the approximate entropy part of the Efficiency Index so that we have $R_{AE} = 2$ and $R_D = R_H = 1$.

2.2. Long-range dependence and its estimators

Long-range dependent series can be formally described as the ones with a power-law decaying autocorrelation function (in time domain) and/or a divergent at origin spectrum (in frequency domain). Specifically, the autocorrelation function $\rho(k)$ with time lag k of a long-range dependent process decays as $\rho(k) \propto k^{2H-2}$ for $k \rightarrow +\infty$, and spectrum $f(\lambda)$ with frequency λ scales as $f(\lambda) \propto \lambda^{1-2H}$ for $\lambda \rightarrow 0+$ (Geweke and Porter-Hudak, 1983; Beran, 1994; Robinson, 1995). The characteristic parameter H is Hurst exponent which has several interesting values and intervals of existence. For $H < 0.5$, the processes are anti-persistent and switch their sign frequently compared to an uncorrelated process. For

$H = 0.5$, the processes are not long-range dependent, and for $H > 0.5$, the processes are persistent. The last group of processes can be further categorized according to stationarity and (non)existence of variance. For stationary processes, it holds that $H < 1$. For the purposes of the Efficiency Index construction, it is important that for an efficient market, we have $H = 0.5$, as well as is the fact that the index is bounded for stationary processes. Out of plethora of Hurst exponent estimators (Beran, 1994; Taqqu et al., 1995; Taqqu and Teverovsky, 1996; Robinson, 1995; Geweke and Porter-Hudak, 1983; Di Matteo et al., 2003; Di Matteo, 2007; Barunik and Kristoufek, 2010; Teverovsky et al., 1999), we choose the local Whittle estimator and the GPH estimator as they are suitable for short time series with possible weak short-term memory, and they are consistent and asymptotically normal (Geweke and Porter-Hudak, 1983; Beran, 1994; Robinson, 1995; Taqqu et al., 1995; Taqqu and Teverovsky, 1996; Phillips and Shimotsu, 2004).

2.3. Fractal dimension

Long-range dependence can be seen as a global characteristic of a time series. Contrary to this view, fractal dimension D can be interpreted as a measure of local memory of the series since it captures roughness of the series (Kristoufek and Vosvrda, 2013). Fractal dimension ranges between $1 < D \leq 2$ for univariate series and this range is separated by the value of $D = 1.5$ for uncorrelated processes, which represents the efficient markets value. Low fractal dimension signifies lower roughness and thus local persistence. Reversely, high fractal dimension characterizes rougher series and thus locally negatively correlated. Fractal dimension is thus well defined for an efficient market and it is bounded for univariate series, which makes it a perfect candidate to be included into the Efficiency Index. Specifically, we utilize two estimators of fractal dimensions which share desirable statistical properties for short time series – Hall-Wood and Genton estimators (Gneiting and Schlather, 2004; Gneiting et al., 2010).

2.4. Approximate entropy

Entropy is considered as a measure of complexity. High entropy suggests little or no information in the system and thus high uncertainty whereas low entropy is characteristic for deterministic systems (Pincus and Kalman, 2004). From the efficiency perspective, systems with maximum entropy can be seen as efficient as these are serially uncorrelated. The lower the entropy level, the less efficient the market is. For the construction of the Efficiency Index, we utilize the approximate entropy which is bounded and thus well suited for the index (Pincus, 1991).

2.5. Statistical inference

The original Efficiency Index (Kristoufek and Vosvrda, 2013) is a point estimate of the true index value. This poses problems when discussing the results and their statistical validity. We tackle this issue by introducing a new approach to estimating EI which stems in the following steps:

1. Obtain the estimated components \widehat{M}_i of the Efficiency Index according to Eq. 1.

2. Shuffle the underlying return series.
3. Estimate the components of the Efficiency Index for the shuffled series, and label these as $\widehat{M}_{i,shuffle}$.
4. Use $\widehat{M}_{i,shuffle}$ in place of M_i^* in Eq. 1.
5. Obtain \widehat{EI} based on the previous steps.
6. Repeat N times.
7. Obtain necessary statistics based on these N estimates.

This way, we obtain an estimate of the Efficiency Index which controls for the potential finite sample bias and the influence of distributional properties of the analyzed series. For purposes of our study, we set $N = 100$.

