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Development of a Metal Supply Risk Assessment Method

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Development of a Metal Supply Risk Assessment Method

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Abstract

Measuring the supply risk of metals is of great importance for corporations to control market risks, for nations to make strategical investments or trading plans, and for humanity to achieve sustainability in the long run. Academically, supply risk of metals was discussed in metals' criticality studies, where, "supply risk" represented one aspect of criticality together with "importance to economy" and "environmental implication". In these studies, "supply risk" was mainly measured by the weighted average of a series of arbitrarily selected risk indicators. Due to the subjective selection of the risk indicators and invalid weighting methods used in the studies, the results of those studies are too ambiguous to obtain practical significance. In view of these shortages, this doctoral study is aimed at finding solutions to evaluate supply risk of metals at different periods, and thereby, help relevant stakeholders take informed decisions.

The sources of supply risk of metals vary according to the time periods. In the short term (one year or lesser), market risk should be considered a priority. It could come from the price volatility of metal commodities, which dominates the profitability of a project. In the medium term (one to five years), risks related to international investments should be considered a priority. This is because no country can stand alone in terms of natural resources; countries heavily depend on each other. For foreign direct investments, institutional conditions of countries with resource sovereignty are the primary consideration, especially in an era where mining is increasingly concentrated in developing countries. In the long term (ten years or more), human society, as a community with a shared future, will have to face physical depletion of natural resources, since resources buried in the earth's crust are limited, and recycling rates had hardly reached 100%. Moreover, long before encountering the physical depletion of ores, increased prices of resources may compel some minerals unavailable economically, leading to economic depletion.

This dissertation mainly contains three parallel but independent studies regarding three periods, and an aggregated assessment based on the results of each period's study. Specifically, in the short term, the objects are copper, nickel, zinc, lead, tin, silver, gold,

platinum, and palladium. A new method called Spline-Generalized Autoregressive Conditional Heteroskedasticity was applied to generate the low frequency price volatility series from the original price volatility series. Using this low frequency price volatility, empirical evidence of the impact of macroeconomic variables on price volatility was confirmed. Also, the impact of world unemployment rate; inflation rate of the U.S. dollar; Treasury-EuroDollar spread; Standard & Poor's 500 index; residential property prices in the USA; and exchange rate of the South African rand, the Russian ruble, and the Canadian dollar to the U.S. dollar were found to be significant. Moreover, based on world economic performance in 2017, we found that the riskiest metal in 2018 would be copper with a volatility of 48%, followed by lead (36%) and silver (33%).

In the medium term, the objects are the same nine metals as that studied in the short term. Considering the lack of a quantitative analysis on the common causes of resource nationalism due to data limitation, this study started with a data survey in which the occurrence of resource nationalism in 83 metal-supplying countries from 2000 to 2013 was summarized into a binary panel. Then, an empirical analysis was conducted using the binary choice logit method. As a result, several factors such as high technology export, ores and metals exports, rule of law, natural resource rent, and trade openness were found to be dominating the risk of resource nationalism in high-and-upper-middle-income countries. In lower-middle-and-low-income-countries, changes in mineral rent, government effectiveness, high technology export, and policy perception index were determined to be relevant. Finally, a prediction of the risk of resource nationalism of countries and commodities was made. In 2015, North Korea (100%), Panama (100%), Lao PDR (92%), Mongolia (87%), Kazakhstan (84%), Vietnam (81%), Cuba (78%), Guatemala (72%), Peru (71%), Iran (68%), Venezuela (68%), Papua New Guinea (67%), Russian Federation (63%), Chile (60%), Suriname (54%), Congo (DRC) (54%), and Sierra Leone (51%) were predicted to be risky. The top three risky metals were found to be copper (49%), tin (48%), and silver (46%).

In the long term, to estimate the supply shortage of silver, technological progress in the crystalline silicone (c-Si) photovoltaic (PV) industry was investigated using scenarios including PV lifetime prolongation, technology shift, efficiency improvement, silver demand rate reduction, PV recycling, and total effects. Classic curve fittings and theories (logistic curve, Weibull distribution, intensity of use) were introduced to complete the task. Mining supply was estimated based on parent metal sources, such as copper, zinc, lead, gold and silver. Recycling supply was estimated using a product of silver weighted life-time and end-of-recycling-rate. Demand for silver was divided according to usage, including those for jewelry and silverware, electronics and batteries, photography, c-Si PV, and others. The result shows that silver supply shortage for manufacturing demand will occur from 2030. Technology improvements in the PV industry could delay when the shortage begins, but they will not prevent it. Silver supply shortage for c-Si PV could be eliminated under the total effects scenario.

Finally, we aggregated the results of the three periods into four risk ratings: low, marginal, risky, and crucial. For price volatility, the market Volatility Index (VIX) published by the Chicago Board Options Exchange was used as the risk scale because this index represents implied volatility of the options market. For resource nationalism, Value at Risk was used to divide relative risk levels among countries. For supply shortage, historical supply deficit (real-time balance of supply and demand) was considered as a measurement. As a result, a route map of the supply risk of metals was produced. Taking silver as an example, the result shows that the supply risk of silver would reduce from risky to marginal but rebound to crucial in the long term.

Chapter 1 Introduction

1.1 Background

Modern civilization has greatly enriched the material wealth of human beings by increasing productivity, promoting science and technology innovation, improving trade openness, and so on. Meanwhile, it has brought about new challenges to the current and future generations. Specifically, obtaining metals in a sustainable manner has become a thorny problem. In other words, supply risk of metals is in the spotlight.

In view of the extreme importance of metals in modern society and the increasing supply risk of metals across different periods, it is not difficult to realize that assessing the supply risk of metals is very important. Normally, supply risk of metals is evaluated by the weighted average of numerous risk factors regardless of time periods and the corresponding shareholders. This kind of an evaluation method provides the general risk level of metals, which is helpful for selecting the risky ones but cannot give specific indications on risk sources and guide risk optimized behaviors. Given these disadvantages, this study aims at developing a comprehensive assessment framework in which metals' supply risk can be quantitatively measured in the short, medium, and long term for their corresponding stakeholders: corporations, nations, and the whole human community.

Regarding the sources of supply risk of metals, it varies according period. In the short term, market uncertainty such as the price volatility of metal commodities has surged ever since the last financial crisis. In the medium term, geopolitical factors as well as institutional risks have been increasingly frequently threatening the security of supply. In the long term, physical depletion of natural resources is inevitable because the resources buried in the earth's crust are limited and recycling rates have hardly reached 100%. Moreover, long before encountering physical depletion, increased prices of resources may compel some minerals unavailable economically.

Speaking of the market level of metals, the supply risk of metals could stem mainly from market failures and commodities' price volatility, mainly. A market failure is a situation in which allocation of scarce resources is in-efficient. It could be an outcome of a non-competitive market like monopoly. Specific to metals, they are unevenly distributed geographically, especially some critical metals like rare earth elements (REEs), platinum group metals (PGMs), and so on. In a monopoly, or oligopoly market, productions are most likely to be restricted to a lower level relative to demands in the natural state to grab super profit. Considering the REEs market for instance (Figure 1-1), supply of rare earth oxides (REOs) was dominated by China. It is not difficult to imagine that the REOs market was very fragile to Chinese suppliers. From 2006 to 2009, China gradually reduced its annual export quotas, and further during 2010, cut allowable export quantity by over half. This immediately led to wild swings in REOs' price—spiked followed by slumps. This is a typical market failure directed by an oligopoly supplier.

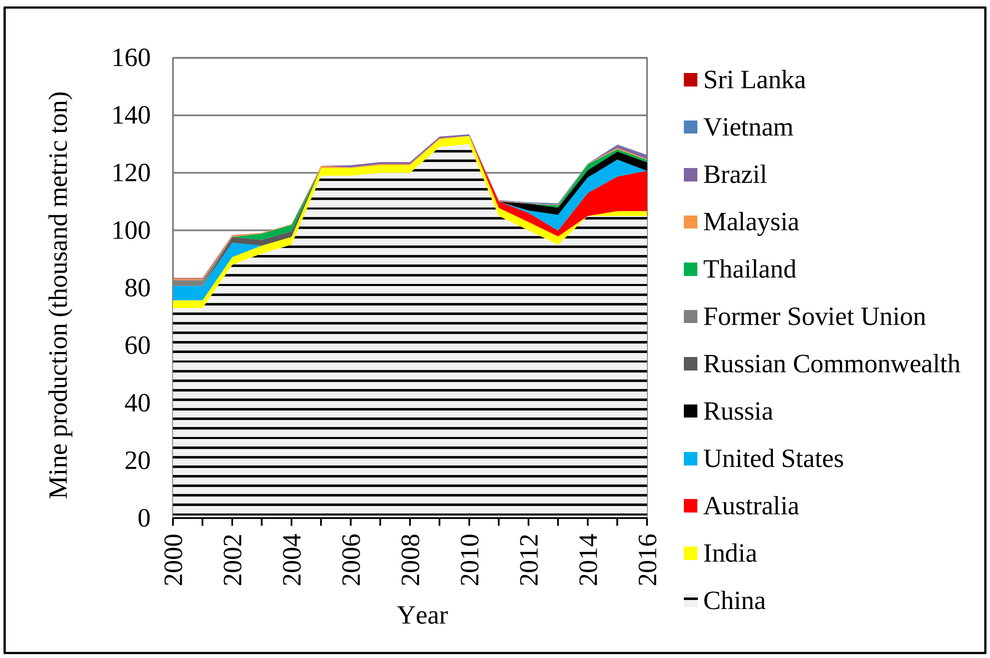


Figure 1-1 Mine production of REOs (Data source: USGS).

Price volatility first appeared as a risk measurement of stock returns, which is frequently mentioned in financial affairs. Applying to commodity prices, it serves as one of the dominant uncertainty factors in mineral-resources-related business investments. Price volatility of energy and agriculture commodities have long been closely followed due to OPECs or seasonal changes. However, price volatility of metal commodities has just emerged in the queue because it has escalated ever since 2003 (Figure 1-2), and has been deeply reshaping the project value of a mine. Furthermore, the mechanism of identifying metals' price volatility remains unclear despite a variety of claims.

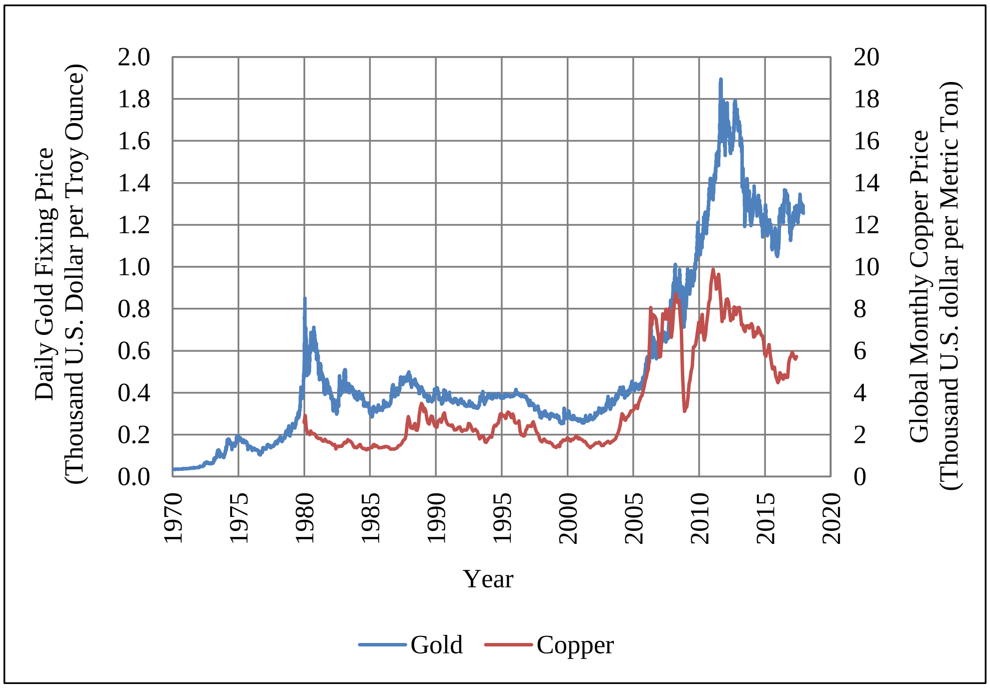


Figure 1-2 Historical price of gold and copper (Data source: Archival Federal Reserve Economic Data).

Regarding national supply security, cross-border transactions and investments play increasingly important roles. In the contemporary era, none of the countries can be self-sufficient economies, especially in terms of metals. They are heavily concentrated in several resource-rich countries (Figure 1-3). Other states have to rely on imports. Unlike manufacturing where a favorite site is picked, mining activities have to be performed where resources were discovered regardless of the institutional risks of resources sovereign states. These institutional risks could be led by geopolitical considerations under which resources are used as a bargaining chip for political, economic, or even military benefits; in addition, it could also be aroused by a series of behaviors summarized as "resource nationalism". By resource nationalism, we mean a phenomenon where resources sovereign governments increase their benefits from natural resources by claiming sovereign rights over the resources.

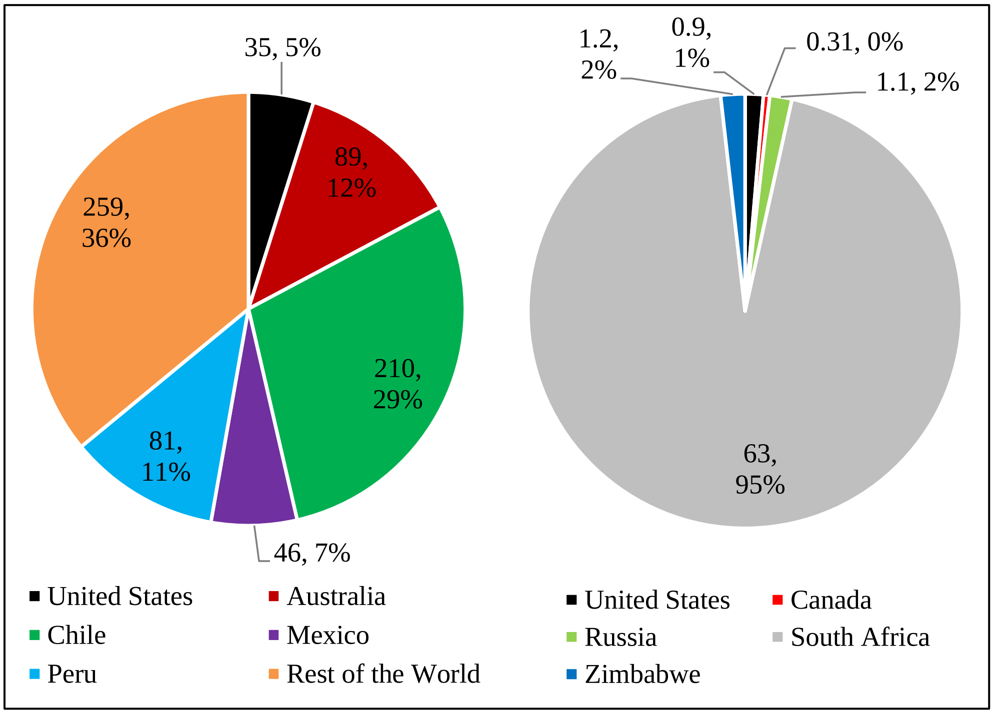


Figure 1-3 Reserve of copper (left, million ton) and PGM (right, thousand ton) for 2017 (Data source: USGS).

From the "a community of shared future" point of view, humanity will be challenged by mineral resources supply shortage one day, without exception. From the supply side, resources embodied in the earth's crust are limited. High-grade and shallow-buried deposits have nearly depleted. The era of deep mining is forthcoming, implied with high mining costs and some technological difficulties. As addressed by Dr. Tilton (Tilton, 2003), long before the physical depletion of most resources, economic depletion will coerce us from using them (Figure 1-4). Without proper material substitutions and recycling, we will be unable to sustain. From the demand side, the increasing world population and emerging middle class should request more materials regardless of resource efficiency. Fundamentally, the contradiction between supply and demand will dramatically lift the costs of metal materials.

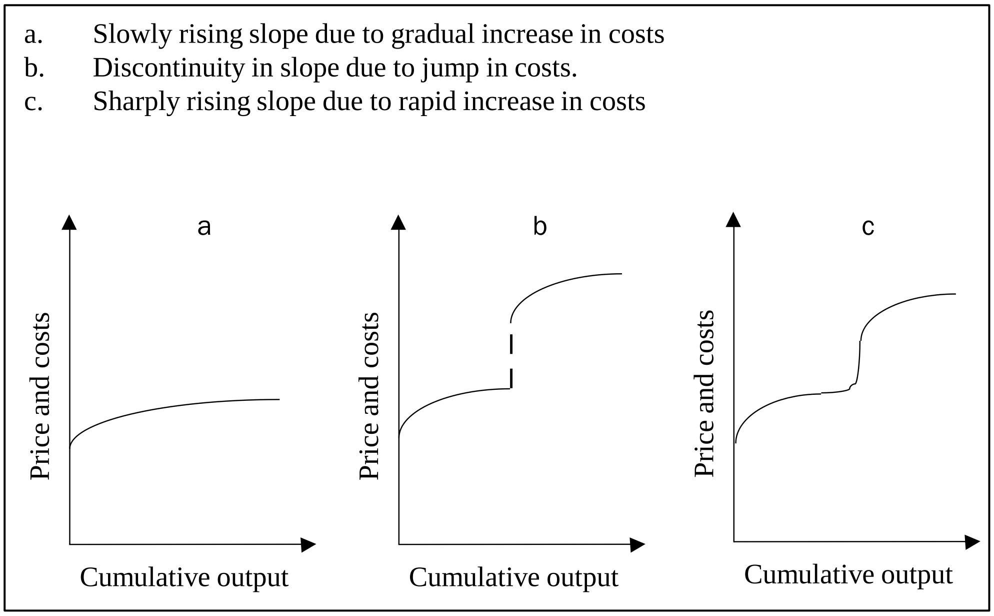
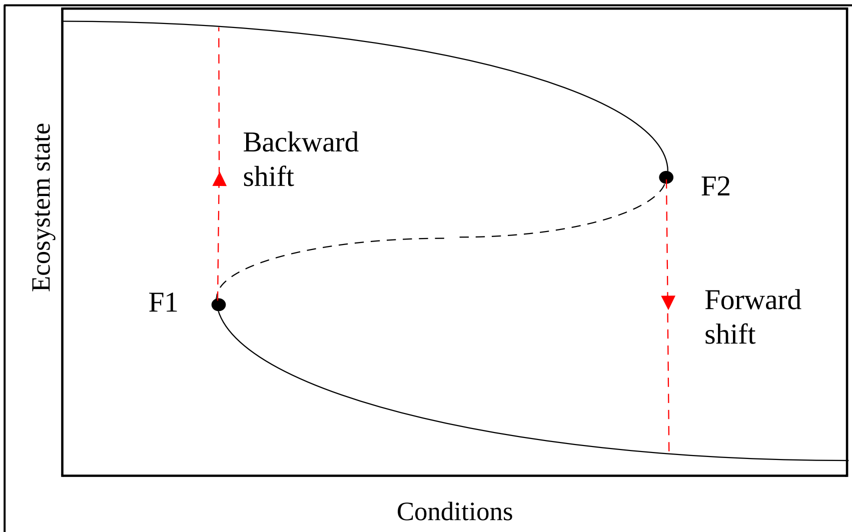


Figure 1-4 Illustrative cumulative supply curves (Source: Tilton, 2003).

Despite all the above, availability of metals across different periods are threatened by environmental risks caused by production processes. Current generations are experiencing irrepressible deterioration in the natural environment and are suffering from the consequences. According to Scheffer et al (2001), nature can be interrupted by sudden drastic switches to a contrasting state (Figure 1-5). Therefore, to avoid catastrophic environmental degradation, we have to select alternative processes which are cleaner, or even terminate some operations in fragile ecosystems. This to some extent further narrows the supply potential for some minerals. In fact, mining activities have been dramatically slashed in some countries like Japan due to environmental considerations.



If the system is on the upper branch, but close to the bifurcation point F2, a slight incremental change in conditions may bring it beyond the bifurcation and induce a catastrophic shift to the lower alternative stable state (‘forward shift’) . If one tries to restore the state on the upper branch by means of reversing the conditions, the system shows hysteresis. A backward shift occurs only if conditions are reversed far enough to reach the other bifurcation point, F1.

Figure 1-5 Shift between alternative stable states (Source: Scheffer et al., 2001).

1.2 Literature Review

Academically, the term “supply risk” appears in metals’ “criticality” studies, serving as one aspect of “criticality”. Criticality describes an evaluation of the holistic importance of a resource, which can be interpreted as an assessment of the risks connected with resources production, uses, and end-of-life treatments (Graedel and Nuss, 2014). There were two types of frameworks created successively to measure the criticality of a metal. First, a criticality matrix was developed by the Committee on Earth Resources of the National Research Council of the United States (National Research Council, 2008). The matrix is composed of a “supply risk” axis measuring the availability of the mineral and an “impact of supply restriction” axis pointing to the mineral’s importance in use and ability to substitute (Figure 1-6). Second, a three-dimension criticality space was added by the research group in Yale University (Graedel et al., 2012), in which an “environmental implications” axis was supplemented (Figure 1-7).

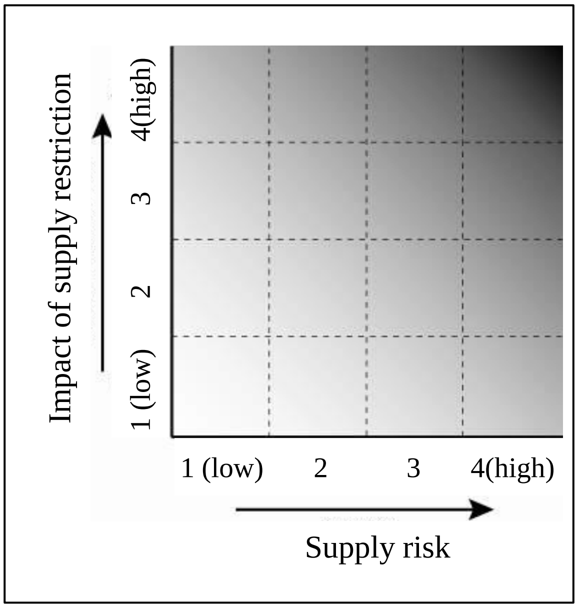


Figure 1-6 Image of criticality matrix diagram (Source: National Research Council, 2008).

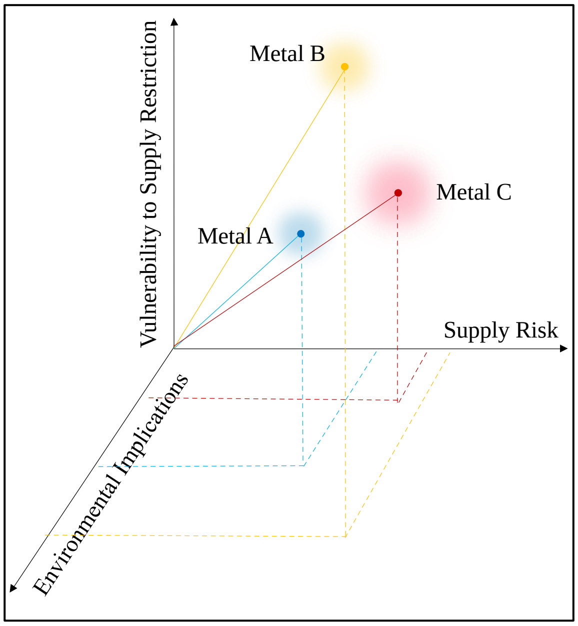


Figure 1-7 Image of criticality space diagram (Source: Graedel et al., 2012).

In these criticality studies, supply risk is usually measured by an aggregated value of selected risk indicators (Achzet and Helbig, 2013). Table 1-1 displays a summary of indicators and aggregation methods of supply risk assessment embedded in most metal criticality studies.

Table 1-1 Summary of supply risk measurement methods.

Source	Indicator	Aggregation method
National Research Council, 2008	1) US Import dependence; 2) World reserve / production ratio; 3) World reserve base / production ratio; 4) World byproduct production as % of total world primary production; 5) US secondary production from old scrap as % of US consumption.	Expert judgement
Tornow et al., 2009	1) Current supply and demand; 2) Stock keeping 3) Mine or refinery capacity utilization; 4) Production cash cost; 5) Country related risks; 6) Country concentration; 7) Company concentration; 8) Future market capacity; 9) Degree of exploration; 10) Investment in mining.	Weighted average
European Commission, 2010	1) Level of concentration of producing countries; 2) Substitutability; 3) Old scrap recycling as % of European consumption.	Defined equation
Graedel et al., 2012	1) World reserve / production ratio; 2) World byproduct production as % of total world primary production; 3) Policy potential Index; 4) Human development index; 5) World governance indicator: political stability; 6) Level of concentration of producing countries;	Weighted average

Moss et al., 2013	1) Likelihood of rapid demand growth; 2) Limitations to expanding production capacity; 3) Level of concentration of producing countries; 4) Political risk related to major supply countries.	Expert judgement

This evaluation methodology is criticized for lacking in empirical verifications and comparative values. First, varied indicators are selected arbitrarily without addressing any empirical verifications of why a variable should be embodied or dropped. Then, variables are aggregated by weighted averages in most cases without specifying or verifying their sensitivity to supply risk. Finally, results from these assessments are not comparable with each other, embody high uncertainty, and can only deliver general information with limited practical values.

1.3 Purpose of the Study

This study is aimed at evaluating different periods' supply risk of metals and supporting corresponding shareholders' in decision making. Specifically, it is pivotal to understand the real-time patterns of price volatility for corporations; it is crucial to get some insights into some dominant factors of resource nationalism for nations in the medium term; and it is sensible to notice the long-term supply potential for industries. Accordingly, the research framework was developed, as displayed in Table 1-2. They were then aggregated into a "supply risk route map" to display the expected route of a metal's supply risk level from period to period (Figure 1-8). By this way, each study stands alone to guide the corresponding risk management; through aggregating, they can provide general risk ratings.

Table 1-2 Research framework.

Time Scale	Short term	Medium term	Long term
Stakeholder	Corporations	Nations or FDIs	Human society (for an industry or a certain technology)
Supply risk source	Market uncertainty	Transboundary trade-openness /capital freedom	Imbalance of supply and demand
Indicator	Price volatility	Resource nationalism	Supply shortage
Research question	Dominant factors to predict price volatility	Dominant factors of resource nationalism	Supply potential for certain technology
Specific study object	Au, Ag, Pt, Pd, Cu, Ni, Zn, Pb, Sn.	Au, Ag, Pt, Pd, Cu, Ni, Zn, Pb, Sn, Coal, Gas, Oil.	Silver
	Commodity market	For 90~ countries	For c-Si PV technology
Analytical method	Econometrics	Econometrics	Curve fitting & scenario analysis

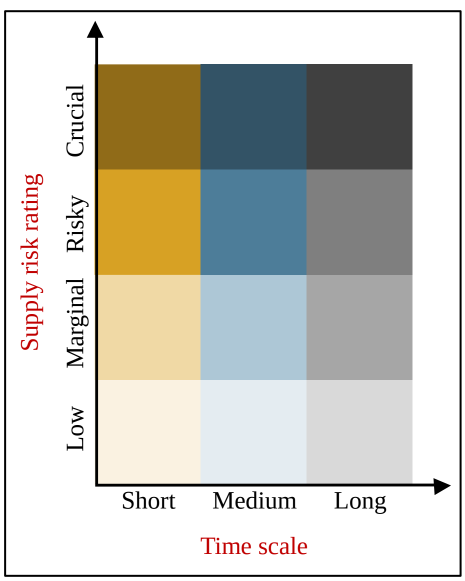


Figure 1-8 Metals supply route map.

1.4 Structure of Chapters

In the next chapter, a study of "the short-term supply risk measured by price volatility" is described. It provides empirical evidence of the impact of the macroeconomic variables on metals' price volatility. The chapter starts with an introduction to the measurements of price volatility and is followed by a literature review of the studies carried out. From the first two parts, readers can gain some understanding of why this study is being carried out. From the third to the sixth parts, regression and statistical estimation methods are introduced. The last two parts summarize the results and the whole study.

In chapter 3, a study of "the medium-term supply risk measured by resource nationalism" is presented. The chapter starts with a commonly recognized hypothesis of the causes of resource nationalism (depending on local conditions) and its controversy with the author's opinion (existing common factors globally). Thus, this study is aimed at proving the common genesis of resource nationalism. The second part is a literature review of the historical resource nationalism movements. The third and fourth parts are method, and results and discussions, followed by a conclusion.

In chapter 4, a case study of "the long-term supply risk measured by supply shortage" is presented. The case analyzed in this study is "the supply shortage of silver for c-Si PV". The study starts with the information about the PV market (in the first part) and the academic studies carried out on silver (in the second part). The third part intensively explains the estimation methods. And in the fourth part, scenario analysis considering the technological changes of the PV sector is introduced. The fifth and sixth parts discuss the results and the conclusions

In chapter 5, using the results gained from chapters 2-4, a study of "supply risk route assessment" is performed. All the risk rating methods are introduced, respectively, followed by the rating results. In the end, the chapter comes up with the supply risk route map. In the last chapter, a conclusion of the whole dissertation is provided.

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Chapter 2 Short-term supply risk measured by price volatility

2.1 Introduction

Metals's price volatility could be an index of short-term metals supply risk (Gleich et al., 2013). By adopting price volatility, supply risk can be made use of in mining project evaluations considering market uncertainties (Mayer and Gleich, 2015). By this way, the results of the metals supply risk assessment can obtain practical significance.

There are mainly three streams of measures of price volatility. First, the realized/historical price volatility (Rvol) can be defined as the standard deviation of stock price returns using historical price data. It is normally referred to as a backward-looking volatility (Hull, 2012). Second, the implied volatility of the option prices, often referred to as forward-looking volatility, is the volatility implied in options price market (Hull, 2012). For metal commodities, their implied price volatility could be derived from the Black-Scholes model. Third, the autoregressive conditional heteroskedasticity (ARCH) model proposed by Engle (1982) and the generalized autoregressive conditional heteroskedasticity (GARCH) model developed based on ARCH by Bollerslev (1986) are universally acknowledged as time series measures of price volatility, which indicate that the previous price volatility can indicate the future ones. Recently, numerous studies on price volatility have adopted the modified ARCH/GARCH models, like Chkili et al. (2014), Hammoudeh and Yuan (2008). In addition, the results of these ARCH/GARCH dominated studies showed that volatility of metal prices exhibit a clustered characteristic (Watkins and McAleer, 2008; Caeter et al., 2011). It implies the existence of exogenous variables affecting the evolvement of metals price volatility.

This study applies a modified GARCH process called “Spline-GARCH” to predict the evolvement of metals’ price volatility. The macroeconomic factors’ explanatory power is in focus. The reasons to look at macroeconomic variables, are explicated in next section. Specifically, the objects of this research are silver, gold, platinum, palladium, copper, nickel, tin, lead, and zinc. First, Low frequency volatility (Lvol) of these metals' prices are generated using the Spline-GARCH model. Next, ordinary least square (OLS) regressions are carried out to identify significant macroeconomic variables dominating the Lvol of these metals' prices at quarterly and annual levels. Finally, the robustness of in-sample consistency and out-of-sample forecasting ability of these OLS regressions are verified.

Different from previous studies, we have considered metals' spot price volatility instead of futures price volatility. Theoretically, the futures price of a commodity represents the expected spot price of the commodity in the future based on current market information (Frankel, 2008). But the relation between spot prices and futures prices has not been consistent over time as expected theoretically (Dwyer et al, 2011; Groen and Pesenti, 2010). Therefore, we look at metals spot prices directly. Moreover, this study concentrates on important base and precious metals solely, rather than taking a few representative metals and analysing them together with other types of commodities in a mixed pool. This is because, according to Batten et al. (2010) and Karali and Power (2013), there is little evidence that the same macroeconomic variables jointly influence the evolvement of commodities price volatility, even among metals.

The chapter is organized in a particular order. The following section is a literature review. The third to sixth sections present the research content. Because there are several modelling steps with logical causal relationships, each step's result is provided right after the explanation of each step's method. Specifically, the third section displays the process and results of generating the Lvol of metals' prices using ARMA and Spline-GARCH models. The fourth section summarizes the regression procedures and results of Lvol of metals prices and macroeconomic variables. The fifth section verifies the out-performance of Lvol compared to standard deviation represented Rvol when regressing with macroeconomic variables. The sixth section tests the out-of-sample forecasting ability of macroeconomic variables using the rolling window method. Then, a summary of the main results of the chapter are discussed, followed by a conclusion.

2.2 Literature Review

Researches which are focused on identifying exogenous factors dominating the development of metals' price volatility are rare. A majority of the studies were on energy resources. Despite of relatively limited references, the following studies do give us some clues to investigate metals' price volatility. Dwyer et al. (2011) discussed the relation of financialization to price volatility of global commodities which embodied copper and gold representatively. They concluded that price volatility of commodities appears to be primarily determined by fundamental factors rather than the increased financial investments in the commodity derivatives market.

Symeonids et al. (2012) empirically analysed the behaviour of commodities' price volatility predicted by the inventory level using theory of storage. They found that metals, gold in particular, exhibit the lowest correlation with inventory and further explained that it is because of the low storage costs relative to metals' values and sufficiently high inventory levels relative to metals' demands. In addition, the metals' price volatility they used is generated from futures market, thus representing the implied volatility.

Chen (2010) proved that, on average, roughly 34% of metals' price volatility could be attributed to global macroeconomic factors during 1972–2007 using a single factor asset pricing model, in comparison to 16% during 1900–1972. But generally speaking, previous explorations inclined to conclude that macroeconomic variables' effects on metals' price volatility turned out to be weaker than expected (Officer, 1973; Schwert, 1989; Batten et al., 2010; Hammoudeh and Yuan, 2008; Kroner et al., 1995; Pindyck, 2004). One of the key reasons lies in the mismatch of the much lower frequently dated macroeconomic variables relative to the very high frequency price information, which contain a lot of market noises (Engle and Rangel, 2008). McMillan and Speight (2001) suggested that the half-life of shocks to Lvol of non-ferrous metals' prices can extend over 190 days, that is, more than half a year, using a component-GARCH model.

To solve the mismatch problem, Engle and Rangel (2008) invented a Spline-GARCH model to generate Lvol components of commodities' price volatility and then used them to regress with macroeconomic variables. The breakthrough of the method is that it relaxes the assumption of the constant mean reverting feature in the volatility process and introduces a trend to the volatility series using a non-parametrically exponential quadratic spline. Recently, Karali and Power (2013) applied the Spline-GARCH method to identify macroeconomic determinants of commodity futures market price volatility embodying copper, gold, and silver. The results proved the outperformance of the model compared to using Rvol directly. They also revealed that explanatory variables are different for different commodities. Specifically, percentage change in Consumer Price Index (CPI), industrial production and trade weighted foreign exchange rate, and the difference between 10-year and two-year constant maturity rate show potential to trace metals' price volatility. Liu et al. (2015) confirmed that volatility of gold futures prices in the Shanghai futures market is a result of both macroeconomic fluctuations and investor behaviours, also using an asymmetric Spline-GARCH model. Particularly, they discovered that the volatility of Chinese CPI and U.S. dollar are two main determinants.

Above all, metals' price volatility has become higher on average since the breakdown of the Bretton Woods fixed exchange rate system in 1972 (Chen, 2010). Even though Brunetti and Gilbert (1995) and Watkins and McAleer (2008) summarized that the price volatility of metals has not necessarily increased since then, price volatility of metals does become very volatile. This is partially because that the plummeted metals' prices since the financial crisis in 2008 and hardly any rebound afterwards severely damaged many metal exporting countries' trade balances and brought about economic contractions. Therefore, increasing attention should be paid to reveal the evolvement principle of metals' price volatility in addition to those of energy resources. The Spline-GARCH could be a useful method to complete this task, as finally proven through this study.

2.3 Estimation of Low Frequency Volatility

As mentioned above, the nine types of metals considered in the study are silver, gold, platinum, palladium, copper, nickel, tin, lead, and zinc. We use their weekly spot prices data from the 1st week of 1992 to the 28th week of 2014 reported by Raw Materials Data to estimate their Lvol (SNL Metals & Mining, 2014), except for the price data of palladium that starts from the 1st week of 1994 due to limited data source. Before introducing the modelling process, it is necessary to reiterate that price volatility is about fluctuations in price returns (could be represented by the log price changes) rather than the price itself. Therefore, raw prices data are transformed into the first order differencing of log transferred metals prices series. Concretely, there are two steps, which are similar to the classical ARCH/GARCH regressions to generate the price Lvol of these metals. To start with, it is necessary to specify the mean equations. We use ARMA (p, q) models to remove predictable trends and intercepts of the prices log return series. Parameters p and q represent the order of lags of auto-regressions and the number of periods of moving averages, which are selected according to Akaike Information Criterion (AIC). Table A-1 (in Appendix A) displays the regression results of ARMA models for the nine metals. Second, because residuals as well as the squared residuals of ARMA regressions show clustered characteristics, we need to adopt the Spline-GARCH models to the residuals of ARMA models to reveal the source of the clusters. As explained in the introduction part, the Spline-GARCH model can remove high frequency fluctuating noises from low frequency macro economy led price volatility, and thus can help identify macroeconomic determinants of metals' price volatility. Equations (2-1) to (2-3) display the algorithm of Spline-GARCH:

$$r_t = \sqrt{\tau_t g_t}\varepsilon_t \,, \quad \text{(2-1)}$$

$$g_t = (1 - \alpha - \beta) + \alpha\left(\frac{r_{t-1}^2}{\tau_{t-1}}\right) + \beta g_{t-1} \,, \quad \text{(2-2)}$$

$$\tau_t = c\,\exp\left(w_0 t + \sum_{i=1}^{k} w_i((t - t_{i-1})_+)^2\right) . \quad \text{(2-3)}$$

Wherein, r_t is the residual of the ARMA model; τ_t is the square of Lvol component and g_t is the square of the high frequency volatility component; ε_t follows standard normal distribution; α and β are coefficients of ARCH and GARCH terms, respectively; t_i denotes an equally spaced partition of the time horizon; $(t - t_{i-1})_+$ is equal to $(t - t_{i-1})$ only if the difference of t and t_{i-1} is greater than zero, otherwise it equals to zero; k represents the number of knots, which depends on the number of cycles of Lvol during a specified time period and is selected by Bayesian Information Criterion (BIC).

Table A-2 and Figure A-1 to A-9 display results of Spline-GARCH estimations. Supplementary materials 1 presents an example of the optimization code of R-Studio to process the above two steps. The results show that during the whole modelled period, metals' price Lvol has a cycle length of around three years on average. In general, before 2000, the cycles' lengths could last for five years and the fluctuation amplitude of a cycle was small. But afterwards, the cycles became more frequent and started fluctuating violently. Among the four types of embodied precious metals, Lvol of gold price was the lowest, followed by platinum and, silver; and the most volatile one was palladium. Among embodied base metals, Lvol of nickel price was the highest, followed by lead. Among all nine types of metals, Lvol of gold price was still the lowest, and the Lvol of all nine metal prices peaked during the last financial crisis in 2008.

2.4 Identification of Macroeconomic Variables

After generating the weekly Lvol using the Spline-GARCH model, average Lvol at quarterly and annual intervals to match the frequency of macroeconomic data are needed for regression. The data lengths are all unified for 20 years starting from 1994 to 2013. The equation for averaging is displayed as follows:

$$\overline{Lvol_t} = \sqrt{\frac{1}{N_t}\sum_{i=1}^{N_t} \tau_i}\ . \qquad (2\text{-}4)$$

Wherein, N_t denotes number of τ_i used for averaging. It should be noted that what we can get from equation (2-4) is a/an quarterly/annual average of weekly Lvol rather than the quarterly/annualized volatility. In the subsequent narrative, "quarterly/annual average Lvol/Rvol" are used to represent quarterly/annual average of weekly Lvol/Rvol.

Then, linear regressions using the OLS method are carried out for each metal's price quarterly/annual average Lvol to quantify the effects of macroeconomic variables. In the OLS regressions, auto-regressions, moving averages, and one stage lag of macroeconomic variables are used selectively according to significance. The representative equation is displayed as follows:

$$y_{m,t} = cons. + \sum_{k=1}^{K} \alpha_{m,k} y_{i,t-k} + \sum_{l=1}^{L} \beta_m^l \, y_{m,t-l} + \sum_{j=1}^{J} \gamma_{j,m} \, x_{j,m,t-1} + e_{m,t} \; . \qquad (2\text{-}5)$$

Wherein, subscript "*m*" denotes types of metals; subscript "*k*" denotes orders of auto-regressions; subscript "*l*" denotes orders of moving averages; subscript "*j*" denotes numbers of macroeconomic variables; *cons.* represents the interception/constant of the regression; *x* represents macroeconomic variable; α, β, γ are coefficients; and $e_{i,t}$ represents the error term.

For quarterly average Lvol regressions, the first difference of Lvol is applied to ensure stationarity of variables. The results show that quarterly average price Lvol of metals are highly auto-correlated (Table C-1), and little evidence has been found for explanatory powers of macroeconomic variables. However, regression results show that macroeconomic variables significantly dominate the evolvement of annual average price Lvol of metals (Table 2-1). Therefore, in the study, we mainly focus on the economic explanation of the performance of annual average Lvol of metal prices.

Table 2-1 Regression results of annual average Lvol with macroeconomic variables.

	Lvol_Ag	Lvol_Au	Lvol_Pt	Lvol_Pd	Lvol_Cu	Lvol_Ni	Lvol_Sn	Lvol_Pb	Lvol_Zn
cons.	0.781 [0.001]	0.077 [0.022]	0.004 [0.365]	0.848 [0.000]	0.549 [0.002]	-0.012 [0.088]	0.110 [0.011]	0.092 [0.046]	0.121 [0.009]
AR(1)		-0.350 [0.058]					0.345 [0.030]	0.484 [0.002]	0.335 [0.040]
UNE(-1)	-0.030 [0.000]	-0.014 [0.001]			-0.019 [0.000]		-0.018 [0.006]	-0.016 [0.021]	-0.019 [0.005]
INF_CORE(-1)	-0.552 [0.006]			-0.825 [0.000]	-0.396 [0.009]				
TED(-1)		0.012 [0.004]	0.004 [0.000]	0.016 [0.009]		0.023 [0.000]			
SP500(-1)		9.88E-6 [0.006]			-1.60E-5 [0.004]				
ER_SA(-1)		0.002 [0.001]							
ER_RUS(-1)			4.66E-4 [0.002]						
ER_CAN(-1)				0.021 [0.031]					
RP_USA(-1)					1.38E-4 [0.018]	3.68E-4 [0.000]	1.45E-4 [0.013]	2.24E-4 [0.002]	1.36E-4 [0.030]
R-squared	0.64	0.86	0.63	0.64	0.76	0.80	0.83	0.87	0.80
Durbin-Watson statistics	1.91	2.20	2.51	2.29	2.25	2.31	2.23	1.90	2.39

*Note: the numbers in the “[ ]” below coefficients represent probability, and this applies to following tables as well.

For annual average Lvol, we run the estimations using data at level because the results of unit root tests (Table B-1) and cointegration tests (Table B-2) show that long-term integration relations exist among variables for respective metals in at least 90% confidence interval, except those for gold and lead. Since the residuals of all regressions are stationary at level and show no significant series correlations (Table 2-2), we have reason to believe that our modelling settings are rational for all nine metals.

Table 2-2 Summary of residual diagnostics of regressions of annual average Lvol with macroeconomic variables.

	Unit Root Test at level I(0) without exogenous: Residuals		**Correlogram of Residuals**		**Correlogram of Residuals Squared**		**Jarque-Bera Normality**	**Breusch_Godfrey LM test**	**Heteroskedasticity Test: White (exclude While cross terms)**
	ADF Prob.	**PP Prob.**	**Lag**	**Prob.**	**Lag**	**Prob.**	**Prob.**	**F statistics Prob.**	**F statistic Prob.**
Lvol_Ag	0.003	0.003	1	0.959	1	0.264	0.606	0.872	0.823
			2	0.861	2	0.293			
			3	0.893	3	0.388			
Lvol_Au	0.001	0.001	1	0.601	1	0.207	0.659	0.203	0.805
			2	0.678	2	0.210			
			3	0.826	3	0.175			
Lvol_Pt	0.000	0.000	1	0.207	1	0.782	0.391	0.108	0.454
			2	0.139	2	0.955			
			3	0.181	3	0.251			
Lvol_Pd	0.000	0.000	1	0.364	1	0.872	0.913	0.205	0.665
			2	0.156	2	0.984			
			3	0.265	3	0.809			
Lvol_Cu	0.000	0.001	1	0.397	1	0.829	0.458	0.713	0.668
			2	0.510	2	0.945			
			3	0.594	3	0.979			
Lvol_Ni	0.000	0.000	1	0.398	1	0.141	0.897	0.734	0.640
			2	0.598	2	0.128			
			3	0.792	3	0.111			

Lvol_ Sn	0.000	0.000	1	0.443	1	0.666	0.615	0.518	0.448
			2	0.586	2	0.793			
			3	0.652	3	0.927			
Lvol_ Pb	0.001	0.001	1	0.742	1	0.525	0.833	0.700	0.589
			2	0.866	2	0.817			
			3	0.957	3	0.776			
Lvol_ Zn	0.000	0.000	1	0.256	1	0.181	0.269	0.393	0.943
			2	0.502	2	0.100			
			3	0.710	3	0.163			

Table 2-1 displays the regression results of annual average Lvol. In the table, UNE(-1) represents the lag of world unemployment rate as a percentage of total labour force from the International Labour Organization; INF_CORE(-1) represents the lag of inflation rate which is calculated by the annual difference of “Consumer Price Index for All Urban Consumers: All Items Less Food & Energy” from the U.S. Bureau of Labour Statistics; TED(-1) represents the lag of Treasury-EuroDollar spread which calculates the spread between three-month London Inter-bank Offered Rate (LIBOR) based on U.S. dollars and the three month Treasury Bill; SP500(-1) represents the lag of Standard & Poor's 500 index from Yahoo Finance; ER_SA, ER_RUS, and ER_CAN represent the official exchange rate of local currency to the U.S. dollar in South Africa, Russia, and Canada respectively, from the International Financial Statistics of the International Monetary Fund; and RP_USA(-1) represents the lag of real residential property prices in the U.S. from Bank for International Settlements.

According to the regression results (Table 2-1), world unemployment rate (UNE) is negatively correlated with annual average Lvol of silver, gold, copper, tin, lead, and zinc prices. Since unemployment rate is an index of economic recessions (Stock and Watson, 2010), it indicates that Lvol is higher during economic booms and lower during recessions. It may be because high demands of metals during economic booms will create short-term market supply shortages which can lift prices up until new suppliers appear. That is, the busier the commodity market, the more volatile metal prices may be. The value of the U.S.

dollar also plays a role in explaining annual average Lvol, especially for precious metals. INF_CORE represents the value of the U.S. dollar; higher the inflation rate, the weaker the U.S. dollar's purchasing power will be. ER_SA, ER_RUS, and ER_CAN represent the relative values of metal-producing states' local currencies; higher the exchange rates, the cheaper the local currencies will be, and the more valuable the U.S. dollar becomes. According to the regression results, stronger the U.S. dollar, the higher the Lvol of precious metal prices are likely to be. As known, metal commodities are priced by U.S. dollar. Dollar appreciation will directly cause an increase in metal prices. As a result, holding precious metals becomes more attractive and brings about more price volatility of them. U.S. residential property prices (RP_USA) are found to positively correlate with base metal prices volatility. Based on Drehmann et al. (2012) and Borio (2014), RP_USA is a sign of financial cycles. A financial cycle can be regarded as a long-term credit cycle or debt cycle. It is a medium- to long-term cycle which has a cycle length of more than 10 years. It means that base metal prices Lvol will move synergistically along with financial booms and busts because financial system not only allocates resources but also generates purchasing power. The demand booms along with financial booms can inject fluctuations into market prices. In addition, TED spread, which represents short-term credit risk cycles, is positively correlated with Lvol of gold, platinum, palladium, and nickel prices. Theoretically, when the credit risk of the market increases, TED spread will be increased accordingly. In such a condition, gold, as one of the most important risk-averse commodities, will be demanded increasingly, which adds to the volatility of the metal's price. Also, it is interesting to see that platinum, palladium, and nickel's price volatility are not dominated by unemployment rate, but affected by credit risks, similar to gold. We also find that Standard & Poor's 500 index is positively correlated with gold price Lvol, but negatively correlated with copper price Lvol. Standard &Poor's 500 index is a barometer of market returns. In the good times of businesses, money floods into capital markets, which will increase gold bullion investments and further increase gold price volatility. In the bad days of businesses, entrepreneurs swarm into derivative markets and further bring about excess volatility in copper's commodity price. The results also show that gold price Lvol is negatively auto-regressed, and tin, lead, and zinc prices Lvol are positively auto-regressed. It indicates a downward movement trend for gold price Lvol and upward movement trends for tin, lead, and zinc prices Lvol. In the case of the other five metals, their prices Lvol are independent of previous ones and mainly dominated by exogenous variables.

