An empirical approach to determine specific weights of driving factors for the price of commodities—A contribution to the measurement of the economic scarcity of minerals and metals

Benedikt Gleich [b,*], Benjamin Achzet [a], Herbert Mayer [b], Andreas Rathgeber [b]

[a] Chair of Resource Strategy, Department of Physics, University of Augsburg, 86135 Augsburg, Germany
[b] Professorship for Finance, Information & Resource Management, Institute of Materials Resource Management, University of Augsburg, 86135 Augsburg, Germany

A R T I C L E I N F O

Article history:
Received 11 January 2013
Received in revised form
20 March 2013
Accepted 26 March 2013
Available online 17 July 2013

JEL classification:
Q30
Q31
G14
G15

Keywords:
Commodities
Scarcity
Criticality assessment
Commodity prices

A B S T R A C T

In recent years, commodity markets show a large amount of volatility and substantial price jumps, indicating an increasing economic scarcity in many cases. As this scarcity makes commodity procurement a critical issue for national economies, industry sectors and manufacturing companies, a number of criticality indices have been presented and utilized in science as well as in practice. These indices are mostly based on an aggregation of different key figures, both qualitative and quantitative. However, the weighting of the different factors is in most cases arbitrary or based on rough estimates.

While this may be inevitable in some areas, we believe that an empirically based aggregation is desirable and to some degree attainable. While the broad concept of criticality is certainly hard to operationalize from a quantitative point of view, the economic scarcity is not only one important factor of criticality, but can be measured to some extent by the material's market price.

Therefore, in this paper we show that each single raw material comes with a fundamentally different set of relevant factors for its economic scarcity. We determine those by performing an extended regression analysis on the market price (dependent variable) of 42 (out of about 60 industrially relevant) chemical elements, based on a broad range of empirical datasets, covering 11 driving factors (independent variables) and a 26 year time span. Our analysis determines specific weights for the factors of scarcity of each raw material and takes into account the material's individual characteristics.

We expect these results to be valuable for refining the aggregation of criticality assessments, as scarcity is at least one aspect of criticality and many influence factors we analyzed are currently utilized in criticality studies. However, our results are contrary to a number of well-known studies on criticality of raw materials, which assign generic weights to the different driving factors of different commodities and therefrom derive a criticality index. Instead, our results suggest a specific model for every single material when assessing availability risks in criticality evaluation methods. Therefore we hope that our results provide an additional empirical perspective regarding the weighting of factors for criticality based on the economic scarcity of minerals and metals.

Introduction

Commodity markets have been volatile for a long time; in the recent past, however, the magnitude of price fluctuations has increased dramatically and in many cases caused commodity prices to double or even triple within only a few years (e.g. copper or tin, LME, 2012). These price jumps indicate a strongly rising economic scarcity of these metals and put enormous financial stress on many companies and entire economies essentially depending on raw materials (Angerer et al., 2009; U.S. Department of Defense, 2009).

To cope with these risks, companies and economies try to understand current and forecast future raw materials prices and availability in order to facilitate sensible long term planning. However, the level of heterogeneity and complexity of the underlying data requires extensive familiarization, and decision makers are often overburdened with this task that usually does not coincide with their regular responsibilities. Therefore, indicators providing an aggregated estimate of the overall scarcity, or more generally of the “criticality” of raw materials have been developed to support the decision making process (Achzet et al., 2010) and to simplify the development of long term commodity utilization strategies.

* Corresponding author. Tel.: +49 171 483 3480.
E-mail address: benedikt.gleich@mrm.uni-augsburg.de(B. Gleich)

Currently there is a number of widely used approaches for such criticality or scarcity indicators. For instance, Graedel et al. (2012) present a comprehensive framework to assess raw material criticality considering three dimensions: supply risk, environmental implications, and vulnerability to supply restriction. Bauer et al. (2010) from the U.S. Department of Energy use fixed weighting factors for five different criticality aspects. Rosenau-Tornow et al. (2009) present a criticality assessment based on five indicators as well, but aggregated graphically by using a spider web diagram. And the European Commission (2010) promotes a method that basically aggregates supply risks and economic importance, characterizing this as a “pragmatic approach”. In addition, there is a large number of other pragmatic sectoral and company-specific approaches mostly based on a commodity-independent weighted average of the utilized indicators. However, these pragmatic approaches consist of rather arbitrary aggregations based on fixed percentages or other static aggregates that universally apply to all commodities and are not validated quantitatively or empirically. Moreover, most presented methods use different aggregates. In practice, the reliability of these approaches often remains unclear in particular when it comes to their selection of relevant factors and to the aggregation utilized.

Therefore, in this paper we present an empirical analysis based on a number of input factors that determines what factors account for which part of commodity prices. Here, we regard the commodity price as preliminary indicator for scarcity (following Tilton, 2003) and thus for the economical aspects of criticality. By doing so, we want to contribute to an improved understanding of the interrelation between the commodity price, that after the theory of efficient markets represent current and future risks, and a number of common criticality factors like mine production, country concentration or economic growth. While this section presents an introduction and motivation, the following section outlines the relevant literature and the research question. In the Methodology section, we describe our methods and our proceeding, while the results of the different regressions and a number of additional tests are given in the Empirical results section. These results are discussed and interpreted in the penultimate section, while the last section offers an outlook and a short conclusion.

Literature and theory

In the past years, a lot of research has been conducted regarding the economical importance and scarcity of commodities. With the emerging concept of raw material criticality, researchers try to evaluate and assess the correlation between the two topics. It is therefore still a very young and heterogeneous research area, and a broadly accepted definition of criticality has yet to be established. In the context of raw materials, the term first came up in 1939 within the Material Stock Piling Act, that regulated the securing of militarily relevant materials for which availability had become uncertain due to geopolitical developments (National Research Council, 2007). Nowadays, the exact selection and weighting of factors that make a raw material critical or scarce are still open research questions. For instance, raw materials are considered critical if they are highly significant for national economies and if their current or future supply is threatened in any way (European Commission, 2010). In the broadest sense, criticality denotes the extent of current and future risks associated with a certain metal, but this fuzzy definition is certainly hard to operationalize. Moreover, it can be observed that criticality also relates to ecological, social, or political considerations, which makes it a holistic and complex concept (European Commission, 2010; Graedel et al., 2012). All in all, a high criticality index basically at least indicates that the material's current or future usage requires increased attention.