3. Results and discussion

We study the efficiency ranking of the gold¹ prices quoted in different currencies. The portfolio of study comprises 142 worldwide currencies, which are described in Table 1. The dataset has been obtained from oanda.com, which provides a large set of FX pairs as well as gold (and other precious metals) prices in various currencies. The covered period ranges between 1.1.2011 and 30.11.2014, which totals 1430 observations for each of the 142 analyzed currencies². These currencies cover almost all available and traded fiat currencies in addition to Bitcoin, the most popular and used cryptocurrency.

For the efficiency ranking, we use the Efficiency Index (Eq. 1) with adjustments described in Sec. 2.5. Specifically, we utilize two measures of long-range dependence – the local Whittle estimator and the GPH estimator –, two measures of fractal dimension – the Hall-Wood estimator and the Genton estimator – and the approximate entropy as proposed by Pincus and Kalman (2004). In the procedures, we follow the standard procedure of using the logarithmic returns for the Hurst exponent and approximate entropy estimators, and logarithmic prices for the fractal dimension estimation. Using 100 repetitions (shuffling), we obtain the estimated Efficiency Index as a median value with a corresponding standard error for more information about precision of the estimate.

The resulting ranking of gold prices with respect to the used currency is presented in Table 2. The ranking is rather unexpected or even surprising. Practically all of the most liquid currencies – the US dollar, the British pound, the Australian dollar, the New Zealand dollar, the Japanese yen, the Euro, the South Korean won, the Norwegian krone – are among the least efficient gold markets (the least efficient third of the sample). Among these, also the Bitcoin currency lays at the very bottom of the ranking. On the other side of the ranking, the Top 5 is formed by the the Liberian dollar, the Seychellois rupee, the Maldivian rufiyaa, the Comorian franc, and the Somali shilling. The differences between levels of EI are stunning as the most efficient markets share the index between 0.1 and 0.2

¹Gold is selected as a numéraire due to its historical reputation as a safe haven as well as its reserve status and a relative long-term price stability.

²We prefer a width of the portfolio to its depth to be able to compare as many currencies as possible.

whereas the least efficient ones jump close to 0.4. Such divergence is further accentuated by very low standard errors of the estimates usually below 0.01 (medians and standard errors are reported in Table 2).

To further investigate the contribution of the three different parts of the Efficiency Index, i.e. Hurst exponent, fractal dimension, and approximate entropy, we present Fig. 1. We observe that overall Hurst exponent is the biggest contributor to the index. However, the strength of contribution varies with the efficiency ranking. For the most efficient currencies, Hurst exponent and approximate entropy play a similar role in the index. The influence of the latter declines with a decreasing efficiency, and vice versa for the former. The role of fractal dimension is also efficiency dependent. For the most efficient markets, it forms only a small fraction of the index but its role slightly increases for the less efficient currencies. For approximately the lower two thirds of the ranking, the contributions are rather stable with Hurst exponent at around 50%, and fractal dimension and approximate entropy each at around 25%. All three components of the Efficiency Index thus form its important parts. But apart from the most efficient markets, the long-term memory plays a prominent role. The gold prices in various currencies exhibit a persistent behavior with long-term trends even from the global perspective. Such stable results accentuate the advantages of using the adjusted methodology proposed here.

Returning back to the overall results which can be labelled as unexpected ones (contrary to the quite expected results found for the stock markets (Kristoufek and Vosvrda, 2013, 2014b) and other commodities (Kristoufek and Vosvrda, 2014a)), we highlight the specific connection between the gold market and the currency markets and further discuss potential causes.

The analyzed period of 2011 and 2014 covers very unorthodox times with regards to monetary policies of the developed world as reactions to the Global financial crisis, the Eurozone crisis, the Greek crisis and connected phenomena. Various waves of the quantitative easing (QE) in the USA and the UK, together with parallel actions of the European Central Bank eventually leading to the quantitative easing as well, have formed an enormous pressure on the relevant currencies and their depreciation. The first two waves of QE in the USA pushed the gold prices upwards as these rallied till the end of 2011. The last wave of the USA QE, which was much weaker than the previous two had no significant effect on the USD gold prices. The connection between the currency depreciation and the consequent gold price (in the given currency) boosting, together with a long-term effect of QE known in advance forms a perfect environment for inefficiency of the gold market. This is well in hand with most of the currencies the central banks of which participated in QE or other forms of practical money-printing being among the least efficient markets. It also further puts forward the gold's speculative asset status during the QE periods.