2.5 Robustness Analysis of Low Frequency Volatility Used Models

To verify whether models perform better than models adopting regular measurements of volatility, namely realized volatility (Rvol), we repeat the regressions and residual tests conducted in the previous section by replacing quarterly and annual average Lvol with quarterly and annual average Rvol and then compare their explanatory power and consistency. The Rvol can be calculated by Equations (2-6), (2-7), and (2-8):

$$R_t = \ln \frac{P_t}{P_{t-1}} \ , \qquad (2\text{-}6)$$

$$\overline{Rvol_t} = \sqrt{\frac{1}{N_t} \sum_{i=2}^{N_t} [R_i - E_{i-1}(R_i)]^2} \ , \qquad (2\text{-}7)$$

$$E_{t-1}(R_t) = \frac{1}{T} \sum_{i=1}^{T=t-1} R_i \ , \qquad (2\text{-}8)$$

In the equations, R_t represents log return of metal prices; $\overline{Rvol_t}$ is calculated by the standard deviation of R_t; and $E_{t-1}(R_t)$ represents expected current time (*t*) log return under one stage lagged (*t-1*) information, which is calculated by the mean of previous returns.

The regression results of the first order difference of quarterly average Lvol and Rvol are displayed in Tables C-1 and C-2. According to the estimated probability of coefficients' significance and the regressions' R-squared, we can conclude that the explanatory power of auto-correlation terms become much weaker after replacing Lvol with Rvol. It is because the Spline-GARCH model can remove unpredictable high-frequency volatility parts from the full volatility and the generated slowly evolving-low-frequency parts can consistently change along with the macro-economy. Rvol contains massive high-frequency unpredictable noises, which reduce the traceability of volatility movements. Looking at the results of the unit root tests on residuals (Tables C-1 and C-2), we find that the regression residuals are stationary for both Lvol and Rvol used models, except for quarterly average Lvol of copper price. Also, according to the results of the Jarque-Bera Normality tests (Tables C-1 and C-2), we find that only regression residuals of silver and lead prices Lvol are weakly normally distributed at 90% confidence interval (Probability of Jarque-Bera Normality tests), and all the regression residuals for both Lvol and Rvol used models show significant fat-tails (Kurtosis of Jarque-Bera Normality tests). These test results indicate that auto-correlations explained by quarterly average Lvol and Rvol lack precision and are not efficient. In addition, for Rvol used models, we find that regression residuals are all positively skewed (Skewness of Jarque-Bera Normality tests). It indicates that the Rvol used models are more likely to produce underestimated results. According to the results of correlogram tests on residuals and squared residuals, and the results of Breusch_Godfrey LM tests (Tables C-1 and C-2), we can see that residuals of Rvol used models are likely to suffer less from series correlations than those of Lvol used models, which benefited from the interferences of high-frequency unpredictable volatility components. It is also the reason residuals of Rvol used models do not show heteroskedasticity, other than those for Lvol used models (Table sC-1 and C-2). These results indicate that regression consistency for Rvol used models outperforms the Lvol used ones. But neither of them produces consistent estimations. In short, the movements of quarterly average Lvol of metal prices can be partially explained by auto-correlated terms, and the models are unbiased but lack accuracy and efficiency. The movements of quarterly average Rvol of metal prices are not significantly correlated with their auto-correlation terms, and the Rvol is likely to be underestimated if only using auto-correlations. Neither quarterly average Lvol nor Rvol can be consistently predicted by auto-correlations; thus, there are exogenous variables dominating their movements.

The regression results of annual average Rvol are displayed in Table 2-3. Compared with the estimation results of annual average Lvol presented in Table 2-1, macroeconomic variables are less significant and show weaker explanatory power (represented by R-squared) for the evolvement of annual average Rvol. While the magnitude and direction of macroeconomic variables' effects on Rvol and Lvol are consistent, it indicates that removing high-frequency volatility parts from full volatility is conductive to uncover the relation of metal prices volatility with macroeconomic variables and won't cause estimation distortion. According to the results of unit root tests and Jarque-Bera Normality tests on regression residuals of annual average Lvol and Rvol used models (Tables 2-2 and 2-4), we can see that residuals of both are stationary at level and normally distributed. It proves that the macroeconomic variables we used can be unbiased and effectively explain the movements of annual average Lvol and Rvol. Also, according to the results of Correlogram tests on residuals and squared residuals and the results of Breusch_Godfrey LM tests on residuals (Tables 2-2 and 2-4), we find that residuals of both Rvol and Lvol used models are free from series correlations, except those for platinum and palladium prices Rvol. It indicates that the macroeconomic variables we used can consistently predict annual average Rvol and Lvol of metal prices, except for platinum and palladium prices. Also there must exist missing explanatory variables for annual average Rvol of these two metal prices. In short, the explanatory power of macroeconomic variables and the significance of macroeconomic variables can be improved by using annual average Lvol instead of Rvol, without affecting the rightness of regressions. Also, the models we developed can effectively, consistently, and in an unbiased manner predict the performance of annual average Lvol of metal prices.

Table 2-3 Regression results of annual average Rvol with macroeconomic variables.

	Rvol_ Ag	**Rvol_ Au**	**Rvol_ Pt**	**Rvol_ Pd**	**Rvol_ Cu**	**Rvol_ Ni**	**Rvol_ Sn**	**Rvol_ Pb**	**Rvol_ Zn**
cons.	0.729	0.084	0.006	0.846	0.521	-0.011	0.150	0.088	0.044
	[0.016]	[0.020]	[0.364]	[0.019]	[0.031]	[0.224]	[0.015]	[0.091]	[0.491]
AR(1)		-0.609					0.175	0.493	0.366
		[0.026]					[0.414]	[0.004]	[0.137]
UNE(-1)	-0.030	-0.015			-0.021		-0.024	-0.016	-0.009
	[0.005]	[0.009]			[0.003]		[0.009]	[0.040]	[0.326]
INF_CORE(-1)	-0.499			-0.823	-0.360				
	[0.066]			[0.022]	[0.087]				
TED(-1)		0.010	0.017	0.017		0.019			
		[0.068]	[0.028]	[0.106]		[0.003]			

SP500(-1)		1.36E-5 [0.008]			-1.32E-5 [0.082]				
ER_SA(-1)		0.003 [0.014]							
ER_RUS(-1)			4.17E-4 [0.060]						
ER_CAN(-1)				0.022 [0.184]					
RP_USA(-1)					1.75E-4 [0.039]	3.78E-4 [0.000]	1.79E-4 [0.030]	2.68E-4 [0.001]	3.07E-4 [0.003]
R-squared	0.45	0.75	0.33	0.36	0.66	0.69	0.72	0.85	0.66
Durbin-Watson statistic	2.67	2.59	3.08	2.98	2.29	2.65	2.44	2.39	2.52

Table 2-4 Summary of the residual diagnostics of regressions of annual average Rvol with macroeconomic variables.

	Unit Root Test at level I(0) without exogenous: Residuals		**Correlogram of Residuals**		**Correlogram of Residuals Squared**		**Jarque-Bera Normality**	**Breusch_Godfrey LM test**	**Heteroskedasticity Test: White (exclude While cross terms)**
	ADF Prob.	**PP Prob.**	**Lag**	**Prob**	**Lag**	**Prob**	**Prob**	**F statistics Prob.**	**F statistic Prob.**
Ag	**0.000**	**0.000**	1	0.084	1	0.314	0.528	0.347	0.871
			2	0.199	2	0.595			
			3	0.317	3	0.551			
Au	**0.000**	**0.000**	1	0.158	1	0.746	0.321	0.2094	0.862
			2	0.306	2	0.599			

			3	0.294	3	0.497			
Pt	**0.000**	**0.000**	1	0.011	1	0.546	0.091	0.011	0.570
			2	0.036	2	0.770			
			3	0.084	3	0.682			
Pd	**0.000**	**0.000**	1	0.018	1	0.771	0.802	0.012	0.716
			2	0.050	2	0.573			
			3	0.064	3	0.755			
Cu	**0.000**	**0.000**	1	0.360	1	0.308	0.815	0.717	0.938
			2	0.654	2	0.462			
			3	0.820	3	0.632			
Ni	**0.000**	**0.000**	1	0.073	1	0.167	0.596	0.193	0.458
			2	0.200	2	0.198			
			3	0.358	3	0.327			
Sn	**0.000**	**0.000**	1	0.192	1	0.286	0.645	0.514	0.078
			2	0.406	2	0.482			
			3	0.460	3	0.395			
Pb	**0.000**	**0.000**	1	0.162	1	0.194	0.529	0.411	0.331
			2	0.294	2	0.428			
			3	0.358	3	0.579			
Zn	**0.000**	**0.000**	1	0.156	1	0.582	0.881	0.490	0.921
			2	0.287	2	0.278			
			3	0.338	3	0.299			

2.6 Verification of Forecasting Ability of Macroeconomic Variables

Since macroeconomic variables show consistent relation with annual average Lvol of metal prices (Tables 2-1 and 2-2), it is important to statistically test whether these macroeconomic variables can predict the annual average Lvol of metal prices better than the normally used constant means and auto-regressions. The rolling window method is used to conduct the test. The method uses a constant number of observations, which are defined by the window size to generate one-step-forward predictions of the explained variables and rolls the window according to step size. Specifically, we define a window size of 15 years and a step size of 1 year, and then generate year-ahead predictions of annual average Lvol of metal prices continuously under each data window.

Then, to verify the significance of the outperformance of macroeconomic variables included models, we adopt the Clark and West (2007) statistic, presented as follows:

$$\Delta MSE^{adj} = N^{-1}\sum_{t=15}^{T-1} e_{bench,t+1|t}^2 - N^{-1}\sum_{t=15}^{T-1} e_{mac.,t+1|t}^2 + N^{-1}\sum_{t=1}^{T-1}\left(Lvol_{bench,t+1|t} - Lvol_{mac.,t+1|t}\right)^2 . \quad (2\text{-}9)$$

Wherein, N is the number of predicted annual average Lvol of metal prices; e is the error between forecasted Lvol by rolling window method and the actual Lvol generated from theSpline-GARCH process; and the subscripts "*bench*" and "*mac*" are abbreviations of benchmark and macroeconomic variables, respectively. So e_{bench} and $e_{mac.}$ represent the errors of benchmark models and macroeconomic variables explained models. Positive value of the statistic suggests that macroeconomic variables dominated models are associated with smaller forecast errors and thus outperform the benchmark models. The benchmarks of the study are constant mean represented models and first order auto-regression models, which can be obtained by Equations (2-10) and (2-11).

$$y_{m,t} = \frac{1}{N}\sum_{i=1}^{N=t-1} y_{m,i} + e_{m,t} , \qquad (2\text{-}10)$$

$$y_{m,t} = cons. + \alpha_m y_{m,t-1} + e_{m,t} . \qquad (2\text{-}11)$$

The results of the Clark and West (2007) statistic are presented in Table 7. As seen from the table, macroeconomic variables can predict the evolvement of annual average Lvol of metal prices better than constant means and first order auto-regressions, except for gold price. For annual average Lvol of gold price, constant mean dominated model performs the best. It reflects the risk hedging property of gold commodity against macroeconomic system risks. In all, according to the regression results showed in Tables 2-1,2 and the results of Clark and West (2007) statistic, we can conclude that macroeconomic variables we included can consistently forecast annual average Lvol of metal prices, and in general the macroeconomic variables explained models perform better than those using constant means and auto-regressions. The annual average Lvol of gold price is the lowest among nine analysed metal prices benefited by its risk aversion feature (Figures A-1 to A-9). Its annual average Lvol is affected by macroeconomic variables and can be predicted simply by constant means.

Table 2-5 Verification results of the forecasting ability of the macroeconomic variables explained annual average Lvol model.

	Lvol_Ag	Lvol_Au	Lvol_Pt	Lvol_Pd	Lvol_Cu	Lvol_Ni	Lvol_Sn	Lvol_Pb	Lvol_Zn
ΔMSE^{adj} [bench=mean; Eq.10]	3.01E-4	-1.03E-5	2.47E-4	1.76E-4	1.09E-4	3.44E-4	1.70E-5	2.60E-4	7.79E-5
ΔMSE^{adj} [bench=AR (1); Eq.11]	2.32E-4	7.79E-5	1.40E-4	8.17E-5	1.22E-4	4.32E-4	3.53E-4	3.89E-4	1.81E-4

2.7 Discussion

Although acknowledging the impact of macroeconomic variables on metals' price volatility is commonplace, finding the right macroeconomic indexes and quantifying the sensitivity of metals' price volatility to these indexes have been a challenging subject for years. Benefitting from the Spline-GARCH model, we were able to separate the Lvol component out to solely concentrate on the macroeconomic factors led volatility, without the interference of high-frequency and short-lived market noises. As a result, we identified significant macroeconomic variables for each annual average volatility of nine types of metal prices and proved that the Lvol used models outperform the models that directly adopted Rvol without distorting the relations of macroeconomic factor and volatility. Moreover, we verified that the forecasting ability of macroeconomic variables explained models are superior to constant means and auto-regressions, except for annual average Lvol of gold price.

Also, we find that metals price volatility fluctuates with inertia, especially for quarterly average Lvol. The inertia is manifested by significant auto-correlations. Two aspects of factors may explain that. First, in the Spline-GARCH model, Lvol is predefined as a quadratic splines function. The shape of the function makes Lvol more likely to be auto-correlated, theoretically. Second, signals from the macro economy need to accumulate until they are significant enough to affect metals' price volatility, and the accumulation process takes time. Therefore, longer time interval of volatility data is required when regressing with macroeconomic variables. In terms of metals price volatility, annual average data are more suitable than quarterly averages, according to the regression results.

In addition, the cycle of metals' price volatility are found to be around three to five years, and the cycle length shortens as volatility increases. According to our regression results, the cyclical fluctuations of metal prices Lvol are attributable to two sources. The first one is the short-term business cycle which can be represented by the INF_CORE, TED, SP500, and ER_SA/RUS/CAN indexes. A business cycle's duration is also three to five years on average, which is consistent with the cycle length of metal prices' Lvol, that is, business cycles dominate the frequency of metals' price volatility. The other is the long-term financial cycle which can be represented by UNE and RP_USA indexes. A financial cycle can last for more than 15 years. It can significantly increase the frequency and the amplitude of metals' price volatility, as witnessed during the last financial crisis.

Moreover, we find that the macroeconomic factors that affect metals' price volatility are different from metal to metal. But in general, the effect of the same index is at the same direction, except for the effect of SP500 on annual average Lvol of gold and copper prices. According to the regression results, annual average Lvol of platinum and palladium prices are dominated by short-term business cycles, while the annual average Lvol of tin, lead, and zinc prices are dominated by long-term financial cycles. The remaining four metal prices' Lvol are dominated by both cycles. But all nine metal prices' Lvol show similar cycles and trends. It is because the financial cycles and business cycles are interactive in the real world.

However, the study has some shortcomings. On the one hand, through robustness analysis and forecasting ability verification, we confirmed that macroeconomic variables can characterize and forecast metal prices Lvol. The results are obtained from limited time periods of observations, from 1994 to 2013. Therefore, we are not confident about the models' applicability to long-term predictions. On the other hand, to remove predictable trends and intercepts of metal prices, we adopted ARMA models which exclude exogenous variables. In reality, metal prices are the outcome of combined effects of financial, economic, and fundamental factors. It could be better to include some exogenous variables in the regressions. But to identify factors that dominate metal prices evolvement will be another huge project. That is why we settled for non-exogenous ARMA.

2.8 Conclusion

By using the Spline-GARCH model, the study discussed macroeconomic factors' explanatory power and forecasting ability on nine types of metals' price volatility. Essentially, it uncovered the effect of market system risk on metals' price returns; the identified macroeconomic variables are indexes of relevant market risk. Regarding specific results, we found that macroeconomic variables play dominant roles in explaining and predicting annual average volatility of metal prices, but their roles in forecasting quarterly average volatility are negligible. The dominant variables include world unemployment rate indicated economic recession, inflation rate and exchange rate represented value of U.S. dollar, United States' residential property price indicated financial booms and busts, TED spread identified credit risk, and Standard & Poor's 500 index represented market return level. In other words, annual average volatility of metal prices is the outcome of business risk cycles and financial risk cycles. They share a similar fluctuation law with business risk cycles. Financial risks can add extra fluctuations on their cycles as well as increase frequencies of them. Among the nine metals, annual average volatility of platinum and palladium prices can be mainly predicted by business risk cycles; annual average of tin, lead, and zinc prices are dominated by financial risk cycles; and those of silver, copper, and nickel prices are controlled by both business and financial risk cycles. The annual average volatility of gold price converges to a constant mean caused by its risk hedging function. In general, the study improves our understanding of the evolvement of metals' price volatility and provides a tool to them.

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Chapter 3 The medium-term supply risk measured by resource nationalism

3.1 Introduction

As for medium term metal supply risk, transboundary supply security containing geopolitical factors and resource nationalism are essential, as we pointed out in chapter 1. Geopolitics can affect resources related policies but it is not originated from resources sector most of the time. However, resource nationalism is one types of country risks that directly generated from resource industry. Therefore, we use resource nationalism to indicate medium term metals supply risk.

By resource nationalism, it refers to a phenomenon that states control or dominance of natural resources, and the resulting potential to use this power for political and economic purposes (Click and Weiner, 2010). According to Stevens (2008), it is composed of limitation to operation of international companies and assertion of control power of the nation over natural resource development. Bremmer and Johnston (2008) classified resource nationalism into four types: revolutionary resource nationalism, economic resource nationalism, legacy resource nationalism, and soft resource nationalism.

Historically, many poor countries planned to develop their economy by nationalizing natural resources turned out to be trapped by "resource curse", as witnessed in Latin America, Middle East, and recently in Sub-Saharan Africa. The harmfulness of resource nationalism for investors is that one event can quickly escalate and lead to a chain of events which make projects commercially unavailable (Willis, 2014). According to Ernst & Young (2011, 2012, 2013, 2014, 2015), resource nationalism was ranked as the most risky factor for mining and metal business during 2011 and 2012, the third risky factor in 2013, the fourth in 2014, and 2015.

In the author's opinion, resource nationalism is essentially mandatory government intervention in natural resources business by political or economic means in order to benefit the nation and the people it on behalf of. However, the super profit from selling natural resources is a double-edged sword. In addition to immediate boosts to economy and employment rate, it fosters dependency on natural resources, discourages investments from moving toward diversified directions and therefore limits a nation's long term development potential. Over time, those nature resources pumped economies can become too fragile to volatile prices of resources and even go back to poverty when productions of resources suspend or stop. Unfortunately, historical lessons failed to radically protect succeeding generations from resource nationalism but induced disguised resource nationalism measures like beneficiation, windfall tax, etc. Just as discussed by numerous literatures, cyclical feature has been witnessed over the issue (Chang et al. 2010).

Resource nationalism is a result of multiple factors including economic status, political situations, and very specific local conditions. Despite numerous descriptive studies on the topic (Childs, 2015; Ward, 2009; Ghandi and Lin, 2015; Stevens, 2008; HM, 2014; Schurman, 1998; Kohl and Farthing, 2011; Jasimuddin and Maniruzzaman, 2016; Stefan, 2015; Butler, 2013; Cawood and Oshokoya, 2013a; Cawood and Oshokoya, 2013b; Humphreys, 2012; Humphreys, 2013; Sarsenbayev, 2011; Bremmer and Johnston, 2009; Mares, 2011.), the common genesis and drivers of resource nationalism haven't been quantified at global level. It probably attributes to the vague definition boundary of resource nationalism and the lack of integrated surveillance data on it.

In view of the academic gap between qualitative characterization and quantitative regression on the causes of resource nationalism, the study uses econometric regression (STATA) to quantify probability of resource nationalism by its dominant variables under binary choice logit modelling of panel data. We focus on analyzing impact of domestic economic situation, quality of governance, and policy perception toward resource sector, rather than geopolitical status and specific local condition which cannot be measured and compared at global level. Because we are aimed at investigating mutual genesis of resource nationalism across countries, and getting some insight into predicting and comparing the probability of it based on easily accessible indexes.

The remainder of the article is arranged as followings. The following section displays a literature review of historical resource nationalism. The third section describes you the data and the regression method. The penultimate section presents results and discussion on the modeling results, followed by a concluding section.

3.2 Literature Review

From historical prospect of view, the first cycle of resource nationalism broke out in Latin America (Sarsenbayev, 2011). In 1938, Mexican government nationalized its oil assets and created a National Oil Company (NOC) to deliver benefits to Mexican people (Mares, 2011). The Chaco War (1932-1935) between Bolivia and Paraguay over oil resources seeded the outbreak of 1952's Bolivia revolution which led to nationalization of the country's mining sector (Dunkerley, J., 1984; Kohl and Farthing, 2011).

After the World War II, along with the popularity of Keynesian economics (Keynes, 1938), another high tide of resource nationalism intensively exploded in the Middle East. Specifically, during 1950s, it emerged in oil producing countries of the region and resulted in a growing upsurge of NOCs. By year 1960, OPEC was firstly formed by Iran, Iraq, Kuwait, Saudi Arabia, and Venezuela and later joined by another 8 countries during the period from 1961 to 1975, in order to raise oil price by artificially creating supply shortages. Since then, resource nationalism ruled the oil sector and pushed oil price up. After two times of oil price shocks in 1973 and 1979, oil importing countries managed to decrease dependency on OPEC oil by exploration and energy substitution. Finally, oil price collapsed in 1986 (Stevens, 2008). By 1989, the Washington Consensus was agreed in order to pull the Latin American states out of debt crisis. It brought about an increased demand and consolidation of private sector.

Since the beginning of the 21 century, under the impetus of increased energy and mineral resources prices, a new wave of resource nationalism spewed from natural resource exporting countries again. The distinguish feature of the recent wave is that it is not only involved in energy resources producing countries, but spread to mineral commodities mining states; and resource nationalism policies diffused from Latin America and Middle East to a global level; in addition, instead of revolutionary and legacy resource nationalism, more and more economic and soft resource nationalism appeared in a much higher frequency compared to that in the last century (Appendix E). All of above reveal the urgency of a better understanding of the genesis of resource nationalism, especially of the current century under the context of economic globalization.

3.3 Method

Three steps are implemented in this study to find out significant variables dominating the occurrence of resource nationalism and to quantify their effects. To start with, yearly data survey from 2000 to 2013 of total 83 oil, coal, natural gas, and metal producing countries on occurrence of resource nationalism is conducted to generate binary data for modelling, among which countries occurred at least one time of resource nationalism of a year are recorded as 1 for the year, otherwise they are recorded as 0. Secondly, modelling by binary choice logit regression of panel data is carried out to find significance of variables that may play a role in occurrence of resource nationalism across countries, and to quantify the magnitude of their marginal effects. In addition, countries are divided into two groups according to their income levels in 2013 defined by the World Bank and modeled separately to capture respective influence factors. Thirdly, respective cut-off ratios of the two groups' models are selected according to their sensitivities and specificities. And probability of occurrence of resource nationalism is predicted by unifying the threshold to 50%. Because data used for modelling is an unbalanced panel set, some years' probability prediction are dropped out. Thus, interpolations of missing data for variables by means or trend lines are adopted to achieve continuous prediction. In addition, for countries that are excluded in the modelling stage but cannot be overlooked for some specific natural resources commodities, their probabilities of occurrence of resource nationalism are estimated by simply applying the modeled equation.

3.3.1 Data Survey

Lacking of integrated data that continuously document resource nationalism related events at global level, we conduct a data survey among countries had at least one year during 2000-2013 that their rounded contribution of natural resources rents to GDP is not less than 5%. Natural resources rents as a percentage of GDP used in the study are sum of rents gained from crude oil, coal (both soft and hard coal), natural gas, and minerals (a stock of minerals including tin, gold, lead, zinc, iron, copper, nickel, silver, bauxite, and phosphate) productions, among which definitions and statistics of oil, coal, natural gas, and mineral rents (% GDP) are from world development indicators of the World Bank. To be specific, 83 countries are remained after screening. Survey starting year is set to be 2000 according to our interest in the currently ongoing wave of unprecedentedly widely spread resource nationalism, and ending year is set to be 2013 due to data availability. Information of every country's mining state is referred to the United States Geological Survey (USGS) Minerals Information: Minerals Yearbook Volume III--Area Reports: International, where government policies and programs, and structure of the mineral industry are documented and updated annually. Appendix A displays the resource nationalism events panel summarized from the USGS. To convert the event based date to binary panel data, countries that are caught by resource nationalism of any year are noted as "1" of the year regardless of times or types of occurrence; countries that are not attacked by resource nationalism of a year or not documented in the USGS's reports (yellow highlighted in Table 3-1 and 3-2) are noted as "0" of the year. It should be noticed that South Sudan haven't been independent from Sudan until July 9th of 2011, thus its occurrence of resource nationalism before independence is represented by Sudan's. Table 3-1 and 3-2 show you events transformed binary data.

Table 3-1 Occurrence of resource nationalism in lower middle and low income countries.

Country	Region	Binary transforemed Occurrence by year (2000-2013)													
		0	0	0	0	0	0	0	0	0	0	1	1	1	1
		0	1	2	3	4	5	6	7	8	9	0	1	2	3
Papua New Guinea	**East Asia & Pacific**	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Solomon Islands		0	0	0	0	0	0	0	0	0	0	0	0	0	0
Philippines		0	0	0	0	0	0	0	0	0	0	0	0	1	0
Indonesia		0	0	0	0	0	0	0	0	0	1	0	0	1	0
Lao PDR		0	0	0	0	0	0	0	0	1	1	0	0	0	0
Vietnam		0	0	0	0	0	0	0	0	1	1	0	1	1	0
Ukraine; Uzbekistan.	**Europe & Central Asia**	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Kyrgyz Republic		0	0	0	0	0	0	0	0	0	0	0	0	1	1
Guyana	**Latin America & Caribbean**	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Bolivia		0	0	0	0	0	1	1	1	0	1	1	1	1	1
Egypt, Arab Rep; Morocco; Syrian Arab Republic; Syrian Arab Republic; Yemen, Rep.	**Middle East & North Africa**	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Bangladesh; Pakistan.	**South Asia**	0	0	0	0	0	0	0	0	0	0	0	0	0	0
India		1	0	0	0	0	0	0	0	1	1	1	1	1	1
Burkina Faso; Chad; Mozambique; Niger; South Sudan; Togo; Côte d'Ivoire; Nigeria.	**Sub-Saharan Africa**	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Mali		0	0	0	0	0	0	0	0	0	0	0	0	1	0
Cameroon		0	0	0	0	0	0	0	0	0	0	0	0	0	1
Congo, Rep.		0	0	0	0	0	1	0	0	0	0	0	0	0	0
Congo, Dem. Rep.		0	0	0	0	0	0	0	1	0	0	0	0	1	0
Eritrea		0	0	0	0	1	1	0	0	0	0	0	0	0	0
Guinea		0	0	0	0	0	0	0	0	0	1	0	1	0	0
Tanzania		0	0	0	0	0	0	0	0	0	0	1	0	1	0
Zimbabwe		0	0	0	0	1	0	0	0	1	0	0	0	0	0

Mauritania		0	0	0	0	0	0	0	0	0	1	0	0	1	0
Zambia		0	0	0	0	0	0	0	0	1	0	0	0	0	1
Ghana		0	0	0	0	0	0	1	0	1	0	0	0	1	0

Table 3-2 Occurrence of resource nationalism in high and upper middle income countries.

Country	**Region**	**Binary transforemed Occurrence by year (2000-2013)**													
		00	01	02	03	04	05	06	07	08	09	10	11	12	13
Brunei Darussalam; Thailand.	**East Asia & Pacific**	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Australia		0	0	0	0	0	0	0	0	0	0	0	0	1	1
Malaysia		0	0	1	0	0	0	0	0	0	0	0	0	1	0
Mongolia		0	0	0	0	0	1	1	0	0	0	0	0	1	0
China		0	0	0	0	0	0	0	1	0	1	1	1	1	0
Albania; Norway; Azerbaijan; Macedonia, FYR; Romania; Turkmenistan.	**Europe & Central Asia**	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Bosnia and Herzegovina		0	0	0	0	0	0	0	0	0	0	0	0	0	0
Russian Federation		0	0	0	0	0	0	1	1	0	0	0	0	0	0
Kazakhstan		0	0	0	1	1	1	0	1	0	0	0	0	0	0
Trinidad and Tobago; Belize; Cuba.	**Latin America & Caribbean**	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Suriname		0	0	0	0	0	0	0	0	0	0	0	0	0	0
Brazil		0	0	0	0	0	0	0	0	0	0	1	0	0	0
Colombia		0	0	0	0	0	0	0	0	0	0	0	0	1	0
Mexico		0	0	0	0	0	0	0	0	0	0	0	0	0	1
Peru		0	0	0	0	0	0	0	0	0	0	0	1	0	0
Ecuador		0	0	0	0	0	0	0	1	0	1	0	0	0	0
Chile		0	0	0	0	0	1	1	0	0	0	1	0	0	0
Argentina		0	0	0	0	1	0	0	1	0	0	0	1	1	0
Venezuela, RB		0	1	0	0	0	1	0	0	1	1	0	1	0	1

Bahrain; Kuwait; Saudi Arabia; United Arab Emirates; Jordan; Tunisia.	**Middle East & North Africa**	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Oman		0	0	0	0	0	0	0	0	0	0	0	0	0	1
Qatar		0	0	0	0	0	0	0	0	0	0	0	0	1	0
Algeria		0	0	0	0	0	0	1	0	0	0	1	0	0	0
Iran, Islamic Rep.		0	0	0	0	0	0	0	0	0	0	0	0	1	0
Iraq		0	0	0	1	0	0	0	0	0	0	0	0	0	0
Libya		0	0	0	0	0	0	1	0	0	0	0	0	0	1
Canada	**North America**	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Botswana; Gabon.	**Sub-Saharan Africa**	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Equatorial Guinea		0	1	0	0	0	0	0	0	0	0	0	0	0	0
Namibia		0	0	0	0	0	0	1	0	0	0	0	0	0	0
Angola		0	0	0	0	0	0	0	0	0	0	0	1	1	0
South Africa		0	0	0	0	0	0	0	0	0	1	1	0	0	0

3.3.2 Modelling

The basic model setting is static binary choice logit regression of panel data (ID=83; T=14) by maximum likelihood method, as presented in equations (3-1) to (3-4). Wherein, 'β' denotes the coefficient, 'x' denotes the independent variables, 'e and u' denote error terms, subscript 'M/m' denotes numbers of variables, subscript 'id' represents countries, and subscript 't' displays year. The full data set are subdivided into "high and upper middle income group" (ID=46, T=14) and "lower middle and low income group" (ID=37, T=14), in order to span the respective impact factors of resource nationalism. Because, logically speaking, relatively well-off countries prefer to put natural resources into a strategical and sustainably developmental context over short term economic interests, while relatively poor countries are likely to think the opposite. Following steps summarize the simulation process. Firstly, variables are tested for stationarity by unit root test and cointegration test, and for multicollinearity by covariance analysis. Secondly, they are modeled by pooled, fixed effects, and random effects methods simultaneously to test the significance of variables. Through trial and error, significant variables are retained in the model while insignificant ones are removed. Best performed method is selected by Likelihood-ratio test and Hausman test. Then, we test the existence of state dependence to verify the robustness and consistency of the static regression method. According to Bartolucci and Nigro (2010), state dependence of this article refers to the influence of occurrence of resource nationalism in the past on the occurrence of resource nationalism in the future. We follow the method developed by Bartolucci, et al. (2015) and use the R package published by Bartolucci and Pigini (2016) to proceed the test. Finally, Marginal effects of explanatory variables to resource nationalism are estimated under the best method.

$$y_{id,t} = \begin{cases} 1 & \text{occurrence of resource nationalism event} \\ 0 & \text{no resource nationalism event} \end{cases} \qquad (3\text{-}1)$$

$$l = \begin{cases} \beta_0 + \sum_{m=1}^{M} \beta_m x_{m,id,t} + e_{id,t} & \text{pooled} \\ \beta_i + \sum_{m=1}^{M} \beta_m x_{m,idi,t} + e_{id,t} & \text{fixed effects} \\ \sum_{m=1}^{M} \beta_m x_{m,id,t} + e_{id,t} + u_{id} & \text{random effects} \end{cases} \qquad (3\text{-}2)$$

The probability that $y = 1$ can be written as: $p = \exp(l)/[1 + \exp(l)]$ (3-3)

The probability that $y = 0$ is: $1 - p = 1/[1 + \exp(l)]$ (3-4)

3.3.3 Probability Prediction and Estimation

Using modeled coefficients and variables, predicting countries' probability of resource nationalism can be realized. There are two steps to do that. Firstly, cut-off ratios should be selected for the two groups. The cut-off ratio represents threshold of occurrence of resource nationalism. The principal of selecting the cut-off is maximizing sensitivity of the model, and at the same time not severely damage model specificity. Sensitivity of a model measures the ability to predict that a country occurred resource nationalism has a probability of occurrence of resource nationalism above the cut-off ratio. And specificity measures the ability to predict that a country without occurrence of resource nationalism has a probability of that below the cut-off. Because two groups have respective cut-off ratios (*C*), we adjust them to 50% by introducing transforming parameter '*b*' for both groups as displayed in equations (3-5) and (3-6). After the adjustment, countries with over 50% probability of resource nationalism are likely to impose resource nationalism policy, while countries with less than 50% probability of that probably won't take resource nationalism measures at all. Secondly, because the data set is unbalanced panel, we have to do some simple estimation to complete probability prediction. Two types of estimations are done. One is to estimate missing data of independent variables. In that case, interpolation either by trend line or average is used. The other is to estimate probabilities of resource nationalism of countries that are not included in the modelling process. In the circumstance, we apply the country's raw data of independent variables to the modeled equations to calculate their probability of resource nationalism.

$$b = -ln(1/C - 1) \qquad (3\text{-}5)$$

$$Prob\left(y_{id,t} = 1\right) = 1/[1 + exp(b - l)] \qquad (3\text{-}6)$$

Using predicted countries' probability of resource nationalism, we can produce the prediction of probability of that for natural resources commodities. In the study, we use weighted average of a commodity producing countries' probability of resource nationalism to represent the commodity's exposure to resource nationalism, as presented in equations (3-7) and (3-8). Wherein, '*w*' represents the weight coefficient, which is the share of a main producing country's production (*P*) to the total production by those main producing countries of a commodity. Subscript 'c' represents types of commodities. Average ratio of main producing countries' production used for weighting to world total production of each commodity during the period from 2003 to 2012 is presented in the Table 3-3. This ratio indicates the representativeness of our predicted commodities' probability of resource nationalism. Commodities contained in the study are base metals: copper, lead, nickel, tin, zinc, precious metals: gold, silver, platinum, palladium, and energy resources: coal (primary coal), natural gas (dry natural gas), oil (crude oil including lease condensate). For metals, metric ton is used as production scale; for energy resources, Joule is used. Data of metals' mining production by country are from Raw material database (SNL). Data of coal, natural gas, and oil are from U.S. Energy Information Administration.

$$w_{id,t,c} = P_{id,t,c} / \sum_{i=1}^{I} P_{id,t,c} \qquad (3\text{-}7)$$

$$Probability(y_{c,t} = 1) = \sum_{i=1}^{I} [w_{id.t,c} \times Prob(y_{id,t} = 1)] \qquad (3\text{-}8)$$

Table 3-3 Average ratio of production used for weighting to total production.

Commodity	Ratio
Copper	97%
Lead	97%
Nickel	99%
Tin	98%
Zinc	95%
Gold	90%
Silver	97%
Platinum	100%
Palladium	100%
Coal	96%
Natural gas	90%
Oil	94%

3.4 Results and discussion

3.4.1 Distribution and Status of Risk of Resource Nationalism

A summary of binary data of resource nationalism is presented in the Table 3-4. In the table, 'H/L ()' is the abbreviation of high and upper middle income group/lower middle and low income group (Number of countries involved in the data survey). 'R.N.' is the abbreviation of resource nationalism. According to the summary, resource nationalism rose globally from 1 record in 2000 to as many as 19 records in 2012. During the investigated 14 years, 41 out of 83 countries imposed 95 times of resource nationalism policies measured in years. It reveals that almost half of the natural resources producing states which had over 5% of GDP from natural resources rent took resource nationalism actions for more than 2 times on average since the beginning of this century. Specifically, 15 Sub-Saharan Africa countries were involved in resource nationalism, and in which 11 of them are lower middle and low income countries. This region experienced the most concentrated outbreaks of resource nationalism at the beginning of its primitive accumulation. 9 Latin America & Caribbean countries were also involved. 8 of them belong to high and upper middle income level. It suggests that the completion of primitive accumulation could not immune resource dependence states from the attack of resource nationalism. East Asia & Pacific countries witnessed severe exploding of resource nationalism as well. The feature of this region' resource nationalism is that it spread evenly in both income groups. In the above three regions, more than half of the investigated resource producing states were reported by resource nationalism policies. It indicates relatively high risk warnings of resource nationalism in those places. In Middle East & North Africa, half of the investigated high and upper middle income countries imposed resource nationalism policies, and all of them are oil and natural gas producing countries. It reflects the high geopolitical risk of crude oil's supply. Regions that are relatively less involved in resource nationalism include North America, South Asia, and Europe & Central Asia. From the point view of income level, roughly 52% of investigated high and upper middle income mining countries imposed resource nationalism policies, and around 46% of investigated lower middle and low income countries did so as well. And in high and upper middle income group, it is scattered in several regions. But in lower middle and low income group, it concentrated in Sub-Saharan African countries. In addition, as presented in Appendix A, in the new century, instead of revolutionary and legacy resource nationalism, more and more economic and soft resource nationalism were taking place in an increasing frequency. It spread from energy sector to mineral resources, and thus swept the globe.

Table 3-4 Summary of binary data of resource nationalism.

Region	East Asia & Pacific		Europe & Central Asia		Middle East & North Africa		Latin America & Caribbean		North America	South Asia	Sub-Saharan Africa		Number of R.N. events	
Income level / Year	H (6)	L (6)	H (9)	L (3)	H (12)	L (4)	H (12)	L (2)	H (1)	L (3)	H (6)	L (19)		
2000	0	0	0	0	0	0	0	0	0	1	0	0	1	95
2001	0	0	0	0	0	0	1	0	0	0	1	0	2	
2002	1	0	0	0	0	0	0	0	0	0	0	0	1	
2003	0	0	1	0	1	0	0	0	0	0	0	0	2	
2004	0	0	1	0	0	0	1	0	0	0	0	2	4	
2005	1	0	1	0	0	0	2	1	0	0	0	2	7	
2006	1	0	1	0	2	0	1	1	0	0	1	1	8	
2007	1	0	1	0	0	0	2	1	0	0	0	1	6	
2008	0	2	0	0	0	0	1	0	0	1	0	3	7	
2009	1	3	0	0	0	0	2	1	0	1	1	2	11	
2010	1	0	0	0	1	0	2	1	0	1	1	1	8	
2011	1	1	0	0	0	0	3	1	0	1	1	1	9	
2012	4	3	0	1	2	0	2	1	0	1	1	5	19	
2013	1	0	0	1	2	0	2	1	0	1	0	2	10	
R.N. involved countries	4	4	2	1	6	0	8	1	0	1	4	11		
	8		3		6		9		0	1	15			
	41													

3.4.2 Significant Factors and Economic Explanations

For high and upper middle income countries, high-technology export as a percentage of manufactured export (HTEX), ores and metals exports as a percentage of merchandise exports (MEX), rule of law from world governance indicator (RoL), trade as a percentage of

GDP represented trade openness (TOP), natural resource rent except forest rent as a percentage of GDP (RRT) and its square (SQRRT) are found to be significant. Stationarity and multicollinearity tests' results are presented in Appendix F. According to the tests' results, HTEX and SQRRT are stationary at level, others are stationary after first difference (Table F-1 to F-3). Since the result of panel cointegration test provides evidence of long term stable proportional relationship among variables, data at level are directly applied to regression (Table F-4). And there is no strong correlation between variables observed from covariance analysis (Table F-6). So multicollinearity is not considered to be a problem. Appendix G displays the evidence of modelling methods selection. Through Likelihood-ratio test (Table G-1), rho ($corr(u_i, e_{it})$) is found to be not significantly different from zero, so there are no random effects exist. Hausman test (Table G-2) doesn't provide any proof of the existence of systematic coefficients, thus fixed effects method is not suitable either. Pooled method corrected by panel-robust standard error performs the best, therefore it is selected to be the suitable one (Table 3-5). Results of state dependence test are presented in Appendix H. As shown in Table H.1, lag of dependent variable is insignificant. Thus, there is no evidence of state dependence. It proves the robustness and consistency of the pooled method.

Table 3-5 Modelling result for high and upper middle income group under pooled method.

Number of obs. = 475

Log pseudo-likelihood = -121.763

Wald chi2 (6) = 51.46 Prob. > chi2 =0.0000 Pseudo R2 = 0.1279

Var.	**Scale**	**Coef.**	**Robust Std. Err.**	**P>|z|**	**Average dy/dx**	**Delta-method Std. Err.**	**P>|z|**
HTEX	[0,1]	4.651	1.619	0.004	0.335	0.127	0.008
MEX	[0,1]	2.935	0.936	0.002	0.211	0.072	0.003
RoL	[-0.5,0.5]	-2.788	1.181	0.018	-0.201	0.088	0.022
RRT	[0,1]	12.02	3.725	0.001	0.865	0.279	0.002
SQRRT	[0,1]	-19.84	7.869	0.012	-1.427	0.578	0.014
TOP	[0,1]	-1.297	0.622	0.037	-0.093	0.047	0.045
_cons		-3.355	0.598	0.000			

For lower middle and low income countries, government effectiveness from world governance indicator (GE), policy perception index from The Fraser Institute (PPI), high-technology export as a percentage of manufactured export (HTEX), and the first difference of mineral rent as a percentage of GDP represented changes of mineral rent (CMRT) are detected to be significant. Regarding stationarity test, HTEX and CMRT are stationary at level, the other two are stationary after first difference (Table F-1 to F-3). Data at level are used according to the result of cointegration test (Table F-5). Regarding multicollinearity, it is weak covariance analysis (Table F-7). Pooled model (Table 3-6) is also selected according to the results of Likelihood-ratio test (Table G-3) and Hausman test (Table G-4). In addition, since no significant state dependence is found (Table H-2), robustness and consistency of the pooled method is verified.

Table 3-6 Modelling result for lower middle and low income group under pooled method.

Number of obs. = 127

Log pseudo-likelihood = -50.625

Wald chi2 (6) = 14.63 Prob. > chi2 =0.0055 Pseudo R2 = 0.2827

Var.	Scale	Coef.	Robust Std. Err.	P>|z|	Average dy/dx	Delta-method Std. Err.	P>|z|
CMRT	[-0.5,0.5]	-122.9	60.42	0.042	-15.842	6.840	0.021
GE	[-0.5,0.5]	11.07	4.967	0.026	1.426	0.557	0.010
HTEX	[0,1]	-6.018	2.088	0.004	-0.776	0.235	0.001
PPI	[0,1]	-8.245	2.269	0.000	-1.063	0.214	0.000
_cons		2.856	1.175	0.015			

According to the regression results (Table 3-5 and 3-6), HTEX turned out to be a double-edged sword. It is positively correlated with occurrence of resource nationalism in high and upper middle income countries, but negatively in lower middle and low income countries. In general, increasing export contribution from high-technology products can decrease a state's dependency on natural resources. For relatively rich countries, long term resources supply security and sustainability are more important than short term rents. Therefore, on the one hand, they probably put natural resources in a strategic position and try to protect them by economic or soft resource nationalism measures, such as China's export quotas to rare earth metals in 2010; on the other hand, they are more sensitive to negative impacts of mining activities on environment and societies, such as Australia's carbon tax in 2012 and rehabilitation charges in 2013. That's to say, the more advance (represented by the higher HTEX) the country is, the stronger willingness to protect resources it has. However, in relatively poor countries, the economic development comes first. States have other sources of incomes besides natural resources rents will squeeze less of the resources sector. While states totally depend on natural resources rents have to optimize the resource revenues in order to support the government. Therefore, higher HTEX makes less resource nationalism in lower middle and low income countries. Quantitatively, 1% increase in HTEX is expected to increase the probability of resource nationalism by 0.335% in high and upper middle income countries on average, and decrease the probability of resource nationalism by 0.776% in lower middle and low income countries on average.

Regression results also proves that the more profit natural resources brings, the greedier the government gets, and accordingly, the higher probability of resource nationalism there will be. Because governments can always claim for benefits as the owner of the natural resources assets whenever they want, and natural resources always carry the responsibility to benefit the sovereign states as well as the local people. In high and upper middle income countries, we find that MEX and RRT are positively correlated with occurrence of resource nationalism. The marginal effect of MEX is 0.211. It means that 1% increase of ore and metals exports value in total merchandise export brings the risk of resource nationalism up by 0.211% in average in high and upper middle income countries. That's to say, the more important natural resources is to earn foreign exchange, the higher probability of resource nationalism there is for the country. Marginal effect of RRT suffers decline along with the increase of RRT itself in high and upper middle income countries. Because the square of

RRT (SQRRT) is found to be significantly negatively correlated with resource nationalism. According to the regression results, the average marginal effect of RRT is 0.865, and the average marginal effect of SQRRT is -1.427. Since the computer calculates the two variables marginal effects independently, we have to calculate the real average marginal of RRT manually. Equation (3-9) to (3-10) present the calculation process. As shown, the average marginal effect of RRT is 0.244. The economic reason why RRT's marginal effect gets weaker when it increases is that all of the surveyed high and upper middle income countries with over 30% of RRT are oil and natural gas producing countries, their energy resources sectors have already been highly nationalized during the last wave of resource nationalism. Therefore, their appeals of resource nationalism have become weak. In lower middle and low income countries, change of contribution of mineral rent to GDP (CMRT) turns out to be significant rather than the concrete contribution of resources sector. It is strongly negatively correlated with occurrence of resource nationalism. It indicates that resource nationalism in those countries are sensitive to fluctuations of the sector. In other words, as long as the mineral sector keeps on dragging a state's GDP, the sovereign state is reluctant to make trouble. The reason why CMRT rather than CRRT dominate resource nationalism policy making is that most surveyed lower middle and low income countries are mineral producers with little energy resources. Quantitatively, 1% decrease of CMRT leads the risk of resource nationalism increase by 15.84% on average. And CMRT is the most sensitive factor for lower middle and low income countries. This reflects high dependency on resources sector and vulnerability to fluctuations of the sector for lower middle and low income states. CMRT is also the source of high volatility of probability of resource nationalism of these countries, which will be presented in 3.4.3.

$$Real(dy/dRRT) = dy/dRRT + dy/dSQRRT \times 2RRT \qquad (3\text{-}9)$$

$$Average\ Real(dy/dRRT) = 0.865 - 1.427 \times 2 \times \overline{RRT} = 0.244 \qquad (3\text{-}10)$$

Besides economic factors, the regression also takes governance of a state into consideration. For high and upper middle income countries, Rule of Law is proved to be significantly negatively correlated with occurrence of resource nationalism. Quantitatively, 1% improvement of RoL can reduce the risk of resource nationalism by 0.201%. According to the World Bank's definition, RoL captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. That's to say, the higher credibility of compliance with established rules a country has, the less it is likely to break the contract, and therefore the less probability of resource nationalism there will be. For lower middle and low income countries, we find that Government Effectiveness (GE) is significantly positively correlated with occurrence of resource nationalism. Specifically, 1% improvement of GE can lead probability of resource nationalism to increase by 1.427%. Based on the World Bank's definition, GE captures perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies. It indicates that effective functioning of the governments of lower middle and low income countries is largely at the expense of severely exploiting industries, especially the natural resources sector. Because improving public and civil services need financial support from those revenues. Looking at the effects of RoL and GE, we find that the marginal effect of GE is almost 7 times higher than that of RoL in absolute value. It indicates that occurrence of resource nationalism in lower middle and low income countries is more sensitive to governance situations than that in high and upper middle income countries. Other aspects of governance of a state such as regulatory quality, voice and accountability, political stability and absence of violence terrorism, and control of corruption don't impact risk of resource nationalism directly, according to the regression results.