The widespread scientific and practical relevance of criticality and the broad variety of relevant criticality factors is strikingly demonstrated by a number of well-known and frequently discussed studies, for instance Graedel et al. (2012), Massachusetts Institute of Technology (2010), Geological Survey of Finland (2010), Rosenau-Tornow et al. (2009), Wouters and Bol (2009), Waeger et al. (2010), Behrendt et al. (2007), and Smith (2005). Table 1 shows a selection of these and other studies especially focusing on the utilized criticality factors. Category 1 deals with raw materials on a national economy perspective, category 2 analyzes materials from a company's perspective, category 3 from a functional perspective (e.g. mobility, energy), and category 4 discusses raw materials considering specific criteria, such as toxicity or demand trends. Categories 3 and 4 show that criticality assessment highly depends on sector specific aspects or different viewpoints on what is considered a criticality driver. Moreover, the representation shows the heterogeneity and even arbitrariness when selecting and aggregating indicators. It is common to examine the criticality of raw materials according to a top–down method, starting with a rough scan using categories 1 and 2, followed by a detailed analysis using categories 3 and 4.

When taking into account the criteria frequently discussed in the current studies as listed in Fig. 1, it becomes obvious that identifying the criticality of raw materials requires a high amount of interdisciplinary efforts. Information from different disciplines, such as geology, economics, social science and engineering, is indispensable. Thus, the aggregation of these results is by no means easy to accomplish.

In most studies, it is common to define general weightings for each variable. For instance, Rosenau-Tornow et al. (2009) analyze copper supply risks by aggregating the factors *supply/demand*, *geostrategic risks*, *market power*, *supply/demand trends* and *production costs* into a spider web diagram. Bauer et al. (2010), on behalf of the U.S. Department of Energy, also present a selection of the most important criticality criteria which are aggregated by predefined weightings. Here, 40% is assigned to basic availability, 20% to political, regulatory and social factors, 20% to producer diversity, 10% to competing technology demand, and 10% to co-dependence on other markets. Using this specific form of aggregation, Dysprosium has been rated the element with the highest long term supply risk for the energy industry.

In the current state of research, the aggregation and especially the weighting of different information is mostly compiled by expert opinion. This is a very important aspect when it comes to individual ratings for national economies or companies, addressing their specific needs, since the assessment of criticality always depends on the perspective from which it is conducted. However a quantitative approach on determining potential driving factors could help to confirm or to revise expert opinions on important indicators and their influence on different raw material markets.

Thus, while the exact definition of criticality depends on the respective field of application, in the following we assume that economic scarcity is at least one dimension of criticality, as every utilized commodity has to be bought for some price and large price fluctuations or increases constitute at least some degree of critical implications for companies as well as economies. While it is clear that this dimension is not sufficient to capture all aspects of criticality, we believe that definitions of criticality that do not incorporate economic scarcity are heavily restricted in their practical applicability.

Methodology

As we have seen the evaluation of raw material criticality is an extensive heterogeneous research area, which considers ecological, social, political and economic impacts of the usage of raw materials. However, when taking a closer look at all these perspectives almost all criticality studies are using supply risks and economic scarcity for their

Table 1
Selection of different studies dealing with criticality from different viewpoints.

Cat.	Study	Scope	Main supply risk indicators (impact factors)
1	Behrent et al. (2011), Critical raw materials for Germany*	Identifying critical materials on a national perspective	Global main production countries **(10%)** Main import countries **(10%)** Concentration of global reserves **(10%)** Company concentration in global production **(25%)** Global Reserves/global production quotient **(25%)** Share of global extraction as main or by-product **(10%)** Recyclability **(10%)**
2	Rosenau-Tornow et al. (2009), Assessing long term supply risk for raw materials	Identifying critical materials for companies	Current market balance **6,6%** Stock keeping **6,6%** Mine/refinery capacity utilization **6,6%** Production costs **20%** Country related risk **10%** Production country concentration **10%** Company concentration **20%** Future market capacity **6,6%** Degree of exploration **6,6%** Investment in Mining **6,6%**
3	Bauer et al. (2010), Critical Materials Strategy	Identifying critical materials for energy technologies	Global main production countries **(20%)** Basic Availability **(40%)** Competing Technology Demand **(10%)** Share of global extraction as main or by-product **(10%)** Political, Regulatory and Social Factors **(20%)**
4	Thorenz and Reller (2011), Discussion of risks of platinum resources based on a function orientated criticality assessment	Further ecological criteria for criticality assessments	Toxicity of dissipating materials **(no specific impact factors, qualitative weighting)**

*Original work published in German

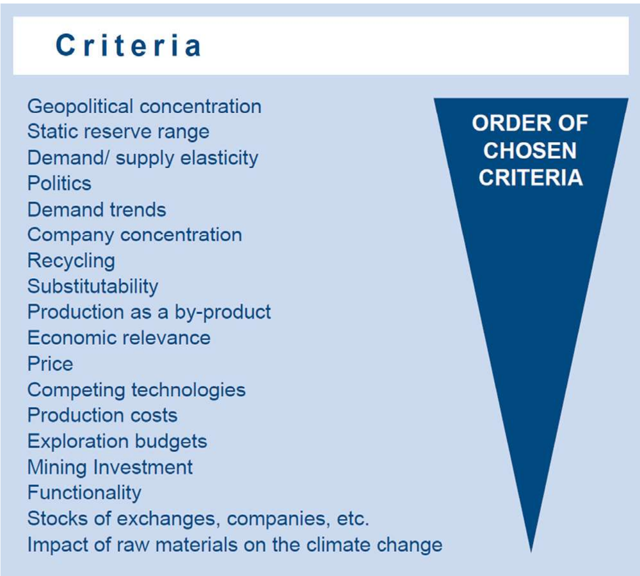

Fig. 1. Order of frequency for criteria used as supply risk indicators in current criticality assessment methods.

assessments. We want to support future criticality methods by analyzing the relationship between well known supply risk and scarcity indicators and the raw material price. Based on the hypothesis that prices represent economic scarcity and thus to some degree criticality as well, we address current research questions on the selection, rating and aggregation of supply risk and scarcity indicators in criticality assessment methods.