Such reasoning is further supported by gold being used as a hedge against inflation (Narayan et al., 2010). During the initial stages of QE, there was a serious concern about uncontrolled inflation as a reaction to the virtual money-printing. As investors were hedging against expected inflation by purchasing gold, its price was pushed further up. In time, the concern slowly vanished as there were no signs of dangerous inflation pressures. Nonetheless, the predictability and inefficiency of the gold markets under QE currencies

have come out as the final effect.

The following complementary explanation of the ranking structure can be quite counterintuitive in the efficient market logic. The fact that a central bank or a central authority of a country is transparent and holds up to its word can actually lead to market inefficiency. Consider a central bank announcing a new wave of QE. If the central bank is trustworthy, the investors will start behaving accordingly and maximize their profit by acting upon it. However, the QE process is a gradual one and it thus does not affect the market instantly but in steps. Putting these factors together leads us to a quite well predictable market behavior with relatively low risk assuming the authority holds up to its promises. From the other side, the authorities which are not too trustworthy are prone to change the announced policy repeatedly so that the shocks to the currency market are unpredictable. Such unpredictability leads to higher efficiency.

Additionally, the current situation at the foreign exchange markets has uncovered another potential source of inefficiency in the most traded currencies. In 2013, Bloomberg News reported that global regulators had started investigation of major banks in the foreign exchange markets for front-running orders and colluding to rig the foreign exchange rate benchmarks (Bank of England, 2014). This affair is now referred to as the “forex probe” and it has been claimed that the exchange rates manipulation had been realized for about a decade. Such collusion goes majorly against the notion of market efficiency and it provides a firm ground to the reported results of currency efficiency ranking.

To summarize, the combination of gold prices and currencies forms a very interesting and unique structure, the dynamics of which is much different compared to other assets such as stock or commodity markets. We have shown that the least efficient gold prices are mostly the ones quoted in major currencies such the US dollar, the Euro, and the British pound. On the other side of the spectrum, the most efficient gold prices are the ones quoted in smaller and less traded currencies. From the practitioners’ perspective, we have two possibilities of utilizing the results. We can either speculate on gold prices in the major currencies, or we can hedge gold prices using the minor currencies to obtain stable and efficient market position. Only the time will tell whether the “forex probe” scandal and its resolution as well as the end of the quantitative easing(s) will bring major currencies closer to efficiency.

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Contributions to the Efficiency Index