Effects of government's attitude toward overseas or private investors on the investment of resources sector is considered in the regression as well. For lower middle and low income countries, we find that Policy Perception Index (PPI) is negatively correlated with occurrence of resource nationalism. According to The Fraser Institute, PPI is a composite index that measures the effects of government policy on attitudes toward exploration investment. Namely, governments who welcome private capital investments are less likely to impose resource nationalism measures at the same time. Specifically, 1% increase of PPI can reduce probability of resource nationalism by 1.063%. It indicates that attitudes toward mining investors or governments' acceptance degrees to capital liberalization play a significant role in resource nationalism policy making for relatively low income countries. For high and upper middle income states, trade openness (TOP) is proved to be significantly negatively correlated with occurrence of resource nationalism, although the marginal effect of it (-0.093) is relatively small. Since TOP represents openness of a country's economy, it can represent a government's attitude to overseas or private investors. Countries are extremely reluctant to damage their established business value chain if they are highly relying on trade. That's explains why countries with high TOP are unlikely to impose resource nationalism measures.

3.4.3 Prediction of Countries' Probability of Resource Nationalism

As shown in Figures 3-1 and 3-2, the cut-off ratio is set to be 9.39% for high and upper middle income group. The model for the group can correctly pick out 73.2% of countries imposed resource nationalism, and specify 69.1% of safe countries. The general correctly classification rate is 69.5%. For lower middle and low income group, the cut-off ratio is set to be 25.50%. The model for the group can correctly pick out 77.4% of countries imposed resource nationalism, and specify 76.0% of safe countries. The general correctly classification rate is 76.4%. From the perspective of classification quality, the model for lower middle and low income group performs better than the other.

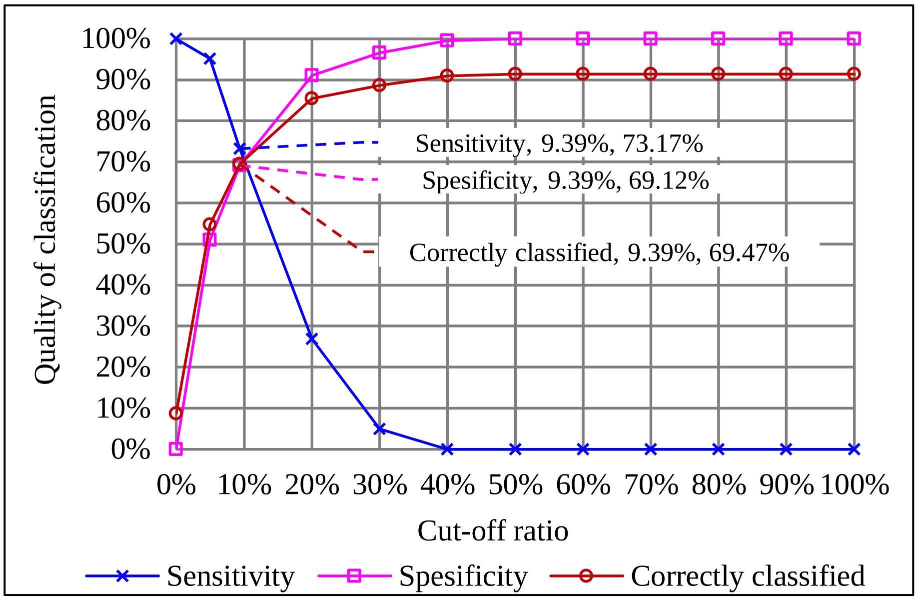

Figure 3-1 Cut-off ratio selection for high and upper middle income group.

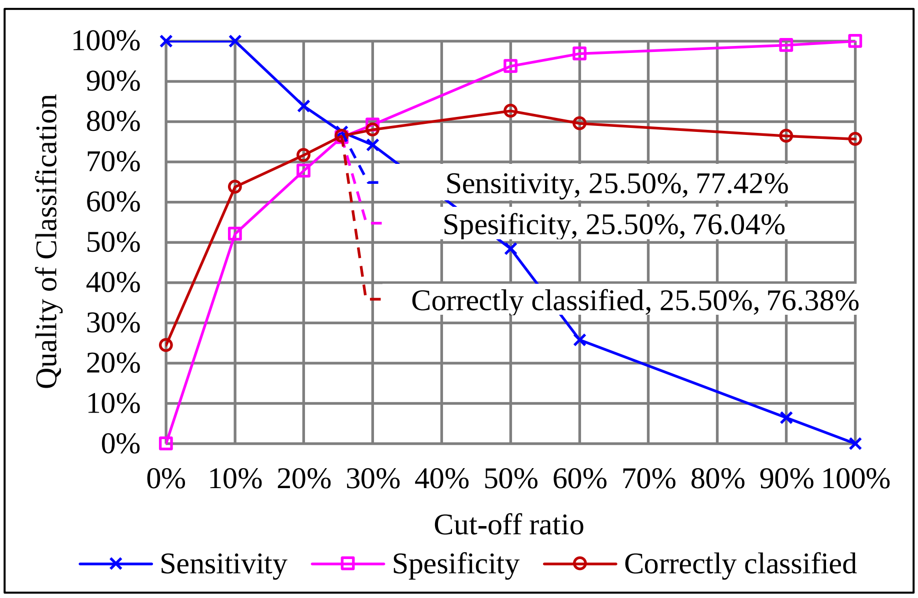

Figure 3-2 Cut-off ratio selection for lower middle and low income group.

After adjusting the cut-off ratio to 50% (Equation (3-5) and (3-6)), we are able to predict the countries' or commodities' probabilities of resource nationalism regardless of their income level. We focus on the period during 2003-2012 due to data availability. 90 countries' probability of resource nationalism are predicted including the estimated ones. 65 out of 90 countries are included in modelling stage. Their probability of occurrence of resource nationalism are either predicted directly from the regression results or by estimation of some missing independent data. Rest 24 countries who are important producers of some natural resources are predicted by applying the modelled equation. Probability of resource nationalism for North Korea is set to be 100% due to its self-isolated regime. Probabilities of resource nationalism in year 2012 for all 90 states are presented in Figure 3-3 and 3-4 as an example. In the figures, numbers: '1, 2, 3' that follow countries' name represent probabilities estimation methods respectively, '1' represents estimation of missing independent variables data, '2' represents estimation for countries excluded in modelling stage, '3' represents special treatment to North Korea, the legend '2012' represents countries' probability of resource nationalism in 2012, the legend 'Average probability' denotes the average probability of resource nationalism during 2003-2012, and the legend 'Annual volatility' denotes the average annual volatility of probability of resource nationalism during the same period. As shown in the figures, average probabilities of resource nationalism are generally higher than the probabilities of that in 2012 for low risk countries, but lower than the probabilities of resource nationalism in 2012 for high risk countries. It indicates polarization of resource nationalism risks. Namely, risky countries tend to be riskier, and safe countries tend to be safer. Moreover, in general volatility of resource nationalism (legend: Annual volatility) shows positive correlation with the probability of resource nationalism (legend: 2012). It means that countries have high probability of resource nationalism are likely to face high volatile resource nationalism policies at the same time. Comparing the probability of resource nationalism from time dimension, we observe that countries passed the threshold (50%) have almost doubled from 18 countries in 2003 to 34 countries in 2012. It indicates the increased risks of resource nationalism globally.

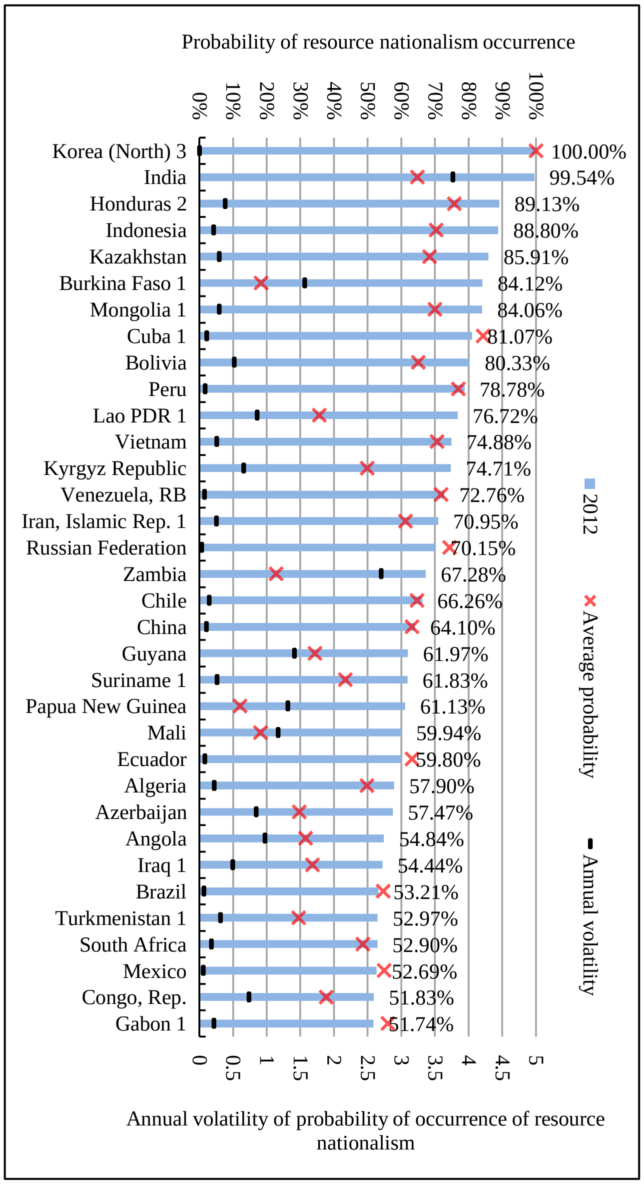

Figure 3-3 Countries' probability of resource nationalism occurrence in 2012 for countries excessed the threshold.

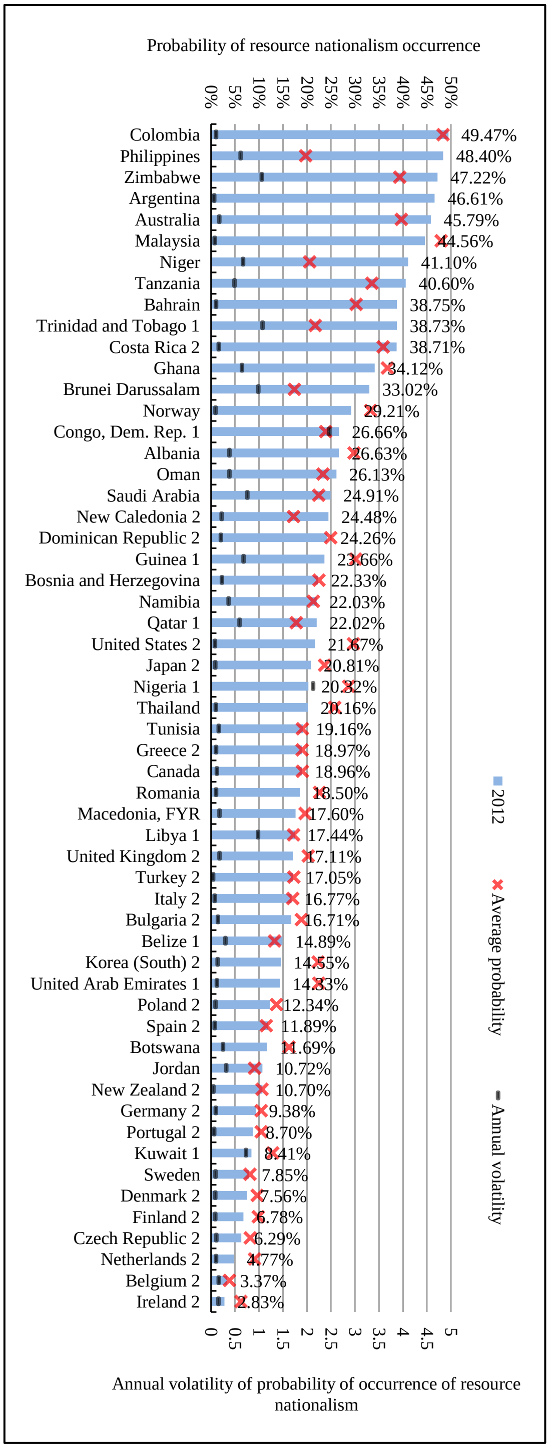

Figure 3-4 Countries' probability of resource nationalism occurrence in 2012 for countries below the threshold.

The following paragraphs of this section 3.4.3 present you the evolvement of probabilities of resource nationalism by region. In East and South Asia & Pacific (Figure 3-5), probability of resource nationalism in North Korea, Indonesia and China were high and were above the threshold (Prob. > 50%) throughout the period. Wherein, Indonesia's probability of resource nationalism witnessed increased trend. Mongolia's and Vietnam's risk of resource nationalism were high as well during the whole predicting period, as presented in Figure 3-6. Malaysia's probability of resource nationalism wondered around 50% (Figure 3-6); this indicates that the country was at the margin of resource nationalism explosion and should be noticed. Australia's probability of resource nationalism crept and was around the threshold since 2010 (Figure 3-6); because the country starts to be cautious on environmental issues relating to natural resources sector (Table E-1). The probability of occurrence of resource nationalism in Papua New Guinea was very low during 2003-2011, but it suddenly surged to above 60% in 2012; it was attributed to a sudden decrease of HTEX of the country in the year. The probabilities of that in Lao PRD and India were very volatile which deserve investors' caution, in which the risk of India became very high since 2007; it is mainly caused by downward fluctuations of CMRT. Relatively less risky countries are Philippines, New Zealand, Brunei Darussalam, Japan, South Korea, New Caledonia and Thailand. While the Philippines's probability of resource nationalism increased largely since the last global financial crisis, and by 2012, it almost approached the threshold; it is mainly due to the consistent decrease of HTEX of the country.

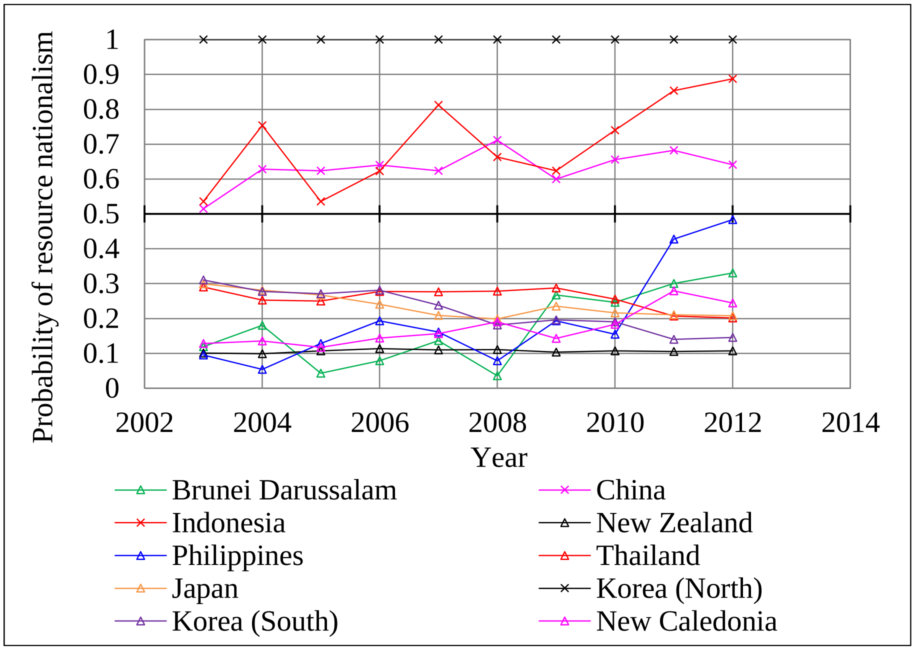

Figure 3-5 East and South Asian & Pacific countries' probability of resource nationalism for countries located at either side of the threshold.

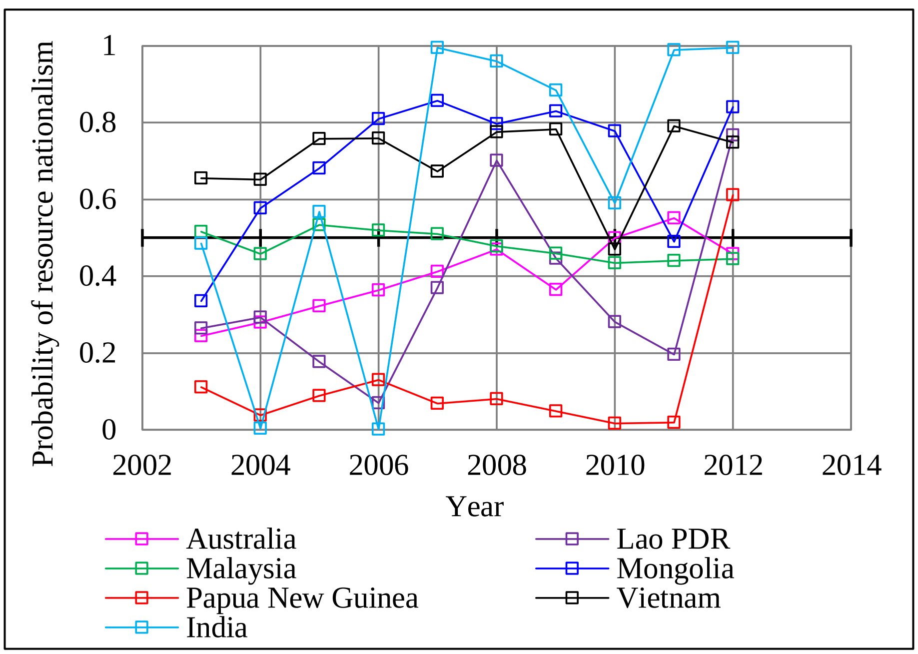

Figure 3-6 East and South Asian & Pacific countries' probability of resource nationalism for countries waved across the threshold.

Most European and Central Asian countries had low probability of resource nationalism during 2003-2013, as displayed Figure 3-7. It mainly benefited from high TOP level. The only country that above the threshold during the whole period is Russian Federation (Figure 3-8) due to the country's high RRT level. But its risk showed declined trend along with the decline of its RRT. Risk of resource nationalism in Kazakhstan was high due to its high MEX and RRT levels and showed increased trend because of the consistent decline of the country's TOP level. And since 2009, the country became the most risky country of the region. Probability of resource nationalism in Azerbaijan and Turkmenistan increased largely since 2008 and excessed the threshold in 2012 (Figure 3-8). For Azerbaijan, it is due to the declined HTEX. As for Turkmenistan, it is caused by sudden increase of RRT in 2009. Kyrgyz Republic's probability of resource nationalism became very volatile since 2008, and became the second risky country of the region since 2011. This is mainly caused by its largely reduced PPI. The probability of occurrence of resource nationalism in Albania once approached to 50% in 2006 due to the peak of MEX of the year, but fell down to safe level since then.

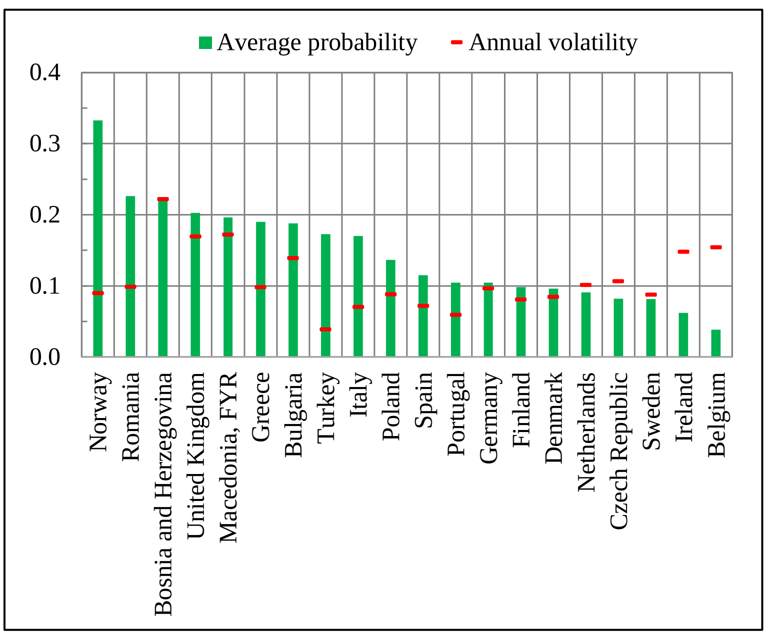

Figure 3-7 European and Central Asian countries' probability of resource nationalism for countries below the threshold.

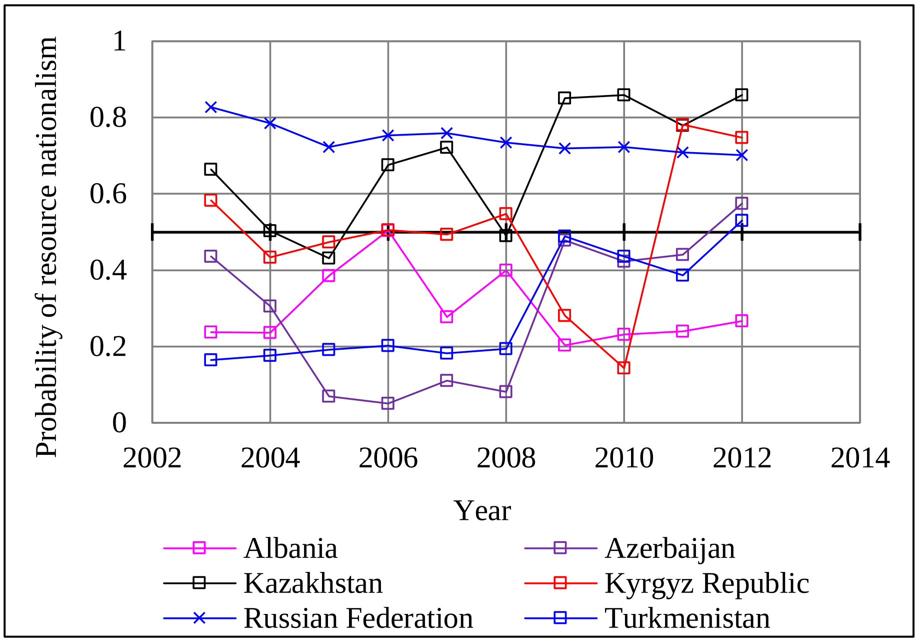

Figure 3-8 European and Central Asian countries' probability of resource nationalism for countries waved across the threshold and above the threshold.

In Middle East & North Africa, the most risky country is Iran in terms of resource nationalism (Figure 3-9). Other two risky countries are Algeria and Iraq (Figure 3-9). Probability of occurrence of resource nationalism in Iraq increased significantly along with the broke out of Iraq War. Probability of resource nationalism in Algeria and Iran shared a "W" shaped growth trend, and stabilized after 2009. This 'W' shaped fluctuation was also witnessed in some other oil producing countries including Kuwait, Oman, Saudi Arabia, Libya, and Qatar (Figure 3-10). It was caused by the peak of crude oil price in 2007 which increased the contribution of resource rent in GDP (RRT). The reason why risk of resource nationalism were not as high as people expected is that despite of heavy dependency on crude oil rent, the region's dependency on trade (TOP) is high. The two aspects dependence can effectively check and balance the abusive resource nationalism behavior.

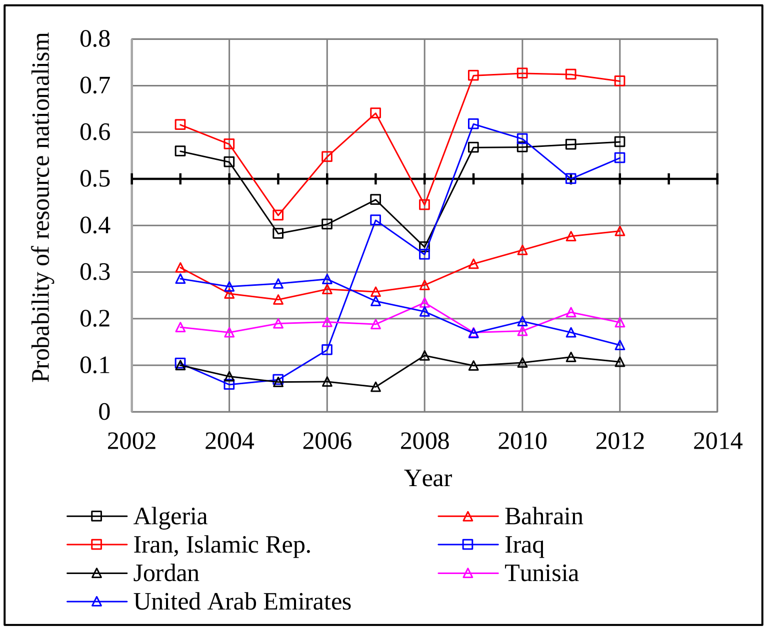

Figure 3-9 Middle East & North African countries' probability of resource nationalism for three risky countries and some safe countries.

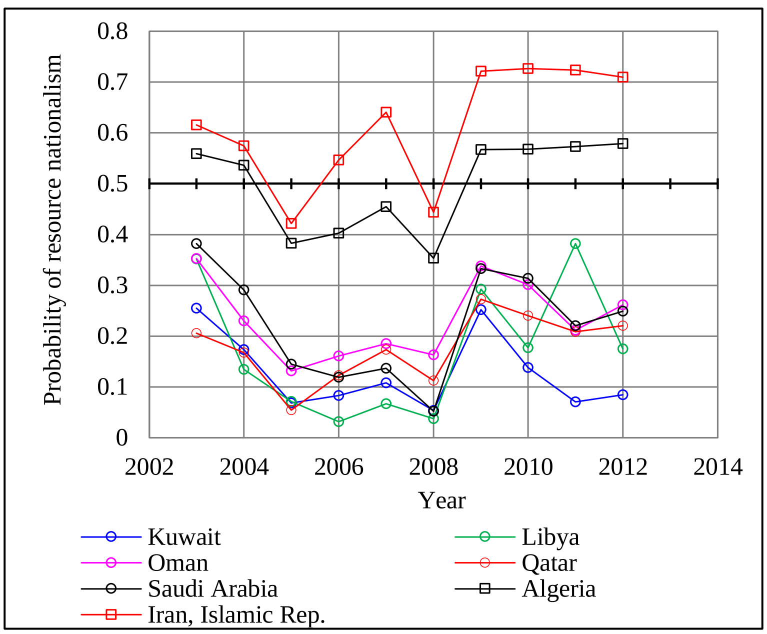

Figure 3-10 Middle East & North African countries' probability of resource nationalism for countries show 'w' shaped fluctuations.

In Latin America & Caribbean and North America, probability of resource nationalism that over 50% throughout the period includes Cuba, Peru, Venezuela, Ecuador, and Mexico (Figure 3-11). High risks of resource nationalism in Cuba, Peru, and Mexico were contributed by their high dependency on ore and metals exports (MEX) to earn foreign currencies. And the high risks of resource nationalism in Venezuela and Ecuador were due to their high economic dependency on resources rents (RRT). As presented in Figure 3-12, Chile's probability of resource witnessed rise during 2003-2006 along with its increased dependency on resources rent, and then remained high afterwards. Bolivia's probability of resource nationalism steeply increased during 2003-2007 along with the country's rapidly deteriorated PPI condition. Probability of resource nationalism in Honduras and Guyana were very volatile due to the fluctuations of CMRT. Countries' risk of resource nationalism that wondered around the threshold are Suriname, Colombia, Argentina, and Brazil, in which the risk in Argentina declined to below 50% since 2009, and the risk in Suriname increased to above 60% in 2012. Oil producing country Trinidad and Tobago also experienced a "W" shaped probability caused by oil price. North American countries are relatively safe and stable. The probability of resource nationalism in Canada and United States converged to 20% by the end of 2012.

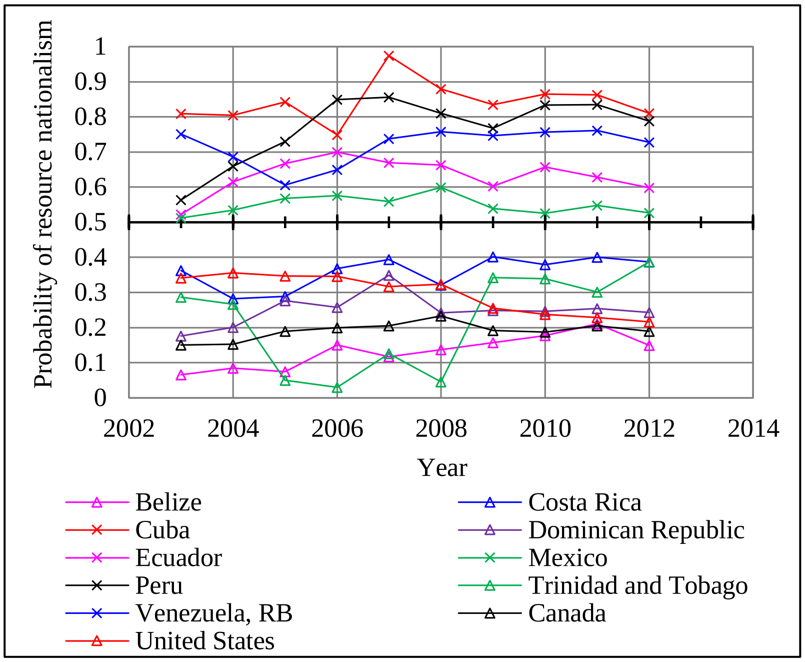

Figure 3-11 Latin American & Caribbean and North American countries' probability of resource nationalism for countries located at either side of the threshold.

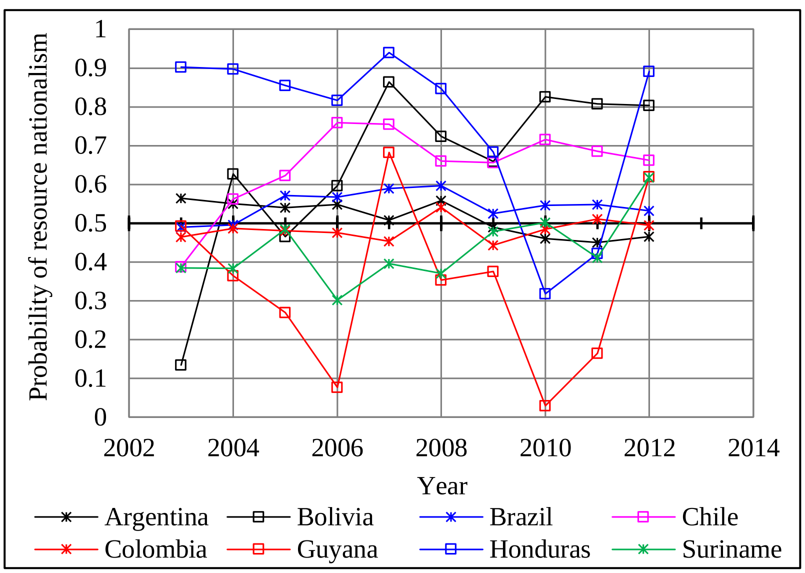

Figure 3-12 Latin American & Caribbean and North American countries' probability of resource nationalism for countries waved across the threshold.

Probability of resource nationalism in Sub-Saharan African countries were very volatile during 2003-2012, as shown in Figure 3-13. It is because that three-fourths modelled countries of the region belong to the lower middle and low income group. In the group, probability of resource nationalism is very sensitive to CMRT. Thus we use 'three periods' moving average' to represent the real modeled probability. Based on the moving average, four risky countries: Angola, Republic of Congo, Gabon, and South Africa are identified, as presented in Figure 3-14. Wherein, Angola's and Republic of Congo's probability of resource nationalism increased since 2009 and were approaching 50% by 2013. According to the modeled result, probability of occurrence of resource nationalism in Botswanan, Ghana, Guinea, Namibia, Niger, and Tanzania were below the threshold throughout the prediction period. It is largely benefited from quickly growing resources sectors (CMRT) which effectively curbed resource nationalism.

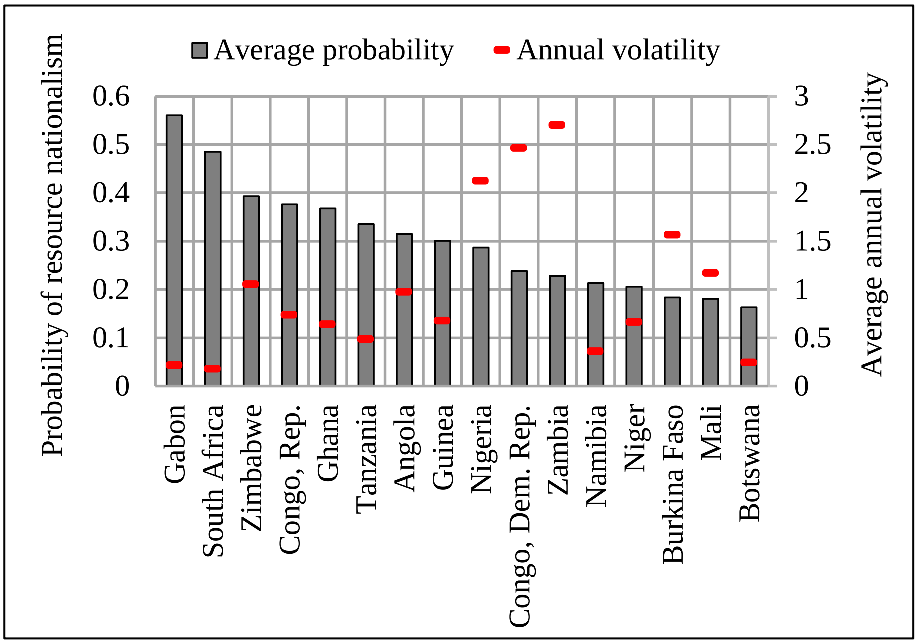

Figure 3-13 Sub-Saharan African countries' probability of resource nationalism.

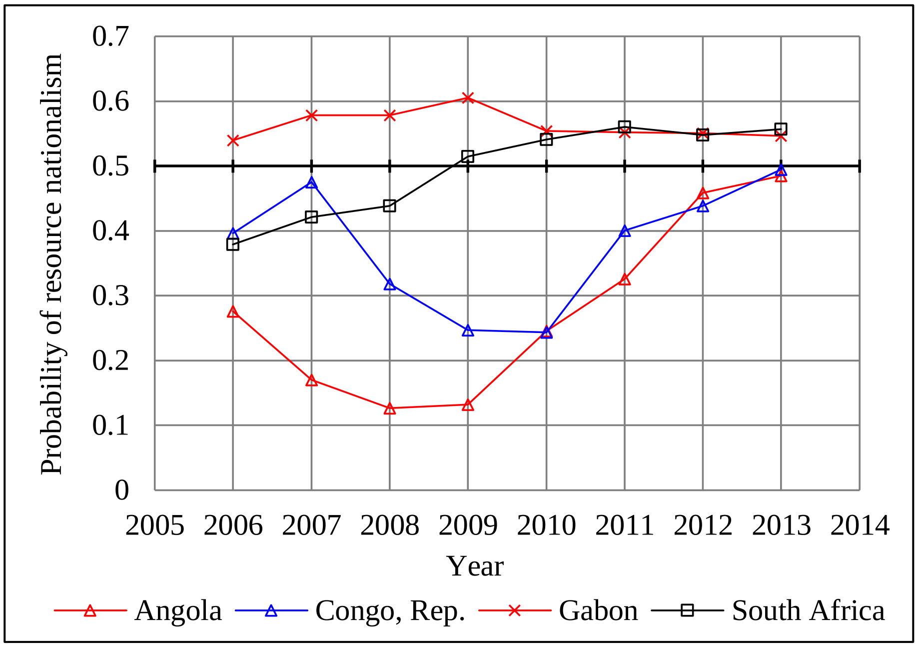

Figure 3-14 Sub-Saharan African countries' three periods' moving average of resource nationalism probability for four risky countries.

3.4.4 Prediction of Commodities' Probability of Resource Nationalism

Regarding metals' probability of resource nationalism, it increased during 2003-2012 for both base and precious metals, except palladium, as presented in Figure 3-15 and 3-16. In general, all of their probability exceeded the threshold by year 2011 and became risky. For tin, its risk of resource nationalism was mainly attributed to China, Indonesia, Peru, and Bolivia, in which China alone contributed around 44% of the risk in average (Figure 3-16). The increased risk level of tin was mainly caused by China and Bolivia. The increased production share of China made Chinese contribution to total risk of resource nationalism grow. And the increased probability of resource nationalism in Bolivia led tin's risk of resource nationalism in the country increase as well. For copper, its risk of resource nationalism was mainly attributed to Chile, Peru, China, Australia, Indonesia, Kazakhstan, Russia, United States, and Zambia (Figure 3-16). The increased risk of copper during 2003-2007 was mainly caused by the increase of probability of resource nationalism in Chile. And the increased risk in 2012 was caused by increased production share of China and increased probability of resource nationalism in Zambia. For lead, its risk of resource nationalism was mainly attributed to China, Peru, and Australia (Figure 3-16). For zinc, its risk mainly came from China, Peru, India, and Australia (Figure 3-16). The increased risks for lead and zinc were led by increased production share of China. For nickel, its risk of resource nationalism was mainly attributed to Russia, Indonesia, Australia, and Philippines (Figure 3-16). And the increased production share of Philippines was the main cause that lifted nickel's probability of resource nationalism up above the threshold during 2011-2012.

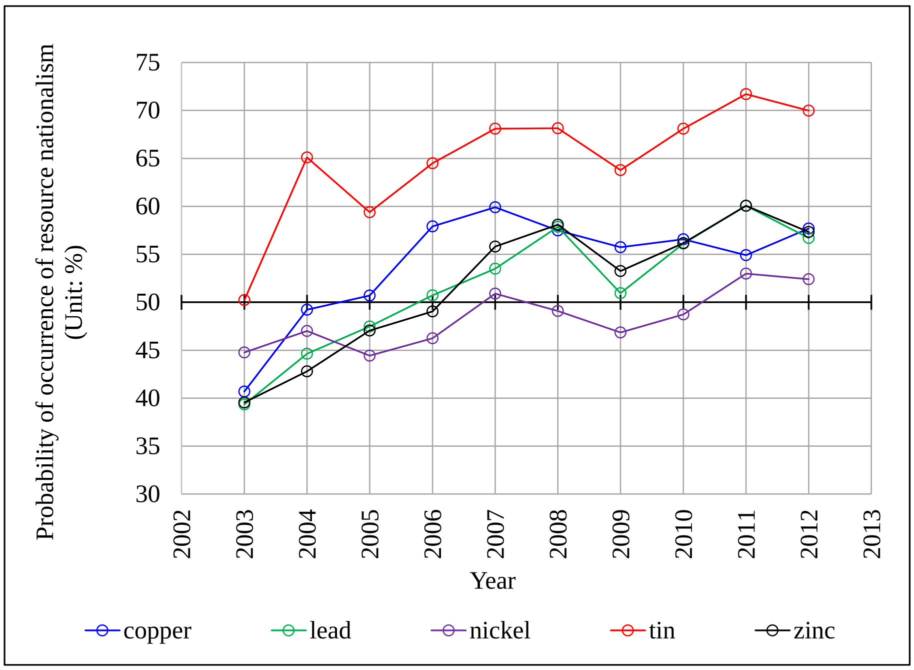

Figure 3-15 Base metals' probability of occurrence of resource nationalism.

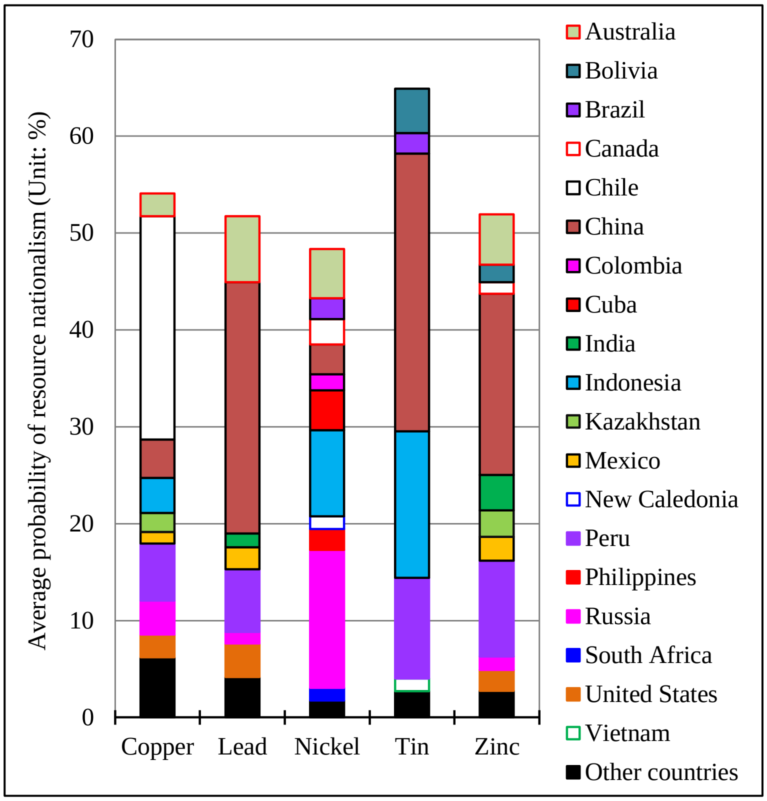

Figure 3-16 Base metals' average probability of resource nationalism during 2003-2012 discomposed by source.

For palladium and platinum, their risks of resource nationalism mainly came from Russia and South Africa (Figure 3-18). Their risks peaked in 2008 and the increased risk for platinum were caused by the increased probability of resource nationalism in South Africa. For silver, its risk of resource nationalism was mainly attributed to several producing countries including Peru, Mexico, China, Russia, Kazakhstan, Chile, Bolivia, and Australia (Figure 3-18). Its increased risk during 2003-2007 was caused by the rose of probability of resource nationalism in Peru. For gold, its risk of resource nationalism was mainly attributed to China, Australia, Peru, Russia, South Africa, Indonesia, United States, and Mexico, in which China and Peru were the main causes of increases during 2003-2008 (Figure 3-18). And during 2009-2011, its increase was caused by China and Australia. In 2012, surged probability of resource nationalism in Burkina Faso, Mali, and Papua New Guinea lifted the risk of resource nationalism for gold further up.

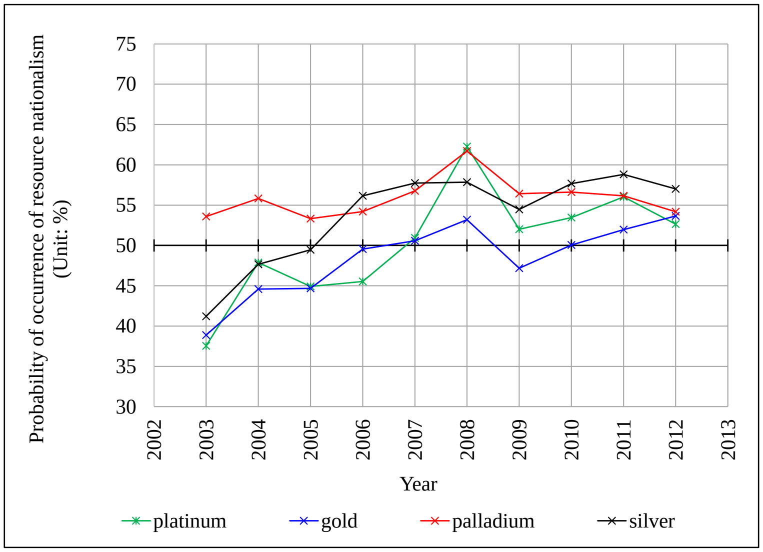

Figure 3-17 Precious metals' probability of occurrence of resource nationalism.

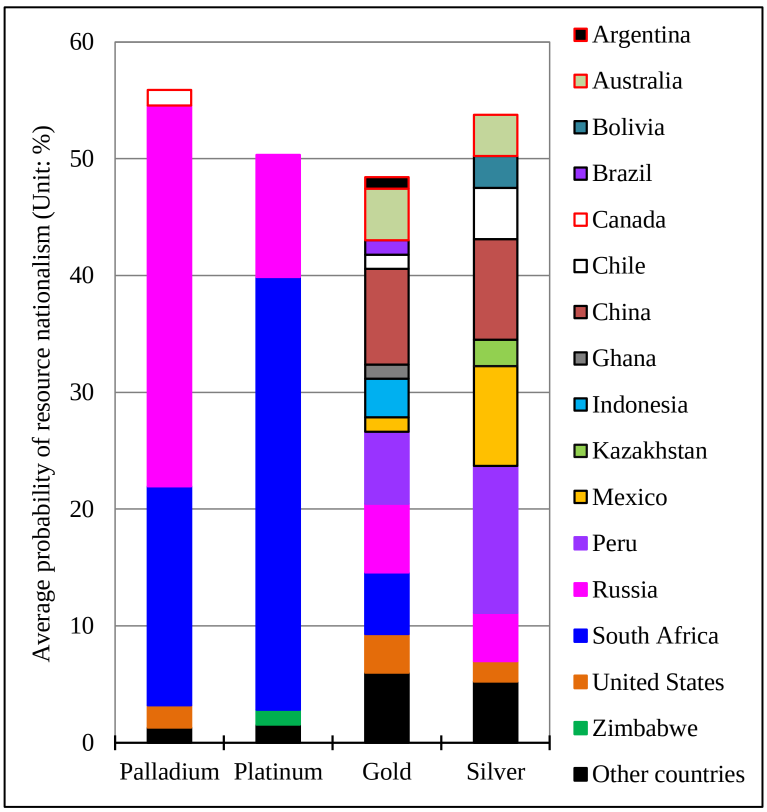

Figure 3-18 Precious metals' average probability of resource nationalism during 2003-2012 discomposed by source.

Probabilities of occurrence of resource nationalism for oil and natural gas turned out to be lower than that for coal (Figure 3-19). For oil, its risk of resource nationalism was mainly caused by Russia, Saudi Arabia, Iran, China, Venezuela, United States, and Mexico (Figure 3-20). The peak in 2009 was caused by the sudden increased probability of resource nationalism in Nigeria. For natural gas, its risk of resource nationalism mainly attributed to Russia, United States, Iran, Indonesia, China, and Algeria (Figure 3-20). The declined risk in Russia roughly compensated the increased risk in Indonesia, China, Iran, and India, thus the risk of resource nationalism for natural gas kept stable. For coal, its risk of resource nationalism mainly came from China, India, Indonesia, United States, Australia, Russia, and South Africa (Figure 3-20). The increased risk mainly caused by China, Indonesia, and India.

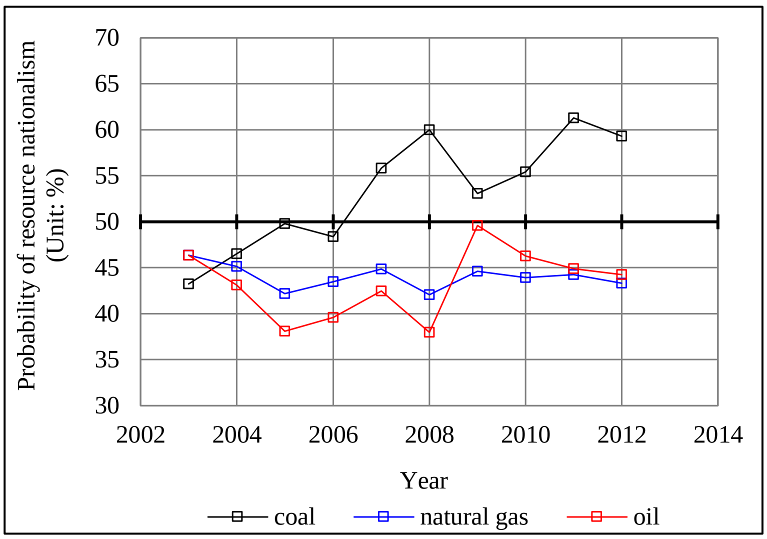

Figure 3-19 Energy resources' probability of resource nationalism.

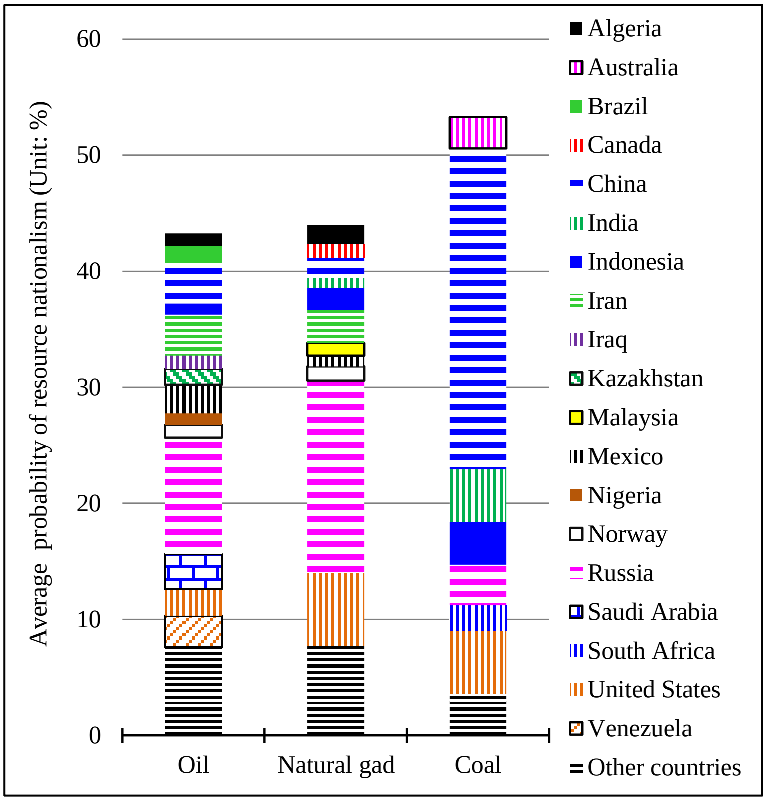

Figure 3-20 Energy resources' average probability of resource nationalism during 2003-2012 discomposed by source.