Therefore, regarding our methodology, we use a classical linear regression analysis with the purpose to assess assumed correlations between potential indicators on the one hand and the resource shortage on the other hand, for which we use the resource price as a proxy. For the regression analysis we use six indicators which are most frequently used in criticality assessment methods to determine supply risks as geopolitical concentration or secondary and primary production volumes. In addition to these well known metal-specific criteria we use general economic indicators to assess further potential driving factors for the raw material price development.

Data

The following analysis is based on 26 years of historical time series data with yearly frequency from 1984 to 2009. This time frame offers broad data availability and allows a consistent dataset. A wide range of industrially used elements (see Table 2) provides a broad empirical basis to analyze to what extent the eleven considered indicators affect the resource price. All metal prices are measured in U.S. dollars per metric ton – most commodities, besides, are traded in U.S. dollars, the world's leading reference currency – and originate from the U.S. Geological Survey (USGS).

While commercial sources like MetalBulletin (www.metalbulletin.com) or Metal-Pages (www.metal-pages.com) would – in some cases – offer data on specific qualities of commodities, the respective time series hardly cover the prices before 2000 and do not offer as a broad selection of commodities as the USGS prices do. In addition, the USGS provides a consistent and scientifically revised dataset that is publicly available and therefore considerably simplifies the reproduction of our results.

This selection represents 42 out of roughly 60 industrially relevant chemical elements (see Fig. 2). Although not covering the full range of chemical elements, it includes the large part of the economically important ones, offering a very broad data basis. The analyzed raw materials range from sulfur, the cheapest one, to rhodium, the most expensive one, providing a wide variation of prices and consumption levels.

When selecting potential indicators for resource price development, according to Chambers and Bailey (1996) indicators from both supply and demand have to be examined. Therefore, our analysis includes major components from both dimensions.

Considering the supply dimension, resource specific indicators were chosen according to their frequency in current criticality assessment studies (see Table 1) and based on their data availability. The respective data originate from the Raw Materials Group database

Table 2
Analyzed raw materials. All resource prices are taken from USGS, 2011.

Mineral resources					
Ag (silver)	Al (aluminium)	As (arsenic)	Au (gold)	B (boron)	Be (beryllium)
Bi (bismuth)	Br (bromine)	Cd (cadmium)	Co (cobalt)	Cr (chromium)	Cu (copper)
Fe (iron ore[a])	Ga (gallium)	Ge (germanium)	Hg (mercury)	I (iodine)	In (indium)
K (potassium)	Li (lithium)	Mg (magnesium)	Mn (manganese)	Mo (molybdenum)	Na (sodium)
Ni (nickel)	P (phosphorus)	Pb (lead)	Pd (palladium)	Pt (platinum)	Re (rhenium)
Rh (rhodium)	S (sulfur)	Sb (antimony)	Si (silicon)	Sn (tin)	Sr (strontium)
Ta (tantalum)	Ti (titanium)	V (vanadium)	W (tungsten)	Zn (zinc)	Zr (zirconium)

[a] We use the iron ore prices, as steel prices strongly depend on the grade and quality.

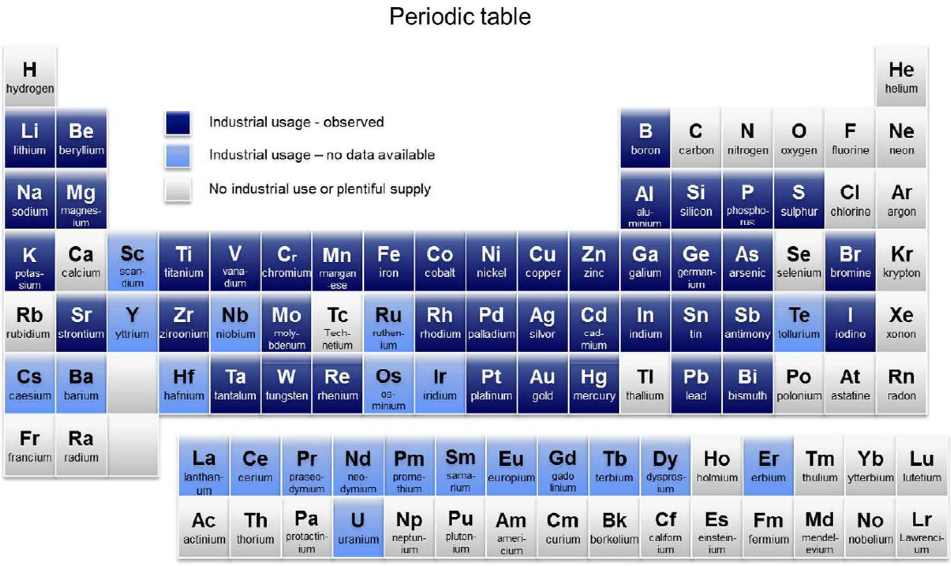

Fig. 2. The periodic table showing the industrial use of chemical elements (Hagelüken and Meskers, 2008). The elements marked in dark blue (dark gray in print) are addressed in this paper. For the elements marked in light blue (medium gray in print) no information was available. Gray (light gray in print) elements are not used in industrial applications or are abundant, respectively, and have therefore not been addressed.

Table 3
Overview resource specific factors.