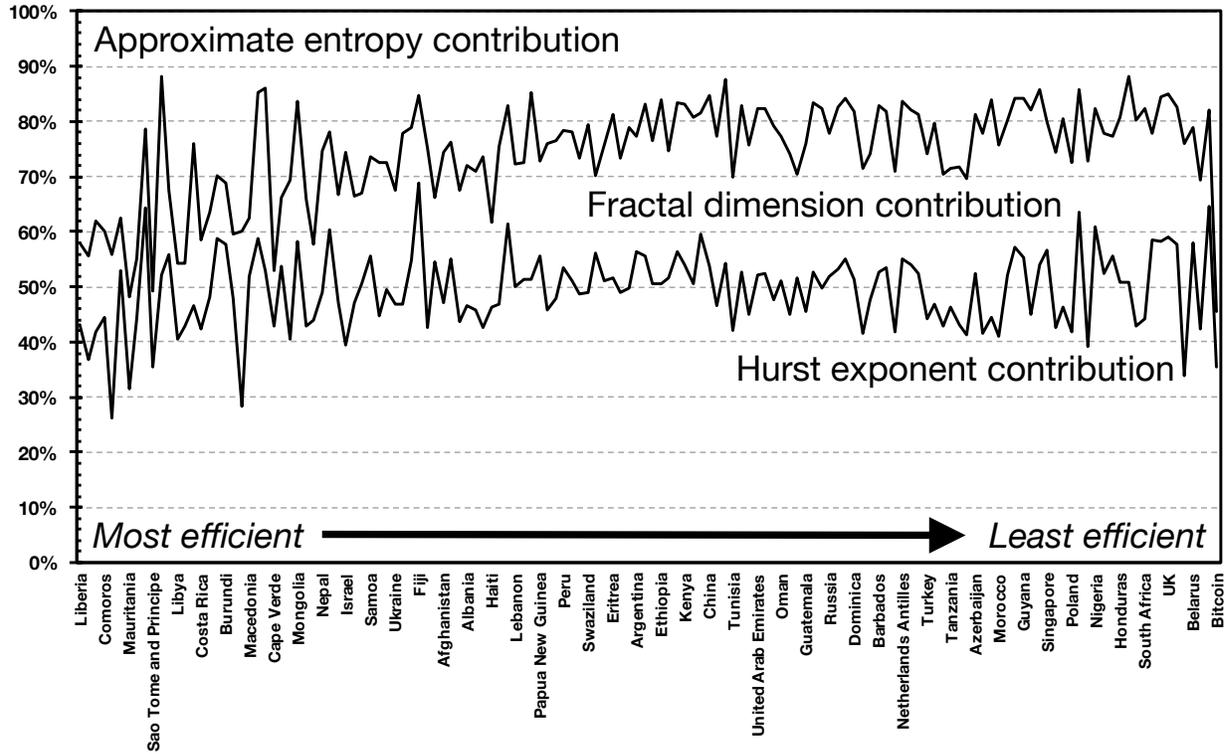


Figure 1: **Contributions to the Efficiency Index.** Contributions of the three factors – Hurst exponent, fractal dimension, and approximate entropy – are illustrated here in percentage (y -axis). The currencies are ranked from the most efficient ones (*from the left*) to the least efficient ones (*to the right*). Note that not all the labels are visible on the x -axis due to the high number of analyzed currencies. Nonetheless, the values and contributions are present for all the currencies. The contributions are stacked. The bottom part represents the Hurst exponent contribution, the middle part illustrates the fractal dimension contribution, and the upper part shows the approximate entropy contribution. Hurst exponent plays an important role for all currencies and its contribution around 50% is quite stable across all currencies. For the most efficient ones, the contributions is slightly lower. The fractal dimension contribution is quite small for the most efficient markets and its value increases for the less efficient markets. The reverse is true for the approximate entropy contribution.

Table 1: Analyzed currencies

Currency name	Code	Currency name	Code	Currency name	Code
Afghan afghani	AFN	Ghana cedi	GHS	Pakistani rupee	PKR
Albanian lek	ALL	Gibraltar pound	GIP	Panamanian balboa	PAB
Algerian dinar	DZD	Guatemalan quetzal	GTQ	Papua New Guinean kina	PGK
Angolan kwanza	AOA	Guyanese dollar	GYD	Paraguayan guarani	PYG
Argentine peso	ARS	Haitian gourde	HTG	Peruvian nuevo sol	PEN
Armenian dram	AMD	Honduran lempira	HNL	Philippine peso	PHP
Aruban florin	AWG	Hong Kong dollar	HKD	Polish zloty	PLN
Australian dollar	AUD	Hungarian forint	HUF	Qatari riyal	QAR
Azerbaijani manat	AZN	Icelandic krona	ISK	Romanian leu	RON
Bahamian dollar	BSD	Indian rupee	INR	Russian ruble	RUB
Bahraini dinar	BHD	Indonesian rupee	IDR	Rwandan franc	RWF
Bangladeshi taka	BDT	Iraqi dinar	IQD	Saint Helena pound	SHP
Barbadian dollar	BBD	Israeli new shekel	ILS	Samoan tala	WST