3.5 Conclusion

A large number of social science reports were unable to summarize out the common genesis of resource nationalism and form theoretical framework on the subject. The author built a binary choice logit model to achieve quantitative analysis of the impact factors of resource nationalism. The study selected 83 natural resources producing states as subjects, investigated into their resource related policies during 2000-2013 and transformed these policies into binary data panel, subdivided these countries into two groups according to income level, and then modelled by group. Regression results indicate that High-technology export (% manufactured export), ores and metals exports (% merchandise exports), rule of law (world governance indicator), trade (% GDP), and natural resource rent except forest (% GDP) are significant for high and upper middle income group countries; government effectiveness (world governance indicator), policy perception index (The Fraser Institute), high-technology export (% manufactured export), and change of mineral rent (% GDP) are significant for lower middle and low income countries. Using modeled results and supplementary estimations, we are able to predict 90 countries probability of resource nationalism during 2003-2012. Top 10 risky countries in 2012 are predicted to be North Korea, India, Honduras, Indonesia, Kazakhstan, Burkina Faso, Mongolia, Cuba, Bolivia, and Peru. Combining with resource production data, we are able to predict the probability of resource nationalism for 5 base metals including copper, nickel, zinc, lead, tin, 4 precious metals including gold, silver, palladium, platinum, and 3 energy resources including oil, natural gas, coal. The most risky commodity is tin among 9 types of metals. Other metals are above the threshold as well, which requires attention. Most risky energy resource is coal compared to oil and natural gas. The study is the first step from qualitative description to quantitative estimation on causes of resource nationalism. It can support primary evaluation of resource nationalism for countries and commodities and provide some insights to theoretical analysis of the issue. But the study cannot deliver too much information on specific issue, project based survey at local level is still required for investments. We take countries as independent individuals, so the effects of geopolitical status are not measured. Further study may investigate into the effects of geopolitical and economic environment to resource nationalism.

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Chapter 4 The long-term supply risk measured by supply shortage

4.1 Introduction

Long term raw material supply risk consideration should focus on imbalance of supply and demand prospects. Because physical constraints is an insurmountable and one of the most important source of unrenewable resources' supply risks. Even though metals won't perish after using, but limited recovery and substitution indicate that there will be a depletion date, economically, technically, and finally physically. To measure supply shortage, estimation of supply and demand are necessary. And to dynamically evaluate the shortage, estimating the technology progresses led demand changes are of great importance. Therefore, rather than looking at metal supply and demand in general, it is more reasonable to concentrate on a specific industry or technology. In summary, we carry out a case study of silver supply risk for c-Si PV. The case represent a core framework of supply shortage according to our view.

The number of installed PV capacity had been rapidly growing worldwide, from less than 13 GW in 2000 to more than 178 GW in 2014 (EPIA, 2014; SPE, 2015). Among them, c-Si PV cells account for roughly 85–90% of the market (IEA, 2010; IEA, 2014; The CPM Group, 2015; ITRPV, 2015). Thin film PV once took 16% of the market share in 2009, but decreased to 10% by 2013 (IEA, 2014). Silver is contained in metallization pastes of c-Si PV cells, and is one of the most process-critical raw materials for PV manufactures (ITRPV, 2014; Radziemska and Ostrowski, 2010). The demand of silver for them witnessed sharp surges from 1.0 million troy ounces to 62.7 million troy ounces during 2000-2014. The demand accounted for 7.2% of silver manufacture demand in 2014 (The CPM Group, 2015). According to official PV installation projections for China, the United States, Japan, and the European Union (EPIA, 2010; IEA-PVPS, 2010; U.S. Department of Energy, 2012; IEA-PVPS, 2013), PV technology holds high installation potential. And seeing that c-Si PV technology is likely to maintain dominant position in PV market (The CPM Group, 2015), its demand of silver will surge. Thus, c-Si PV industry is likely to compete with other industries for silver and aggravate silver supply shortage accordingly.

I In this study, we focus on estimating the global silver supply shortage for the deployment of c-Si PV technology over the long term, spans from 2015 to 2050. By saying for c-Si PV, we mean discussing the impact of uncertainty of silver demand in the c-Si PV industry on silver supply shortage for manufacturing demand overall, and especially for the c-Si PV industry. Even though a supply shortage will be equally allocated to various demanders, the implementation of PV recycling may decrease the c-Si PV industry's dependence on the silver raw material supply market. Therefore, a supply shortage of silver for the c-Si PV sector may differ from that for other usages.

Specifically, silver supply shortage is measured by the difference of manufacturing demand and stock outflow, where silver manufacturing demand is estimated by usage and the stock outflow depends on remaining stocks from previous periods and real-time supply. Silver supply is made up of mining supply which is estimated by source, and recycling supply which is estimated by silver weighted lifetime and end-of-life recycling rate. PV industry's technological uncertainties are intensively discussed by using seven scenarios. They are: base scenario, PV lifetime prolongation, technology shift, efficiency improvement, silver demand rate reduction, PV recycling, and total effects (of foresaid five aspects of technological considerations). According to the estimated results, we put forward policy advice for the PV sector, in order to decrease potential silver supply risk. The remainder of the paper is organized as follows: the second part defines the assessment boundary and algorithms. The third part introduces the scenarios we considered. The fourth part presents results and discussion. The last part concludes the article.

4.2 Literature Review

At a global level, long-term supply of silver poses a risk due to its limited resource potential, relatively high by-product ratio, and low human development in producing countries (Nassar et al., 2012) (Nassar et al., 2012; Graedel et al.,2015). At a regional level, silver is classified as being less risky for the EU, but its supply risk for emerging technologies does exist (Angerer et al., 2009; EC, 2010; EC, 2014). At a national level, KfW Banking Group's study indicates supply risk, and vulnerability to silver for German and UK industries is high because of the increasing demand in contrast to its limited resource potential and high by-product ratio (Erdmann et al., 2011; Gloser et al., 2015; Morley and Eatherley, 2008; Nassar et al., 2012). However, silver is not listed among critical materials for the United States and Japan, with regard to supply risk and economic importance (U.S. Department of Energy, 2011; U.S. Department of Defense, 2013; JOGMEC, 2015). At an industry level, UK Energy Research Centre (Speirs et al., 2013) summarized that silver is not risky for photovoltaic (c-Si), Concentrated Solar Power (CSP), and nuclear technologies currently, but has the potential to become more of a risk, according to the results of Angerer et al. (2009), EC (2010), Morley et al. (2008), Moss et al. (2011), and Nassar et al. (2012). Moss et al. (2013) concluded that the supply risk of silver for c-Si PV may come from limitations on expanding production capacity in the short to medium term, and political risk related to major supplying countries. In a word, although silver is generally excluded from the very risky materials category, the outlook of the long-term supply of it is unfavorable. A silver supply shortage probably will emerge in the long run, along with increasing demand for emerging technologies, especially for c-Si PV. In this research, there is an assumption about a certain geological availability, but no account is taken of the presence of political constraints.

Sverdrup et al. (2014) studied long-term supply and demand of silver by system dynamics, in which intensity of use, regardless of specific usages, are used to simulate silver demand. Henckens et al. (2014, 2016) calculated the scarcity of silver and 41 other metals, assuming constant demand growth rates for the metals. Those studies did not take uncertainties in emerging technologies like PV into account. Grandell and Thorenz (2014) researched on the availability of silver in the solar sector, but used a static silver supply level from 2010. As far as we know, dynamic assessment of silver supply for c-Si PV is absent. Choi et al. (2016) analyzed the availability of Indium for the deployment of clean energy technologies, and took Indium demand for other sectors as a constant input. Houari et al. (2014) analyzed Tellurium supply for CdTe PV, and also assumed a constant demand growth rate of tellurium for non-energy sectors. Unlike indium and tellurium, the majority of demand for silver is for other usages, and therefore should be considered in detail.

4.3 Methods

The flow of silver assumed in the model is presented in Figure 4-1, wherein a primary silver resource pool, made up of sources where silver is mainly in existence and sources where silver co-exists, is assumed and technically estimated by the authors. Silver mining production depletes primary resources at respective rates, according to mining sources. Together with recycling production from old scraps, except that end of life c-Si PV panels, they flow to the silver supply market where manufacturers claim demands. Specifically, the market stock absorbs silver supply as stock inflow and distributes to manufacturers by stock outflow. It acts as a buffer to balance real-time supply and demand. The manufacturing demand for silver depends on demand for c-Si PV, jewelry and silverware, electronics and batteries, photography, and other manufacturing products, which can each be predicted by trends of intensity of demand. Recycling of retired c-Si PV is estimated individually due to the absence of a recycling facility and a limited amount of waste (Goe and Gaustad, 2014; McDonald and Pearce, 2010). It is added in the PV recycling scenario and directs to PV manufacturers under an extended producer responsibility framework. Additionally, silver new scraps recycling production is excluded, as it was a historically minimal part of the total silver recycling supply (The CPM Group, 2015).

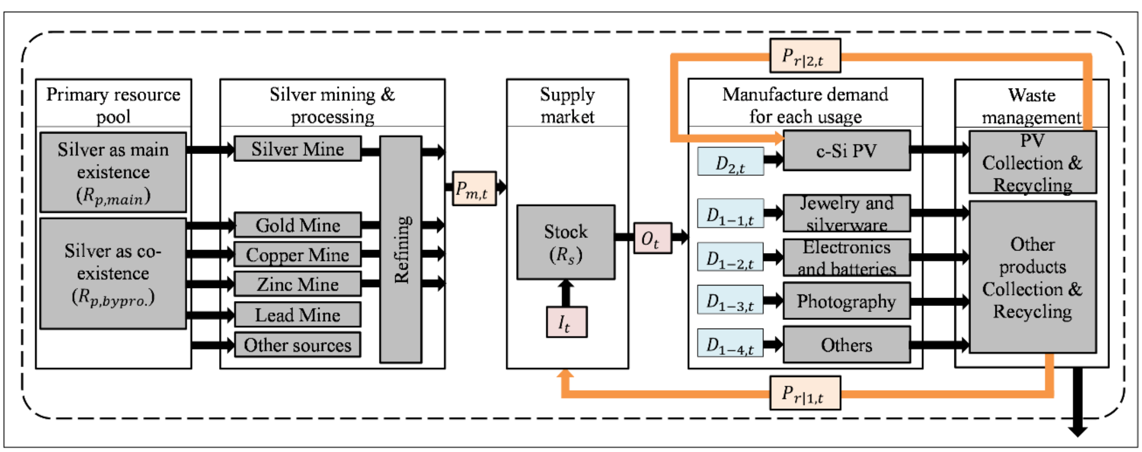

Figure 4-1 Simplified silver life cycle and flow.

In the model, real time silver supply shortage appears when manufacturing demand exceeds the available stock in the supply market. Concretely, stock reservoir (set to zero at the beginning of modeling) digests the real time excess supply when manufacturing demand is less than the mining and recycling supply. When the mining and recycling supply is short, stocked silver in the reservoir makes up for manufacturing demand, whereby, supply shortage appears if stock runs out but demand is not fully fulfilled. The real-time shortage for a year could be met by above-ground sources, thus it is not added to the next year's manufacturing demand. As for silver supply shortage for the c-Si PV industry, in the base scenario, the PV sector suffers the same market risk as other manufacturers. However, if PV recycling were in place, it could be relieved or eliminated by using recycled silver from retired PV panels. In fact, silver resources are profuse according to abundance of the chemical elements (Henckens et al. 2014, 2016), and above-ground stocks held by governments and investors are extensive. Therefore, the shortage of silver supply in our estimated period could be fulfilled by speculative selling of investors, releasing of governments' stocks, or exploration of ultra-low-grade mines. Those silver sources involve excessive uncertainty and extremely high costs, which deserve close attention. In other words, the silver supply shortage estimated in this study represents the quantity involved at high costs, which could be uneconomical. Table 4-1 displays the definitions of parameters and variables used in the model.

Table 4-1 Definitions of parameters and variables of the model.

Symbol	Brief Definition	Unit
$\boldsymbol{R_p}$	Primary resources	Metric ton
$\boldsymbol{R_s}$	Above-ground stock	Metric ton
$\boldsymbol{P_{m,t}}$	Silver mining production	Metric ton
$\boldsymbol{P_{r/1,t}}$	Silver recycling production from old scraps excluding retired c-Si PV	Metric ton
$\boldsymbol{P_{r/2,t}}$	Silver recycling production from end-of-life c-Si PV	Metric ton
$\boldsymbol{O_t}$	Outflows from the stock	Metric ton
$\boldsymbol{I_t}$	Inflows into the stock	Metric ton

$\boldsymbol{D_t}$	Silver manufacturing demand	Metric ton
$\boldsymbol{D_{u,t}}$	Silver demand for u. If u=2, for c-Si PV; If u=1-1, for Jewelry and silverware; If u=1-2, for Electronics and batteries; If u=1-3, for Photography; If u=1-4, for others.	Metric ton
EOL-RR	End-of-life recycling rate	%
$\boldsymbol{\Lambda}$	Maximum silver weighted lifetime	Year
$\boldsymbol{Q_{m,t}}$	cumulative production at year *t* in mine type *m*	Metric ton
$\boldsymbol{URR_m}$	Ultimate recoverable silver resources in *m* mines	Metric ton
$\boldsymbol{p.d.f.}(\boldsymbol{\lambda})$	Probability distribution of silver lifetime	
$\boldsymbol{C_{c-Si\ PV}}$	Installed capacity of c-Si PV cells per year	Giga Watt
$\boldsymbol{E_{c-Si\ PV}}$	Electricity conversion efficiency of c-Si PV cells	kW/m^2
$\mathbf{D}\boldsymbol{R_{c-Si\ PV}}$	Silver demand rate of c-Si PV cells	g/m^2
$\boldsymbol{MS_{c-Si\ PV}}$	Market share of c-Si PV in PV market	%
$\boldsymbol{CR_{PV}}$	Collection rate of retired PV	%
$\boldsymbol{RPE_{Ag\ in\ PV}}$	Silver recycling process efficiency	%

4.3.1 Silver Mining Supply

Silver was mined from mineral deposits (78% in 2014) as primary resources and recycled from old scrap as secondary resources (22% in 2014) (The CPM Group, 2015). For mining supply, around 30% came from silver mines as main product, around 55% were contributed by gold, copper, or lead-zinc mines as by products, the remaining 15% came from some other mine sources (SNL, 2014). Therefore, we estimate silver supply respectively by source.

Silver mining supply is modeled using logistic regression: the Hubbert curve (Hubbert, 1956, 1962). The Hubbert peak theory assumes a bell-shaped production trend due to the addition of discovery and infrastructure before the peak and resource depletion after the peak. The method was invented to predict oil production peaks, and then was adopted to metals (Bardi and Pagani, 2007; Sverdrup et al, 2013, 2014). Although applying the peak theory to metal production suffered criticism from those who questioned the validity of assumptions on URR that underlie the method, and the failure to address the market mechanism in adjusting production and consumption (Crowson, 2011; Ericsson and Soderholm, 2010; Graedel et al., 2014), the method is feasible to our study for following reasons. Firstly, the URR of silver estimated in this model is not limited to currently identified reserves, but also includes future resources potential from low-grade ores. Secondly, the rigidity of mining supply is high due to long project time required, and the high by-product dependency of silver mining production makes its supply less elastic to market demands.

Silver mining productions from gold and silver mines are estimated by Equations (4-1) and (4-2). Specifically, given URR (estimated by authors), production (from SNL, 2014), and cumulative production (from SNL, 2014) data dated back to 1984, parameter b and t_{max} are determined by Solver optimization in excel. URR is identified by the trend that ore's grade (from SNL, 2014) declines with cumulative production (Henckens, 2016; Prior et al. 2012; Tilton, 2003). We take 0.1 gram per ton of ore produced as the lower limit of the grade. As a result, remaining silver resources in silver mines and gold mines are found to be 632,530 ton and 191,591 ton respectively in 2015 (Figure I-1, I-2 and I-9, I-10 in Appendix I).

$$Q_{m,t} = URR_m / \{1 + \exp[-b_m \times (t - t_{max})]\} \qquad (4\text{-}1)$$

$$P_{m,t} = Q_{m,t} - Q_{m,t-1} \,. \qquad (4\text{-}2)$$

Silver mining supply from copper, zinc, and lead mines are estimated indirectly by Equations (4-1) and (4-2). Specifically, we estimate the production of main metals in the respective metal mines from the above equations, using their resource potentials reported by the U.S. Geological Survey (Figure I-3-5 in Appendix I). They are 3.5 billion tons for copper, 1.9 billion tons for zinc, and 2 billion tons for lead. Then, according to the trends of "silver production/main product production" in those sources, silver mining supply from each of them are estimated respectively (Figure I-6-8 in Appendix I). The reason for adopting indirect estimation is that the relations of silver grade and cumulative production in those mines no longer hold true because their silver content is relatively low and does not have to be a principal index for measuring the economic value of these deposits. As a result, remaining silver resources in 2015 from copper, zinc, and lead mines are estimated to be 308,921 tons, 64,625 tons, and 9,107 tons respectively (Figure I-11-13 in Appendix I).

In addition, silver mining supply from other sources counts for 15% (volatility: 3%) of the total mining supply on average during 1993-2012 (SNL, 2014; The CPM Group, 2015), and the ratio is applied to represent silver mining supply from other sources.

4.3.2 Silver Recycling Supply Excluding Those from PV

The authors assume that silver recycling supply from old scraps excluding PV is a function of generation of old silver scrap and EOL-RR, wherein, scrap generation depends on the weighted lifetime of all silver containing products. This is estimated by applying a Weibull probability distribution function (p.d.f.). The Weibull distribution is commonly used for life-time simulation (Murakami et al., 2010; Daniel et al., 2007). The EOL-RR measures recycling rate as a ratio of the recycled amount of a metal to the total amount of the metal contained in end-of-life products of a year (UNEP, 2011). It is assumed to be a constant in the study. Equation (4-3) shows the specific calculations.

$$P_{r/1,t} = \int_{i=1}^{\Lambda}\left[\left(D_{t-i} - D_{2,t-i}\right) \times p.d.f.(\lambda) \times EOL - RR\right] \qquad (4\text{-}3)$$

In the model, Λ is assigned to be 20 years. According to The silver institute (2014), except that for PV, silver are mainly used for electronics, batteries, jewelry, silverware, photography, coins and medals, bearings, brazing alloys and solders, and catalysts. In particular, electronic products' life time ranges from 5 to 15.25 years, summarized by U.S. EPA (2011); silver oxide battery's service time ranges from 1 to 3 years according to

Microbattery (2012); jewelry and silverware are more likely to be traded or scraped for monetary value, thus recycling of them are largely affected by silver price (The silver institute, 2013, 2014; Goonan, 2014); silver coins and medals are likely to be preserved and traded as the way they are, thus they do not contribute to old scrap recycling; films for photography are recycled just after use, their lifetime varies from days to years; life time of bearings varies and the quantity of recycled silver from them are unknown (Goonan, 2014); recycling of silver from used brazing alloys and solders varies depending on where and for what it is used; life time of silver catalysts in ethylene oxide reactors is around 2.5 to 3 years (Goonan, 2014). Therefore, assigning the maximum 20 years life time should be enough for estimation.

Since EOL-RR is assumed to be a constant, the product of silver weighted lifetime and EOL-RR (p.d.f.(λ)×EOL-RR), which represents the generation of recyclable silver, also follows a Weibull distribution. Using historical recycling supply data (from The CPM Group, 2015), given the predefined scale parameter, estimation of shape parameter κ can be achieved by Solver. As a result, κ is determined to be 0.25. As shown in Figure 4-2, estimated average EOL-RR of silver is 30%. It also shows that more than half of recycled silver gets recycled within four years. Within 10 years, roughly 80% of it gets recycled.

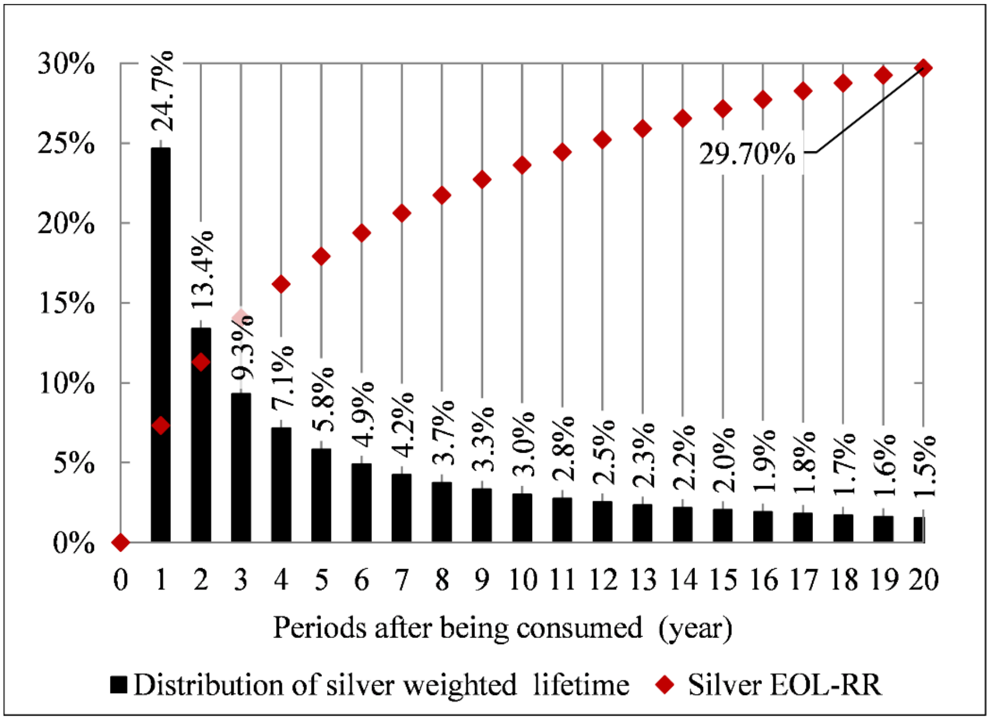

Figure 4-2 Weibull distribution of silver lifetime.

4.3.3 Silver Demand for c-Si PV

Silver demand for c-Si PV depends on expected installation of c-Si PV capacity, silver demand rate, and electricity conversion efficiency of the c-Si PV panels (Eq. (4-4)). In the base scenario, we apply current demand rate and efficiency level to the future and use the High-REN scenario of IEA to predict the expected PV installation.

$$D_{PV,t} = (C_{c-Si\ PV,t} \times DR_{c-Si\ PV,t})/E_{c-Si\ PV,t} \qquad (4\text{-}4)$$

Specifically, International Energy Agency predicted that PV would generate roughly 2500 TWh/Year of electricity in 2050 in the BLUE Map scenario (IEA, 2008). Two years later, an almost doubled outlook (3000 GW of installed PV capacity by 2050 in the Roadmap Vision scenario) was justified by PV market growth and associated cost reduction at that time (IEA, 2010). By 2014, contributed by the unexpected improved technology and costs reduction, a total installation of 1,721 GW by 2030 and 4,671 GW by 2050 globally was predicted in the High-REN scenario (IEA, 2014). We adopt the least one (High-REN scenario) to estimate future installation of PV. To realize the projection, annually installed new PV capacities should increase 9.4% every year from 2014 to 2030, and then decrease 1.8% yearly by the end of 2050, shown in Figure 4-3: Annual installation (New). Considering that lifetime of PV panels vary from 20 years to 40 years, and normally are given to be 25 years at minimum 80% of rated output (ITRPV, 2016; IEA, 2010, 2014). Thus in the base scenario, silver demand for PV for replacement is added after 2025 by assigning a constant lifetime of 25 years, shown in Figure 4-3: Annual installation (New+Replace). Within the installed PV panels, c-Si PV technology persistently dominants the PV market for around 90% due to good performance (IEA, 2008, 2010, 2014; ITRPV, 2014, 2015, 2016), and is expected to dominant PV market in the foreseeable future (The CPM group, 2015). In the base scenario of the study, we assume that c-Si PV will maintain its market share: 90% during the forecasted period.

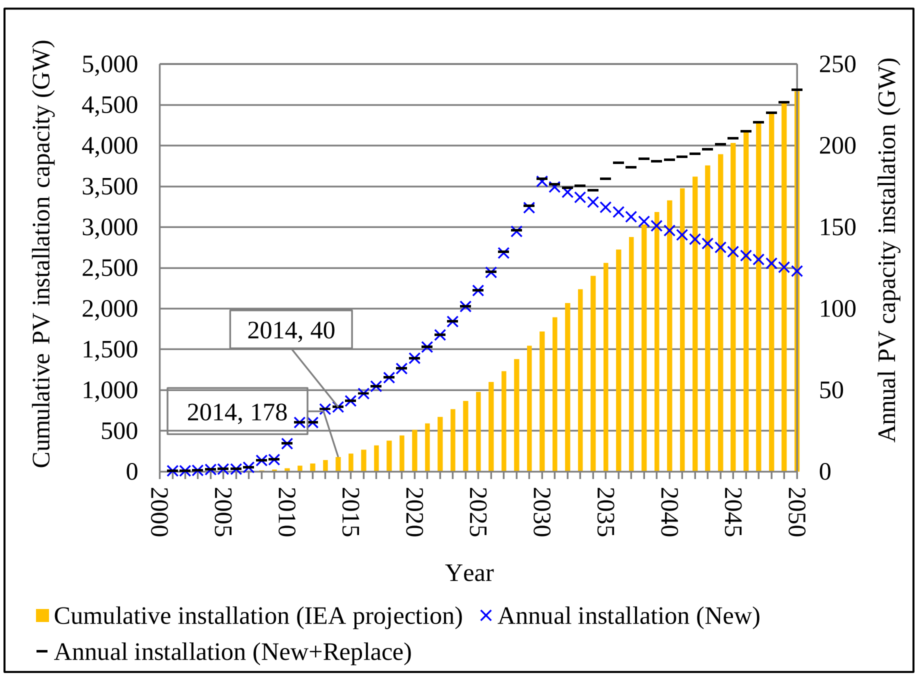

Figure 4-3 Predictions of annual and cumulative installation capacity of PV.

Moreover, according to IEA (2014), the average electricity conversion efficiency of commercial silicon modules reached 0.16 kW/m^2 (kilowatt per square meter of PV cell) in 2013. The current silver demand rate for PV is represented by the ratio of total silver demand for c-Si PV in 2014 (The CPM Group, 2015) and the total installed c-Si PV capacity of the year (SPE, 2015). The calculated ratio indicates that roughly 8.77 g/m^2 (gram per square meter of PV cell) on average is needed currently. Therefore, an E=0.16 kW/m^2 and a DR=8.77 g/m^2 are applied in the base scenario.

4.3.4 Silver Manufacture Demand for Other Applications

Classification of silver manufacture demands is based on statistics from The CPM Group (2015). In 2014, 33% of silver was used in jewelry and silverware, 26% in electronics and batteries, 9% in photography, 7% in PV, and 25% in other manufacturing uses (The CPM Group, 2015). Those demands, except for PV, are simulated on the basis of their historical intensity of demand (ID) by either population or GDP, wherein, the prediction of population is from the World Bank, and GDP is regressed by population (Figure J-1-2 in Appendix J). The reason for considering silver demand for c-Si PV individually is that PV sector is in the emerging stage, which involves high amounts of uncertainty.

Demand of silver for jewelry and silverware is the most sensitive source of manufacture demand to price and price volatility (The CPM Group, 2015). However, in the long run, their per capita demand depends more on people's preference and affluence. Figure 4-4 plots the regional demand of silver per person for them. By the way, be noticed that in all intensity of demand figures, data from 1980 to 2014 are historical documentation (The CPM Group, 2015), data from 2015 to 2050 are estimated ones. In United States (US) and Japan (J), respective average intensity of demands for jewelry and silverware during 2000-2014 are taken as those for 2015 to 2050, because those two countries are developed economies and their demand intensities were relatively stable. It is 1.39 gram per person in United States, and 0.72 gram per person in Japan (Eq. (4-5) and (4-6)). In Western Europe (W.E.), intensity of silver demand for jewelry and silverware was much higher than that in other regions due to their favor of silverware like silver cutters and plates. But it suffered of steadily falling since 1997 which might be caused by declined interests in silverware among young generations. Thus, we apply the decline trend during 1997-2014 to the future stages, displayed in Eq. (4-7). Economic took off of China (CN) made its demand intensity of silver in jewelry and silverware multiplied for almost 10 times since 2000. We apply its current linear trend to forecast future demand intensity, and set the intensity level of United States as upper boundary, displayed in Eq. (4-8). In view of the upward trend of other countries' (O.C.) silver demand intensity for jewelry and silverware, we take average increase rate during 2007-2014 (1.80%) to forecast, and set the same upper boundary as that for China, displayed in Eq. (4-9).

$$ID_{j\&s,US,t} = 1.39 \qquad (4\text{-}5)$$

$$ID_{j\&s,J,t} = 0.72 \qquad (4\text{-}6)$$

$$ID_{j\&s.,W.E.,t} = 9.37 \times 10^{36} \exp(-4.12 \times 10^{-2} \times t) \qquad (4\text{-}7)$$

$$ID_{j\&s,CN,t} = Min(7.77 \times 10^{-2} t - 1.55 \times 10^{2}, ID_{j\&s,US,t}) \qquad (4\text{-}8)$$

$$ID_{j\&s,O.C.,t} = Min(ID_{j\&s,O.C.,2014} \times (1 + 1.80\%)^{t-2014}, ID_{j\&s,US,t}) \qquad (4\text{-}9)$$

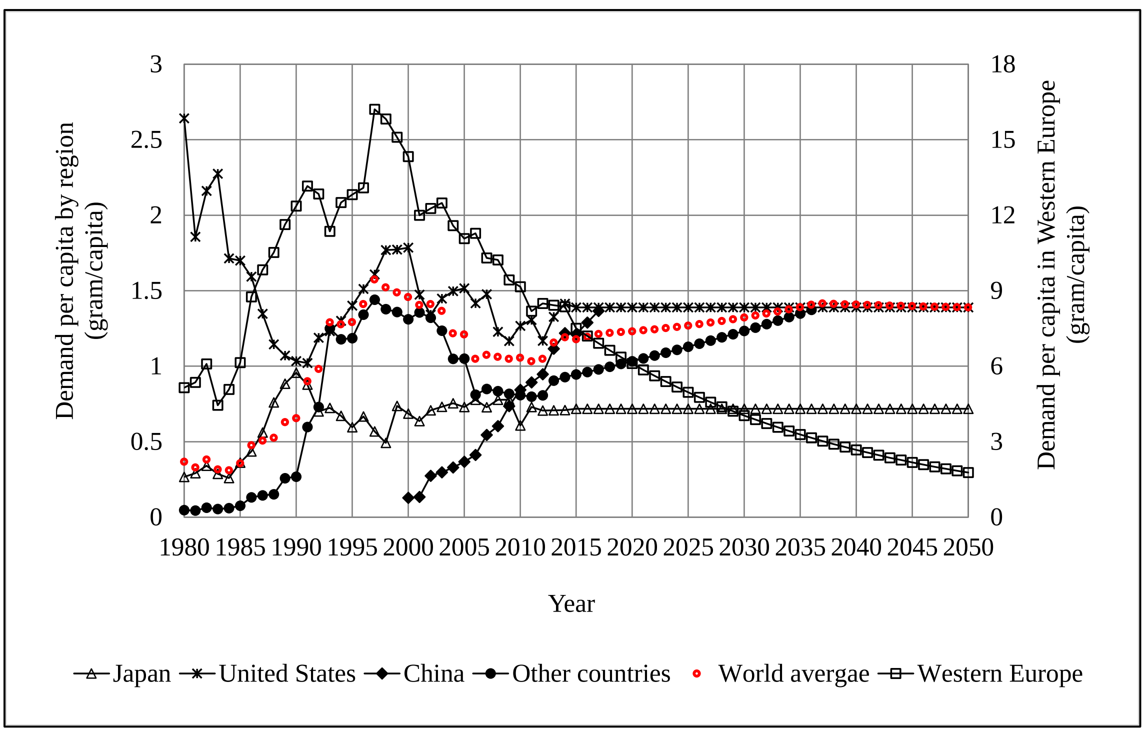

Figure 4-4 Per capita demand of silver for jewelry and silverware sector by region.

Demand of silver for electronics mainly includes demands for personal electronic items, automobiles and many other manufactured products. For personal electronic items, silver demand was hurt recently because of the shift from laptops to tablets which requires less silver content per unit. While silver demand remains robust in automobiles, especially in developing countries (The CPM Group, 2015). Silver oxide batteries are increasingly applied in watches, cameras, and electrical products due to their superior power-to-weight characteristics (The silver institute, 2014). Shown in Figure 4-5, overall intensities of silver demand for electronics and batteries fell slightly in past few years in Japan, United States, and Western Europe due to popularity of portable smaller electronic products and increasing Original Equipment Manufacturer in developing countries. Accordingly, silver demand intensity rose consistently in China and other countries driven by the increasing products demand and manufacture capacity in developing states. Therefore, for Japan, United States, and Western Europe (3C), average silver demand intensity and its decreasing rate (0.88% annually) in recent five years (2010-2014) is used for estimation. For China and other countries, recent three years' (2012-2014) average growth rates of intensities (3.02% annually in China; 5.18% annually in other countries) are applied. The calculations are presented in Eq. (4-10) to (4-12).

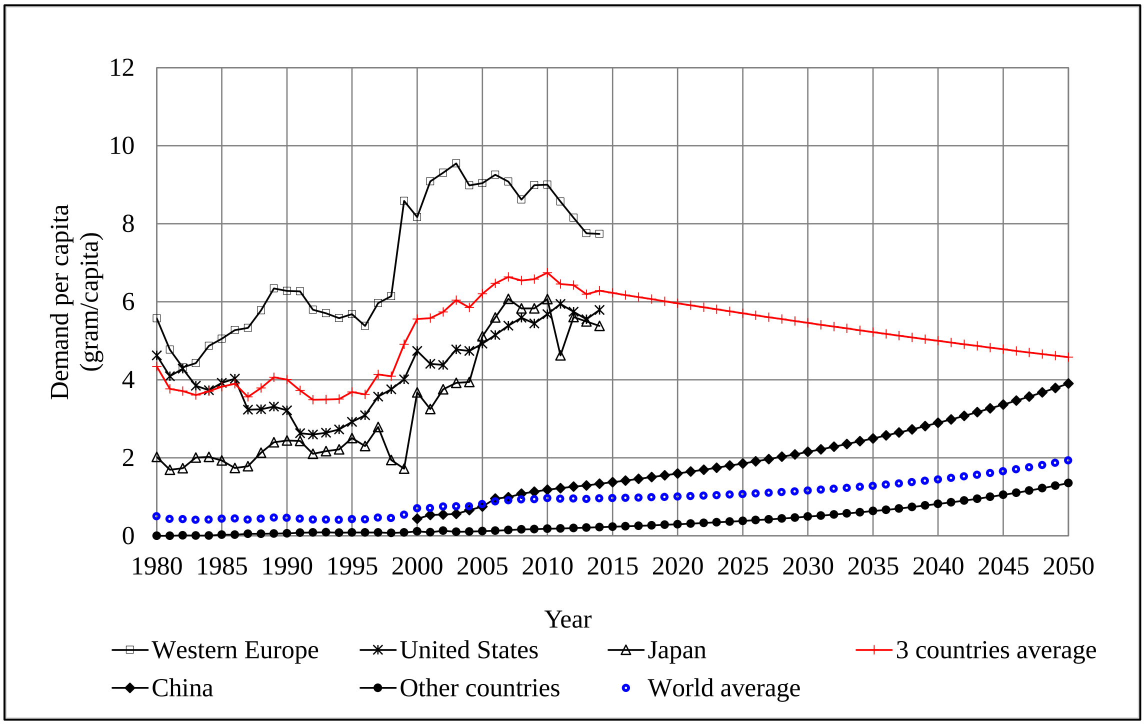

Figure 4-5 Per capita demand of silver for electronics and batteries sector by region[1].

$$ID_{e\&b.,3C,t} = ID_{e\&b,3C,2014} \times (1 - 0.876\%)^{t-2014} \quad (4\text{-}10)$$

$$ID_{e\&b,CN,t} = ID_{e\&b,CN,2014} \times (1 + 3.02\%)^{t-2014} \quad (4\text{-}11)$$

$$ID_{e\&b,O.C.,t} = ID_{e\&b,O.C.,2014} \times (1 + 5.18\%)^{t-2014} \quad (4\text{-}12)$$

Demand of silver for consumer photography suffered of consistent decline since 2000 due to the substitution of films to digital cameras. It is expected to decline further more in the coming years along with the growing availability of digital technology (The CPM Group, 2015; the silver institute, 2014). Although, demand of silver in radiography for medical and dental uses encountered the least impact from digital technology, it is expected to decline as well along with the updating of digital images especially in developing countries (The CPM Group, 2015; the silver institute, 2014). Yearly decline rate of silver demand intensity for photography peaked at 18.35% during 2007-2008, and afterwards, slowed down gradually

[1] "3 countries average" represents average of Japan, United States, and Western Europe.

(Figure 4-6). We use average annual decline rate of demand intensity for photography ($IDR_{phy,t}$ = 14.6 %) during 2009-2014 to estimate the future intensity of silver demand, displayed in Eq. (4-13).

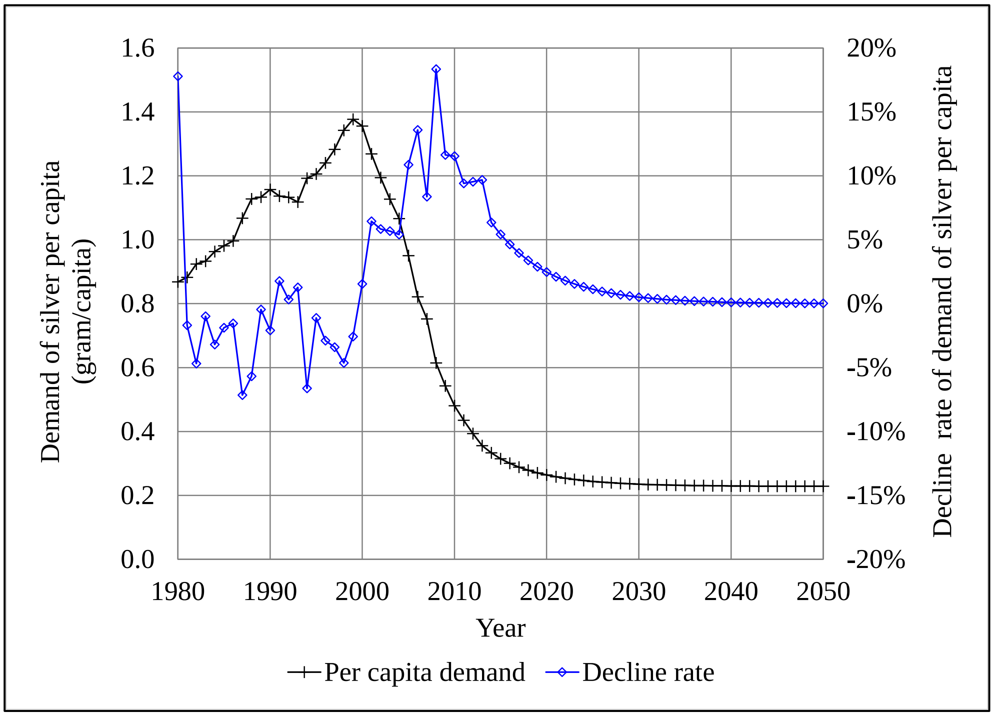

Figure 4-6 World average per capita demand of silver for photography and its decline rate.

$$ID_{phy,t} = ID_{phy,2014} \times \left[1 - IDR_{phy,2014} \times (1 - 14.6\%)^{t-2014}\right]^{t-2014} \quad (4\text{-}13)$$

Demand of silver for other uses mainly includes brazing alloys, ethylene oxide catalysts, and biocide according to statistics from the CPM Group (2015). Brazing alloys are one of the most important uses, and their demands are greatly influenced by housing market (The CPM Group, 2015). Demand of silver in ethylene oxide catalysts depends on the demand of new catalysts and the replacement of existing catalysts. Demand of silver in biocide has been rising during the last decade (The CPM Group, 2015). In a long run, it is difficult to give an expectation to silver demand trend for these uses as a whole. We thus apply average demand of silver per GDP (0.123 gram per constant U.S. dollar in 2005) during the 1977 to 2014 for prediction (Eq. (4-14)).

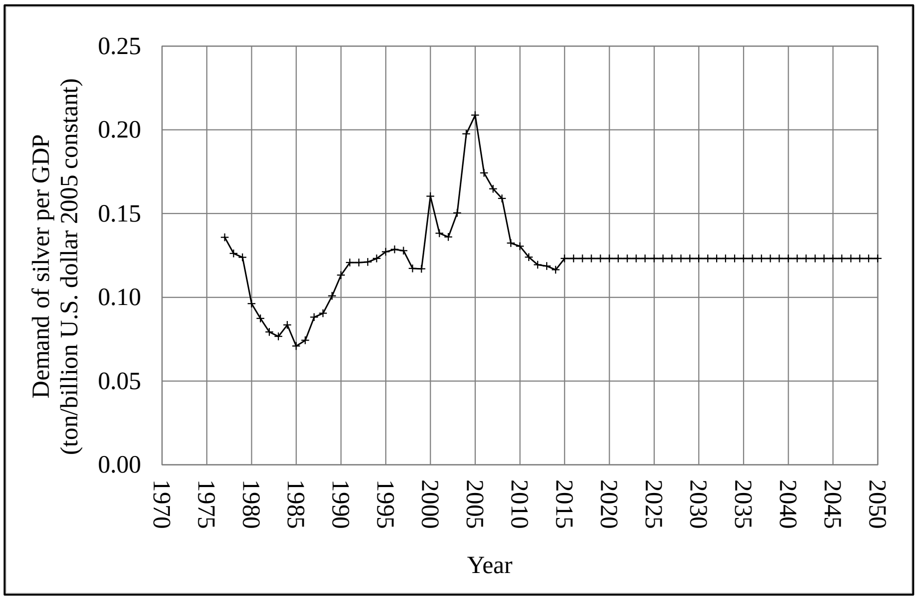

Figure 4-7 World average per unit GDP demand of silver for other uses.

$$ID_{otr,t} = 0.123 \qquad (4\text{-}14)$$

4.4 Scenario Design

According to IEA (2010), lifespan of PV (Λ_{PV}) is expected to prolong to 30 years by 2020, 35 years by 2030, and 40 years by 2050 without addressing specific PV technologies. In the PV lifetime prolongation scenario, we apply the projection by assuming a stepped increase of lifetime, displayed in Figure 4-8. By prolonging PV life time, replacement of retired PV could be delayed, so do demand of silver for replacement purpose.

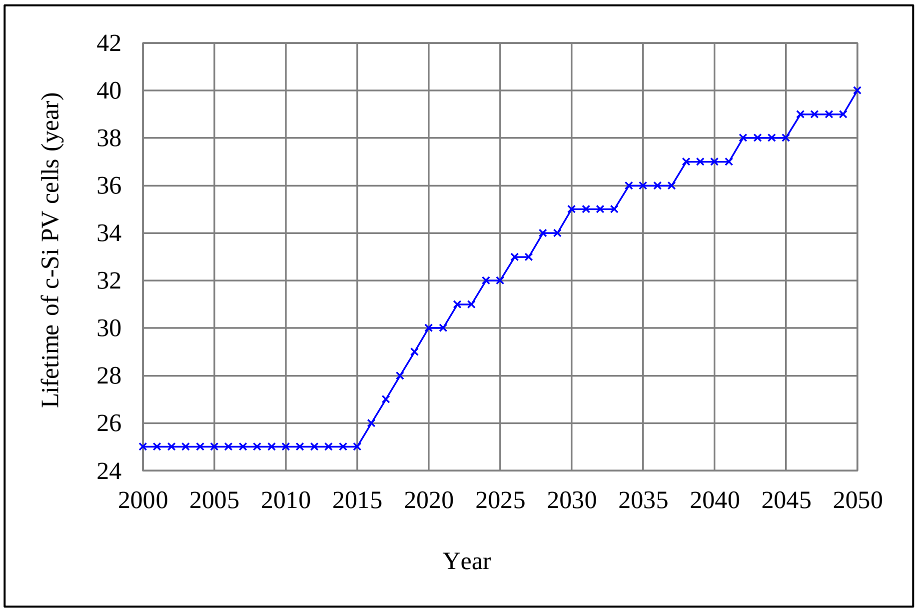

Figure 4-8 PV lifetime prolongation scenario.

According to IEA (2008), market share of c-Si PV in total PV market will consistently decline to 50% by 2020 and to 15% by 2050. So far, c-Si PV keeps dominating 90% or more of the PV market (ITRPV, 2016). In fact, takeoff of thin films and other novel devices were not that fast as expected, competing with cost reduction and improved performance of c-Si PV technology. Therefore, in the technology shift scenario, we assume that market share of c-Si PV will keep at 90% until 2020, and linearly decline to 50% by the end of 2050 (Figure 4-8). To be noticed that thin-film technologies and the third generation of technologies may need silver as well (Konagai & Ueda, 2013). So far, attention has been given to the recycling probability of the semi-conductor materials, recycling probability of silver from those technologies was not reported (Tao & Yu, 2015). Only if the development of non-silver used new technologies or recycling of silver from those technologies is available, can silver supply shortage be mitigated as expected in this scenario. If not, this scenario can be a proper presumption for silver shortage mitigation. In addition, some new technologies will consume some other even more critical metals like tellurium, indium, which need further studies.

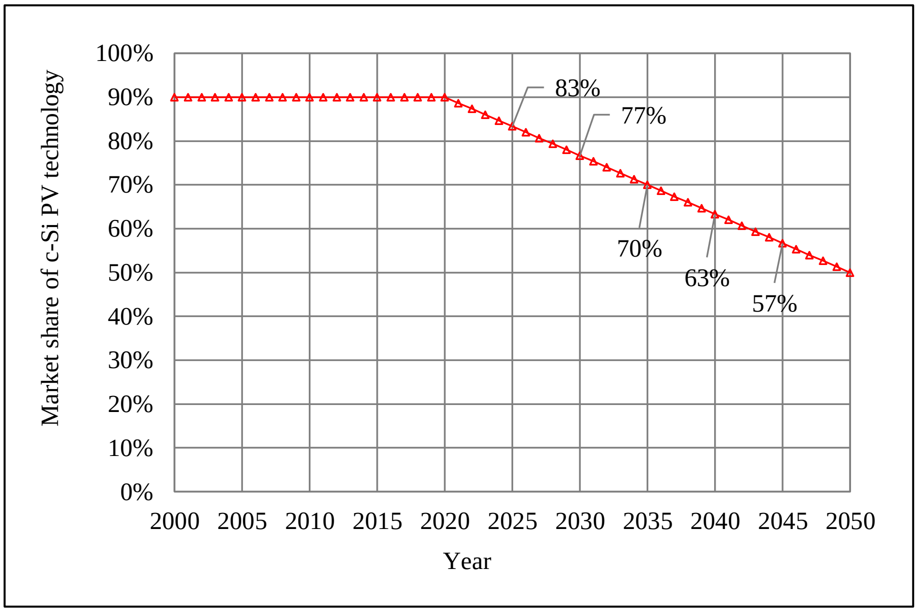

Figure 4-9 Technology shift scenario.