Indicator	Country concentration	Producer concentration	World mine production	Apparent consumption	Secondary production	Stocks
Shortcut	HHI_Country	HHI_Comp	MineProd	AppConsum	X2Prod	Stocks
Measure	HHI	HHI	[t]	[t]	[t]	[t]
Geographic focus	Global	Global	Global	U.S.	U.S.	U.S.
Data source	Raw Material Group, 2012	Raw Material Group, 2012	USGS, 2012	USGS, 2012	USGS, 2012	USGS, 2012

(RMG) and the U.S. Geological Survey (USGS). Table 3 provides a detailed overview of the resource specific parameters. We use the indicator *world mine production* mainly determining supply. In addition, *U.S. secondary production* as proxy for recycling rate of materials, could increase the supply as well. Moreover, again the U.S. proxy *U.S. stocks*, i.e. inventory, could both increase or reduce demand and supply. Thus, these indicators consequently are supposed to influence the price of raw materials. Lastly, the Herfindahl–Hirschman indexes (HHI) are commonly used to describe *country concentration* and *producer concentration*, ranging from 0 (total dispersion) to 1 (all production in one country or by one company, respectively), with values close to 1 representing oligopolies or monopolies. Both can influence the supply and, hence, price structure. Besides the presumptively more explanatory generic economical demand parameters, which will be explained next, we use the *U.S. consumption* as an available proxy for resource specific demand. The factors static reserves or reserve base are not included referring to Tilton (2003) and the European Commission (2010), as geological reserve figures are not a reliable factor for scarcity and thus for demand and supply ratio at equilibrium. Hence, this potential indicator may lead to wrong conclusions. By the use of the U.S. proxies and the importance of the U.S. dollar as major international trading currency, we expect to identify further correlations between the described factors and the resource price. All in all, these six material specific indicators – *world mine production*, *U.S. consumption*, *secondary production*, *stocks*, *country concentration*, and *producer concentration* – represent the better part of relevant information on the supply side of non-renewable resources.

Table 4
Overview economic and demographic factors.

Indicator	Logarithmic world GDP	Logarithmic world population	Inflation rate	Real interest rate
Shortcut	LN_GDP	LN_Pop	US_Infla	Interest
Measure	Billion $	Billion	Annual in %	Annual in %
Geographic focus	Global	Global	U.S.	U.S.
Data source	IMF, 2011	IMF / NPG, 2011	WDI, World Bank, 2012	FRBNY, 2011

In addition, the extent to which economic and demographic factors influence the development of prices needs to be taken into account. Here, the *GDP* (gross domestic product) is certainly one of the most important factors for economic growth and can – by rising demand – cause supply shortages and price increases. The *world population* could also have great influence, as every human has certain needs and therefore – based upon its available income – creates an additional demand for resources (cf. e.g. Meadows et al., 1974). Another important aspect in the context of price development is *inflation*, as for instance Svedberg and Tilton (2006) state that the question whether copper prices have actually risen or fallen depends on the specific measure of inflation. They show several systematic biases in inflation measurement that in turn have influenced our view of long term price development. Nevertheless, the official inflation rate is an interesting reference point when analyzing nominal prices. An alternative, quite widespread approach is to associate the price development of raw materials with the *rate of interest*. This idea can be traced back to Hotelling (1931) and has been supported since then Krautkraemer (1998). Lastly, we want to analyze if there is a general trend in prices, i.e. if they are falling or rising over the years. Of course, such a trend would most likely originate from a number of different factors, which is why the indicator of *time* is an interesting aggregate, but most probably does not represent a direct causality itself. Here, we use U.S. data as proxy in case of inflation and real interest rate, as these indicators do not exist on a global scale. As most commodities are traded in U.S. dollars, these U.S. monetary figures should have a considerable influence on the commodity prices.

The indicators listed above were obtained from various issues from the World Bank – World Development Indicators, International Monetary Fund (IMF), Negative Population Growth (NPG), and Federal Reserve Bank of New York (FRBNY). Table 4 gives an overview of the examined economic and demographic factors. Furthermore, we obtained additional global data, e.g. on stocks or secondary production, of copper, lead and zinc from the International Copper Study Group (ICSG) and the International Lead and Zinc Study Group (ILZSG) to validate our results. In all following tables, shortcuts are used as names for indicator classes of our analysis. Tables 7 and 8 give a brief overview of statistical key figures of data samples, presenting the mean and the standard deviation of the respective variable for each resource.

Data processing

With respect to the requirements of the linear regression model, some data adjustments were necessary. To ensure scale invariance, which is a characteristic feature of factors not changing by transformation, and with respect to the linear regression model, the resource price, the world gross domestic product and the world population were converted to a logarithmic scale. As, for instance, the GDP is rising exponentially in most cases, the logarithmic scale makes this figure compatible with a linear regression model.

To deal with missing values, the established methods *mean substitution* and *case deletion* (list-wise), also known as complete case analysis, were applied. All in all, 76 out of 504 columns were deleted and 151 values out of 13608 were substituted by the mean of the respective column.

Single regression

Since this is, to the best of our knowledge, the first quantitative study including such a broad selection of metals over a long period of time, a classical linear regression seems adequate, as this is a well-known and popular method that often provides a useful first appro-ximation on potential correlations. To gain some basic insight on the importance of the single indicators, we first conduct a linear regression of each indicator on the price individually,

$$\ln(price_r) = \beta_0 + \beta_i \cdot indicator_i + \epsilon. \tag{1}$$

In all our computations, the potential indicators are the independent variables $indicator_i$, and we regress those on the logarithmic raw material price $\ln(price_r)$, the dependent variable. Here, r stands for the respective raw material. Therefore, we individually use the independent variables from Tables 3 and 4. The β_i coefficients represent the marginal effect of $indicator_i$ on $\ln(price_r)$ and are determined based on our data, applying the ordinary least squares (OLS) method.

To provide consistent and reliable results, we tested for each model the assumptions of the linear regression model, i.e. normality (Jarque–Bera test, Jarque and Bera, 1980), heteroscedasticity (Breusch–Pagan test, Breusch and Pagan, 1979), autocorrelation (Durbin–Watson test, Savin and White, 1977) and, especially for the multiple regressions, multi-collinearity (Variance Inflation Factor, Marquardt, 1970).

Multiple regression

As a next step, we use a multiple indicator model to improve the meaningfulness and precision of our model, since a great deal of the variation in the commodity prices cannot be explained by only a single leading indicator, but rather by a combination of different indicators. It determines how well the given set of indicators in combination explains the logarithmic commodity prices of each metal and to what extent each individual factor accounts for the price.

With regard to the requirements of the multiple regression method, first of all the number of independent variables has to be kept in proportion to the number of observations to avoid over-fitting and over-learning. Therefore, the multiple model was reduced by the parameters *time*, *U.S. inflation* and *population* to reduce multicollinearity and to avoid indicators with too high correlation between each other. *U.S. inflation* has already shown a poor performance in the single regressions, and the effect of the parameter *time*, despite its good prima facie performance, is most likely just a pretext for a number of other effects directly influencing the price. Finally, *GDP* and *population* show a correlation close to one, so that their combined usage would create rather misleading results.