Belarusian ruble	BYR	Jamaican dollar	JMD	Sao Tome and Principe dobra	STD
Belize dollar	BZD	Japanese yen	JPY	Saudi riyal	SAR
Bitcoin	BTC	Jordanian dinar	JOD	Serbian dinar	RSD
Botswana pula	BWP	Kazakhstani tenge	KZT	Seychellois rupee	SCR
Brazilian real	BRL	Kenyan shilling	KES	Sierra Leonean leone	SLL
British pound	GBP	Kuwaiti dinar	KWD	Singapore dollar	SGD
Brunei dollar	BND	Kyrgyzstani som	KGS	Solomon Islands dollar	SBD
Bulgarian lev	BGN	Lao kip	LAK	Somali shilling	SOS
Burundian franc	BIF	Lebanese pound	LBP	South African rand	ZAR
Cambodian riel	KHR	Lesotho loti	LSL	South Korean won	KRW
Canadian dollar	CAD	Liberian dollar	LRD	Sri Lanka rupee	LKR
Cape Verdean escudo	CVE	Libyan dinar	LYD	Surinamese dollar	SRD
Cayman Islands dollar	KYD	Lithuanian litas	LTL	Swazi lilangeni	SZL
CFP franc	XPF	Macanese pataca	MOP	Swedish krona	SEK
Chilean peso	CLP	Macedonia denar	MKD	Swiss franc	CHF
Chinese yuan	CNY	Malagasy ariary	MGA	Syrian pound	SYP
Colombian peso	COP	Malaysian rigit	MYR	Tajikistani somoni	TJS
Comorian franc	KMF	Maldivian rufiyaa	MVR	Tanzanian shilling	TZS
Congolese franc	CDF	Mauritanian ouguiya	MRO	Thai baht	THB
Costa Rican colon	CRC	Mauritian rupee	MUR	Tongan pa'anga	TOP
Croatian kuna	HRK	Mexican peso	MXN	Trinidad and Tobago dollar	TTD
Cuban convertible peso	CUC	Moldovan leu	MDL	Tunisian dinar	TND
Czech koruna	CZK	Mongolian togrog	MNT	Turkish lira	TRY
Danish krone	DKK	Moroccan dirham	MAD	Turkmenistan manat	TMT
Djiboutian franc	DJF	Mozambican metical	MZN	Ugandan shilling	UGX
Dominican peso	DOP	Namibian dollar	NAD	Ukrainian hryvnia	UAH
East Caribbean dollar	XCD	Nepalese rupee	NPR	United Arab Emirates dirham	AED
Egyptian pound	EGP	Netherlands Antillean guilder	ANG	United States dollar	USD
Eritrean nakfa	ERN	New Taiwan dollar	TWD	Uruguayan peso	UYU
Ethiopian birr	ETB	New Zealand dollar	NZD	Uzbekistani som	UZS
Euro	EUR	Nicaraguan cordoba	NIO	Vanuatu vatu	VUV
Falkland Islands pound	FKP	Nigerian naira	NGN	Vietnamese dong	VND
Fijian dollar	FJD	North Korean won	KPW	Yemeni rial	YER
Gambian dalasi	GMD	Norwegian krone	NOK		
Georgian lari	GEL	Omani rial	OMR		