According to IEA (2010), the manufacturing of c-Si modules currently use silicon in one of two main forms: single-crystalline Si (sc-Si) or multi-crystalline Si (mc-Si). The electricity conversion efficiency of sc-Si modules is expected to increase to 0.23 kW/m^2 by 2020 and 0.25 kW/m^2 in longer term (IEA, 2010). The electricity conversion efficiency of mc-Si is expected to increase to 0.21 kW/m^2 in the long term (IEA, 2010). But recently, top performance sc-Si PV cells' efficiency is expected to increase 0.26 kW/m^2 by 2026, and the top performance mc-Si PV cells' efficiency is expected to surpass 0.21 kW/m^2 (ITRPV, 2016). Currently mc-Si PV takes around 60% of the c-Si PV market, but its share is expected to shrink to below 50% (ITRPV, 2016). Therefore, in the efficiency improvement scenario, we assume that market share of mc-Si and sc-Si in c-Si PV market will converge to 50% linearly by 2026 from 6:4; electricity conversation efficiency of sc-Si and mc-Si will reach 0.26 kW/m^2 and 0.21 kW/m^2 by 2026 respectively from 0.16 kW/m^2 (Figure 4-9). Afterwards, their aggregated efficiency regardless of silicon type will linearly increase to 40% by 2050 according to the general technology target of IEA (2010) (Figure 4-9).

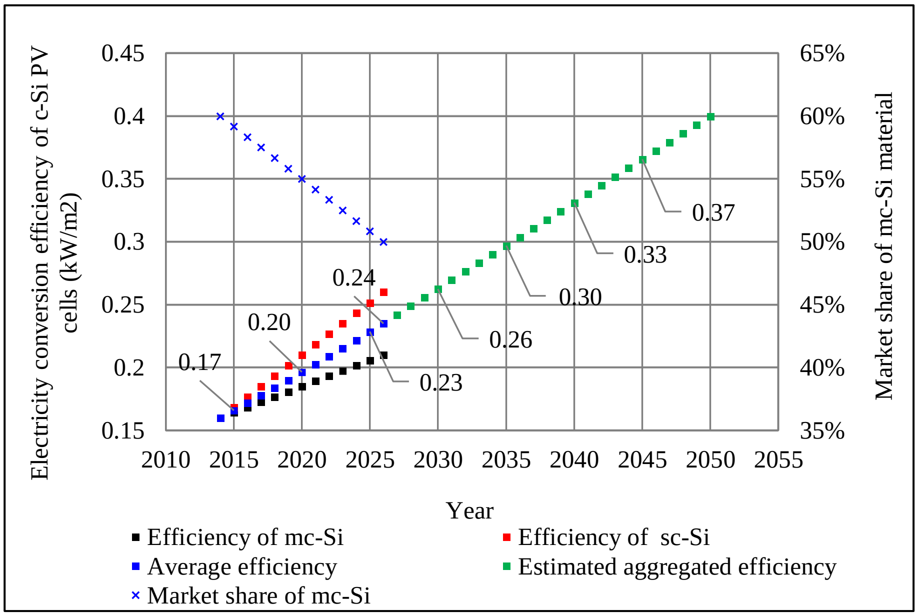

Figure 4-10 Efficiency improvement scenario.

According to ITRPV (2016), developments in pastes and screens allow silver content in PV decrease to 3.9 g/m^2; further improvements in cell processing may allow it fall to 1.64 g/m^2 by 2026. But substituting silver to copper won't start before 2018 at any significant scale due to lack of reliability (ITRPV, 2015). 25% of c-Si PV market may be taken by copper substituted technology by 2026, while silver used technology is expected to remain dominant (ITRPV, 2016). In the silver demand rate reduction scenario, we assume that silver demand rate of c-Si PV will decrease 13% annually until reach 1.64 g/m^2 by 2026 and then maintain that demand rate; market share of copper used technology in total c-Si PV market will linearly increase from 0% in 2018 to 25% in 2026, and then maintain the share until 2050 (Figure 4-10).

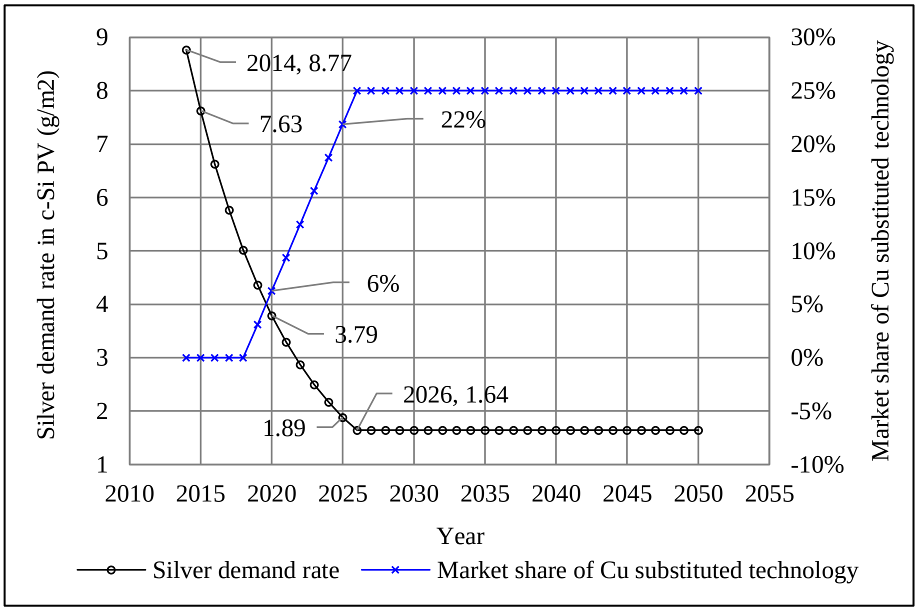

Figure 4-11 Silver demand rate reduction scenario.

Caused by extremely low silver weight content in PV, silver cannot be recycled efficiently using conventional process (Olson et al., 2013). But PV modules have potential to get recycled by some special processes and silver contained in c-Si PV cells can be almost 100% recycled (Kang et al., 2012; Radziemska and Ostrowski, 2010; Yi et al., 2014). But according to McDonald and Pearce (2010), recycling of all silicon based modules are not profitable; they concluded that producer responsibility extension (EPR) is required to motivate PV recycle. In the PV recycling scenario, we assume a society with EPR imposed to retired PV by 2025, so that the first installed PV in 2000 can get recycled. The collection rate (CR_{PV}) is 65% referencing the target set by industrial PV recycling initiative - PV CYCLE (BINE, 2010). The recycling process efficiency for silver ($RPE_{Ag\ in\ PV}$) is assumed to be 100%. Lifetime of PV (Λ_{PV}) consistent with the one (25 years) used in the base case. Equation (4-15) displays you the calculation method.

$$P_{r/PV,t} = D_{PV,t-\Lambda_{PV}} \times CR_{PV,t} \times RPE_{Ag\ in\ PV,t} \qquad (4\text{-}15)$$

In the total effects scenario, dynamics of above five scenarios are combined to represent maximum effect of technology progresses. Equation 4.16 displays the calculation of silver demand for c-Si PV under total effects.

$$D_{c-Si\ PV,t} = MS_{c-Si\ PV,t} \times \left(C_{new\ PV,t} + C_{t-\Lambda_{PV},t}\right) \times DR_t / E_{c-Si\ PV,t} - P_{r/PV,t} \tag{4-16}$$

4.5 Results and Discussion

The seven scenarios confront a mutual predicament that primary silver resources are likely to deplete rapidly. Figure 4-12 shows the physical silver supply (mining and recycling) situation in the base scenario. Silver manufacturing demand will excess silver mining and recycling supply from 2024. By the year 2050, total supply will only be able to meet less than 60% of manufacturing demand. Seeing as silver mining supply as a by-product will consistently make up around 70% of the total mining production, silver mining supply will remain rigid to its demand. To alleviate the silver supply shortage, improving silver recycling supply prospects is the key. Since the EOL-RR of silver is only 30%, according to our estimation, the silver recycling supply should have the potential to increase when a causes a price hike. To pursue an efficient recycling supply, measures should be put into practice to build an effective waste management and recycling system.

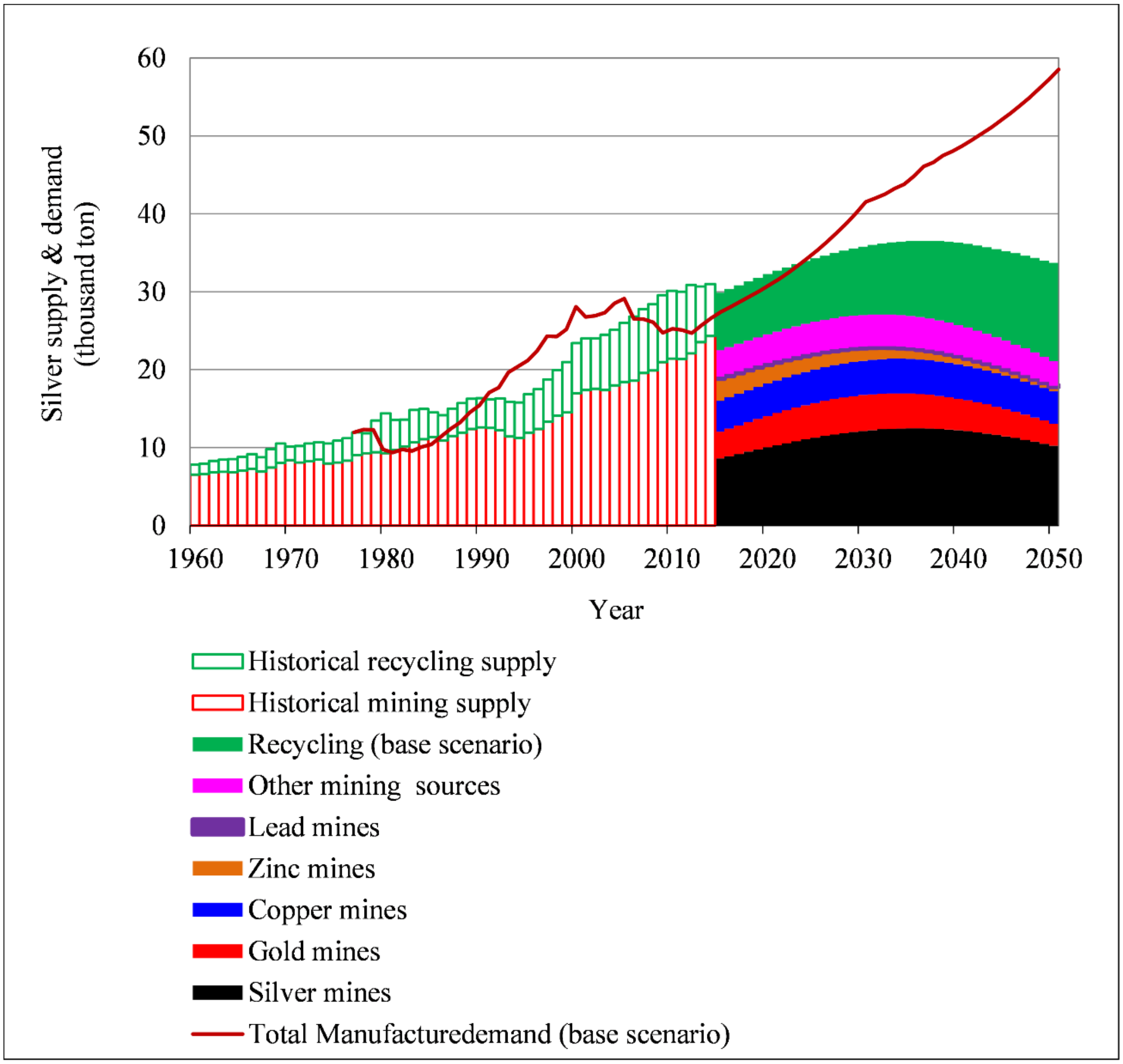

Figure 4-12 Estimation of silver mining and recycling supply in base scenario.

In the base scenario, demand for silver for c-Si PV will increase and take around 20% of total manufacturing demand from 2028 (Figure 4-13). Given the estimated physical silver supply in the base scenario, until 2030, efforts to reduce demand for c-Si PV could eliminate the gap between physical supplies and manufacturing demand. Afterwards, however, some demand will have to rely on outflow of stock. Once the stock is used up, supply shortage will appear. Declining silver demand will be helpful in alleviating the supply shortage. Silver demand for electronics and batteries holds the highest demand prospect. It is mainly attributes to the popularity of electronic products. Currently, modules are updated much more regularly than the physical life times. This pumps raw material demand and generates increasing amounts of e-wastes. Therefore, if those products could be reused, or partially reused, significant tons of silver could be conserved. In addition, demand for silver for jewelry and silverware will also require a very large amount of silver, along with a need for growth in global wealth. Its demand is more elastic than that for industries in the short term. Thus, when a supply shortage arrives, demand for jewelry and silverware may be substantially suppressed.

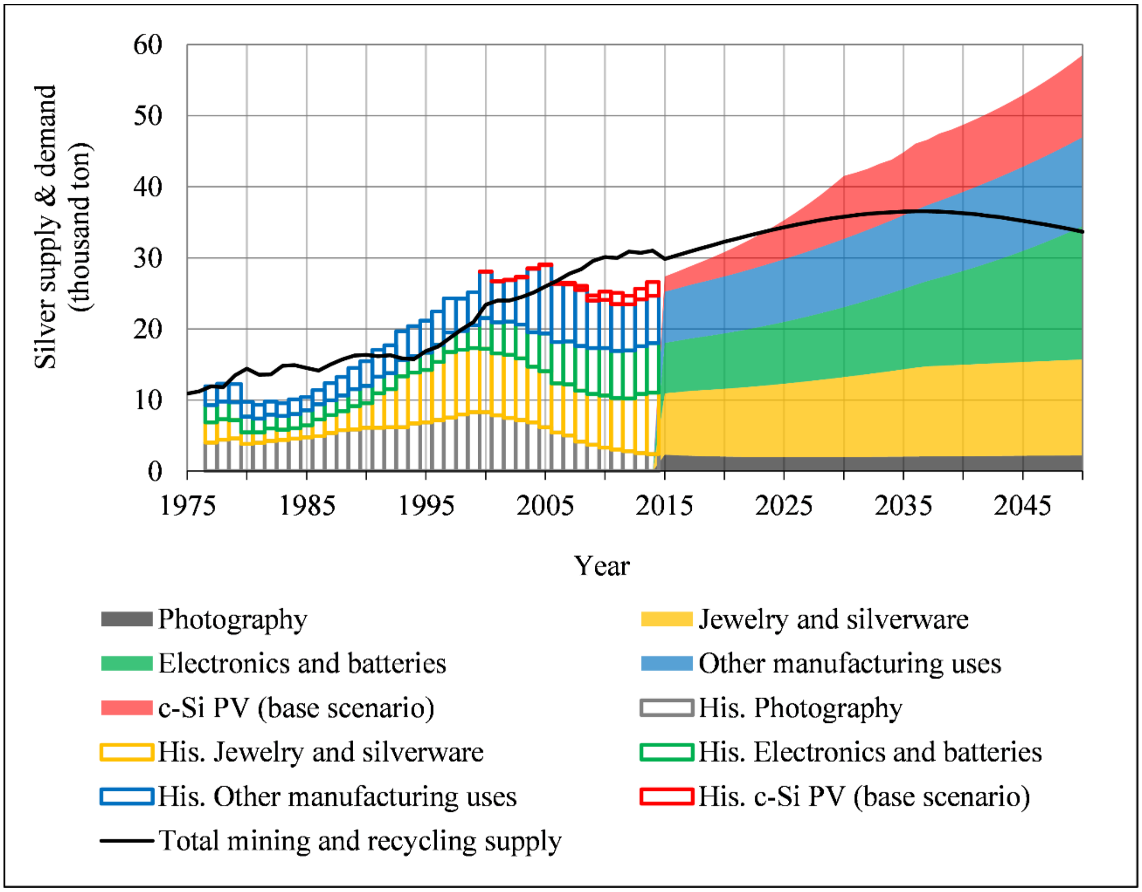

Figure 4-13 Estimation of silver manufacture demand in base scenario[2].

Demand for silver for c-Si PV is likely to increase exponentially until 2030, from around two thousand tons to almost nine thousand tons under the base scenario (Figure 4-14). Afterwards, demand for replacement will pull the total demand for c-Si PV up to 11.56 thousand tons by 2050. In the PV lifetime prolongation scenario, demand for silver after 2040

[2] Data from 1977 to 2014 are historical values, from 2015 to 2050 are predicted values.

fluctuates widely, caused by discontinuous replacement of old PV panels. In the PV recycling scenario, net silver demand can be reduced after 2025. The reduction becomes significant after 2035, along with increased annual installations from 2010. In the technology shift scenario, the potential of installed c-Si PV is low, so demand for silver for the industry becomes low as well. Efficiency improvement and silver demand rate reduction are vital in alleviating the silver supply shortage, as well as to maintaining a competitive advantage for c-Si PV technology. Under total effects, demand for silver for c-Si PV will decline to minimal amounts by 2034. From then, recycled silver from retired PV is expected to exceed demand for it due to high silver content in previous installations. Namely, from 2035, demand for silver for c-Si PV will be entirely fulfilled by PV recycling, and the excess portion can be added to the silver supply. Among the five aspects of technological improvement, silver demand rate reduction is the most effective measure. It can maintain silver demand for c-Si PV at below two thousand tons throughout the forecasting period.

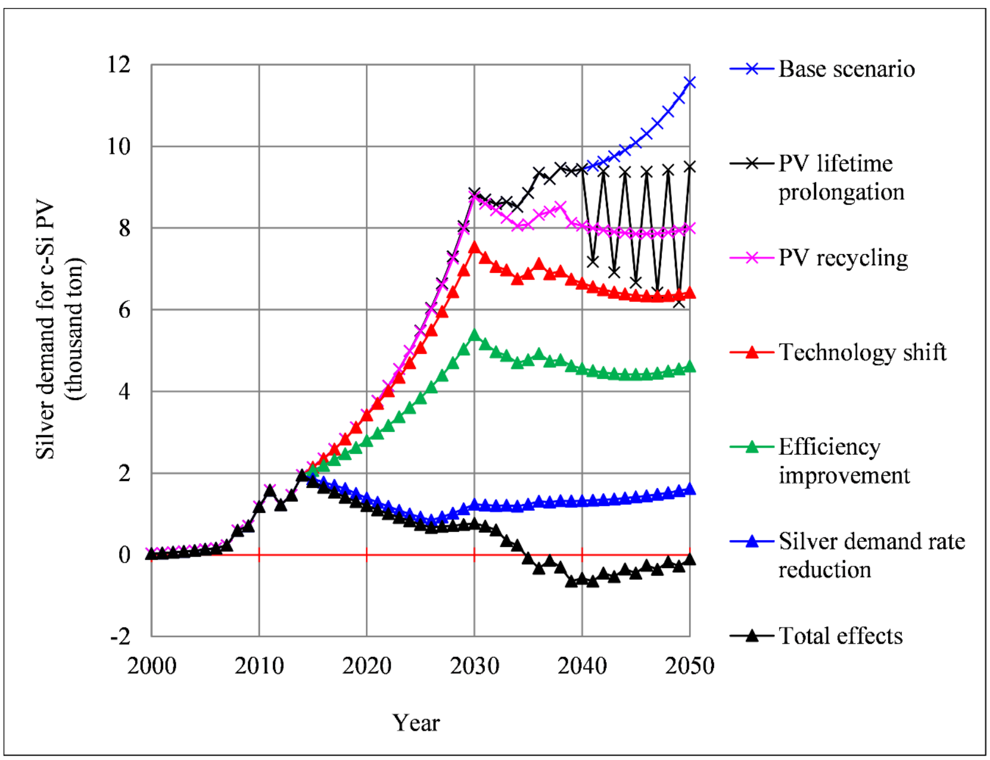

Figure 4-14 Estimation of silver demand for c-s Si PV by scenario.

As defined in the method section, real-time silver supply shortage occurs only if both the cumulated stock from previous periods and the real-time physical supply cannot meet manufacturing demand. Therefore, once shortage occurs, it is fulfilled either by the release of historical stockholdings (before 2015) it is forgotten. In the base scenario, silver supply shortage for manufacturing demand will emerge in 2030 and increase quickly to almost 25 thousand tons by 2050 (Figure 4-15). It can be significantly relieved and delayed through PV technology improvements, but not eliminated, wherein, the most effective factor is a reduction in the silver demand rate. In other words, to reduce silver demand intensity by process innovation and to substitute silver with copper are the most important measures in alleviating silver supply shortage. Under the total effects scenario, silver supply shortage will not appear until 2048, and the quantity of lacking silver can be reduced by half.

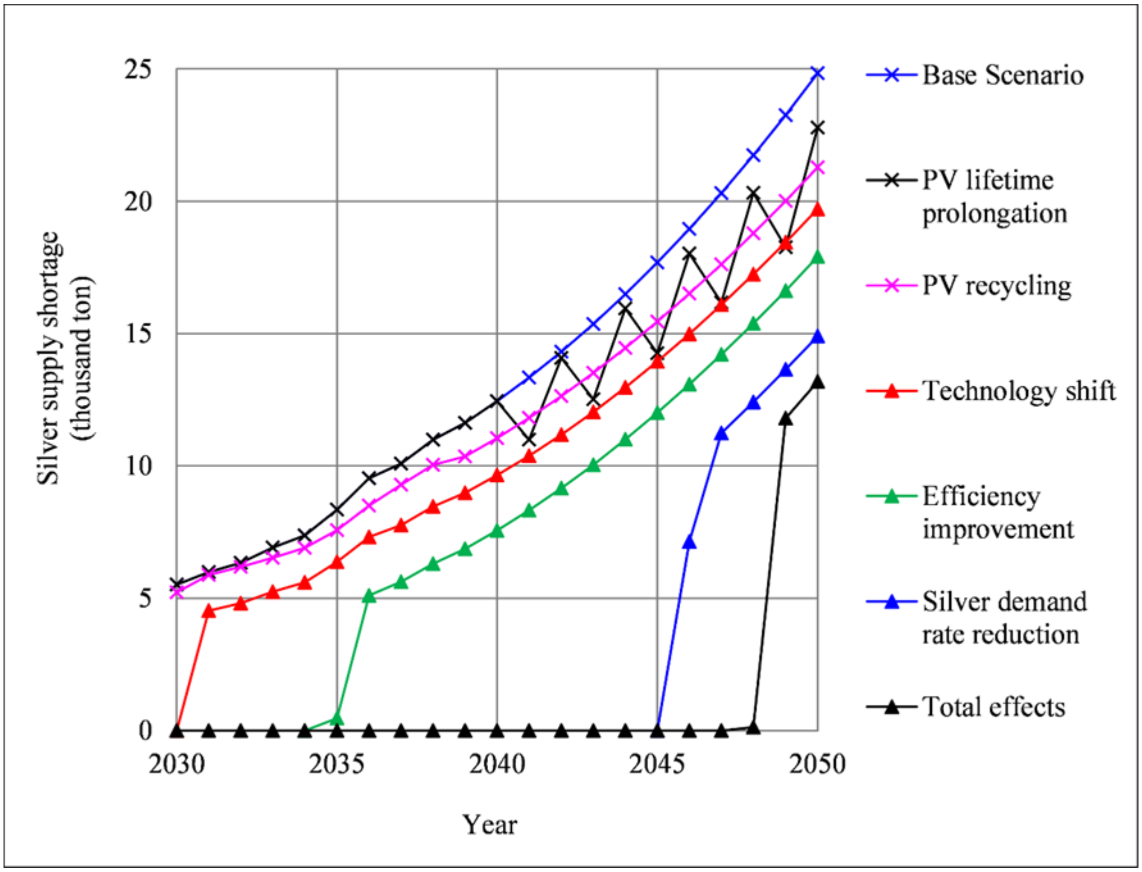

Figure 4-15 Estimation of annually silver supply shortage by scenario.

Market supply shortage will apply equally to all demanders. For the c-Si PV industry, we assumed an EPR framework for recycling. That is to say, in addition to the silver raw material supply market, it gets silver from recycled panels (Figure 4-1). Comparing Figures 4-14 and 4-15, it is easy to see that the silver supply shortage for c-Si PV can be fully eliminated under total effects, regardless of supply shortage in the market, because the c-Si PV sector can produce excess silver through PV recycling from 2035. When the silver supply shortage appears in 2048, the c-Si PV industry will already have become self-sufficient in silver. According to the estimated results, three aspects of technological effort should be made in the PV sector. First, it is important to improve c-Si PV performance and decrease the silver demand rate to reduce unit per unit energy capacity's dependency on silver raw material. Second, to have PV recycling facilities and recycling systems in place is vital to sustain the business. In this way, new demand for silver could be completely fulfilled by recycled silver from retired panels, so that the PV sector does not have to compete for scarce silver resources with other demanders in the market. Third, in the total effects scenario, the market share of c-Si PV will reduce to 50% by 2050. This means that to achieve IEA projected total PV installation, improving the cost effectiveness of the thin film and the third generation of photovoltaic is required.

From above discussion, it is not hard to find that recycling plays an important role. As suggested by Slade (1980) and Blomberg and Soderholm (2009), secondary supply of metals may be affected by other factors like secondary commodity price and cost factors, in spite of those we included (generation of scraps). To make up the shortage, we allow an EOL-RR increase of one percent per year, when physical supply fails to meet manufacturing demand (Figure K-1-2 in Appendix K). The results are presented below in Figure 4-16. In the base scenario, PV lifetime prolongation, PV recycling, and technology shift scenarios, EOL-RR will increase to 57% by 2050. Accordingly, the quantity of supply shortages are significantly cut, and the time they appear is delayed by different degrees. In the efficiency improvement scenario, EOL-RR will increase to 54% by 2050, and accordingly, a similar effect is reached as for the above four scenarios. In silver demand rate reduction and total effects scenarios, silver supply shortages are eliminated during the forecasted period. It also means that if the recycling supply of silver in the market is improved, without EPR being facilitated, only by reducing silver demand intensity can c-Si PV avoid silver raw material supply shortage.

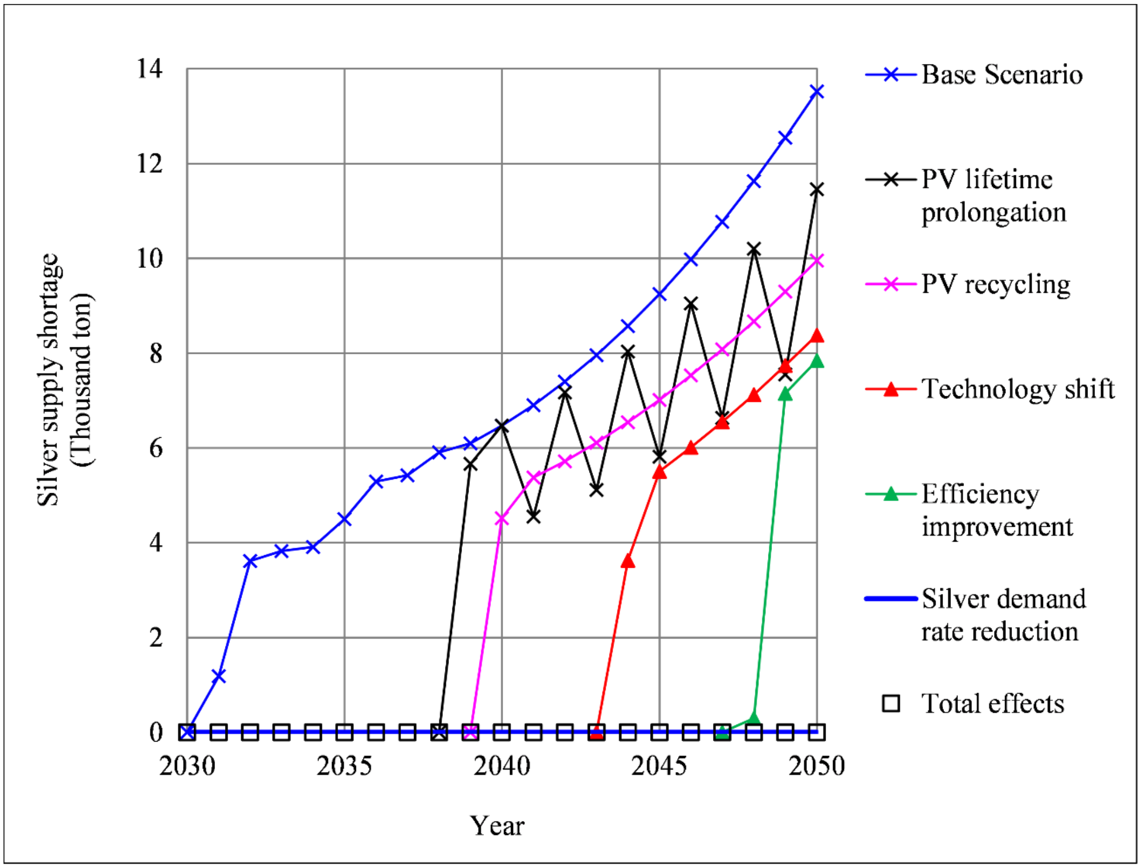

Figure 4-16 Estimated silver supply shortage under increased EOL-RR.

4.6 Conclusion

We estimated silver raw material supply shortage potential for c-Si PV technology between 2015 and 2050, wherein, silver mining supply is estimated by mining sources respectively; silver recycling supply is simulated as a function of the weighted lifetime of silver and a constant EOL-RR; silver demand is estimated by intensity of demand for respective usages. To measure technology uncertainties in the PV sector, seven scenarios are developed, including a base scenario, a PV lifetime prolongation scenario, a PV recycling scenario, a technology shift scenario, an efficiency improvement scenario, a silver demand rate reduction scenario, and a total effects scenario.

Modelling results show that silver manufacturing demand will increase consistently and exceed mining and recycling supply from 2024. Silver supply shortage will appear since 2030 under the base scenario. Technology progress of c-Si PV can alleviate the shortage by half and delay the arrival time of it to 2048 at most. If EOL-RR increases 1% annually when physical supply is less of manufacturing demand, silver supply shortage can be eliminated before 2050. Thus, increasing silver recycling supply is important for the long-term sustainable silver supply. In terms of silver supply shortage for the c-Si PV sector, it could be eliminated under the total effects scenario because silver demand for c-Si PV can be completely fulfilled by recycled silver from retired PV cells after 2035. Additionally, if EOL-RR increased, simply by reducing silver demand rate, a silver supply shortage could be avoided. Therefore, three types of efforts should be made to sustain the PV sector from a silver supply shortage. They are reducing c-Si PV cells' dependency on silver raw material, facilitating PV recycling, and increasing the competitiveness of new PV technologies.

This all remind us of the importance of recycling policy. Moreover, in the presence of supply shortages, prices will be high, thus implying that the market-driven recycling rates will probably be significant (even in the absence of any policies). This study also highlights the importance of balancing natural resources and renewable energy sustainability. A lot of renewable energy technologies require critical metals or materials. This accelerates the depletion rate of natural resources when pursuing a cleaner energy supply. Therefore, it is important to evaluate both the resources and energy aspects of a new technology. Compared to previous studies on supply shortages, this study discussed technology uncertainties by scenario for the first time and considered silver supply and demand in a comprehensive way. The study is informative and the results provide an early warning about balancing renewable energy installation and mineral resources supply.

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Chapter 5 Supply risk route assessment

5.1 Introduction

As pointed out in Figure 1-8 in chapter 1, the study finally comes up with a risk matrix for the supply risk of metals at each (short, medium, and long) period and further, develops their supply risk routes across periods. To obtain the route matrix, aggregating the number of presented risks into specific risk levels is involved. According to Table 1-1 in chapter 1, previous aggregation methods mainly included expert judgement, weighted average, and defined equations. For this study, the aggregation method is carefully selected to maintain the practical value of the aggregated results.

The chapter contains two parts: first, quantifying the supply risk level of metals in the respective periods by defining the risk classification standards; second, summarizing them into a risk matrix. Specifically, for the short-term supply risk, we use the market Volatility Index (VIX) published by the Chicago Board Options Exchange (CBOE) as the aggregation standard. The VIX represents the implied market volatility, thus a proper standard for metal commodities. For the medium-term supply risk, the comparison of all the risks resource nationalism of all countries and periods by the historical Value at Risk (VaR) is applied to produce the relative risk levels of countries and commodities. The method obtains the comparative risk values as classification standards. For the long term, risk levels are classified by historical supply deficit levels. It tells how risky the supply shortage is from a historical point of view.

5.2 Aggregation Method

For the short term, daily VIX values are collected first during 1990–2017 (Archival Federal Reserve Economic Data). Since the VIX is not normally distributed (Figure 5-1), its basic statistical characteristics are used to define risk standards. As displayed in Figure 5-2, daily VIX peaked at 80.86% on November 20, 2008. This was largely caused by the financial crisis of the year. Accordingly, the maximum annual average VIX also appeared in the same year at 32.24%. Looking at the VaR at 1%, it gives 99% confidence to say that VIX is under 46.92%. Thus, metals' price volatility over 50% up to 80% are taken as crucial, because a price volatility over 50% belongs to the 1% extreme spikes, which should be identified as crucial. Metals' price volatility between 30% and 50% is considered risky. Basically, it means when price volatility over 30% , the overall annual average market risk, is identified as risky. From the distribution description in Figure 5-1, the implied market volatility clustered between 10% and 30%. According to the statistics, it is found that the average daily volatility is 19.38%, slightly below 20%. Moreover, the minimum annual average VIX (11.12%) and the minimum daily VIX (9.14%) didn't see much differences, other than that for maximum values. The mode value (11.57%) turned out to be close to the above two minimum values. Therefore, it could indicate that the VIX values are collectively concentrated at 10–20% with several high spikes. Accordingly, 10% is taken as a threshold; below that it is classified as the low risk area; and above that up to 30% it is classified as marginal. After deciding the aggregation cut-offs, the next step is to rescale these risk intervals into 0 to 4, with each unit representing one risk level with a risk increasing trend. This rescaling only involves basic mathematical calculations, which we are reluctant to be expatiate.

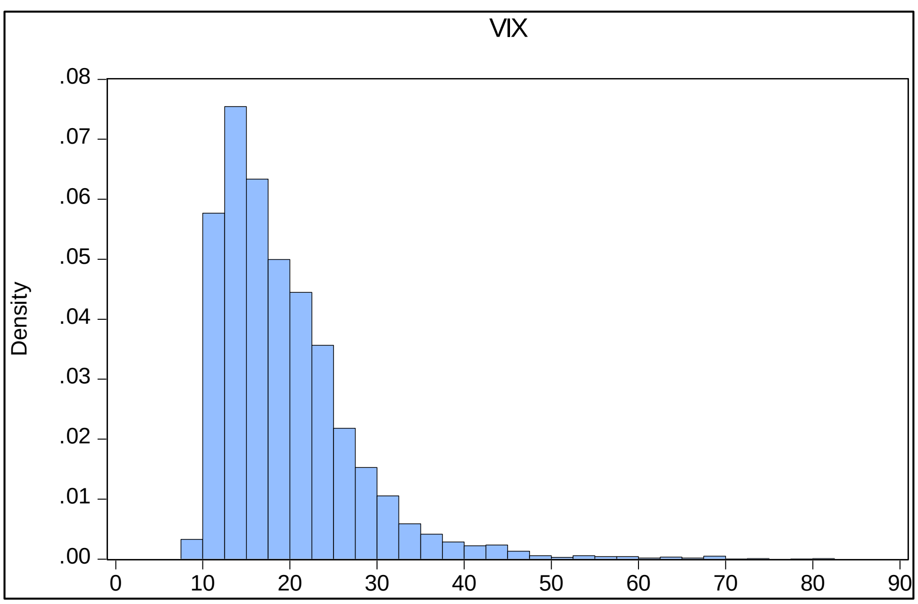

Figure 5-1 Histogram distribution of VIX.

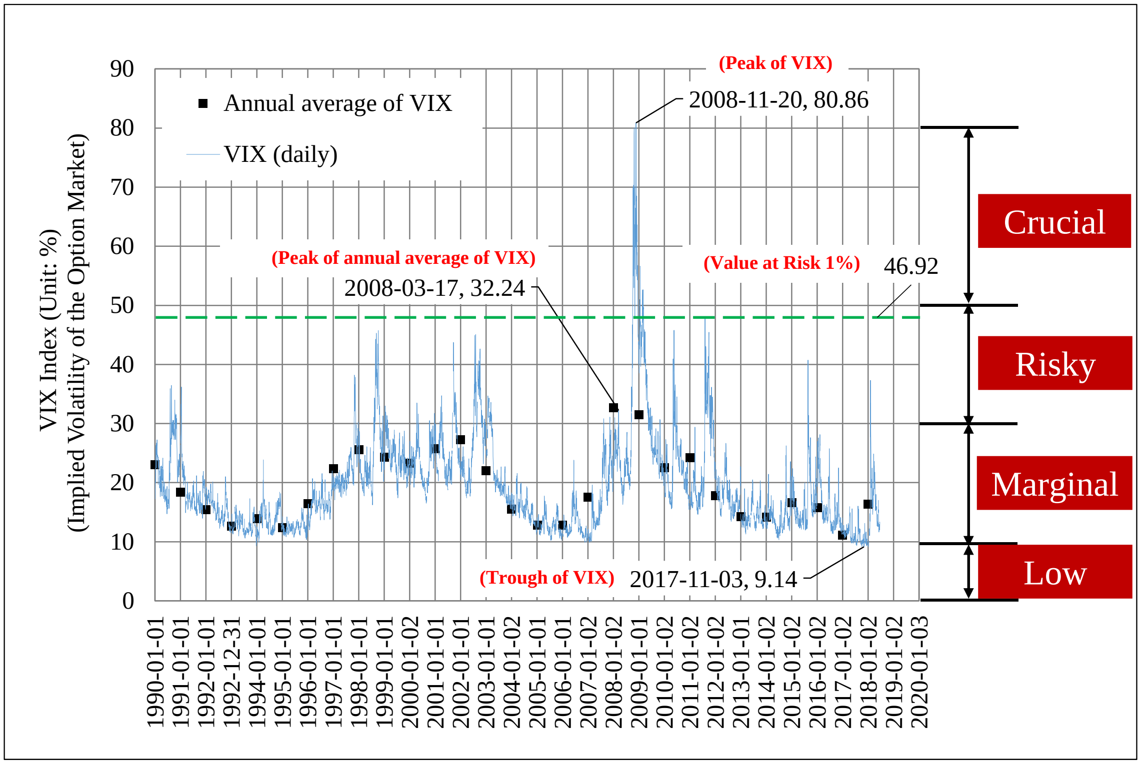

Figure 5-2 Annual average VIX and its statistical characteristics.

For the medium term, partition of risk intervals is based on the comparison of historical risk of resource nationalism (all countries, 2003-2015) by VaR method. The purpose of resource nationalism quantification is to compare (or separate) relatively riskier sovereign states with (or from) safer states. As displayed in Figure 5-3, histogram distribution of probability of resource nationalism is not normally distributed. It is gathered at around 10% to 20% with a slowly abridged long tail in the right. Remember that 50% of probability of resource nationalism was used as the risk cut-off in chapter 3. It is accordingly applied as a risk threshold between the risky level and marginal level. Since there is 90% confidence to say (the result of VaR at 10%) that resource nationalism risk is under 72%, above this value is identified as crucial. Between 50% and 72% is classified as risky, and it takes about 15% of the data population. With the risk of resource nationalism being clustered in the low risk area as mentioned earlier, the bottom 50% (VaR at 50%) is taken as low risk. The left goes to the marginal level and it takes around 25% of the data population. Following the risk level classification, rescaling these risk intervals into zero to four as for short term is carried out (Figure 5-4).

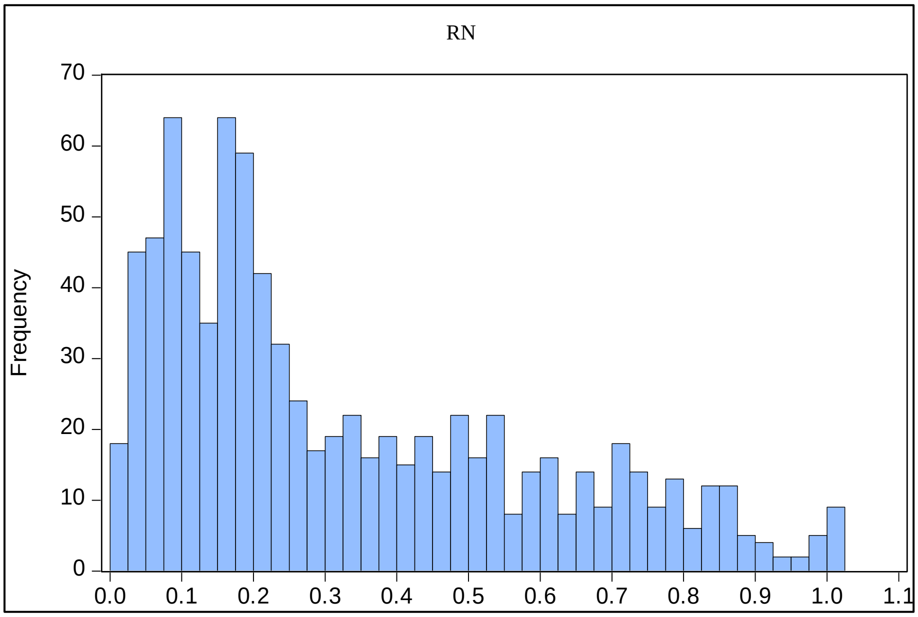

Figure 5-3 Histogram distribution of probability of resource nationalism for countries.

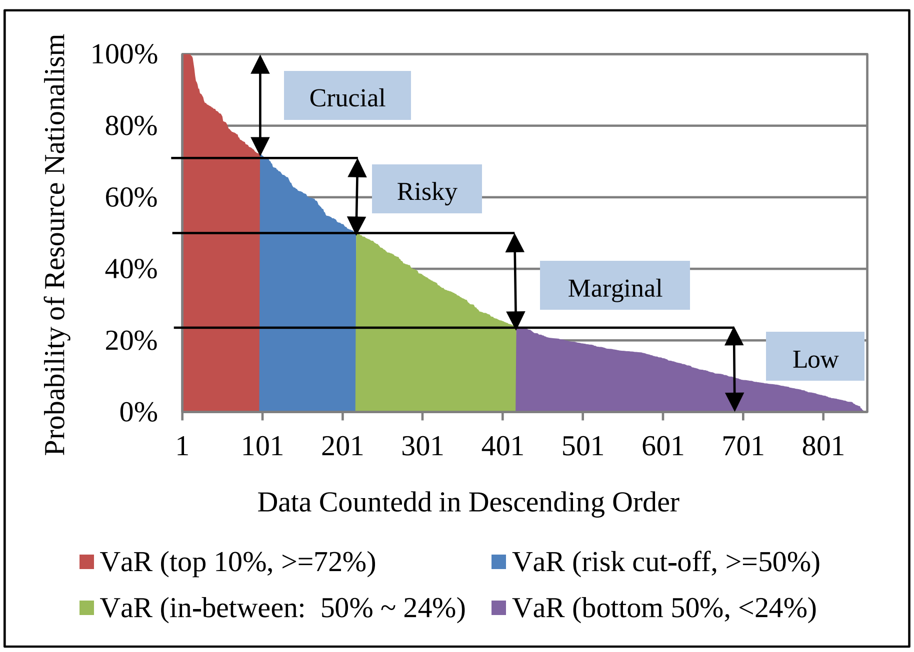

Figure 5-4 Value at Risk of resource nationalism probability.

For the long term, the historical supply deficit level (balance of real time supply and demand) is taken as the reference to classify the risk level of supply shortages. Supply shortage as a percentage of supply (capacity shortage) other than the concrete quantity of silver supply shortage is applied because the magnitude of supply has increased largely along with industrialization and technological improvements (Figure 5-5). As displayed in Figure 5-6, supply deficits occurred during 1977 to 1979, and 1991 to 2005. The capacity shortages were around 10%. Thus 10% is used as a threshold for the marginal risk level. There were several periods of supply deficit reaching almost 20% of the supply. Only once, in 1993, up to 40% supply deficit occurred. Therefore, 20% to 40% is taken as the threshold of the risky, and crucial risk intervals. Different from the short, and medium terms, here we do not rescale shortage percentages into zero to four because low and crucial levels are open ranges.

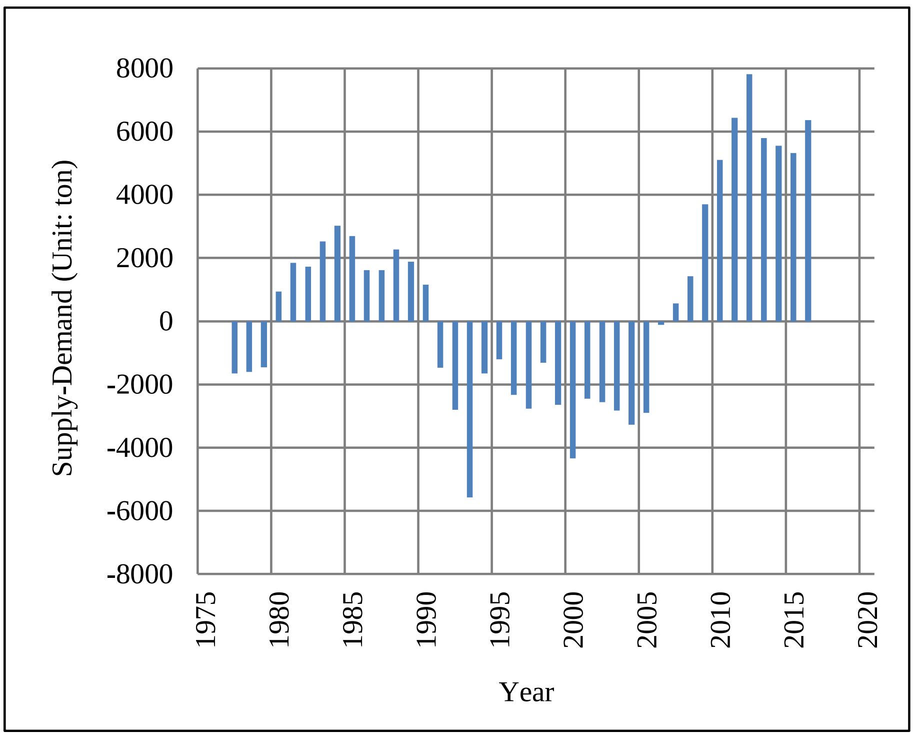

Figure 5-5 Historical silver supply shortage to demand.

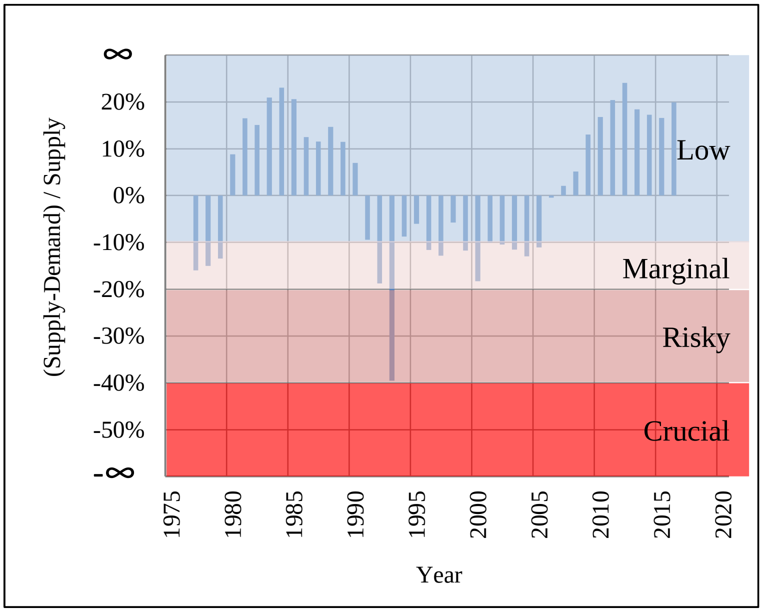

Figure 5-6 Silver relative supply deficit and risk level classification.

5.3 Results and Discussion

5.3.1 Short-Term Supply Risk

According to the regression equations in chapter 2, one-year-ahead metals' price volatility can be predicted based on the relations we discovered. Figures 5-7, 8, 9 &10 present the predicted annual low frequency price volatility, where zero values indicate that the calculated volatility from estimated equations is negative. To make sure the results are meaningful, we round negative values to zero. In addition, the following prices' Lvol series are transferred into annual level, meaning that they have been multiplied by the square root of trading weeks of a year ($52^{1/2}$). Thus, it is different with those displayed in Appendix A, which are weekly ones.

According to Figure 5-7, prices' Lvol of gold and silver increased significantly in the last decade (2005–2015). For gold, its price's Lvol witnessed a five-year continuous increase from less than 15% to more than 30%. A slight decrease converging to 30% is predicted for the year 2018 according to macroeconomic performance in 2017. For silver, another "U" shaped wave of Lvol has realized during 2014 to 2018. It probably touched the bottom of "U" either in 2016 or 2017 and will rise to 33% in 2018. In general, price's Lvol of silver has experienced shock rise ever since the 2008 financial crisis.