The, however, remaining multicollinearity, quantified by the variance inflation factor, does not bias the results, it just causes larger standard errors for the independent variables. Thus, by removing the correlated parameters listed in the previous paragraph, we increase the overall significance in comparison to the full model. To identify the relative weights of each indicator, we use the following multivariate regression equations for each raw material:

$$\begin{aligned}\ln(price_r) = \beta_0 &+ \beta_1 \cdot HHI\_Country + \beta_2 \cdot HHI\_Comp + \beta_3 \cdot MineProd \\ &+ \beta_4 \cdot AppCons + \beta_5 \cdot X2Prod + \beta_6 \cdot Stocks + \beta_7 \cdot Interest \\ &+ \beta_8 \cdot \ln(GDP) + \epsilon \end{aligned} \tag{2}$$

The model parametrization and its data series are identical to the ones introduced in the Data and Data processing sections. Again, the regression assumptions were tested for each of the resulting models.

By considering the parameters in combination, a much higher level of explanatory power can be achieved now. Under these assumptions and by the improved explanatory level the analysis allows the deter mination of weights and importance for each indicator in each mineral raw material model analyzed. To answer the question which of the independent variables have what effect on the dependent variable in this multiple regression analysis, we standardized the coefficients.

The non-standardized regression weights β_i are scale-dependent with respect to the factors. Following Kleinbaum et al. (2007), we therefore standardize them by multiplying them with the standard deviation of the respective independent variable and dividing them by the standard deviation of the dependent variable:

$$\beta_i^{norm} = \beta_i \cdot \frac{\sigma_i}{\sigma_y}. \tag{3}$$

σ_i is the standard deviation of indicator i, and σ_y denotes the standard deviation of the logarithmic price. However, these standardized beta coefficients do not directly show which proportion of the price is caused by what indicator, as they do not add up to one (or any other predefined value). Therefore, we calculate the relative share of variation caused by each specific indicator and normalize this value to R^2, the explanatory power of the model. Thus, we can identify which part of the price, that is explainable by the respective model, can be assigned to what indicator:

$$weight_{\beta_i^{norm}} = \frac{|\beta_i^{norm}|}{\sum_{j=i_1}^{i_n} |\beta_j^{norm}|} \cdot R^2. \tag{4}$$

Based on these values, we can determine which factors are the main determinants for the commodity prices and quantify the respective proportion.

Forecast and time lag

While the statistical correlation of possible quantitative criteria with the raw material price from the same time frame is certainly informative, market participants are especially interested in potential indicators for *future* commodity prices. For this purpose, we provide a general analysis by using the Granger causality test (Granger, 1969) in order to determine whether each indicator is useful for forecasting the price in one, in two and in three years. Therefore an adapted regression model is defined by

$$\begin{aligned} \ln(price_r) = & \sum_{l=1}^{t} \overline{\alpha_{il}} \cdot \ln(price_{r\,t-l}) \\ & + \sum_{l=1}^{t} \overline{\beta_{il}} \cdot indicator_{it-l} + \epsilon. \end{aligned} \tag{5}$$

$\ln(price_r)$ and $indicator_i$ represent the same variables as introduced in the Data section. Additionally, the variables $\overline{\alpha_{il}}$ and $\overline{\beta_{il}}$ represent the adapted coefficients. $\overline{\beta_{il}}$ represents the statistical correlation between the price in period t ($\ln(price_r)$) and the parameters ($indicator_i$) in period $t{-}l$. $\overline{\alpha_{il}}$ stands for the statistical correlation between past prices ($\ln(price_{r\,t-l})$) and the current price ($\ln(price_r)$). The variable t represents the respective time in the examined period and thus l presents the resulting lag.

To examine if these time shifted indicators for the analyzed periods $l \in \{1, 2, 3\}$ generally provide statistically significant information about future values of $\ln(price_r)$, we test the three null-hypotheses,

$$(1)\ H_0 : \overline{\beta_{i1}} = 0, \tag{6}$$

$$(2)\ H_0 : \overline{\beta_{i1}} = \overline{\beta_{i2}} = 0, \quad \text{and} \tag{7}$$

$$(3)\ H_0 : \overline{\beta_{i1}} = \overline{\beta_{i2}} = \overline{\beta_{i3}} = 0. \tag{8}$$

To analyze the causality of lagged indicator values, we look into the relating $\overline{\beta}$−values. If the respective null-hypotheses (the $\overline{\beta_{il}}$'s being 0 and thus having no effect) is rejected, the specific indicator can be supposed to provide some predictive information on the resource price for the considered case and time period.

By applying this method to the different time periods, we can also identify possible early indicators.

Out-of-sample test

After all, the correlations identified by the presented methods could still be the result of overlearning (i.e. the model applies to the sample it has been calibrated for, but fails out of this sample), and therefore would not be useful beyond the calibrated sample. To ensure the robustness of our model, we implemented an out-of-sample test that performs the multiple regressions with a reduced dataset (*rds*), from which the last five years have been removed. In the next step, we use the resulting $\beta_{i_{rds}}$ values to compute the prices for all elements of the dataset (*cds*), including the last five years, for which the reduced model has not been calibrated.

$$\begin{aligned} \ln(price_{rds}) = & \beta_{0_{rds}} + \beta_{1_{rds}} \cdot HHI\_Comp_{ri_{cds}} \\ & + \beta_{2_{rds}} \cdot MineProd_{ri_{cds}} + \beta_{3_{rds}} \cdot AppCons_{ri_{cds}} \\ & + \beta_{4_{rds}} \cdot X2Prod_{ri_{cds}} + \beta_{5_{rds}} \cdot Stocks_{ri_{cds}} \\ & + \beta_{6_{rds}} \cdot Interest_{ri_{cds}} + \beta_{7_{rds}} \cdot Inflation_{ri_{cds}} \\ & + \beta_{8_{rds}} \cdot \ln(GDP_{ri_{cds}}) + \epsilon \end{aligned}$$

The difference between the prices calculated with the original model (see multiple regression section) and the prices calculated with the parameters of the reduced dataset is an important indicator for the validity of the model. However, a difference between the results of the full and the reduced dataset is unobjectionable, if there is a sound reason for this difference, e.g. some new influence on the resource price, that could not be captured by the use of the reduced dataset.