Table 2: Estimated Efficiency Index for gold prices in worldwide currencies

Rank	Country	EI	Rank	Country	EI	Rank	Country	EI
1	Liberia	0.1064±0.0083	49	Albania	0.2233±0.0069	97	Dominica	0.2598±0.0068
2	Seychelles	0.1167±0.0067	50	Pakistan	0.2233±0.0064	98	Sweden	0.2601±0.0054
3	Maldives	0.1447±0.0060	51	Paraguay	0.2251±0.0055	99	Uganda	0.2606±0.0056
4	Comoros	0.1473±0.0076	52	Haiti	0.2264±0.0096	100	Barbados	0.2623±0.0066
5	Somalia	0.1525±0.0064	53	Laos	0.2283±0.0068	101	Angola	0.2624±0.0078
6	Tonga	0.1571±0.0094	54	Solomon Isl.	0.2307±0.0111	102	Denmark	0.2627±0.0059
7	Mauritania	0.1572±0.0063	55	Lebanon	0.2318±0.0060	103	Neth. Antilles	0.2638±0.0075
8	Rwanda	0.1656±0.0098	56	Phillipines	0.2323±0.0065	104	Saudi Arabia	0.2639±0.0081
9	Chile	0.1663±0.0101	57	Tajikistan	0.2339±0.0054	105	Cuba	0.2640±0.0064
10	S. T. & Princ	0.1680±0.0083	58	Papua N. Guin.	0.2341±0.0122	106	Turkey	0.2659±0.0055
11	Mozambique	0.1709±0.0100	59	Mexico	0.2344±0.0053	107	India	0.2665±0.0053
12	Domin. Rep.	0.1727±0.0109	60	Bangladesh	0.2370±0.0053	108	Croatia	0.2674±0.0058
13	Libya	0.1729±0.0088	61	Peru	0.2401±0.0081	109	Tanzania	0.2684±0.0075
14	Belize	0.1743±0.0082	62	Malaysia	0.2419±0.0069	110	Lithuania	0.2687±0.0056
15	Madagascar	0.1752±0.0067	63	Bahrain	0.2436±0.0064	111	Bulgaria	0.2696±0.0049
16	Costa Rica	0.1758±0.0076	64	Swaziland	0.2449±0.0066	112	Azerbaijan	0.2700±0.0066
17	Fr. Polynesia	0.1768±0.0059	65	Taiwan	0.2450±0.0099	113	Czech Rep.	0.2704±0.0049
18	Indonesia	0.1773±0.0068	66	Jamaica	0.2459±0.0071	114	Canada	0.2716±0.0054
19	Burundi	0.1794±0.0103	67	Eritrea	0.2461±0.0069	115	Morocco	0.2727±0.0047
20	Mauritius	0.1798±0.0073	68	Qatar	0.2461±0.0068	116	Macau	0.2732±0.0062
21	Djibouti	0.1828±0.0084	69	Trin. & Tob.	0.2468±0.0071	117	Armenia	0.2733±0.0095
22	Macedonia	0.1834±0.0078	70	Argentina	0.2472±0.0100	118	Guyana	0.2742±0.0074
23	Uzbekistan	0.1836±0.0075	71	Aruba	0.2473±0.0077	119	Serbia	0.2757±0.0057
24	Iceland	0.1840±0.0055	72	Yemen	0.2476±0.0070	120	Congo (DRC)	0.2760±0.0078
25	Cape Verde	0.1841±0.0074	73	Ethiopia	0.2478±0.0060	121	Singapore	0.2770±0.0073
26	Sierra Leone	0.1855±0.0089	74	Botswana	0.2479±0.0092	122	EU	0.2773±0.0051
27	Ghana	0.1870±0.0061	75	Kuwait	0.2479±0.0076	123	Norway	0.2775±0.0058
28	Mongolia	0.1876±0.0090	76	Kenya	0.2481±0.0058	124	Poland	0.2781±0.0069
29	Nicaragua	0.1894±0.0086	77	Jordan	0.2490±0.0065	125	Saint Helena	0.2818±0.0111
30	Cambodia	0.1896±0.0065	78	Thailand	0.2497±0.0073	126	Hungary	0.2819±0.0055
31	Nepal	0.1905±0.0055	79	China	0.2500±0.0069	127	Nigeria	0.2824±0.0092
32	Bahamas	0.1925±0.0086	80	Namibia	0.2509±0.0070	128	Australia	0.2839±0.0067
33	Brazil	0.1936±0.0063	81	Georgia	0.2513±0.0078	129	South Korea	0.2846±0.0079
34	Israel	0.1950±0.0068	82	Tunisia	0.2515±0.0076	130	Honduras	0.2904±0.0082
35	Iraq	0.1987±0.0078	83	Panama	0.2528±0.0069	131	Japan	0.2905±0.0077
36	Colombia	0.2010±0.0076	84	Sri Lanka	0.2539±0.0046	132	Switzerland	0.2921±0.0056
37	Samoa	0.2042±0.0091	85	UAE	0.2551±0.0072	133	South Africa	0.2997±0.0059
38	Moldova	0.2061±0.0062	86	Turkmenistan	0.2555±0.0075	134	New Zealand	0.3101±0.0102
39	Algeria	0.2063±0.0063	87	Lesotho	0.2555±0.0065	135	Falkland Isl.	0.3118±0.0101
40	Ukraine	0.2103±0.0105	88	Oman	0.2559±0.0061	136	UK	0.3172±0.0108
41	Cayman Isl.	0.2105±0.0059	89	Romania	0.2560±0.0070	137	Gibraltar	0.3177±0.0098
42	Suriname	0.2120±0.0090	90	Vietnam	0.2565±0.0117	138	Vanuatu	0.3196±0.0078
43	Fiji	0.2137±0.0099	91	Guatemala	0.2572±0.0056	139	Belarus	0.3373±0.0069
44	Kazakhstan	0.2146±0.0065	92	Hong Kong	0.2576±0.0075	140	Gambia	0.3530±0.0095
45	Syria	0.2149±0.0067	93	Kyrgyzstan	0.2578±0.0059	141	Egypt	0.3574±0.0116
46	Afghanistan	0.2179±0.0060	94	Russia	0.2589±0.0066	142	Bitcoin	0.3846±0.0076
47	Brunei	0.2221±0.0083	95	North Korean	0.2596±0.0064			
48	Uruguay	0.2226±0.0056	96	USA	0.2597±0.0069			