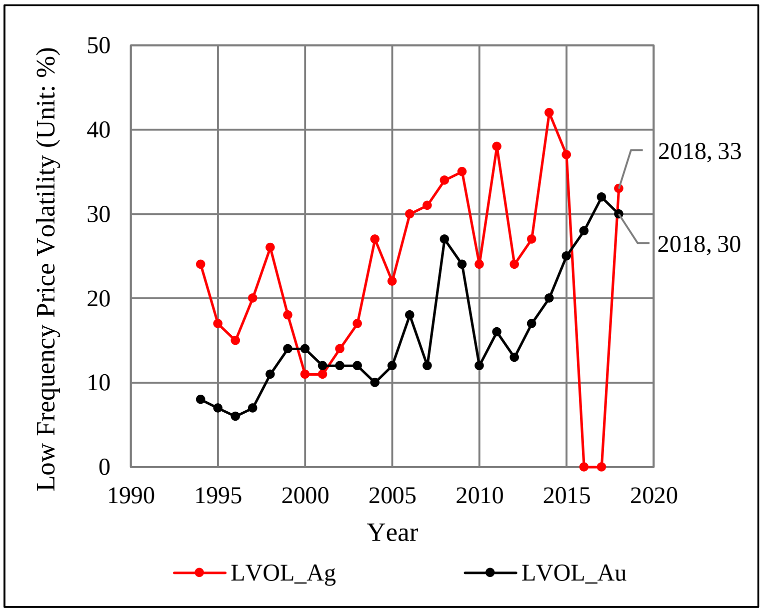

Figure 5-7 Predicted gold and silver price Lvol.

For platinum and palladium (Figure 5-8), their prices' Lvol experienced increases before the twenty-first century, and then fluctuated wildly around their averages. Even though they are mined as a basket of PGMs, their price volatility showed minimum synchronization. According to our prediction, they will converge to 29% (for platinum) and 27% (for palladium) in 2018. For palladium, it is an average risk level, but for platinum it is a relatively high risk level.

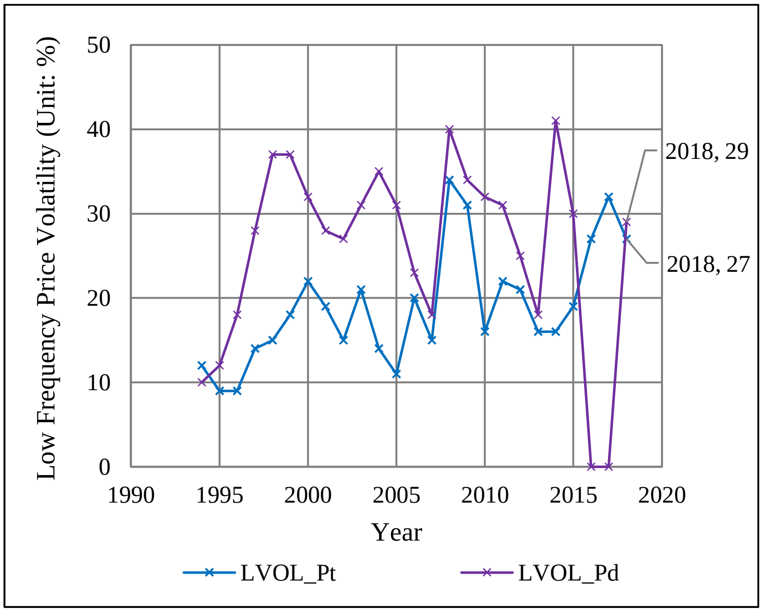

Figure 5-8 Predicted platinum and palladium price Lvol.

Price's Lvol of copper, nickel, and tin are displayed together in Figure 5-9, because they all witnessed volatility spikes during the financial crisis and shortly after the crisis. Around five years after the crisis, their volatility reversed back to the pre-crisis level. Since then, they showed different trends. Nickel price's Lvol increased consistently and slowly; it will slightly fall to 29% in 2018 according our prediction. Tin price's Lvol kept declining until 2015 and stabilized at quite a low level afterwards. It is predicted to be 7% in 2018. Copper price's Lvol, however, suffered wild fluctuations. It rebounded back to very risky level at 50% in 2014 and then decreased minimally in 2016 and 2017. According to our foresight, copper price Lvol will increase to 48% in 2018.

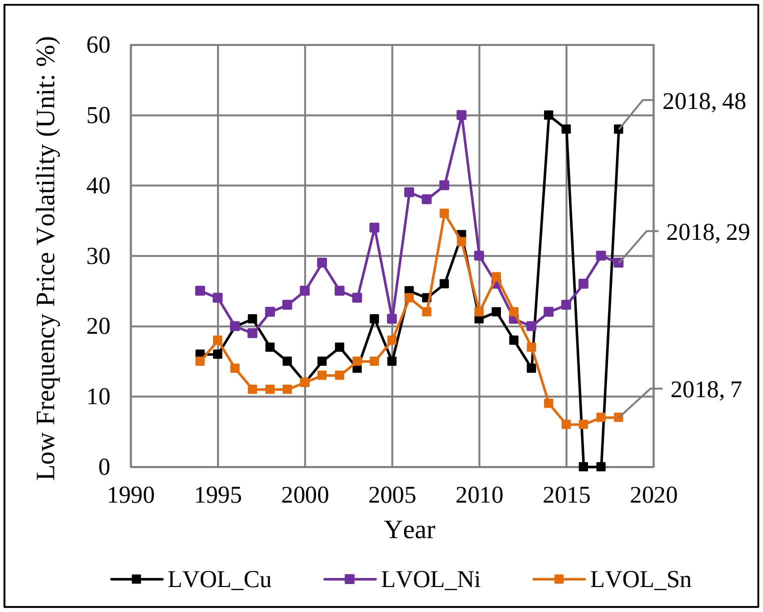

Figure 5-9 Predicted copper, nickel, and tin price Lvol.

At last, zinc and lead prices' Lvol are put in Figure 5-10, because they share quite a synchronized trend. Their prices' Lvol kept increasing since 2000 and peaked during the last financial crisis; later, it touched another bottom and then rebounded again. According to our calculation, price's Lvol of lead will be 36% in 2018 and that of zinc will be 29%.

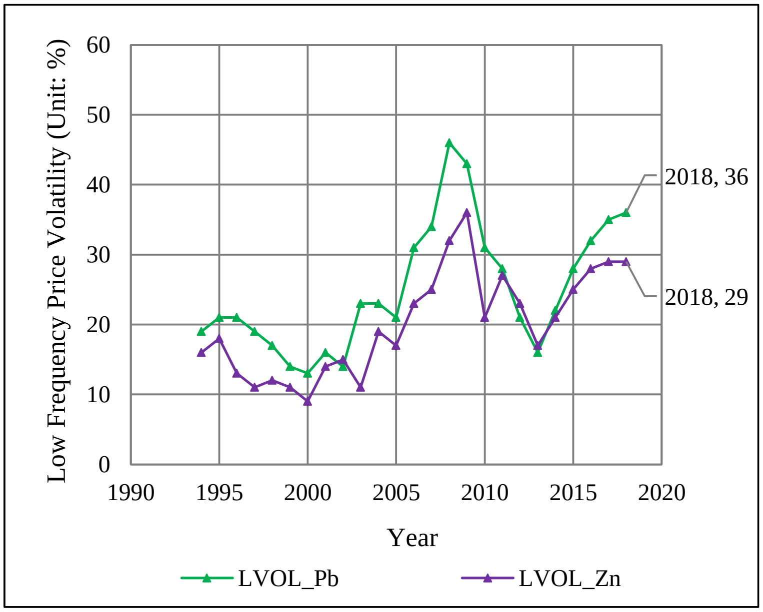

Figure 5-10 Predicted zinc and lead Lvol.

Figures 5-11 to 5-14 present the risk matrix for nine metals' price volatility. In general, they largely fall into the marginal and risky levels. In the marginal risk level, metals' price Lvol are no different with normal implied market risks. In the risky level, metals' price Lvol are higher than the maximum annual average VIX; it means that metal commodities are riskier than most other commodities. When metals' price Lvol increase to the crucial level, metal commodities are risker than 99% of other commodities, and this may indicate a forthcoming crisis. The riskiest commodity in 2018 turns out to be copper, followed by silver, gold, and lead; they are risker than the normal market. Platinum, palladium, nickel, and zinc are likely to perform similar to most other commodities. Only tin has become a very safe commodity which shows low risk and outperforms the market.

To answer why copper price volatility (Figure 5-13) will become risky in 2018, going back to our prediction calculations is necessary. INF_CORE is the most sensitive variable that dominates the risk increases. The inflation ratio of 2017 decreased significantly from 1.33 in 2016 to 1.02 in 2017, which caused the minimal risk in 2017 and spike in 2018. Economically, low inflation is led by technological improvement, aging population, and shifting of labor-intensive industries to lower-cost locations. All these factors weakened the demand for copper but promoted excessive supply of it and further brought about excessive volatility.

For silver (Figure 5-11), its price's Lvol was dominated by INF_CORE as well. A similar mechanism explains for copper could explain the excessive volatility of silver. For gold (Figure 5-14), increasing of its price's Lvol is dominated by SP500. From 2016 to 2017, SP500 increased from 2106 to 2466. Good performance of the stock market brought money into the capital market and increased investment in gold. It led to increases in gold price's Lvol. For lead (Figure 5-14), the recovery of the residential market in the U.S. has made lead price's Lvol grow consistently in recent years. It may indicate that lead, as an important industrial mineral, is growing in importance in the resource reallocations prompted by capital.

Other than other metals, tin price's Lvol (Figure 5-13) has slipped to a very low level since 2015. It benefited from the collapse of residential property prices in 2008. In recent years a slight rebound of RP_USA saved tin price's Lvol from deeper decline but not enough to lift it up again. In fact, prices' Lvol of tin, lead, and zinc are controlled by similar factors, and thus have followed a similar path in the past 25 years. They all have potential to increase if the financial market gets prosperous after recovering from a crisis.

Nickel, platinum, and palladium will have similar market risks in 2018 for different reasons. For nickel (Figure 5-13), changes of TED spread directly reflected in the changes of its price's Lvol. TED and RP_USA both reflect financial risks movements. TED lagged RP_USA for one or two periods, and suffered more minor fluctuations. It led to the performance differences of nickel and lead/zinc/tin, even though they had quite a similar trend generally. For platinum (Figure 5-12), its price's Lvol is dominated by the currency value of the Russian ruble to the U.S. dollar. Considering that Russia is the second largest platinum producing state after South Africa and the monopoly supply market of platinum, it could be inferred that when the Russian ruble becomes weak to the U.S. dollar, production of platinum in Russia will be encouraged to grab more benefit until the commodity price is pushed down. Such behavior adds excessive volatility to the platinum price Lvol. For palladium (Figure 5-12), it shares a similar mechanism with silver and copper, namely affected by INF_CORE.

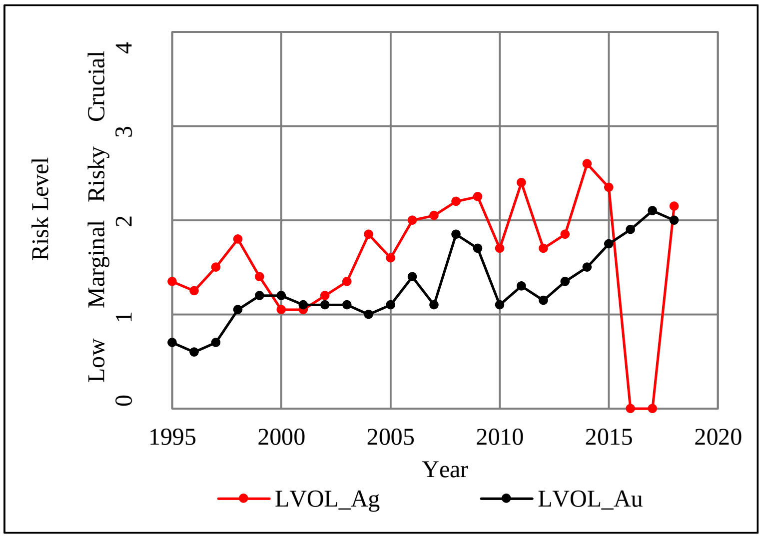

Figure 5-11 Gold and silver supply risks in short term.

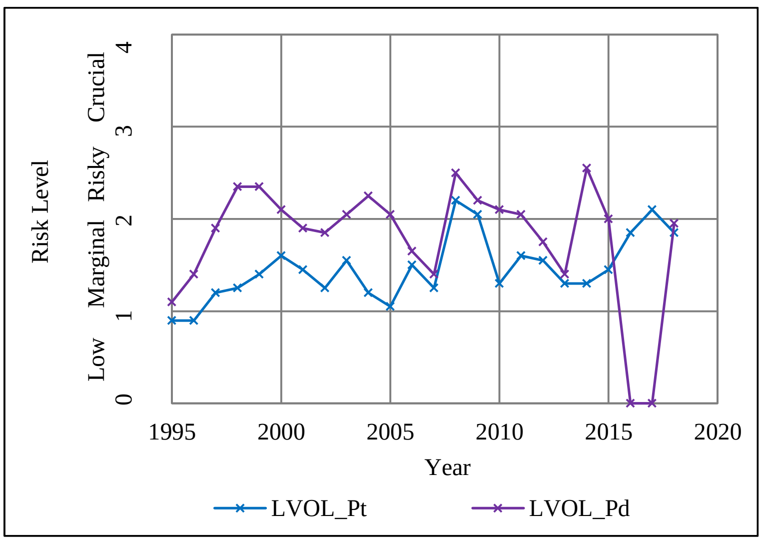

Figure 5-12 Platinum and palladium supply risks in short term.

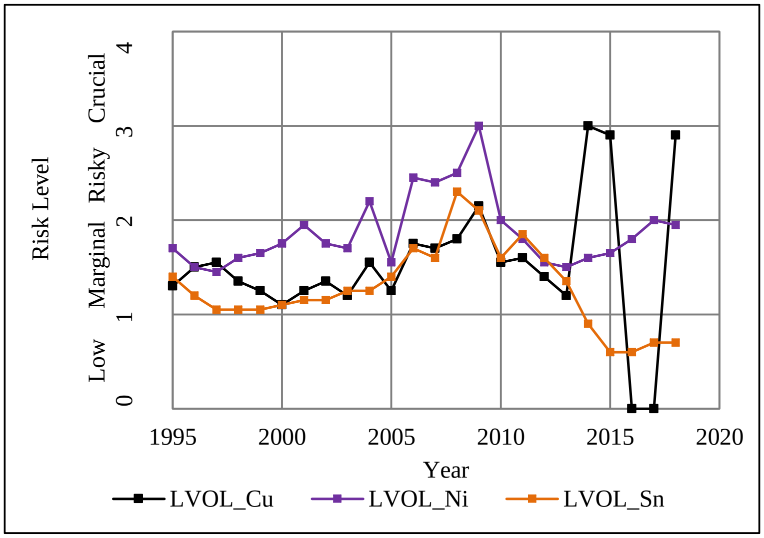

Figure 5-13 Copper, nickel, and tin supply risks in short term.

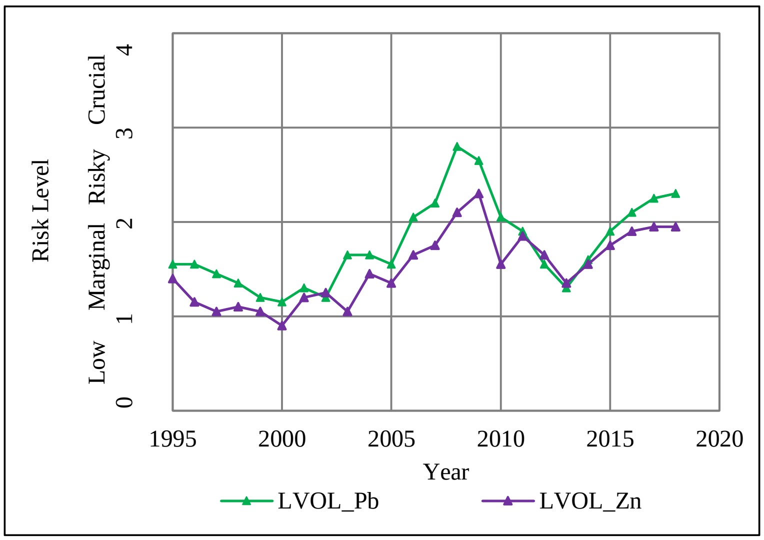

Figure 5-14 Zinc and lead supply risks in short term.

5.3.2 Medium-Term Supply Risk

An updated (compared to Figures 3-3, 3-4) resource nationalism risk map of 2015 is presented in Figure 5-15, which is the prediction results according to the regression formulas in chapter 3. Through this map it could be seen that the coverage of the data for Middle East and Africa is poor. But it does not have significant effects on the overall assessment because the majority of the mineral-producing states are well covered. Folding the map along the right top and left bottom diagonal, it could be found that riskis gathered at the southeast. The riskiest countries are Panama, Lao PDR, Mongolia, Kazakhstan, Vietnam, and Cuba.

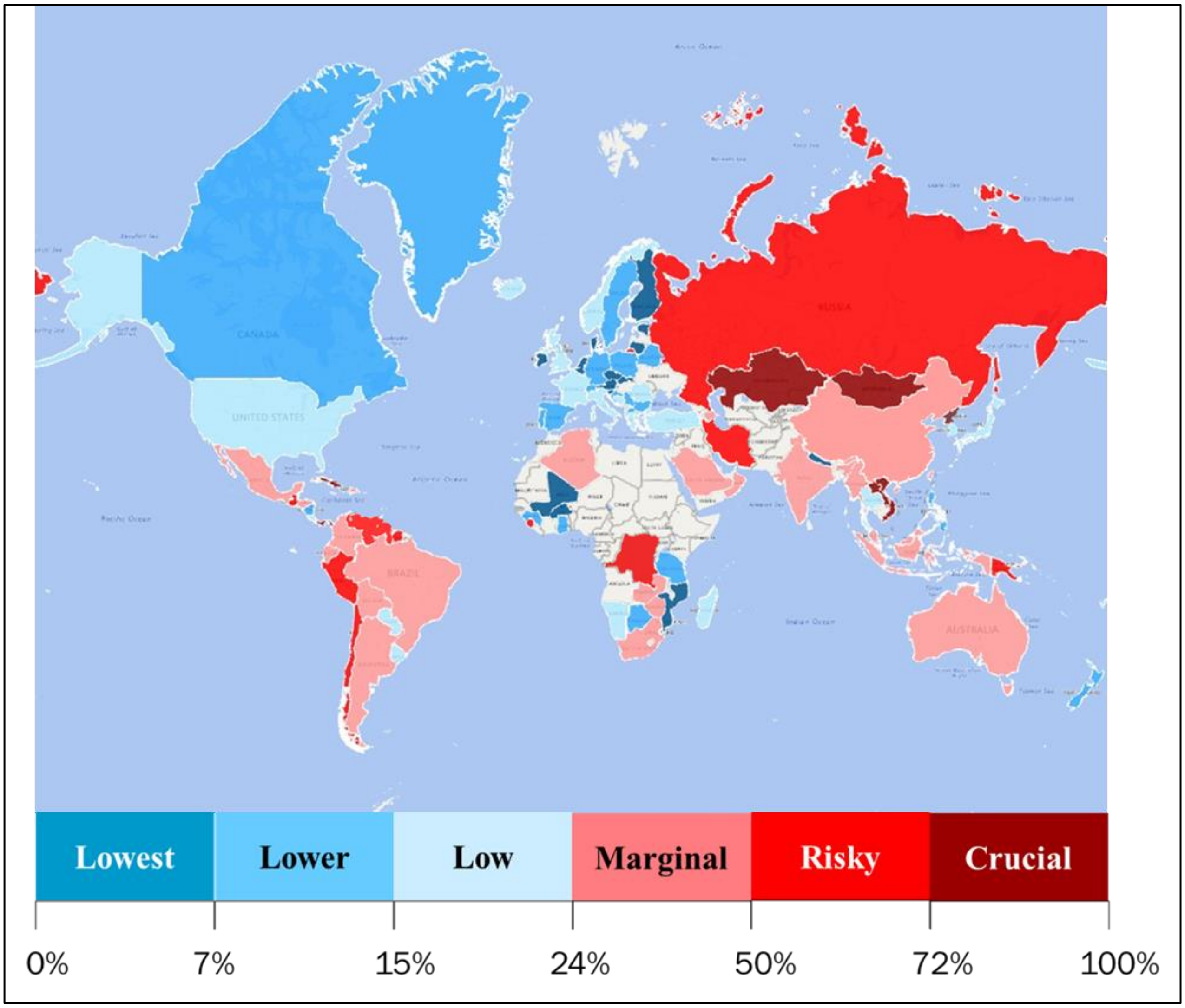

Figure 5-15 Resource nationalism risk map in 2015 (calculated and drew by author).

The medium-term supply risk of metals can be obtained by calculating the weighted average of metals-producing countries' probability of resource nationalism, as those displayed in Figures 5-16 to 5-20. As shown, risk of resource nationalism has decreased significantly ever since 2012 for all nine metal commodities. In 2015, their risks of resource nationalism were well below the 50% threshold. Copper was the riskiest one, followed by tin, silver, and lead.

For silver, the decline was mainly contributed by China, Bolivia, and Australia. China's contribution to world production as well as its risk of resource nationalism have declined slightly. A similar situation was observed in Australia as well. In Bolivia, its risk of resource nationalism declined drastically, which led to the decline of its contribution to silver resource nationalism risk. For gold, the decline was mainly attributed to resource nationalism risk reduction in China, Australia, South Africa, and Indonesia. For platinum, resource nationalism risk decline in South Africa and Zimbabwe contributed to its decreased resource nationalism risk. For palladium, it is due to resource nationalism risk reduction in South Africa and Russia. For copper, its declining trend in resource nationalism was mainly led by China and Chile, while its rebound in 2015 was caused by resource nationalism risk spikes in Congo (DRC). For nickel, because risk of resource nationalism in Indonesia and Philippines has significantly reduced after 2013, its resource nationalism reduced largely. For tin, its reduction in resource nationalism risk was caused by China's, Indonesia's, and Peru's reduced probabilities of resource nationalism, and reduced production share in Bolivia, a high risky country. For zinc and lead, they were mined together most of the time, and their resource nationalism risk was quite similar. The resource nationalism risk of zinc is reduced by China, and India. For lead, it was due to China, mainly.

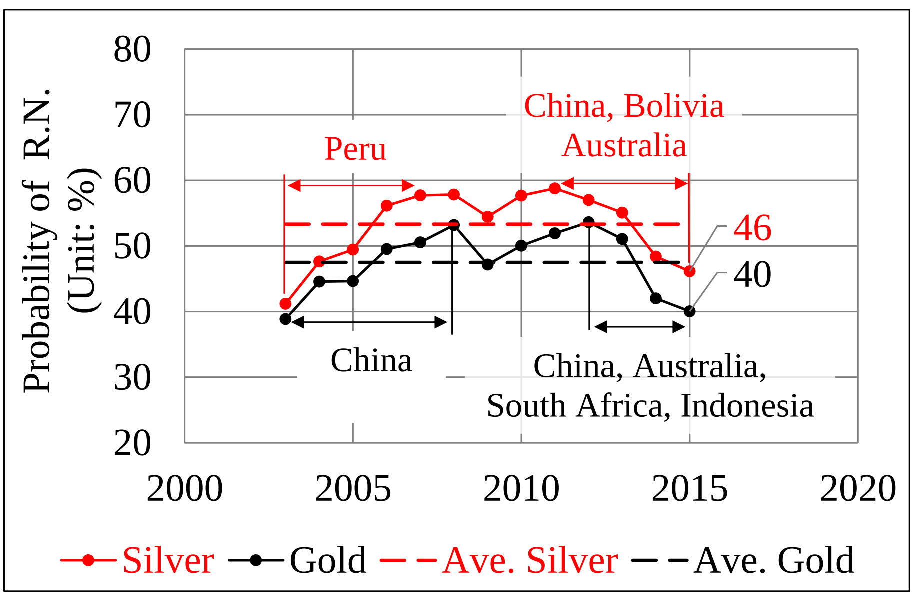

Figure 5-16 Probability of resource nationalism for silver and gold.

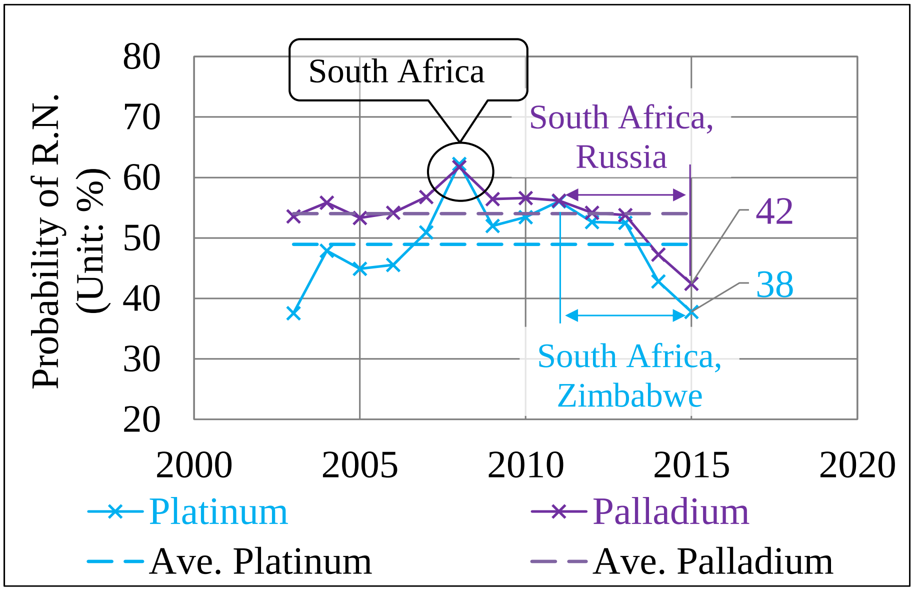

Figure 5-17 Probability of resource nationalism for platinum and palladium.

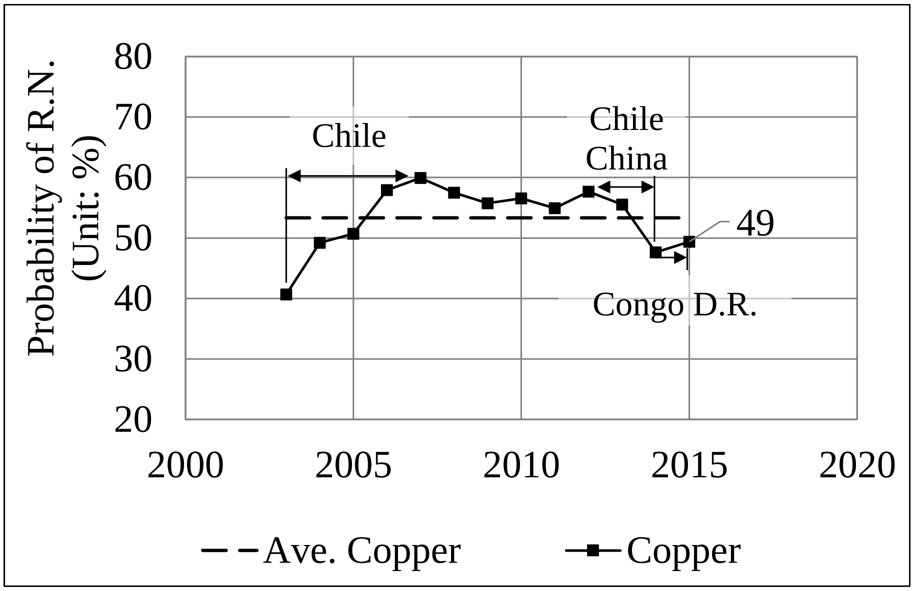

Figure 5-18 Probability of resource nationalism for copper.

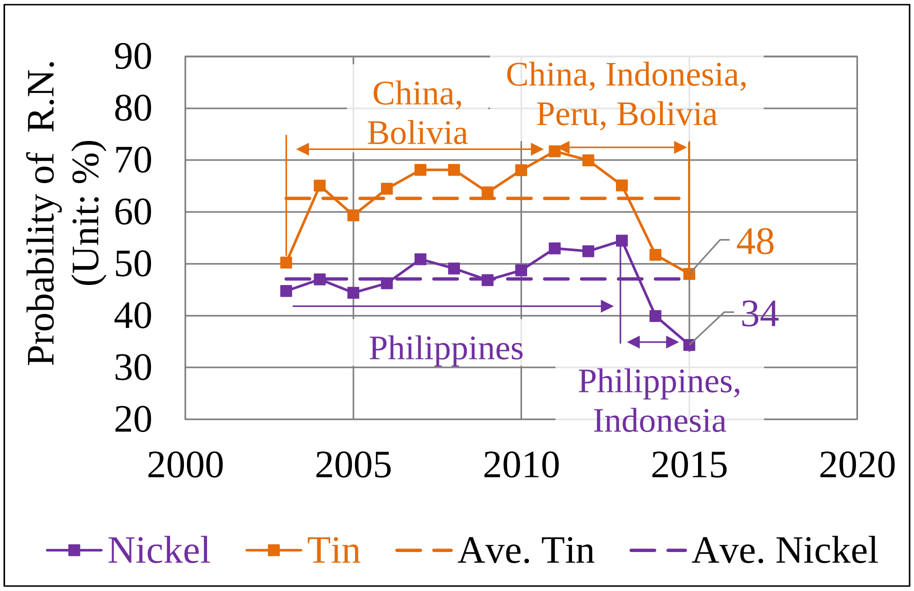

Figure 5-19 Probability of resource nationalism fornickel and tin.

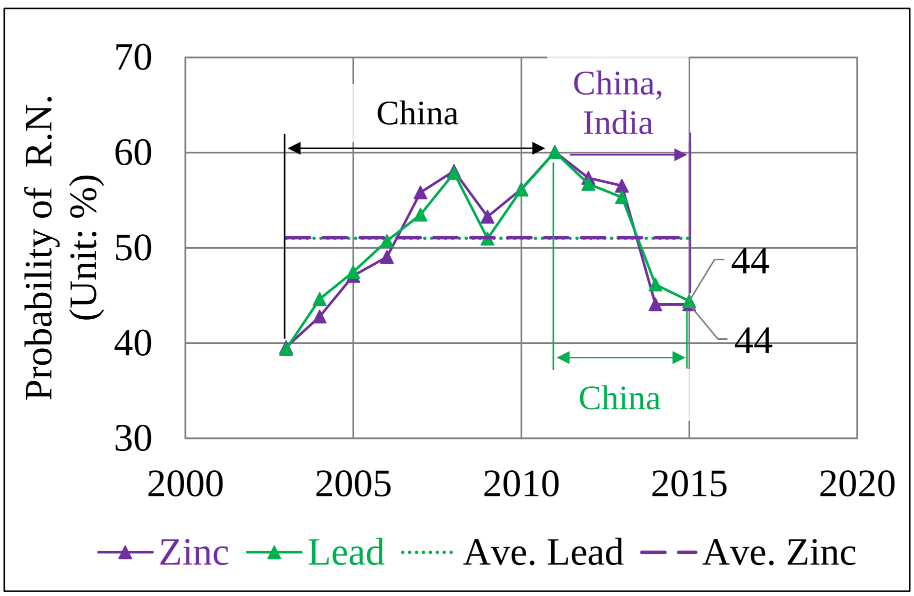

Figure 5-20 Probability of resource nationalism for zinc and lead.

Transforming the probability into risk levels (Figures 5-21 to 5-24), it can be discovered that the nine metals were well in the risky and marginal levels. It means that they are dominated by the top 50% risky states excluding the top 10% riskiest ones. In 2015, they all fit into marginal and risky levels; this explains as that these metals are not exposed to resource nationalism but are frangible to changes because none of them are safe enough.

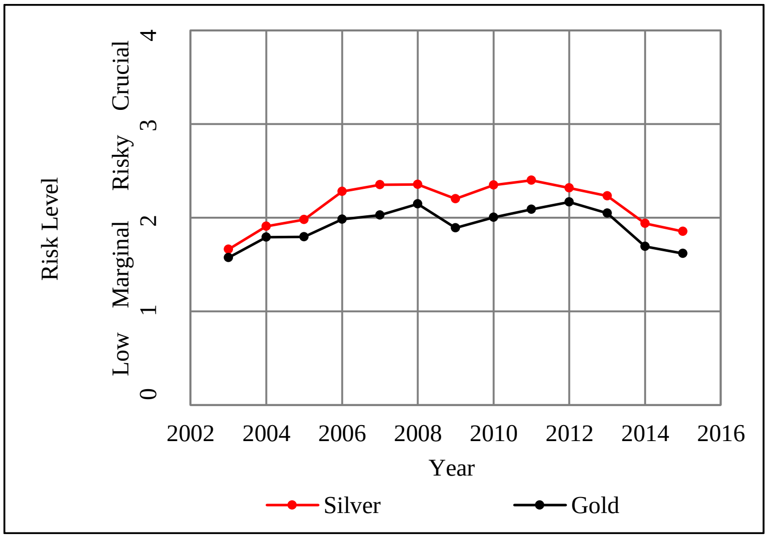

Figure 5-21 Resource nationalism risk level for silver and gold.

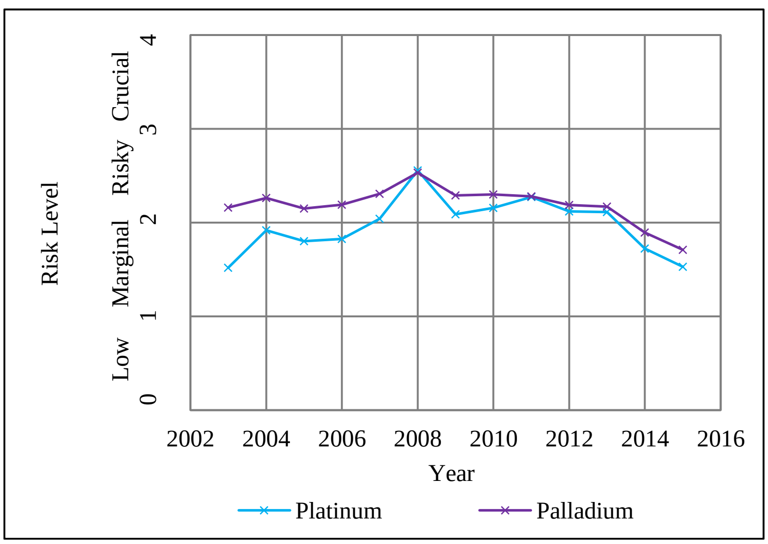

Figure 5-22 Resource Nationalism Risk Level for Platinum and Palladium.

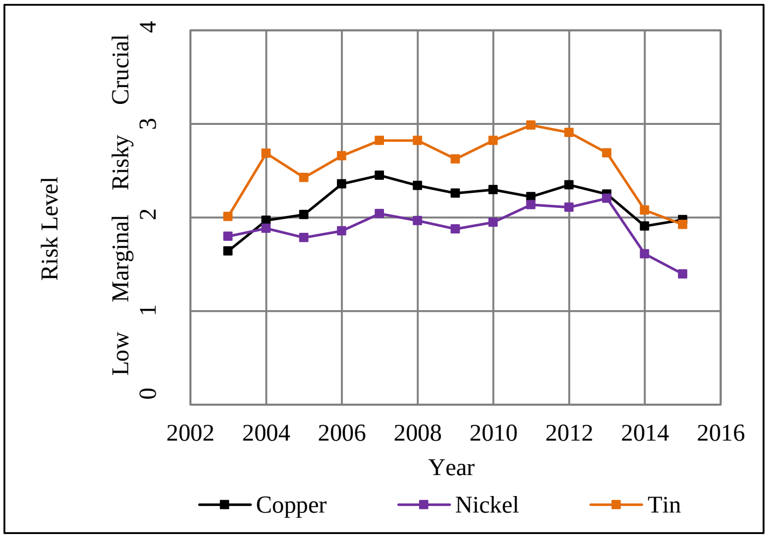

Figure 5-23 Resource nationalism risk level for copper, nickel and tin.

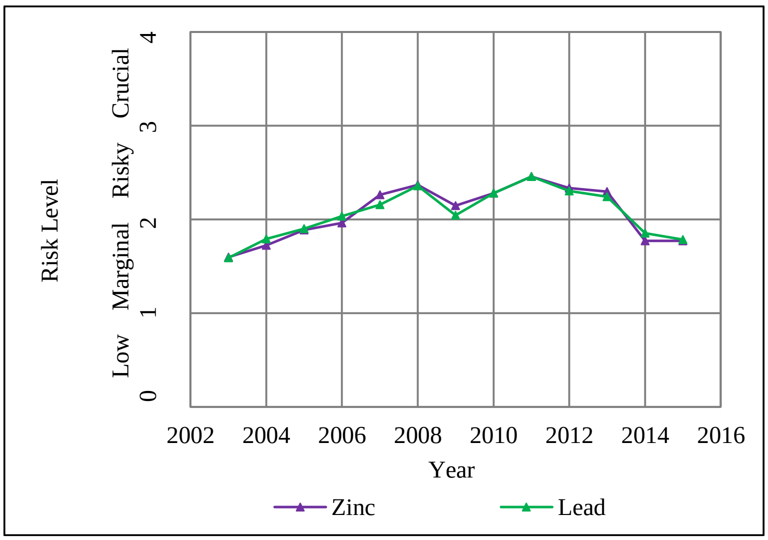

Figure 5-24 Resource nationalism risk level for zinc and lead.

5.3.3 Long Term Supply Risk

According to the results presented in chapter 4, we could transform the results presented in Figure K-1 (Appendix K) into a relative shortage level shown in Figure 5-25. As shown, the shortage will go up to as high as the supply level in the base scenario. Even in the total effect scenario, it still can go as high as 40% of the supply level in 2050.

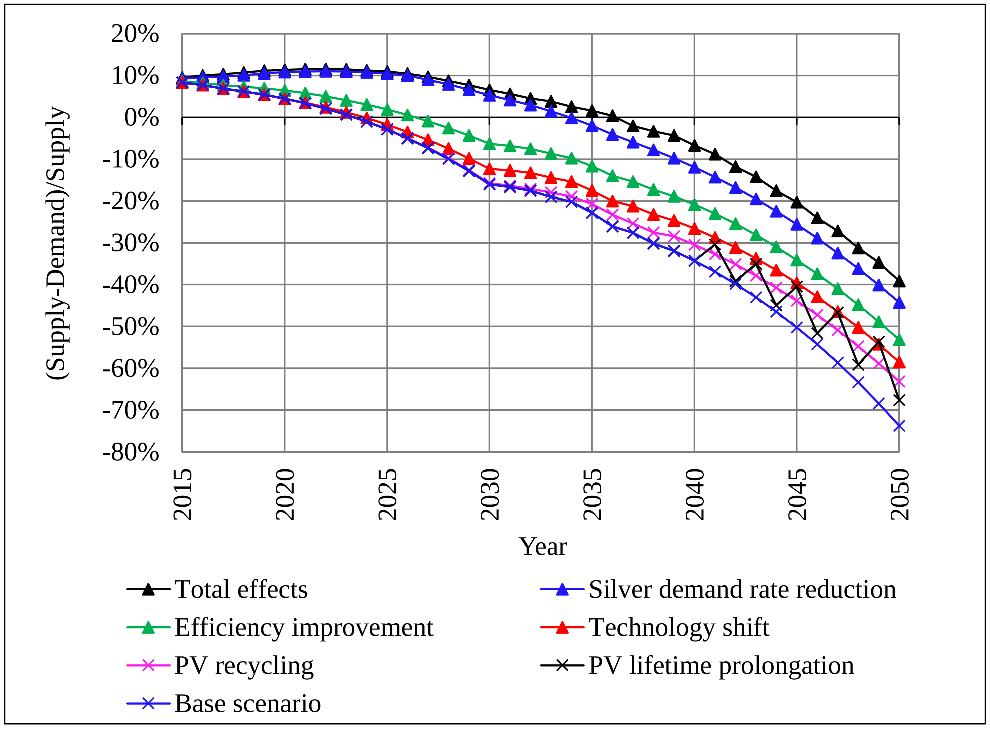

Figure 5-25 Relative silver supply shortage.

5.3.4 Supply Risk Route

Finally, combining all three periods, a supply risk route of above analyzed metals is obtained (Figure 5-26). As seen, tin's supply risk will increase to risky level from low level. Gold's, nickel's, and platinum's supply risk will remain marginal in the medium term. Palladium's and zinc's supply risk will increase to risky level in the medium term from marginal in the short term. Silver's, copper's and lead's supply risk will remain risky in the medium term. Silver's supply risk in the long term will be low until the 2030s depending on technological improvement of the c-Si PV industry. In the longer term, regardless of technological considerations, silver supply risk could be risky.

The route map shows that the supply risk of gold, platinum and nickel is likely to be lower than other base and precious metals. They are expected to perform similarly as the option market as a whole without necessary to add risk premiums, and the resource nationalism risk does not have to be considered for new investments. For silver, copper and lead, their supply risk is likely to continue the current trend and keep risky in the coming 10 years. The risk premiums and the resource nationalism problems have to be carefully managed in order to sustain the businesses. For silver, the physical shortage may come froth after 2030, therefore a resource saving manner is called in urgent. The supply risk of zinc, palladium and tin should be carefully watched because there is a potential to rise, especially for tin. Thus, an addition of risk premium when doing financial analyze and a careful management of resource nationalism when investing are necessary for these metals to sustain the businesses.

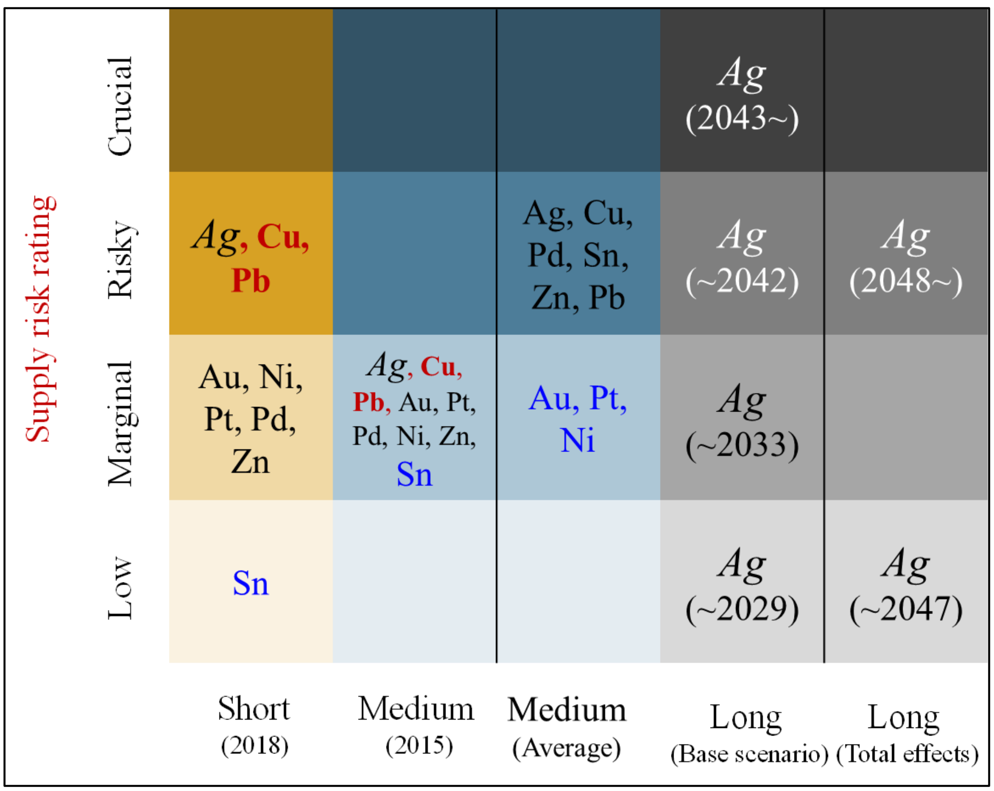

Figure 5-26 Metals' supply risk route map.

Reference

Archival Federal Reserve Economic Data. Link: https://alfred.stlouisfed.org

Chapter 6 Conclusion

Sustainable use of metals is of great importance to support modern society. Knowing "how risky a metal's supply can be" and "where the sources of risk come from" can promote sustainable usage of metals. Therefore, it is necessary to assess metal supply risk. The existing literature simply used weighted average of numerous indicators to express supply risk level of a metal. The method was highly replicated for its simplicity. But besides picking out the relatively risky metals, the results of these studies hardly can guide a specific risk-reducing behavior. This study aimed at developing a comprehensive assessment framework in which metals' supply risk can be quantitatively measured in the short, medium, and long term for their corresponding stakeholders: corporations, nations, and the whole human community.

First, in the short term, the evolvement of metals price volatility from an economic perspective was studied. By using the Spline-GARCH model, a low-frequency price volatility series was obtained and then regressed with macroeconomic variables. Significant regression results were found and further robustness tests and forecasting ability verification tests were conducted. In reality, price volatility is one of the most sensitive factors dominating market volatility and an input to project evaluations. By using our predicted one-year-ahead or one-quarter-ahead volatility, project evaluation under uncertainty, specifically, real option evaluation, could be done. In the medium term, the study focused on the common genesis of resource nationalism and confirmed the dominance of economic, political, and governance' factor on it. By using the model, investors could quickly get a basic overview of how risky a country could be and how risky the metal they are working on without on-site survey. For the long term, a case study of silver was performed, where silver supply shortage during 2015–2050 was estimated. Several technological considerations were taken into account by scenario analysis. The results can benefit governments in long-term strategic stock planning and exploration. The results for the c-Si PV industry could be useful for manufacturers to minimize their raw material supply risk.

Academically, the study has two aspects of contributions, theoretically and practically. Theoretically, we explained the changes of price volatility from an economic perspective. Generally, some scholars think financial markets' behaviors dominate metals' price volatility, while others are inclined to believe that metals' price volatility is stochastic and rarely suspect that macro economy plays a role. By using the Spline-GARCH model, this study confirmed macroeconomic factors' effects on price volatility. It will improve the theory of changes in price volatility. Also, theoretically, the view point of resource nationalism in this study adds evidence to real evolution of the resource nationalism theory. Generally, resource nationalism is a topic in social science where researchers focus on specific conditions either regionally or locally. This study discovered the common characteristic of resource nationalism from an economic point of view. It will help build comprehensive thinking around it. Practically, the estimation on silver mainly provides an estimation on silver supply shortage potential. Especially, the technology scenarios can help the c-Si PV industry towards sustainable productions.

Finally, looking forward, this study offers some ideas for future works. For price volatility, we mainly focused on economic factors' impact. It can be extended to financial and fundamental factors as well to explain price volatility in a more comprehensive way. For resource nationalism, it is also interesting to look at the effects of resource nationalism policy between countries. For c-Si PV, since PV recycling is identified as very crucial, an economic feasibility study on PV recycling using the advanced real option theory may be carried out.

Appendix A

Table A-1 Regression Results of ARMA Models on Log Returns of Metal Prices.

	ARMA (p,q)	Intercept	AR(1)	AR(2)	MA(1)	MA(2)	AIC
Δ(Log_Ag)	(0,1)	0.001			0.197		-4685.19
		(0.001)			(0.028)		
Δ(Log_Au)	(0,2)	0.001			0.167	-0.050	-5973.48
		(0.001)			(0.029)	(0.029)	
Δ(Log_Pt)	(1,0)	0.001	0.166				-5330.29
		(0.001)	(0.029)				
Δ(Log_Pd)	(0,1)	0.002			0.227		-3873.99
		(0.002)			(0.030)		
Δ(Log_Cu)	(2,1)	0.001	1.084	-0.198	-0.799		-5165.16
		(0.001)	(0.125)	(0.055)	(0.119)		
Δ(Log_Ni)	(0,1)	0.001			0.244		-4341.95
		(0.001)			(0.028)		
Δ(Log_Sn)	(1,2)	0.001	-0.879		1.131	0.244	-5153.24
		(0.001)	(0.123)		(0.123)	(0.033)	
Δ(Log_Pb)	(0,1)	0.001			0.240		-4585.61
		(0.001)			(0.028)		
Δ(Log_Zn)	(0,1)	0.001			0.252		-4971.18
		(0.001)			(0.027)		

Note: the numbers in the "( )" below coefficients are the standard error;

Table A-2 Regression Results of Spline-GARCH Model on Residuals of ARMA Models.