Empirical results

A comprehensive presentation of our results can be found in Tables 9 and 11. Table 9 shows the explanatory power on the resource price for each indicator in the single regression models. The multiple regression models presented in Table 11 enable us to investigate the relative influence of the considered indicators on the historical price development. The results of some additional validations can be found in Table 10, where we present four additional regressions with modified data sources. In addition, a number of more detailed results are presented in Tables 6 and 12, in particular the results of the out-of-sample test (Table 6) and the results of the Granger causality test (Table 12).

All in all, the results are rather heterogeneous. While some indicators show significant explanatory power in nearly all cases, others only offer sporadic significance and little explanatory power altogether. Therefore, an indicator specific analysis of these results is required.

In the single regression model, *secondary production* shows a significant influence on the price development for 16 out of 18 raw materials (89%) where data was available, with a 24% average explanatory power. The highest explanatory power can be found for lead (67%) and platinum (83%), since for either one (platinum as in automotive catalysts and lead as in lead acid batteries), the recycling volume has increased over the past ten to twenty years. An acceptable short term forecast quality for secondary production based on the Granger causality test is only given for tantalum. This indicates that the recycling volume should not be used as an indicator for short or medium term price or supply risks. Recycling consists of several time consuming and complex processing steps, such as collecting the old product, screening and dissembling the respective parts, refining the materials, and finally converting it into a high grade secondary raw material. For this reason, there are only few specific products for which the recycling volume can, to a certain extent, react to short term price development. In this context, the significant relationship for tantalum is not a discrepancy: Here the recycling volume refers to "new scrap recycling", which means that the tantalum is "reused" during the production process in the manufacturing industry, and this process can of course be price sensitive. Overall, recycling seems to be a very relevant indicator despite its limited ability to forecast prices.

Mine production shows significant results for 32 out of all 42 considered elements (76%). But while mine production in almost every case has a strong influence on the price, the direction varies extensively.

A remarkable relationship between production and price development in the single and multiple regression models has been observed, for instance, in the case of molybdenum: The strongly positive beta-value indicates that a growing molybdenum production leads to considerably rising prices. A reason for this could be the fact that molybdenum is mainly produced as a co-product of copper mining. Thus, it is not possible to just double molybdenum production by opening new molybdenum mines. On the other hand, a copper mine that also produces molybdenum as byproduct has a rather fixed copper–molybdenum rate and has no economic incentive to produce more molybdenum and thus reduce the price of copper by additional supplies. Here, Langhammer (2010) could show that, due to the strong dependency on copper production, a change in the supply-demand-ratio can have a disproportionately large impact on the molybdenum price. In fact, while gold for instance is less expensive if produced in larger amounts, the opposite is the case for molybdenum. Therefore, it seems likely that molybdenum shows a rather low price elasticity of supply.

Metals that show hardly any or no correlation with mine production at all are rather uncommon. For tantalum and tin, both mainly produced in small scale mining, no significance at all could be detected, which could be caused by the specific mining conditions. Small scale mining or artisanal mining is often operated by individuals and small-scale enterprises, generally working with hand tools under inadequate working conditions. The livelihood of the people is the production of those minerals, and since they depend on their income, production volume is not necessarily correlated with market price development.

Another interesting raw material specific indicator is the *U.S. apparent consumption*, showing significance for 24 out of the 42 investigated elements (57%) and a 30% average explanatory power in the single regressions. Here, for iron ore the model shows the biggest explanatory power with 64%, which is somewhat surprising, as it identifies the U.S. consumption a core determinant for the iron ore prices. Nowadays, usually China with its expanding demand is assigned such a role. The predominant role of the U.S. could however be a historical relict, as our study extends to 26 years and China did not have as strong an impact on the markets back then as it has today.

While the next indicator, *stocks*, shows an average performance in the single regression, it is the second best indicator in the multiple regression, only exceeded by the GDP. However, while explaining in average about 9% of the price in the multiple regression, the stocks show a considerable variance, as for instance they account for only 6% of the copper price, while explaining about 29% of the price chances of cadmium. In addition, stocks show the second best forecast quality (exceeded only by *mine production*), as presumably high stocks have to be depleted at some point and low stocks have to be replenished.

The concentration of producing countries (*HHI_country*) is significant for 14 out of the 26 elements (54%) for which data was available. However, it can be observed that in many cases where a relationship would naturally have been assumed, only small or no significance could be observed. For instance, the market for tungsten or chromium is now dominated by a Chinese monopoly, and characteristic price peaks can already be detected. While the market concentration has substantially changed within the past decades, the indicator *HHI_country* should have captured this structural change with – for instance – a correlation between increasing concentration and increasing prices. Thus, either the *HHI_country* indicator is not suitable to capture these effects (perhaps due to other reasons for the price changes) or our data does not suffice to derive the supposed correlation. This result is confirmed by the multiple regression models, where this indicator shows a measurable influence only for eight materials.

The concentration of producing companies (*HHI_company*) is not able to capture the presumed relationship between the market structure and potential price peaks either. In the case of lithium, an oligopoly of South American mining companies caused characteristic price peaks. But this relationship could not be validated by the single or the multiple regression models. Likewise, the Granger causality test shows forecast qualities only for phosphorous and iron ore.

As for the general economic indicators, the gross domestic product (*ln_GDP*) and the population development (*ln_pop*) show significant results for 35 or 30 out of all analyzed 42 elements, respectively. The average explanatory power in the single regressions is about 40%. The Granger causality test shows only limited forecast qualities for these indicators. However, in the multiple regression the GDP explains about 14% of the price overall and thus is the best indicator in

Table 5
Spread of weights in the multiple regression.
This table shows the minimum and maximum weight of each indicator resulting from the multiple regression and the mean and standard deviation of weights of the respective indicator regarding all analyzed metals.