	Ag	Au	Pt	Pd	Cu	Ni	Sn	Pb	Zn
c	1.54E-4	4.6E-5	1.72E-4	1.99E-4	8.0E-5	2.87E-4	1.52E-3	1.41E-3	4.99E-4
α	4.05E-3	6.15E-3	1.60E-2	2.19E-2	1.13E-2	2.12E-3	1.40E-2	1.62E-2	1.31E-2
β	0.85	0.85	0.79	0.39	0.73	0.81	0.52	0.34	0.33
$\boldsymbol{w_0}$	39.62	26.10	14.05	-0.62	58.34	15.99	-45.71	-21.88	0.54
$\boldsymbol{w_1}$	-144.50	-127.36	-73.12	63.51	-413.31	-4.7.37	311.42	141.64	-29.91
$\boldsymbol{w_2}$	-175.65	-73.77	-70.69	42.36	75.89	-62.46	-3.39	-21.27	24.30
$\boldsymbol{w_3}$	202.93	176.57	131.20	-57.79	543.80	-95.04	-504.41	-128.69	-75.18
$\boldsymbol{w_4}$	303.36	126.71	222.99	-122.72	-321.67	202.37	-246.31	-12.21	318.62
$\boldsymbol{w_5}$	-188.05	-87.50	-404.48	9.12	-62.58	11.10	55.20	51.33	-349.10
$\boldsymbol{w_6}$	-270.17	-69.01	309.16	57.69	190.09	-110.03	-59.31	-81.86	33.36
$\boldsymbol{w_7}$	251.67	-54.34	-201.89	15.50	-165.74	73.36	9.99	219.86	87.78
$\boldsymbol{w_8}$	124.19	136.21	5.74	19.65	300.44	-13.66	-35.16	-279.16	47.72
$\boldsymbol{w_9}$	-215.10	-57.46	217.10	-1.35	-408.24	-118.06	71.39	292.64	-90.88
$\boldsymbol{w_{10}}$	187.44	-38.74	-356.53	-53.06	388.37	262.84	-96.49	-297.36	96.82
$\boldsymbol{w_{11}}$	-240.14	147.35	402.08	12.73	-340.02	-331.75	112.97	224.25	-137.44
$\boldsymbol{w_{12}}$	220.78	-209.14	-312.19	-13.69	297.20	334.21	-117.99	-120.83	187.16
$\boldsymbol{w_{13}}$	-153.92	211.54	215.87	130.77	-239.65	-269.51	109.93	60.74	-211.10
$\boldsymbol{w_{14}}$	99.59	-186.03	-170.35	-168.73	165.75	172.99	-102.80	-53.87	145.27
$\boldsymbol{w_{15}}$	-78.60	114.08	98.07	88.98	-109.19	-107.17	68.03	33.75	-68.54
$\boldsymbol{w_{16}}$	67.45	-43.73	-29.09	-24.25	58.45	50.64	-26.14	-11.45	26.95
$\boldsymbol{w_{17}}$	-44.38	15.07	2.00	1.38	-21.70	-12.81	5.23	3.05	-10.17
$\boldsymbol{w_{18}}$	20.38	-6.10	0.22	1.27	5.56	3.31	-2.33	-0.82	3.72
$\boldsymbol{w_{19}}$	-6.79			-0.88	-0.63	-0.13			-0.17
Log likelihood	2504.83	3185.98	2831.42	2067.74	2688.69	2274.01	2757.91	2464.50	2653.39
BIC	-4847.09	-6216.47	-5507.33	-3975.07	-5214.81	-4385.45	-5360.32	-4773.50	-5144.22

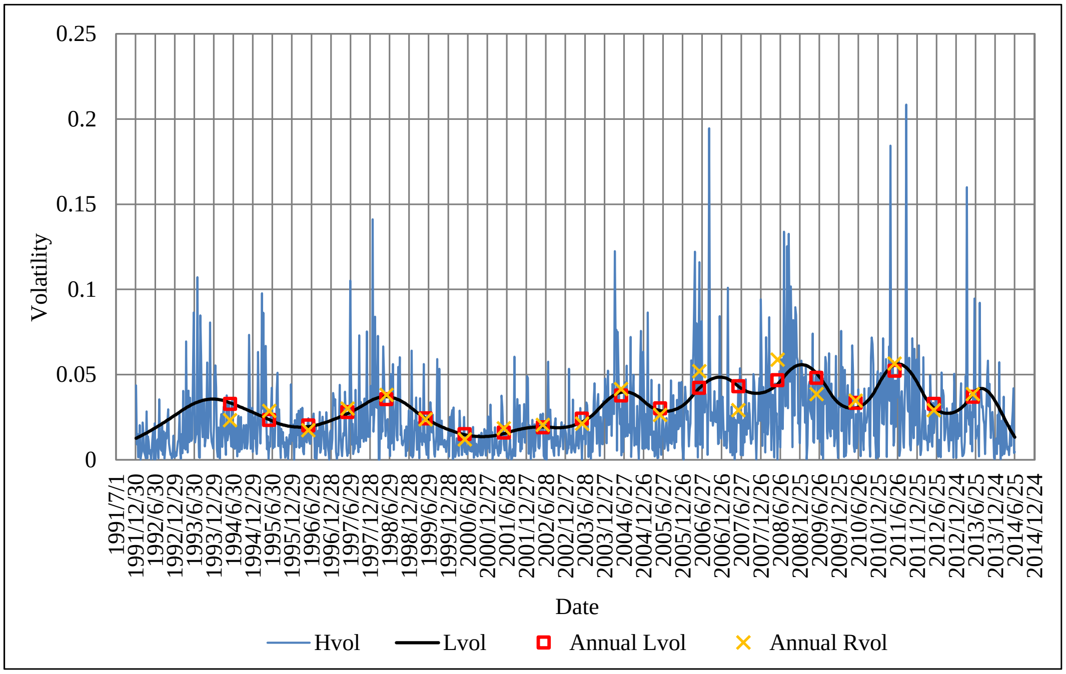

Figure A-1 Silver Price Volatility.

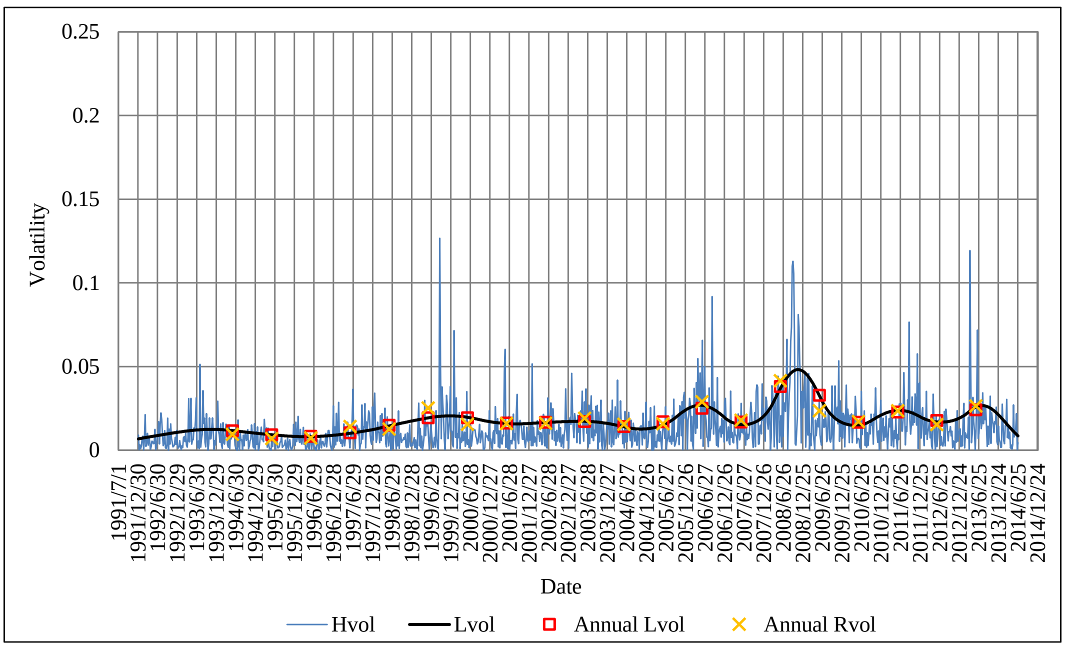

Figure A-2 Gold Price Volatility.

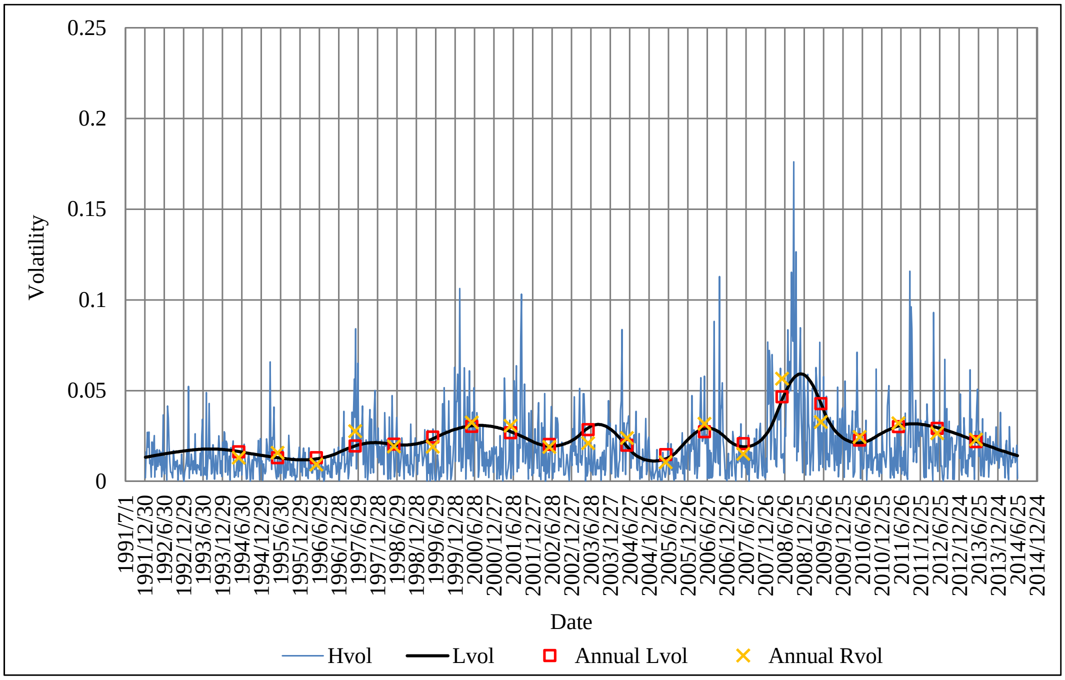

Figure A-3 Platinum Price Volatility.

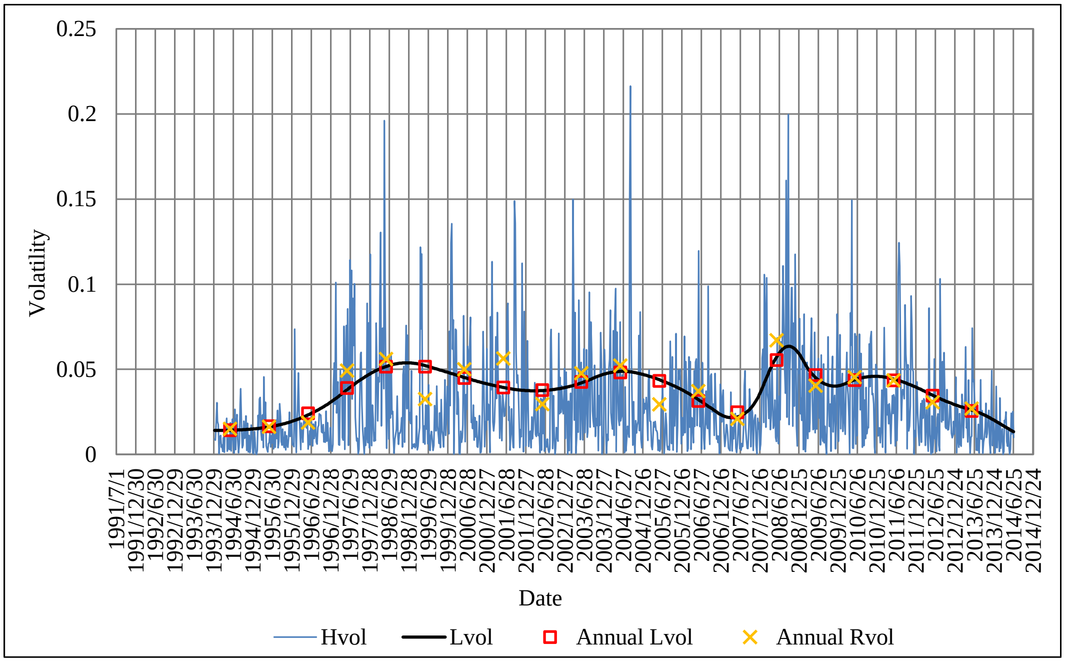

Figure A-4 Palladium Price Volatility.

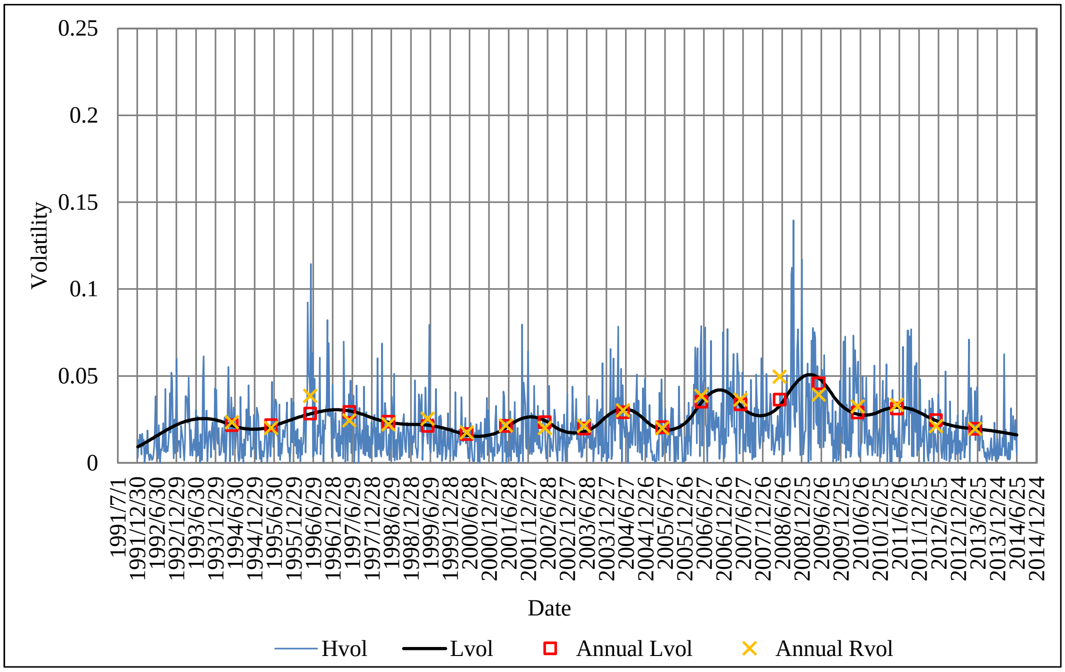

Figure A-5 Copper Price Volatility.

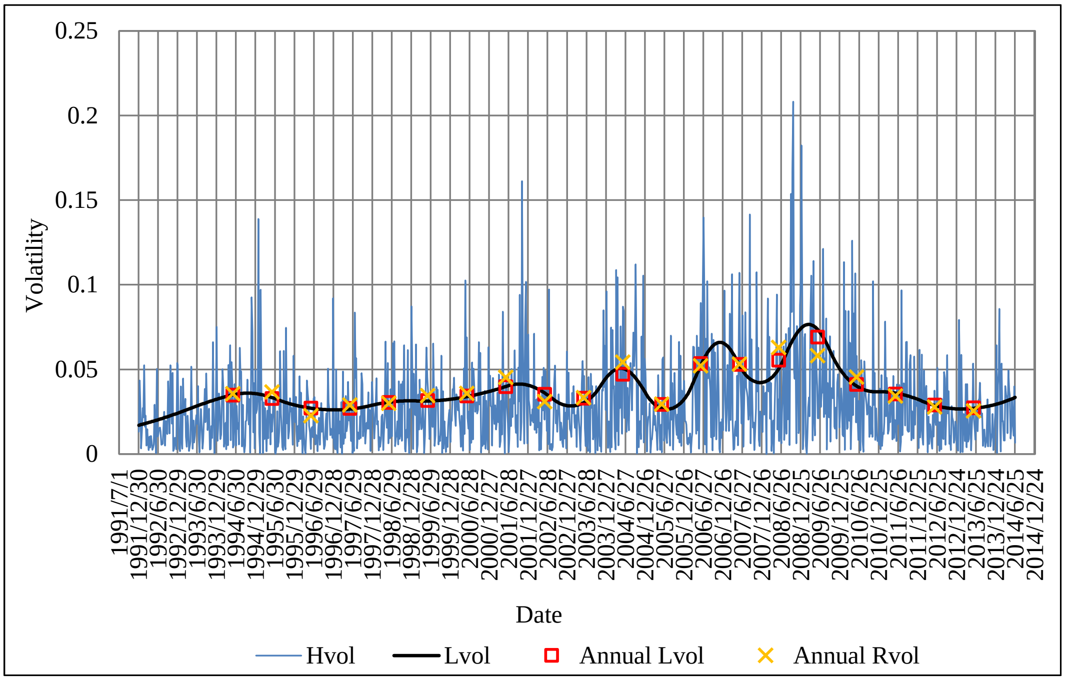

Figure A-6 Nickel Price Volatility.

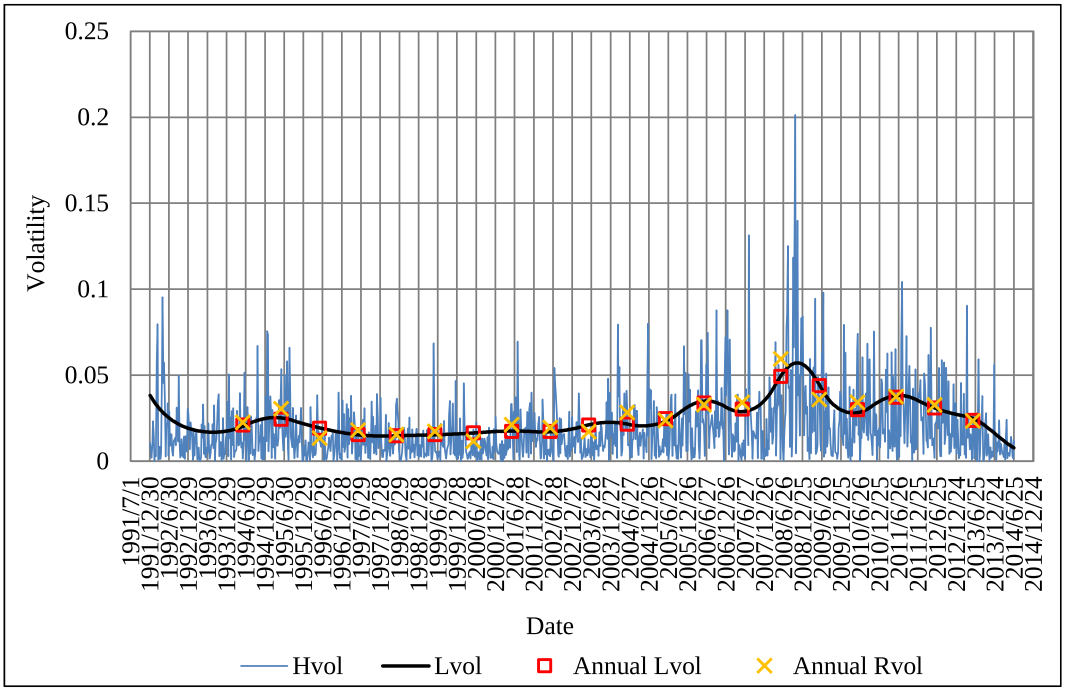

Figure A-7 Tin Price Volatility.

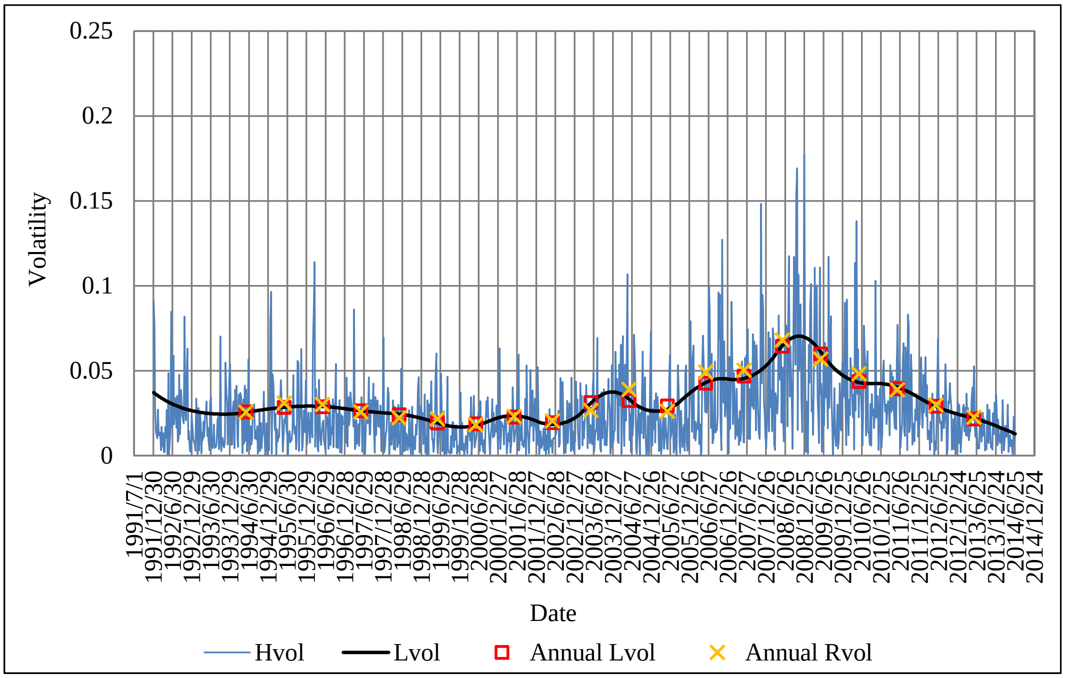

Figure A-8 Lead Price Volatility.

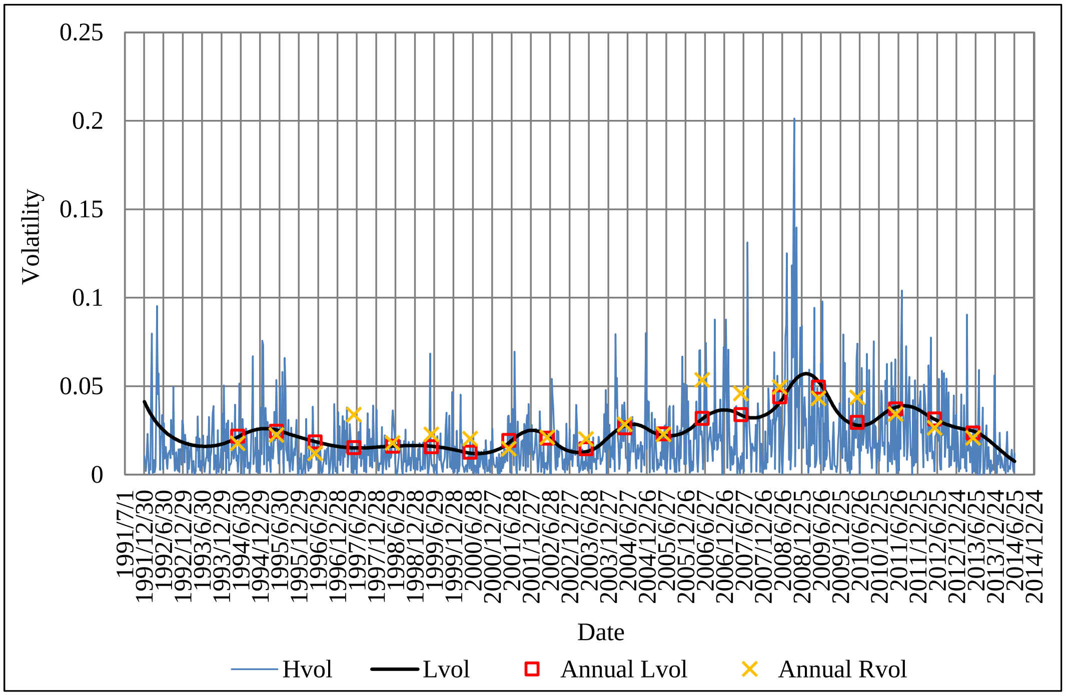

Figure A-9 Zinc Price Volatility.

Appendix B.

Table B-1 Summary of Unit Root Test of Annual Average Lvol/Rvol and Macroeconomic Variables.

	Unit Root Test (ADF) Lag Length: 0 Exogenous: Constant Prob.	Unit Root Test (PP) Lag Length: 0 Exogenous: Constant Prob.	Unit Root Test (ADF) Lag Length: 1 Exogenous: None Prob.	Unit Root Test (PP) Lag Length: 1 Exogenous: Constant Prob.
Lvol_Ag	0.259	0.270	0.000	0.000
Lvol_Au	0.130	0.148	0.000	0.000
Lvol_Pt	0.078	0.090	0.000	0.000
Lvol_Pd	0.021	0.097	0.001	0.001
Lvol_Cu	0.765	0.163	0.005	0.000
Lvol_Ni	0.232	0.228	0.003	0.000
Lvol_Sn	0.466	0.489	0.000	0.000
Lvol_Pb	0.629	0.501	0.003	0.003
Lvol_Zn	0.427	0.474	0.000	0.000
Rvol_Ag	0.484	0.018	0.000	0.000
Rvol_Au	0.033	0.035	0.000	0.000
Rvol_Pt	0.004	0.004	0.000	0.000
Rvol_Pd	0.008	0.005	0.000	0.000
Rvol_Cu	0.216	0.124	0.000	0.000
Rvol_Ni	0.199	0.193	0.000	0.000
Rvol_Sn	0.217	0.256	0.000	0.000
Rvol_Pb	0.317	0.446	0.079	0.000
Rvol_Zn	0.233	0.237	0.000	0.000
UNE	0.428	0.365	0.000	0.001
INF_CORE	0.162	0.000	0.002	0.000
TED	0.196	0.170	0.001	0.000
SP500	0.383	0.389	0.000	0.004
ER_SA	0.251	0.514	0.004	0.006
ER_RUS	0.301	0.317	0.006	0.006

ER_CAN	0.910	0.879	0.008	0.009
RP_USA	0.066	0.493	0.008	0.095

Table B-2 Summary of Cointegration Test of Annual Average Lvol/Rvol and Macroeconomic Variables.

	Engle-Granger Cointegration Test		**Phillips-Ouliaris Cointegration Test**	
	Prob. tau-statistics	**Prob. z-statistics**	**Prob. tau-statistics**	**Prob. z-statistics**
Lvol_Ag	0.052	0.053	0.053	0.045
Lvol_Au	0.198	0.181	0.190	0.242
Lvol_Pt	0.015	0.000	0.002	0.028
Lvol_Pd	0.034	0.025	0.022	0.081
Lvol_Cu	0.096	0.055	0.098	0.037
Lvol_Ni	0.014	0.011	0.016	0.006
Lvol_Sn	0.052	0.031	0.049	0.048
Lvol_Pb	0.152	0.062	0.159	0.100
Lvol_Zn	0.027	0.014	0.028	0.012
Rvol_Ag	0.001	0.002	0.002	0.001
Rvol_Au	0.056	0.042	0.056	0.042
Rvol_Pt	0.000	0.000	0.000	0.001
Rvol_Pd	0.004	0.000	0.000	0.012
Rvol_Cu	0.080	0.050	0.080	0.049
Rvol_Ni	0.001	0.001	0.001	0.003
Rvol_Sn	0.014	0.011	0.016	0.006
Rvol_Pb	0.014	0.006	0.012	0.012
Rvol_Zn	0.015	0.008	0.015	0.007

Appendix C.

Table C-1 Regression Results of Quarterly Average Lvol with Auto-Correlation Terms.

	DLvol_Ag	DLvol_Au	DLvol_Pt	DLvol_Pd	DLvol_Cu	DLvol_Ni	DLvol_Sn	DLvol_Pb	DLvol_Zn
cons.	-1.21E-4 [0.785]	5.72E-5 [0.868]	-1.91E-5 [0.968]	3.69E-5 [0.945]	-4.46E-5 [0.843]	-6.33E-5 [0.898]	-8.48E-5 [0.812]	-1.88E-4 [0.754]	-8.68E-5 [0.811]
AR(1)	1.437 [0.000]	1.796 [0.000]	0.557 [0.000]	1.460 [0.000]	1.526 [0.000]	1.432 [0.000]	0.583 [0.000]	0.295 [0.022]	1.445 [0.000]
AR(2)	-0.855 [0.000]	-1.360 [0.000]	0.485 [0.000]	-0.742 [0.000]	-0.907 [0.000]	-0.821 [0.000]	0.527 [0.000]	0.681 [0.000]	-0.806 [0.000]
AR(3)		0.292 [0.014]	-0.709 [0.000]				-0.727 [0.000]	-0.531 [0.000]	
MA(1)	0.581 [0.000]		1.794 [0.000]	0.922 [0.000]		0.546 [0.000]	1.778 [0.000]	2.386 [0.000]	0.544 [0.000]
MA(2)			0.948 [0.000]				0.928 [0.000]	2.066 [0.000]	
MA(3)								0.616 [0.000]	
R-squared	0.93	0.93	0.96	0.96	0.94	0.94	0.96	0.97	0.94
Durbin-Watson stat	2.09	1.81	2.09	1.83	1.78	2.23	2.06	2.19	2.14
Unit Root of residual at level (ADF) Prob.	0.009	0.000	0.000	0.000	0.139	0.000	0.000	0.017	0.019
Unit Root of residual at level (PP) Prob.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Jarque-Bera Normality Prob.	0.126	0.000	0.000	0.000	0.000	0.057	0.000	0.102	0.069
Jarque-Bera Normality Skewness	-0.53	0.23	0.14	1.51	0.97	0.36	-0.51	-0.41	0.23
Jarque-Bera Normality Kurtosis	3.38	8.70	5.43	7.77	4.36	4.12	6.03	3.88	4.20
Correlogram of Residuals Until lag10 Prob.	< 0.05	< 0.05	< 0.05	< 0.05	< 0.05	< 0.05	< 0.05	< 0.05	< 0.05
Correlogram of Residuals Squared Until lag10 Prob.	< 0.05	< 0.05	< 0.05	< 0.05	Lag4-5 >0.1 Lag6-10 <0.1	< 0.05	< 0.05	< 0.05	< 0.05
Breusch_Godfrey LM test	Prob. F(2, 71) = 0.049	Prob. F(3, 69) = 0.035	Prob. F(3, 67) = 0.185	Prob. F(2, 71) = 0.622	Prob. F(2, 72) = 0.060	Prob. F(2, 71) = 0.035	Prob. F(3, 67) = 0.001	Prob. F(3, 66) = 0.001	Prob. F(2, 71) = 0.278

Heteroskedasticity Test: White (exclude While cross terms)	Prob. F(4, 72) = 0.000	Prob. F(3, 72) = 0.009	Prob. F(6, 69) = 0.000	Prob. F(4, 72) = 0.000	Prob. F(2, 74) = 0.003	Prob. F(4, 72) = 0.000	Prob. F(6, 69) = 0.000	Prob. F(7, 68) = 0.000	Prob. F(4, 72) = 0.000

Table C-2 Regression results of quarterly average Rvol with auto-correlation terms.

Dependent	**DRvol_ Ag**	**DRvol_ Au**	**DRvol_ Pt**	**DRvol_ Pd**	**DRvol_ Cu**	**DRvol_ Ni**	**DRvol_ Sn**	**DRvol_ Pb**	**DRvol_ Zn**
cons.	1.63E-4 [0.889]	1.59E-4 [0.788]	1.52E-4 [0.268]	4.06E-5 [0.836]	-8.55E-5 [0.908]	-8.93E-5 [0.827]	2.53E-4 [0.114]	-6.15E-5 [0.908]	2.01E-5 [0.961]
AR(1)	-0.835 [0.035]	-0.195 [0.094]	-0.515 [0.000]	0.322 [0.001]	-0.541 [0.000]	0.253 [0.148]	-0.606 [0.000]	-1.452 [0.000]	0.118 [0.578]
AR(2)	-0.276 [0.035]	-0.257 [0.032]	0.439 [0.001]	-0.521 [0.140]	-0.330 [0.004]	0.031 [0.834]	0.439 [0.002]	-0.521 [0.140]	-0.044 [0.786]
AR(3)		-0.249 [0.060]	0.083 [0.492]	0.083 [0.484]			0.307 [0.013]	0.052 [0.778]	
MA(1)	0.572 [0.153]		0.012 [0.729]	-0.974 [0.000]		-0.123 [0.000]	-0.003 [0.901]	1.211 [0.000]	-0.701 [0.000]
MA(2)			-0.963 [0.000]				-0.945 [0.000]	-0.311 [0.289]	
MA(3)								-0.653 [0.000]	
R-squared	0.09	0.11	0.27	0.31	0.25	0.25	0.38	0.30	0.26
Durbin-Watson stat	2.01	2.06	1.94	2.00	2.09	1.97	1.86	2.00	2.00
Unit Root of residual at level (ADF) Prob.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Unit Root of residual at level (PP) Prob.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Jarque-Bera Normality Prob.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.039	0.000
Jarque-Bera Normality Skewness	0.92	1.14	1.54	1.05	2.13	1.29	1.26	0.01	1.44
Jarque-Bera Normality Kurtosis	4.55	5.83	6.01	3.60	10.16	6.03	7.64	4.43	6.03
Correlogram of Residuals Until lag10 Prob.	<0.05	Lag5-7 <0.05 Others >0.05	Lag6 <0.05 Lag7- >0.05	Lag8 <0.05 Others >0.05	Lag3 <0.05 Lag4- >0.05	>0.1	>0.05	>0.1	>0.1
Correlogram of Residuals Squared Until lag10 Prob.	<0.1	>0.05	Lag6 <0.05 Lag7- >0.1	Lag4-6 >0.05 Lag7- <0.05	>0.05	>0.1	<0.1	<0.05	>0.1
Breusch_Godfrey LM test	Prob. F(2, 71) = 0.166	Prob. F(3, 69) = 0.019	Prob. F(3, 67) = 0.157	Prob. F(2, 71) = 0.608	Prob. F(2, 72) = 0.256	Prob. F(2, 71) = 0.791	Prob. F(3, 67) = 0.213	Prob. F(3, 66) = 0.483	Prob. F(2, 71) = 0.914
Heteroskedasticity Test: White (exclude While cross terms)	Prob. F(4, 72) = 0.683	Prob. F(3, 72) = 0.597	Prob. F(6, 69) = 0.863	Prob. F(4, 72) = 0.045	Prob. F(2, 74) = 0.878	Prob. F(4, 72) = 0.830	Prob. F(6, 69) = 0.000	Prob. F(7, 68) = 0.824	Prob. F(4, 72) = 0.875

Appendix D.

```
#R_Studio code of Spline-GARCH (example of Ag)

M <- read.csv(file.choose(), header=T)

dim(M)

head(M)

tail(M)

# Mean equation

x=ts(M[1])

plot(x, type="b")

log.x = log(x)

plot(log.x, type="l")

diff.x = diff(x)

plot(diff.x, type="l")

difflog.x = diff(log.x, type="l")

plot(difflog.x, type="l")

# Dickey Fuller test for variables stationary

library(tseries)

adf.test(x, alternative="stationary", k=0)

adf.test(diff.x, alternative="stationary", k=0)
```

```
adf.test(difflog.x, alternative="stationary", k=0)

# ACF and PACF to find p q for ARIMA(p, d, q)

library(astsa)

lag1.plot(difflog.x,1)

acf(difflog.x, xlim=c(1,100))

pacf(difflog.x, xlim=c(1,100),ylim=c(-0.3,0.3))

# ARIMA regression test through all possible groups

arima(difflog.x,order=c(1,0,0))

arimafit <- arima(difflog.x,order=c(1,0,0))

arima(difflog.x,order=c(2,0,0))

arimafit <- arima(difflog.x,order=c(2,0,0))

arima(difflog.x,order=c(0,0,1))

arimafit <- arima(difflog.x,order=c(0,0,1))

arima(difflog.x,order=c(0,0,2))

arimafit <- arima(difflog.x,order=c(0,0,2))

arima(difflog.x,order=c(1,0,1))

arimafit <- arima(difflog.x,order=c(1,0,1))

arima(difflog.x,order=c(2,0,1))

arimafit <- arima(difflog.x,order=c(2,0,1))
```

```
arima(difflog.x,order=c(2,0,2))

arimafit <- arima(difflog.x,order=c(2,0,2))

arima(difflog.x,order=c(1,0,2))

arimafit <- arima(difflog.x,order=c(1,0,2))

arima(difflog.x,order=c(1,0,2))

arimafit <- arima(difflog.x,order=c(1,0,2))

# calculate residuals from best arimafit according to AIC

arima(difflog.x,order=c(0,0,1))

arimafit <- arima(difflog.x,order=c(0,0,1))

plot(arimafit$residuals)

resid = arimafit$residuals

# Residual tests:

# ACF and PACF to test resid. to diagnose if there is cluster feature of volatility.

acf(resid,xlim=c(1,100),ylim=c(-0.3,0.3))

pacf(resid,xlim=c(1,100),ylim=c(-0.3,0.3))

# Ljung-Box test test autocorrelation of resid.

Box.test(resid, lag = 3, type = "Ljung-Box", fitdf = 1)

data <- rnorm(1175, mean=0, sd=1)
```

```
# Shapiro-wilk normality test of resid.

shapiro.test(resid)

# Square Residual tests:

# ACF and PACF to test squared resid. to diagnose if there is cluster feature of volatility.

sqresid = resid^2

plot(sqresid,type = 'l')

acf(sqresid,xlim=c(1,100),ylim=c(-0.3,0.3))

pacf(sqresid,xlim=c(1,100),ylim=c(-0.3,0.3))

# Ljung-Box test test autocorrelation of sqr. resid.

Box.test(sqresid, lag = 3, type = "Ljung-Box", fitdf = 1)

data <- rnorm(1175, mean=0, sd=1)

# Shapiro-wilk normality test of sqr. resid.

shapiro.test(sqresid)

#End of ARIMA

library('BB')

library('alabama')

library('nloptr')

# Spline GARCH

# Specifying time trend for tau-lag1
```

```
k = 19

bounds = floor(1:k * 1175/k)

bounds = c(0, bounds[1:(k-1)])

time.lin = 0:1174

time.nonlin <- matrix(rep(time.lin,k), length(time.lin), k)

for(i in 1:k) {

  time.nonlin[,i] <- time.nonlin[,i] - bounds[i]

  time.nonlin[which(time.nonlin[,i] < 0), i] <- 0

  time.nonlin[, i] <- time.nonlin[, i]^2

}

time.trend = cbind(time.lin, time.nonlin)

head(time.trend)

tail(time.trend)

for(i in 1:dim(time.trend)[2]) time.trend[,i] <-

  time.trend[,i]/time.trend[dim(time.trend)[1], i]

head(time.trend)

tail(time.trend)

# Spline function

splgarch <- function(para)
```

```
{
  alpha <- para[1]
  beta <- para[2]
  cons <- para[3]
  omega <- para[4]
  w <- para[5:(k+5)]
  Tau <- cons*exp(apply(t(diag(w)%*%t(time.trend)), 1, sum))
  arch <- omega + alpha*(c(mean(sqresid),sqresid[-length(resid)])/Tau)
  gt <- filter(arch, beta, "recursive", init = 1) #mean(sqresid) #AR process
  u2t <- gt[2:1175]*Tau[2:1175]
  0.5*sum(log(2*pi)+log(u2t)+sqresid[2:1175]/u2t)+sum((gt-1)^2)+(omega)^2
  #sum(exp((e2[2:1175]-u2t)^2))
}
# Spline parameter initialization
small <- 1e-6
alpha <- 0.4
beta <- 0.4
omega <- (1-alpha-beta)
para <- c(alpha, beta, 0.1, omega, rep(small, length(5:(k+5))))
```

```
lo <- c( small, small, small, small, rep(-10^6, length(5:(k+5))))

hi <- c(1-small, 1-small, 10^6,1-small, rep(10^6, length(5:(k+5))))

# Spline optimization

fit <- nlminb(start = para, objective = splgarch, hessian =TRUE, control = list(x.tol = 1e-6,
trace = 0), lower = lo, upper = hi)

names(fit$par) <- c('alpha', 'beta', 'cons', 'omega',paste('w', sep = '', 0:k))

round(fit$par, 6)

fit.hessian = hessian(splgarch, fit$par, method="Richardson")

#End of Main Model
```

Appendix E.

Table E-1 List of Resource Nationalism Related Events.

Country	Year	Event
Algeria	2006	hydrocarbon 51%
	2010	general government ownership for at least 51%
Angola	2011	new mining code ratidied
	2012	foreign exchange law for oil & gas sector
Argentina	2004	export permit
	2007	benificiation for processed mineral
	2011	keep all revenue in local currency
	2012	use domestic vessel
Australia	2012	MRRT and carbon tax
	2013	charge for rehabilitation
Bolivia	2005	nationalize hydrocarbon sector
	2006	nationalize hydrocarbon sector
	2007	taxes / nationalize
	2009	new constitution
	2010	supereme decree no.0726
	2011	nationalize
	2012	nationalize
	2013	new mining code
Brazil	2010	new mining framework
Cameroon	2013	10% free carried interests
Chile	2005	mining-specific tax
	2006	FRL to increase mining revenue
	2010	royalty for earthquake
China	2007	some sectors invests are forbiden
	2009	exploitation quotas
	2010	export quotas
	2011	tax regime change
	2012	joint venture only
Colombia	2012	define strategic minerals
Congo, Dem. Rep.	2007	terminate contracts

	2012	increase free-carried share to 35%
Congo, Rep.	2005	not less than 10% free carried equity
Ecuador	2007	tax increase
	2009	tax reform
Equatorial Guinea	2001	Decree Law increase surface rent
Eritrea	2004	halt all exploration activities
	2005	increase enquity to 30%
Ghana	2006	new mining law
	2008	cut back elec. Subsidies
	2012	new tax measures
Guinea	2009	political risk
	2011	new mining code ratidied
India	2000	tex on export of iron
	2008	export duty on iron ore
	2009	uranium as strategy minerals
	2010	ban asbestos mining
	2011	coal royaly and tax
	2012	tax on imports of cut and polished diamond
	2013	Increased import tariff and increased royalty rate
Indonesia	2009	new mining law
	2012	regulations
Iran, Islamic Rep.	2012	ban on export
Iraq	2003	restrict foreign ownership
Kazakhstan	2003	land code
	2004	require to develop regional infrastructure
	2005	ownership requirement for offshore
	2007	allow government has greater ability to change contracts
Kyrgyz Republic	2012	law on subsoil
	2013	tax reform, custom duty
Lao PDR	2008	renew mining law to push every license holder to develop mine
	2009	moratorium of mining license
Libya	2006	ownership claim
	2013	ownership claim
Malaysia	2002	tariff increase for imported steel and iron

	2012	safeguard act to prevent cheap imports
Mali	2012	ownership claim and beneficiation
Mauritania	2009	modify mining law for ownership
	2012	new mining code
Mexico	2013	tax claim
Mongolia	2005	wind fall profit tax
	2006	amend mining code
	2012	strategic mineral regulation
Namibia	2006	tax regime change
Oman	2013	beneficiation and local market/community protection
Peru	2011	tax framework change
Philippines	2012	order no. 79 for royalty claim
Qatar	2012	moratorium for new rojects until 2015
Russian	2007	define strategical mineral resources
Federation	2008	restriction for FDI to these strategical minerals
South Africa	2010	ownership for blacks
	2011	purchase domestic products
Tanzania	2010	new mining act for royalty, interest
	2012	ownership claim
Venezuela, RB	2001	claim ownership of hydrocarbon
	2005	ownership claim and trade constraint
	2008	nationalization of private assets
	2009	ownership of hydrocarbon
	2011	ownership and tax claim
	2013	ownership claim
Vietnam	2008	new tarriff
	2009	tax claim
	2011	tax claim
	2012	beneficiation claim
Zambia	2008	tax, royalty, and widfall tax claim
	2013	fee charges increase
Zimbabwe	2004	equity transfer to disadvantaged indigenisation
	2008	ownership claim for indigenisation

Appendix F.

Table F-1 Panel Unit Root Test: Levin, Lin & Chu t*.

Null: Unit root (assumes common unit root process)

Sample: 2000-2013

Exogenous variables: None

Automatic selection of maximum lags based on SIC

Newey-West automatic bandwidth selection and Bartlett kernel

Varibles	Series	Groups	Statistic	Prob.	Cross-sections	Obs	Lags
MEX	**D(1)**	**high and upper middle income**	-19.9763	0.0000	42	418	0-2
RoL	**D(1)**		-21.9895	0.0000	46	455	0-1
RRT	**D(1)**		-26.7968	0.0000	46	548	0-1
SQRRT	**D(0)**		-4.7613	0.0000	46	584	0-2
TOP	**D(1)**		-24.4817	0.0000	46	535	0-2
HTEX	**D(0)**		-1.7455	0.0405	41	449	0-2
CMRT	**D(0)**	**lower middle and low income**	-15.0321	0.0000	32	373	0-2
GE	**D(1)**		-19.5481	0.0000	35	341	0-1
HTEX	**D(0)**		-3.0645	0.0011	29	316	0-2
PPI	**D(1)**		-89.7012	0.0000	16	124	0-1

Table F-2 Panel Unit Root Test: ADF – Fisher Chi-Square.

Null: Unit root (assumes individual unit root process)

Sample: 2000-2013

Exogenous variables: None

Automatic selection of maximum lags based on SIC

Newey-West automatic bandwidth selection and Bartlett kernel

Varibles	Series	Groups	Statistic	Prob.	Cross-sections	Obs	Lags
MEX	**D(1)**	**high and upper middle income**	443.454	0.0000	42	418	0-2
RoL	**D(1)**		503.823	0.0000	46	455	0-1
RRT	**D(1)**		657.183	0.0000	46	548	0-1
SQRRT	**D(0)**		127.064	0.0091	46	584	0-2
TOP	**D(1)**		582.256	0.0000	46	535	0-2
HTEX	**D(0)**		132.987	0.0003	41	449	0-2
CMRT	**D(0)**	**lower middle and low income**	321.715	0.0000	32	373	0-2
GE	**D(1)**		390.44	0.0000	35	341	0-1
HTEX	**D(0)**		92.4184	0.0027	29	316	0-2
PPI	**D(1)**		206.352	0.0000	16	124	0-1

Table F-3 Panel Unit Root Test: PP – Fisher Chi-Square.

Null: Unit root (assumes individual unit root process)

Sample: 2000-2013

Exogenous variables: None

Automatic selection of maximum lags based on SIC

Newey-West automatic bandwidth selection and Bartlett kernel

Varibles	Series	Groups	Statistic	Prob.	Cross-sections	Obs	Lags
MEX	**D(1)**	**high and upper middle income**	476.665	0.0000	42	430	0-2
RoL	**D(1)**		505.171	0.0000	46	460	0-1
RRT	**D(1)**		687.029	0.0000	46	552	0-1
SQRRT	**D(0)**		145.127	0.0000	46	598	0-2
TOP	**D(1)**		592.832	0.0000	46	542	0-2
HTEX	**D(0)**		172.663	0.0000	41	468	0-2
CMRT	**D(0)**	**lower middle and low income**	366.029	0.0000	32	373	0-2
GE	**D(1)**		429.443	0.0000	35	350	0-1
HTEX	**D(0)**		113.921	0.0000	29	330	0-2
PPI	**D(1)**		216.859	0.0000	16	125	0-1

Table F-4 Pedroni Residual Cointegration Test: High and Upper Middle Income Group.

Series: Y MEX RoL RRT SQRRT TOP HTEX

Sample: 2000-2013

Included observations: 644

Cross-sections included: 17 (29 dropped)

Null Hypothesis: No cointegration

Trend assumption: No deterministic intercept or trend

Use d.f. corrected Dickey-Fuller residual variances

Automatic lag length selection based on SIC with lags from 0 to 1

Newey-West automatic bandwidth selection and Bartlett kernel

Alternative hypothesis: common AR coefs. (within-dimension)

Method	Statistic	Prob.	Weighted Statistic	Prob.
Panel v-Statistic	-55.54820	1.0000	-1.426151	0.9231
Panel rho-Statistic	3.310141	0.9995	3.133281	0.9991
Panel PP-Statistic	-4.209931	0.0000	-4.351872	0.0000
Panel ADF-Statistic	-3.416474	0.0003	-3.581868	0.0002

Alternative hypothesis: individual AR coefs. (between-dimension)

Method	Statistic	Prob.
Group rho-Statistic	4.791899	1.0000
Group PP-Statistic	-7.838787	0.0000
Group ADF-Statistic	-4.630310	0.0000

Table F-5 Pedroni Residual Cointegration Test: Lower Middle and Low Income Group.