$weights_{\beta^{norm}}$	Min (%)	Max (%)	Mean (%)	Standard deviation (%)
GDP	0.40 (Rh)	50.20 (Sr)	14.59	13.19
MineProd	0.40 (In)	40.00 (Re)	12.68	9.71
Apparent consumption	0.10 (Re)	37.10 (Fe)	7.38	7.42
Interest	0.20 (Ag)	21.10 (Bi)	6.36	4.56
Stocks	0.00 (K)	28.70 (Cd)	9.54	6.25
Secondary production	0.20 (Mg)	42.10 (Pt)	7.76	9.29
HHI_country	0.00 (Fe)	28.70 (Hg)	7.43	6.94
HHI_company	1.10 (Au)	30.60 (Hg)	7.36	7.71

Table 6
Out-of-sample test-results.
Legend: The uneven columns show the respective metal using common chemical symbols. The even columns show the deviation in percent between the original model and the model using all but the last five years for calibration. A negative percentage indicates that the price predicted by the reduced dataset is smaller than the price predicted by the full dataset. As prices are measured on a logarithmic scale, this scale applies to the presented values in percent, too.

Ag	−5.6%	Ge	0.4%	Pt	33.6%
Al	−2.1%	Hg	−7.5%	Re	−2.3%
As	6.7%	I	−1.7%	Rh	−13.4%
Au	−2.8%	In	−8.3%	S	−8.4%
B	1.1%	K	−9.5%	Sb	−11.5%
Be	6.6%	Li	−3.8%	Si	−2.2%
Bi	−6.0%	Mg	−4.0%	Sn	−8.5%
Br	−0.3%	Mn	−12.5%	Sr	1.4%
Cd	−10.8%	Mo	3.1%	Ta	5.3%
Co	−14.4%	Na	−13.6%	Ti	−4.1%
Cr	0.9%	Ni	−6.5%	V	−10.1%
Cu	−4.7%	P	−12.9%	W	−6.2%
Fe	−13.0%	Pb	−4.8%	Zn	−7.3%
Ga	−0.2%	Pd	19.4%	Zr	−2.0%

comparison. Therefore, economic growth highly influences raw materials prices, while the direction can be both positive and negative.

Lastly, the interest rate performs rather poor, while the inflation shows a moderate performance. For only 7 out of the 42 analyzed raw materials (17%), there is a relationship between inflation and price development, whereas interest rates show significant influence for at least half the raw materials. On the other hand, interest rates are the weakest of all indicators in the multiple regression, explaining only about 6% of the overall price. However, while the inflation has nearly no predictive qualities at all, the interest rate shows the fourth best forecast performance, probably due to the general function of interest rates as medium and long term economic regulator.

When it comes to the general explanatory power in the multiple regression model, the coefficient of determination (adjusted R^2) is about 60%. With over 90% copper and zirconium show the highest values. But the precious metals – gold, silver, platinum and palladium – do have above average price determinations, too. However, the ave-rage amount of price determination of an indicator strongly depends on the element considered. For instance, the price determination of the secondary production is 45% for platinum, but only 0.2% for magnesium. Table 5 shows an overview of the large variation in the price determination of the factors regarding different raw materials.

To validate our main data source, some regressions with other data sources have been performed (see Table 10). For copper, we replaced the figures on secondary production, mine production, aparent consumption and stocks with global figures from the ICSG. For iron ore, we utilized price time series data from the IMF instead of the USGS. For lead and zinc, we replaced the figures on mine production, stocks and secondary production with data from the ILZSG. Here, the ICSG data on copper show better performance for the apparent consumption (which is a global figure, in this case) and to some degree for secondary production. However, the results on mine production are practically identical and for stocks, the USGS data perform better. The ILZSG data on lead show similar results, while for mine production and secondary production the ILZSG data

Table 8
Statistical data analysis – economic variables.
The first column lists the analyzed metals using common chemical symbols. The following columns each show the mean and the standard deviation of the respective variable. We use scientific e notation where needed. For more information on the variables and their units, see Table 4.

Variable	ln_GDP		ln_Pop		US_Infla		Time		Interest	
Mean and variance	10	0.21	8.7	0.1	3	1.1	2e+03	7.5	5	2.5

Table 7
Statistical data analysis – metal specific variables.
The first column lists the analyzed metals using common chemical symbols. The following columns each show the mean and the standard deviation of the values of the respective variable for the respective metal, using scientific e notation. For more information on the variables and their units, see Table 3.