Series: Y CMRT GE HTEX PPI
Sample: 2000-2013
Included observations: 504
Cross-sections included: 8 (28 dropped)
Null Hypothesis: No cointegration
Trend assumption: No deterministic intercept or trend
Use d.f. corrected Dickey-Fuller residual variances
Automatic lag length selection based on SIC with lags from 0 to 1
Newey-West automatic bandwidth selection and Bartlett kernel

Alternative hypothesis: common AR coefs. (within-dimension)

Method	Statistic	Prob.	Weighted Statistic	Prob.
Panel v-Statistic	-3.625294	0.9999	-1.211291	0.8871
Panel rho-Statistic	0.239026	0.5945	0.270518	0.6066
Panel PP-Statistic	-5.730806	0.0000	-4.371984	0.0000
Panel ADF-Statistic	-4.670395	0.0000	-3.611402	0.0002

Alternative hypothesis: individual AR coefs. (between-dimension)

Method	Statistic	Prob.
Group rho-Statistic	1.769007	0.9616
Group PP-Statistic	-8.011212	0.0000
Group ADF-Statistic	-5.152024	0.0000

Table F-6 Covariance Analysis: Ordinary.

Group: High and upper middle income group

Sample: 2000-2013

Included observation: 644

Pairwise sample (pairwise missing deletion)

Correlation	Y	MEX	RoL	RRT	SQRRT	TOP	HTEX
Y	1.000						
MEX	0.119	1.000					
RoL	-0.096	0.202	1.000				
RRT	0.013	-0.252	-0.180	1.000			
SQRRT	-0.020	-0.267	-0.210	0.957	1.000		
TOP	-0.058	-0.114	0.017	0.139	0.183	1.000	
HTEX	0.071	-0.103	0.096	-0.205	-0.231	0.183	1.000

Table F-7 Covariance Analysis: Ordinary.

Group: Lower middle and low income group

Sample: 2000-2013

Included observation: 504

Pairwise sample (pairwise missing deletion)

Correlation	Y	CMRT	GE	HTEX	PPI
Y	1.000				
CMRT	-0.122	1.000			
GE	0.122	-0.004	1.000		
HTEX	0.030	-0.055	0.339	1.000	
PPI	-0.284	0.084	0.213	-0.246	1.000

Appendix G.

Table G-1 Modelling Result for High and Upper Middle Income Group under Random Effects.

Number of obs. = 475

Group variable: id **Number of groups = 43**

Random effects u i ~ Gaussian

Log likelihood = -121.043

Wald chi2 (6) = 23.17 **Prob. > chi2 =0.0007** **Pseudo R2 = 0.1279**

Var.	Scale	Coef.	Std. Err.	P>|z|
HTEX	[0,1]	4.325	1.963	0.028
MEX	[0,1]	3.603	1.336	0.007
RoL	[-0.5,0.5]	-3.166	1.470	0.031
RRT	[0,1]	11.22	4.735	0.018
SQRRT	[0,1]	-17.97	9.123	0.049
TOP	[0,1]	-1.252	0.708	0.077
_cons		-3.586	0.705	0.000
/lnsig2u		-1.066	1.134	
sigma u		0.587	0.333	
rho		0.095	0.097	

Likelihood-ratio test of rho = 0: chibar2(01) = 1.44 **Prob. >= chibar2 = 0.115**

Table G-2 Modelling Result for High and Upper Middle Income Group under Fixed Effects.

Note: multiple positive outcomes within groups encountered.

Note: 25 groups (247 obs.) dropped because of all positive or negative outcomes.

Number of obs. = 228

Group variable: id Number of groups = 18

Log likelihood = -70.047

LR chi2 (6) = 14.90 Prob. > chi2 =0.0210

Var.	**Scale**	**Coef.**	**Std. Err.**	**P>|z|**
HTEX	[0,1]	6.459	5.508	0.241
MEX	[0,1]	14.96	6.744	0.027
RoL	[-0.5,0.5]	-7.340	6.546	0.262
RRT	[0,1]	1.426	10.60	0.893
SQRRT	[0,1]	-4.42	15.48	0.775
TOP	[0,1]	-0.111	2.309	0.962

Hausman fixed random: chi2(6) = 12.35 Prob. >= chi2 = 0.0546

Table G-3 Modelling Result for Lower Middle and Low Income Group under Random Effects.

Number of obs. = 127

Group variable: id **Number of groups = 17**

Random effects u i ~ Gaussian

Log likelihood = -50.050

Wald chi2 (4) = 17.66 **Prob. > chi2 =0.0014**

Var.	Scale	Coef.	Std. Err.	P>|z|
CMRT	[-0.5,0.5]	-128.7	46.82	0.006
GE	[-0.5,0.5]	11.82	4.630	0.011
HTEX	[0,1]	-6.121	2.486	0.014
PPI	[0,1]	9.177	2.488	0.000
_cons		3.139	1.094	0.004
/lnsig2u		-1.198	1.335	
sigma u		0.549	0.367	
rho		0.084	0.103	

Likelihood-ratio test of rho = 0: chibar2(01) = 1.15 **Prob. >= chibar2 = 0.142**

Table G-4 Modelling Result for Lower Middle and Low Income Group under Fixed Effects.

Note: multiple positive outcomes within groups encountered.

Note: 6 groups (20 obs.) dropped because of all positive or negative outcomes.

Number of obs. = 107

Group variable: id   Number of groups = 11

Log likelihood = -29.040

LR chi2 (6) = 27.31   Prob. > chi2 =0.0000

Var.	Scale	Coef.	Std. Err.	P>|z|
CMRT	[-0.5,0.5]	-113.6	44.57	0.011
GE	[-0.5,0.5]	7.101	11.60	0.541
HTEX	[0,1]	-0.574	6.083	0.925
PPI	[0,1]	12.09	3.748	0.001

Hausman fixed random: chi2(4) = 0.35   Prob. >= chi2 = 0.9863

Appendix H.

Table H-1 Result of Modified QE Model for High and Upper Middle Income Group.

Call:

cquad_equ(id = id, yv = yv, X = X, w = w)

Log-likelihood:-59.19409

Var.	Est.	s.e.	t-stat	p-value
HTEX	-0.128	0.074	-1.734	0.083
MEX	0.109	0.089	1.224	0.221
RoL	-1.271	1.817	-0.699	0.484
RRT	-0.002	0.138	-0.013	0.990
SQRRT	3.690e-04	1.921e-03	0.192	0.848
TOP	0.024	0.026	0.900	0.368
t22002	-0.987	1.155	-0.854	0.393
t22003	-1.162	1.134	-1.025	0.306
t22004	-0.571	0.887	-0.644	0.520
t22005	0.307	0.702	0.438	0.661
t22006	0.311	0.632	0.493	0.622
t22007	0.516	0.592	0.871	0.384
t22008	-1.494	1.038	-1.440	0.150
t22009	0.780	0.623	1.284	0.199
t22010	0.893	0.583	1.532	0.126
t22011	0.270	0.606	0.446	0.656
t22012	0.780	0.575	1.357	0.175
t22013	0.337	0.661	0.510	0.610
y_lag	0.296	0.264	1.122	0.262

Table H-2 Result of Modified QE Model for Lower Middle and Low Income Group.

Call:

cquad_equ(id = id, yv = yv, X = X, w = w)

Log-likelihood:-20.47562

Var.	Est.	s.e.	t-stat	p-value
CMRT	-3.571e-01	2.588e-01	-1.380e+00	0.168
GE	2.213e+00	3.338e+00	6.629e-01	0.507
HTEX	-2.050e-03	8.463e-02	-2.422e-02	0.981
PPI	-1.134e-01	5.075e-02	-2.234e+00	0.025
t22002	1.794e-12	1.702e-15	1.054e+03	0.000
t22003	-1.025e+01	5.979e-06	-1.713e+06	0.000
t22004	4.857e-01	1.524e+00	3.187e-01	0.750
t22005	4.290e-01	1.135e+00	3.778e-01	0.706
t22006	1.192e+00	1.173e+00	1.016e+00	0.309
t22007	-2.213e+00	1.534e+00	-1.442e+00	0.149
t22008	2.235e+00	9.443e-01	2.367e+00	0.018
t22009	1.809e+00	9.596e-01	1.885e+00	0.059
t22010	1.591e+00	1.029e+00	1.546e+00	0.122
t22011	1.662e-03	1.226e+00	1.356e-03	0.999
t22012	2.855e+00	8.238e-01	3.465e+00	0.001
t22013	1.859e+00	1.055e+00	1.763e+00	0.078
y_lag	-5.639e-02	4.219e-01	-1.337e-01	0.894

Appendix I.

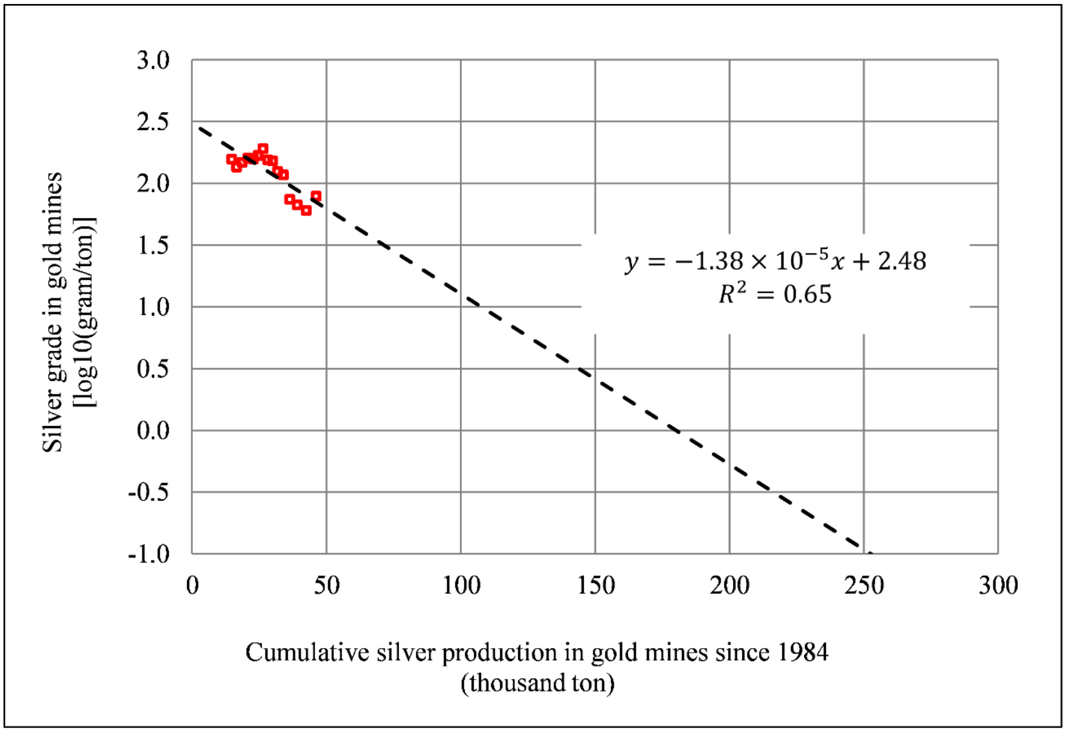

Figure I-1 Silver grade decline trend in gold mines.

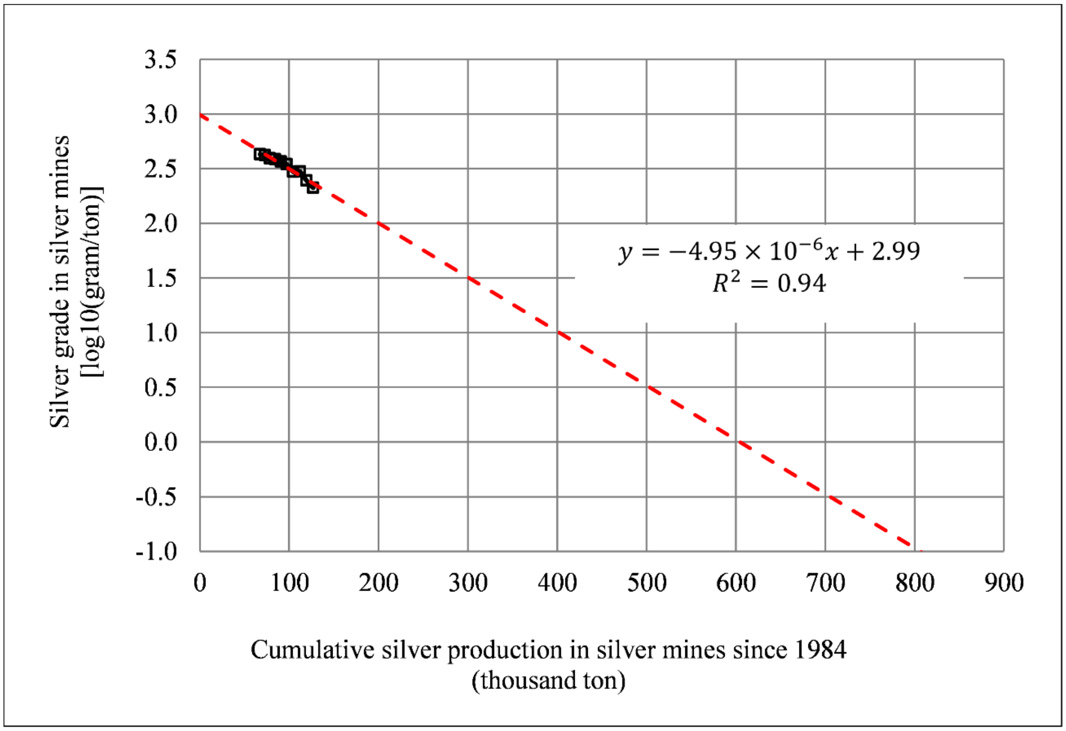

Figure I-2 Silver grade decline trend in silver mines.

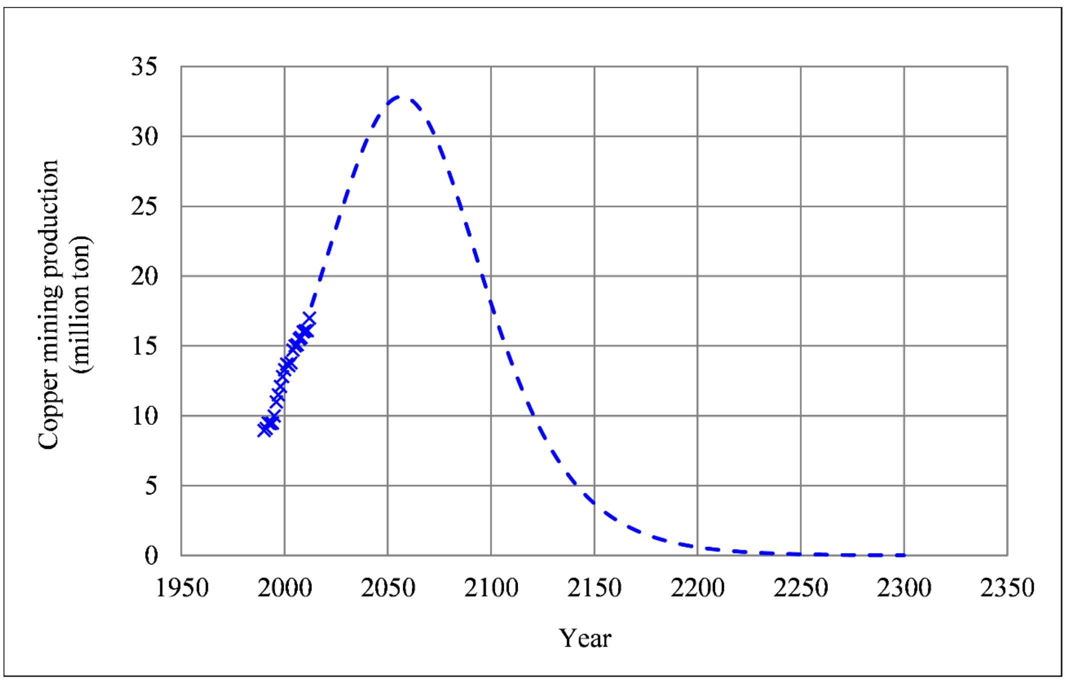

Figure I-3 Estimated copper mining production.

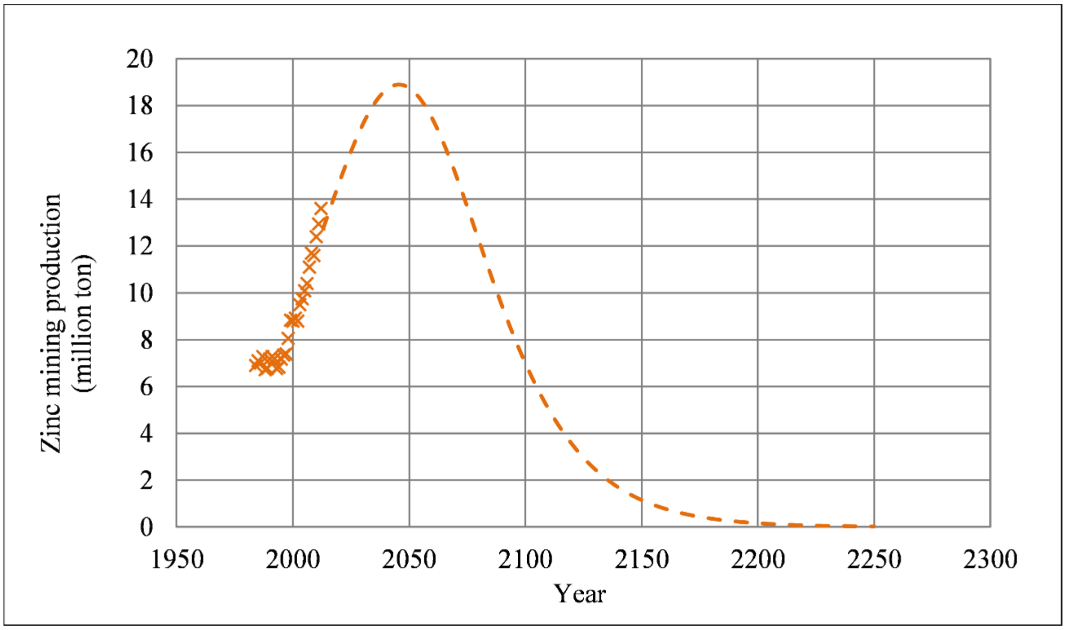

Figure I-4 Estimated zinc mining production.

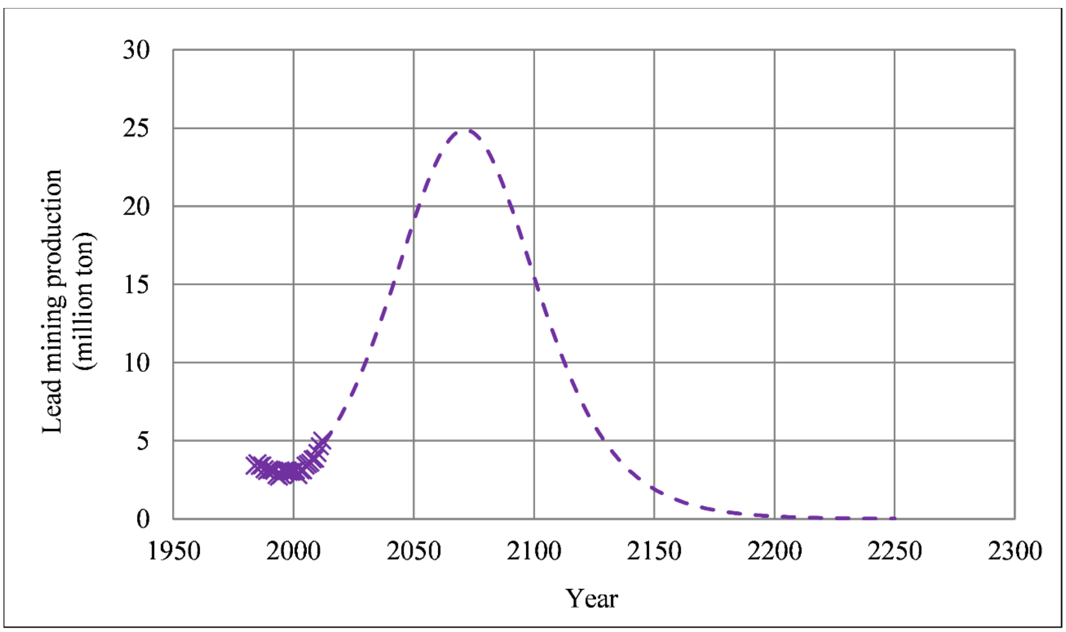

Figure I-5 Estimated lead mining production.

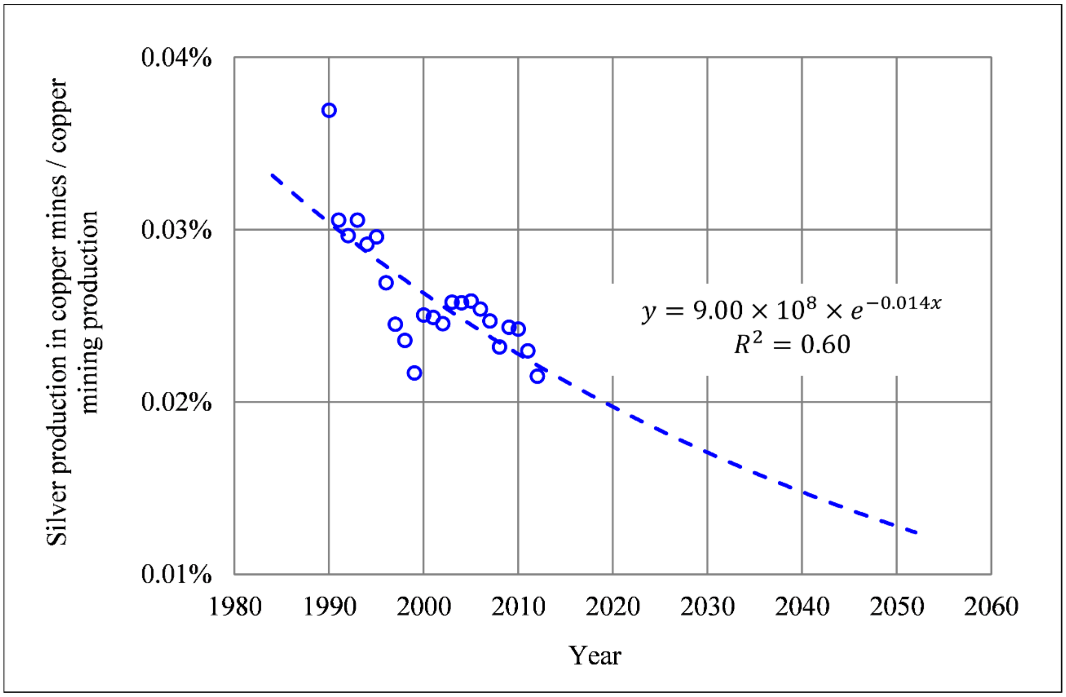

Figure I-6 Silver production from copper mines as a ratio of copper mining production.

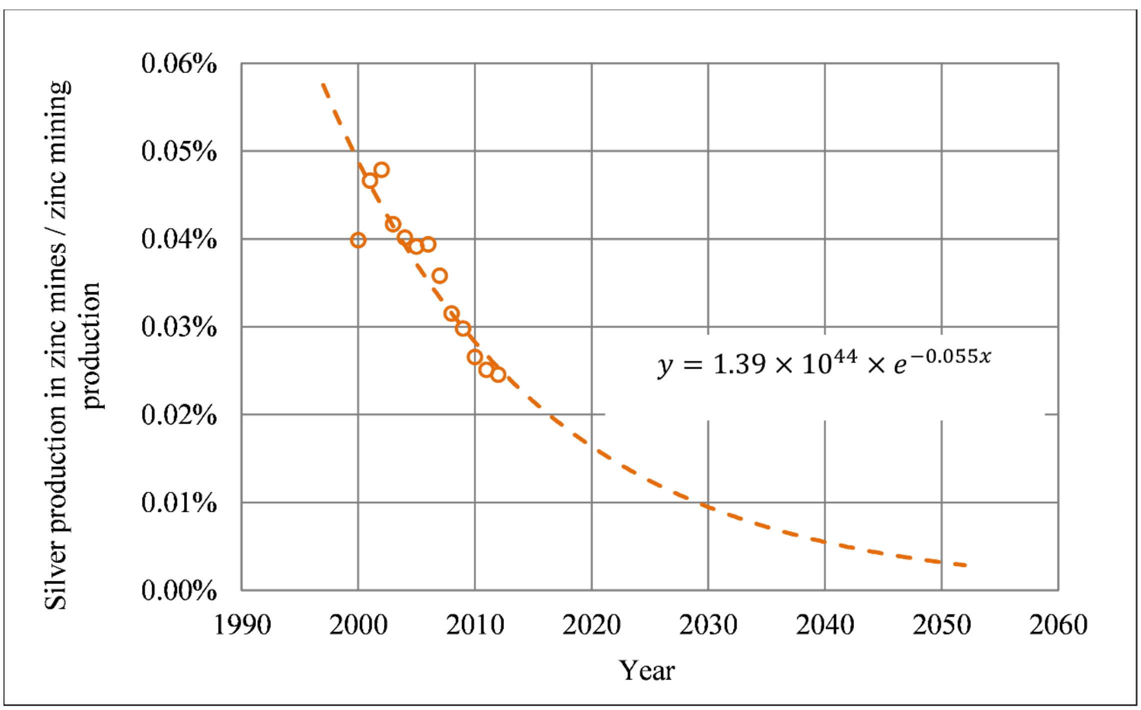

Figure I-7 Silver production from zinc mines as a ratio of zinc mining production.

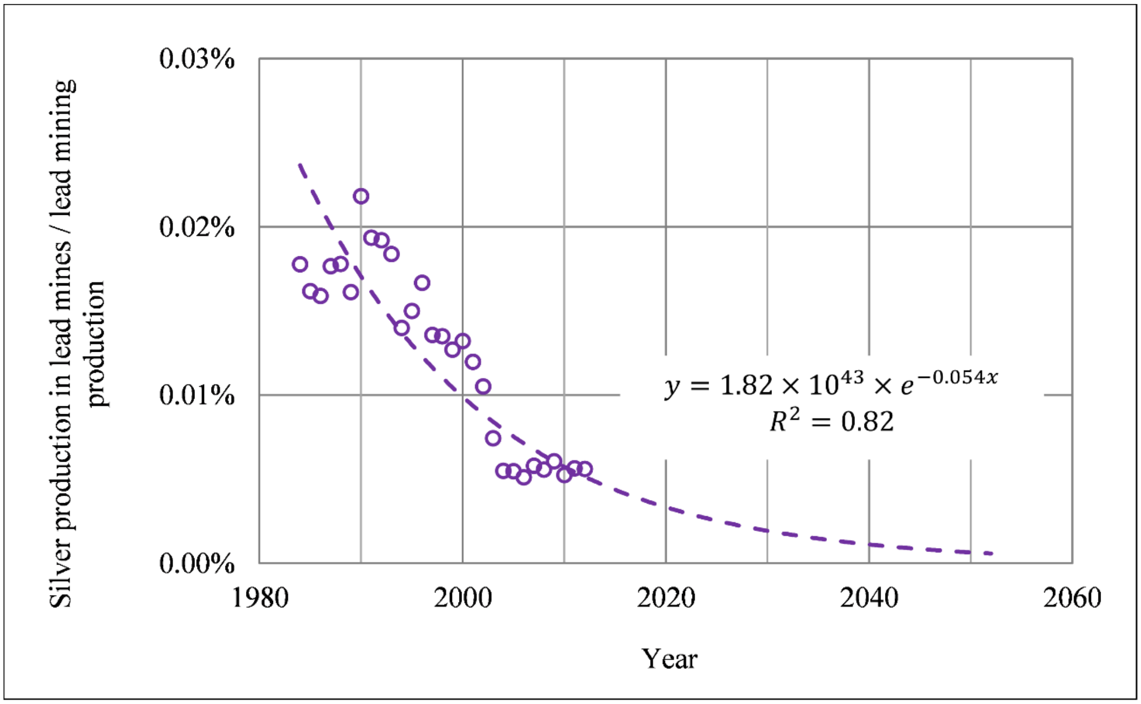

Figure I-8 Silver production from lead mines as a ratio of lead mining production.

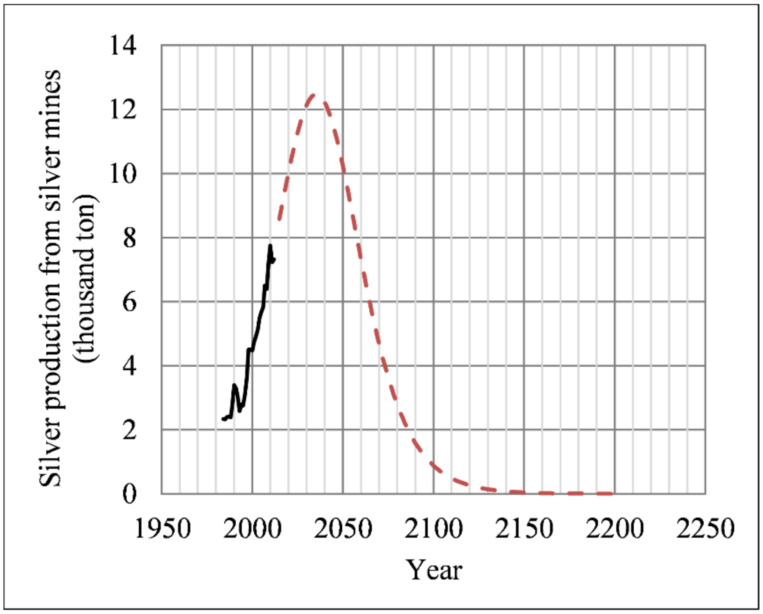

Figure I-9 Estimated silver production from silver mines.

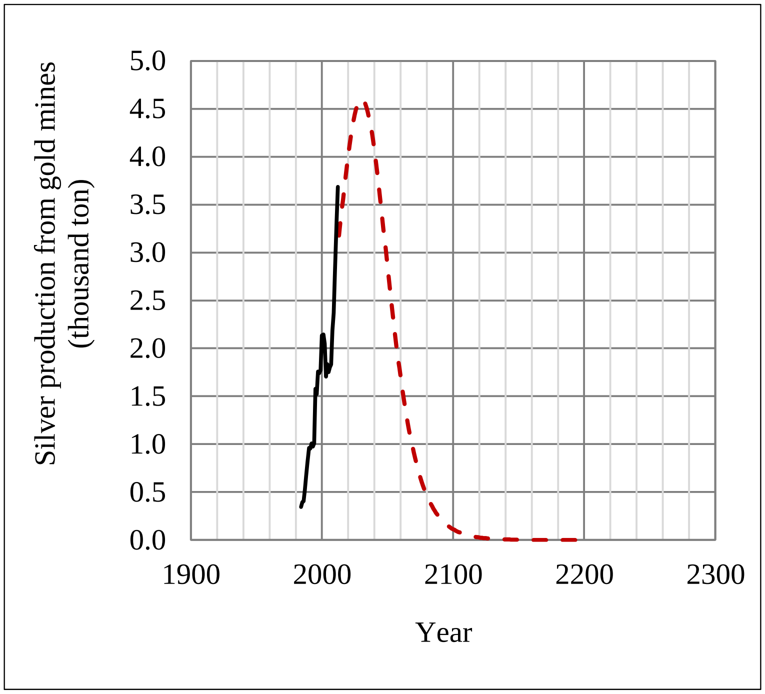

Figure I-10 Estimated silver production from gold mines.

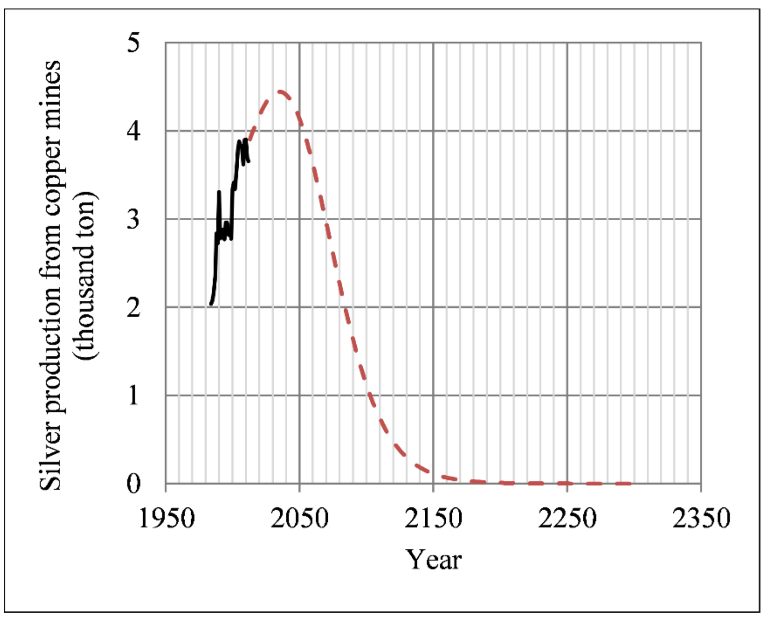

Figure I-11 Estimated silver production from copper mines.

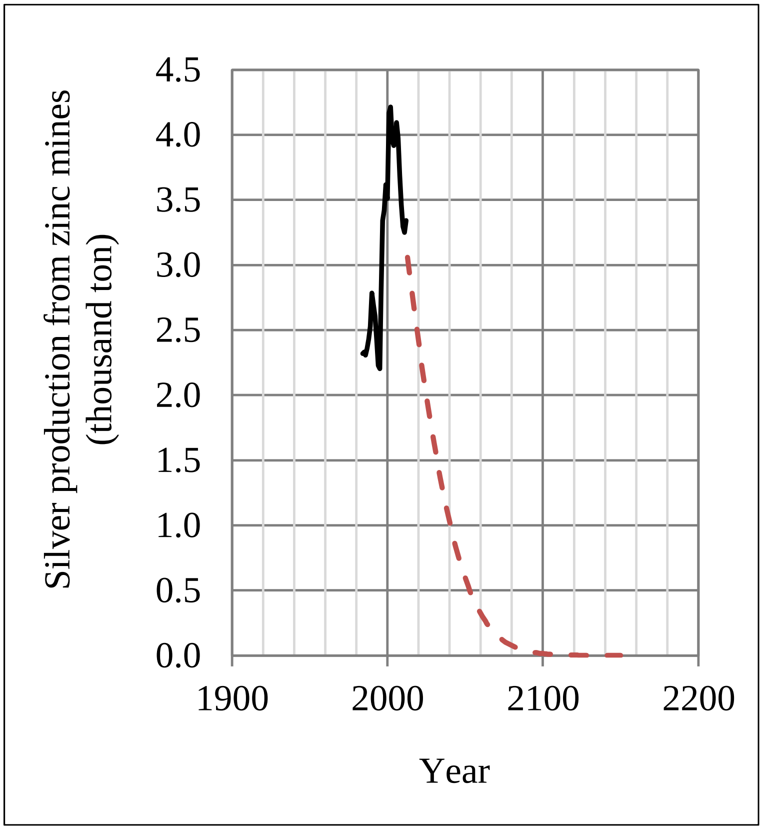

Figure I-12 Estimated silver production from zinc mines.

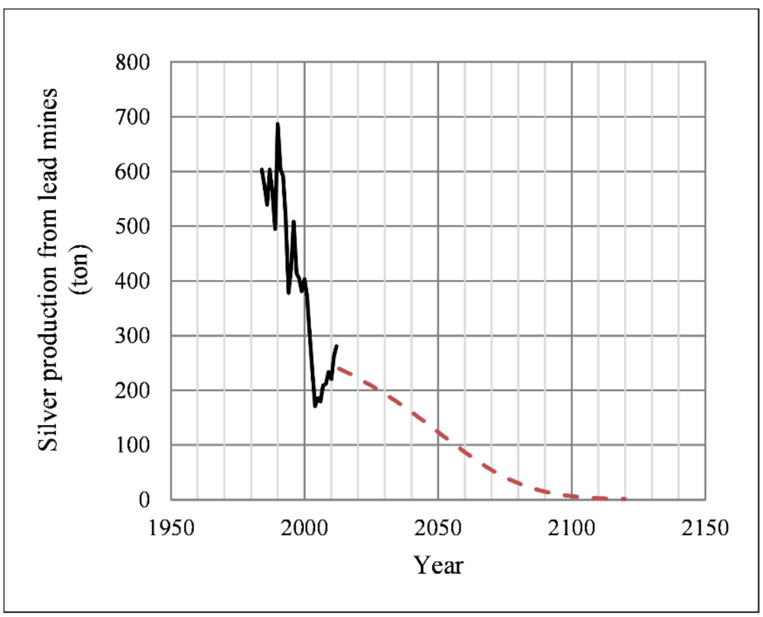

Figure I-13 Estimated silver production from lead mines.

Appendix J.

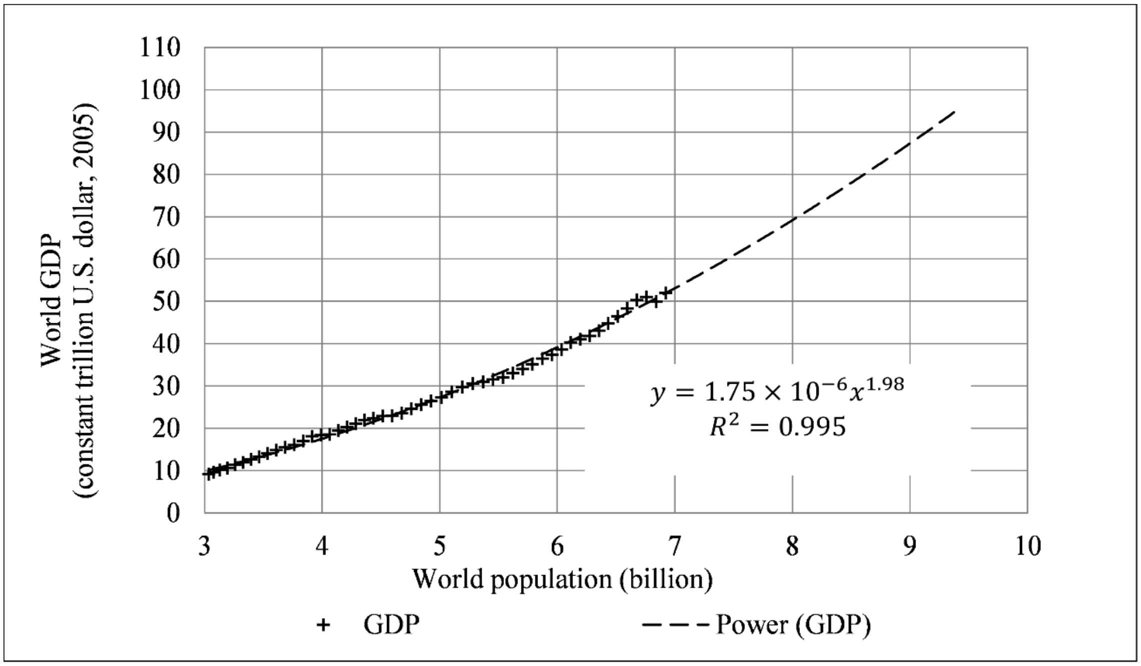

Figure J-1 Estimated of World GDP.

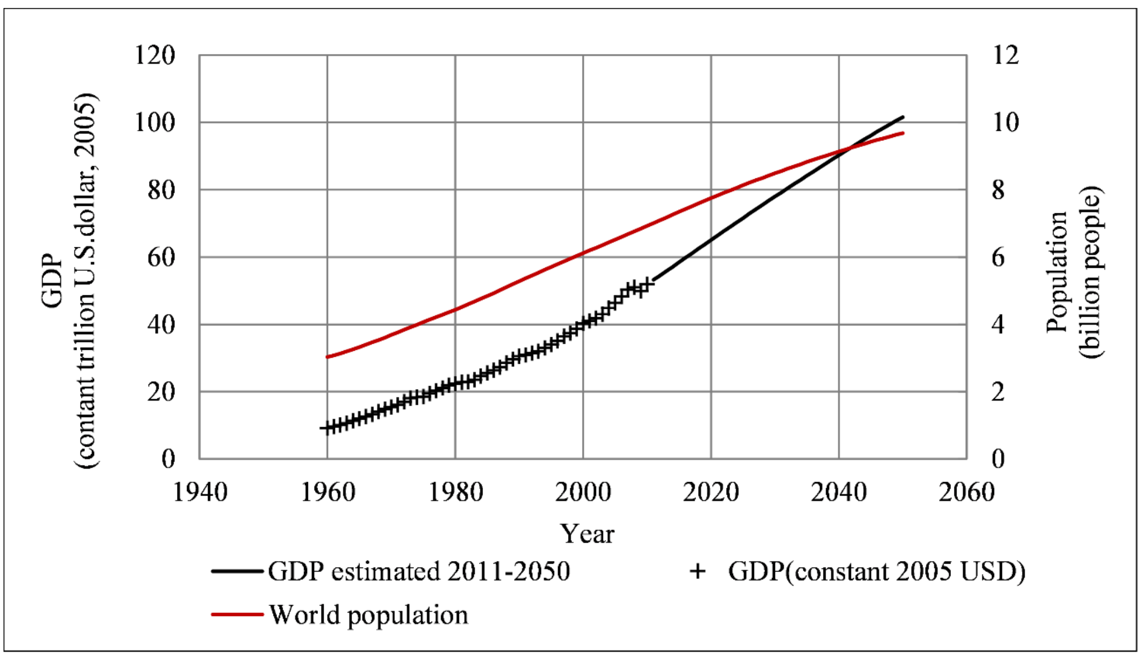

Figure J-2 Predicted GDP and Population.

Appendix K.

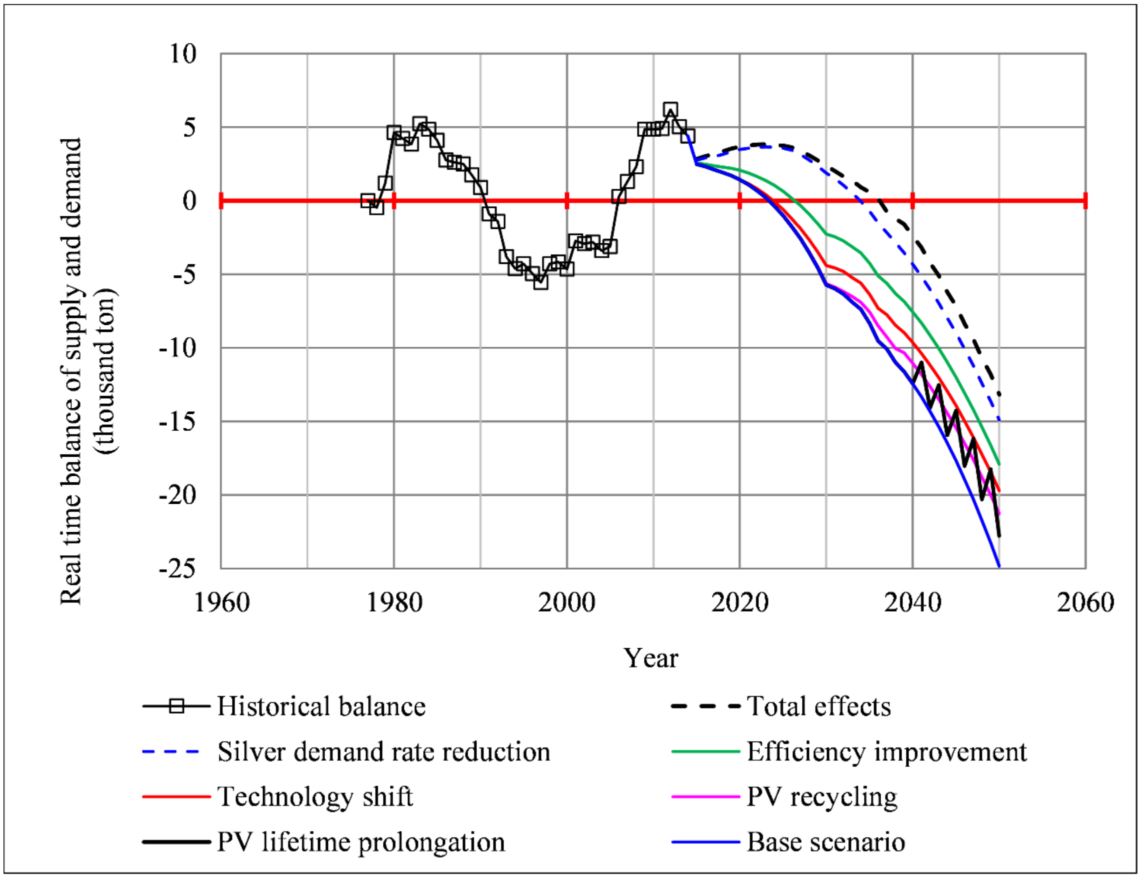

Figure K-1 Estimated difference of the physical supply and the manufacturing demand.

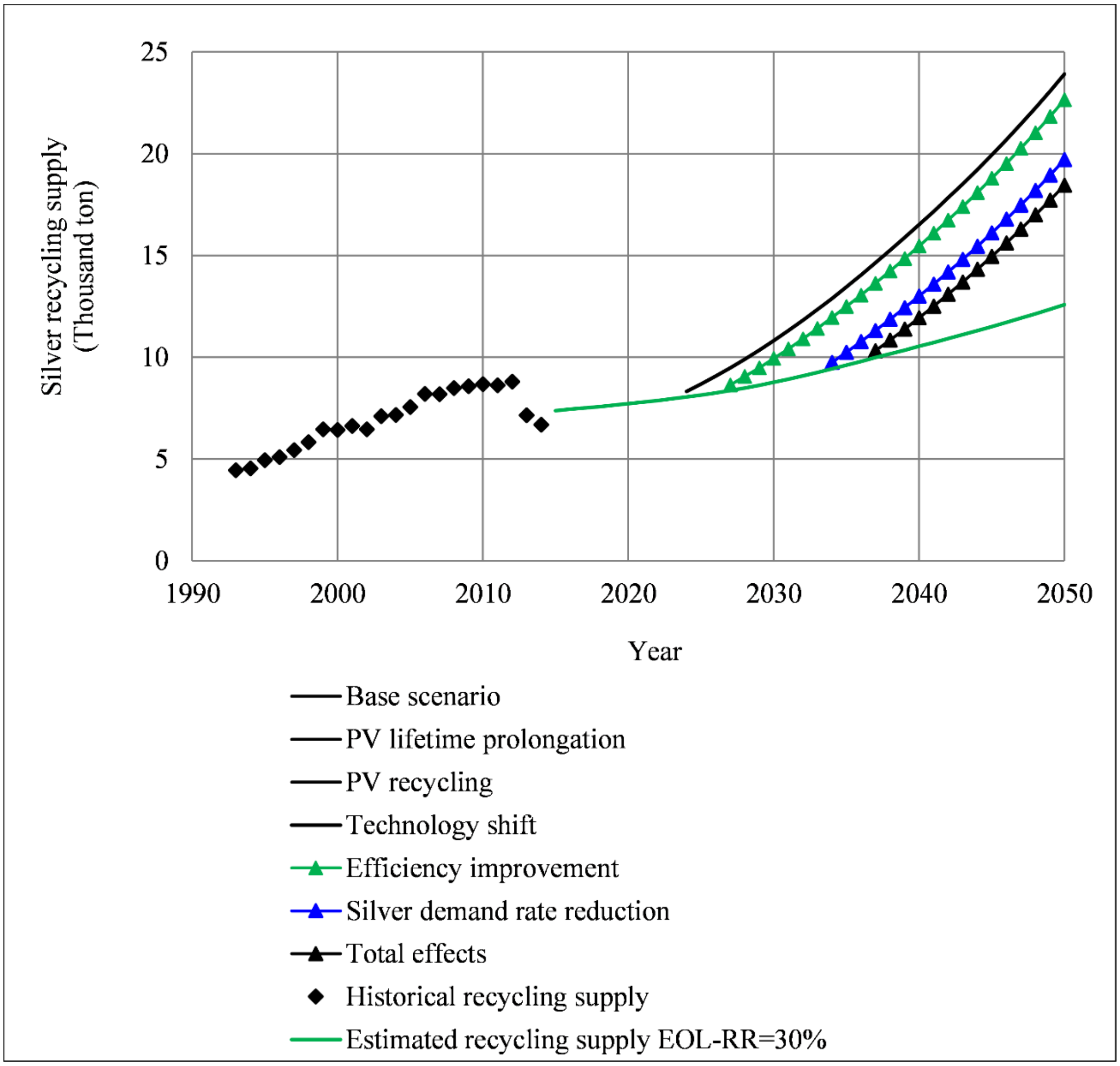

Figure K-2 Estimated silver recycling supply by increasing EOL-RR.