Metal	LN_Price		HHI_Country		MineProd		AppConsum		2Prod		Stocks		HHI_comp	
Ag	12	0.38	0.09	0.0049	1.7e+04	2.7e+03	5.4e+03	1.1e+03	5.8e+02	2.9e+02	2e+03	1.6e+03	0.017	0.0032
Al	7.4	0.25	0.097	0.02	2.4e+07	7.1e+06	5.5e+06	8.7e+05	2.8e+06	6.2e+05	2e+06	4e+05	0.054	0.022
As	6.7	0.23	–	–	4.4e+04	1.1e+04	1.8e+04	7.3e+03	–	–	5.5e+02	8.2e+02	–	–
Au	16	0.32	0.12	0.058	2.2e+03	3.3e+02	5.4e+03	1.1e+03	56	16	–	–	0.032	0.019
B	6.8	0.16	0.3	0.086	3.7e+06	8.7e+05	4e+05	9.1e+04	–	–	–	–	0.26	0.071
Be	13	0.48	–	–	2.4e+02	80	2.1e+02	81	–	–	1.1e+02	50	–	–
Bi	9.1	0.42	–	–	4.5e+03	1.3e+03	1.7e+03	4.5e+02	–	–	2.4e+02	1.1e+02	–	–
Br	6.7	0.16	–	–	4.6e+05	8.4e+04	2.1e+05	4.4e+04	–	–	–	–	–	–
Cd	7.7	1	–	–	2e+04	9.5e+02	2.2e+03	1.2e+03	–	–	5.8e+02	4.7e+02	–	–
Co	10	0.45	0.18	0.076	4.5e+04	1.6e+04	9.2e+03	1.7e+03	1.8e+03	7e+02	2.2e+03	1.6e+03	0.12	0.083
Cr	6.9	0.4	0.23	0.026	4.5e+06	1.2e+06	5.2e+05	1.1e+05	1.8e+05	1.9e+04	6.4e+04	4.7e+04	0.076	0.029
Cu	7.8	0.47	0.12	0.029	1.2e+07	2.7e+06	2.4e+06	3.6e+05	3.8e+05	1.5e+05	3.1e+05	2.6e+05	0.04	0.004
Fe	3.5	0.34	0.13	0.017	5.4e+07	7.8e+06	6.3e+07	1e+07	–	–	1.9e+07	9.6e+06	0.033	0.013
Ga	13	0.18	–	–	62	21	19	8.1	–	–	1.6	1.3	–	–
Ge	14	0.34	–	–	75	22	34	9.8	–	–	44	19	–	–
Hg	8.9	0.5	0.12	0.078	3e+03	2.1e+03	8.4e+02	5.7e+02	3.6e+02	97	4.1e+02	2.4e+02	0.12	0.078
I	9.5	0.3	–	–	1.9e+04	5.1e+03	4.4e+03	1.2e+03	–	–	–	–	–	–
In	12	0.71	–	–	2.7e+02	2e+02	60	37	–	–	1.1	0.53	–	–
K	5	0.25	0.19	0.022	2.8e+07	3.8e+06	5.4e+06	7.3e+05	–	–	2.9e+05	5.2e+04	0.076	0.036
Li	8.1	0.39	0.27	0.11	2.1e+05	8.4e+04	2.4e+03	5e+02	–	–	–	–	–	–
Mg	8.2	0.22	0.15	0.044	4.3e+05	1.4e+05	1.4e+05	2.3e+04	2.7e+04	4.1e+03	2.6e+04	6.6e+03	–	–
Mn	6.5	0.41	0.15	0.044	8.7e+06	1.7e+06	7.2e+05	1.4e+05	–	–	1.5e+06	5.6e+05	0.034	0.026
Mo	9.3	0.87	0.24	0.046	1.4e+05	3.7e+04	2.3e+04	8.8e+03	–	–	1.3e+04	4.4e+03	0.11	0.062
Na	4.4	0.19	–	–	3.5e+07	5.2e+06	6.3e+06	3.6e+05	–	–	–	–	–	–
Ni	9.1	0.55	0.13	0.013	1.2e+06	2.5e+05	2e+05	2.4e+04	7.1e+04	2.1e+04	4.1e+04	2e+04	0.084	0.014
P	3.3	0.42	0.17	0.015	1.5e+08	1.3e+07	3.9e+07	4.4e+06	–	–	–	–	–	–
Pb	6.9	0.43	0.13	0.045	3.2e+06	2.9e+05	1.4e+06	1.9e+05	9.5e+05	2e+05	9.3e+04	2.9e+04	0.046	0.086
Pd	16	0.56	0.41	0.088	5.8e+03	2.1e+03	5.8e+03	2.2e+03	3.7e+02	5.2e+02	3.6e+02	7.9e+02	–	–
Pt	17	0.45	0.6	0.058	1.5e+02	40	5.3e+03	1.8e+03	5.4e+02	5e+02	–	–	0.21	0.028
Re	14	0.4	–	–	34	10	18	11	–	–	–	–	–	–
Rh	17	0.85	0.62	0.079	5.3e+02	1.9e+02	5.7e+02	2.5e+02	79	66	–	–	–	–
S	3.7	0.94	–	–	5.9e+07	5.8e+06	1.3e+07	1e+06	–	–	9e+05	8.3e+05	–	–
Sb	7.9	0.46	–	–	1.1e+05	4.4e+04	3.6e+04	7.7e+03	1e+04	5.7e+03	6.8e+03	3.3e+03	0.012	0.0097
Si	7.1	0.21	–	–	3.9e+06	1.1e+06	5.3e+05	1e+05	–	–	4.4e+04	2.2e+04	–	–
Sn	9.2	0.26	–	–	2.3e+05	4e+04	5e+04	6e+03	9.2e+03	2.2e+03	1.1e+04	2.5e+03	0.052	0.021
Sr	6.5	0.3	–	–	3.3e+05	1.4e+05	2.4e+04	9e+03	–	–	–	–	–	–
Ta	11	0.42	0.27	0.13	6.9e+02	4.1e+02	5.3e+02	1.4e+02	80	32	–	–	0.19	0.13
Ti	9.2	0.25	0.16	0.029	2.7e+03	3.3e+02	2.2e+04	5.4e+03	–	–	6.1e+03	3.6e+03	0.11	0.018
V	9.6	0.63	0.32	0.038	3.7e+04	1.6e+04	–	–	–	–	9.1e+02	8.9e+02	–	–
W	9.4	0.53	0.52	0.18	4.7e+04	9.1e+03	1.1e+04	2.2e+03	3.2e+03	1.3e+03	2.8e+03	1.4e+03	–	–
Zn	7.2	0.36	0.097	0.016	8.2e+06	1.5e+06	1.1e+06	1.3e+05	1.2e+05	2.9e+04	2.9e+05	1.5e+05	0.021	0.0035
Zr	5.9	0.42	0.3	0.042	0.14	0.027	9.2e+05	1.8e+05	1.5e+05	2.2e+04	–	–	–	–

Table 9
Single regression results.

The first column presents every analyzed metal, using common chemical symbols. The following columns each show the results of the single regression for the metal in the respective row with the used independent variable in the respective column. The bar in every cell stands for the R^2 of the resulting model which is additionally presented as a percentage on the right side of the bar. The value at the bottom left is the calculated β_i, supplemented on the right side by a symbol (see below) indicating its significance. To improve readability, the significance also determines the brightness of the text color in the respective cell, while black stands for maximum (***) significance and white for no ($p > 0.1$) significance. Instead of a significance value, the last row shows the number of significant ($p \leq 0.1$) models for each variable and the average values for all key figures. (#⇔$p \leq 0.1$, *⇔$p \leq 0.05$, **⇔$p \leq 0.01$, ***⇔$p \leq 0.001$).

	Time	HHI_comp	Interest	HHI_Country	MineProd	AppConsum	X2Prod	Stocks	ln_GDP	ln_POP	US_Infla
Ag	23.5% / 0.025 *	7.2% / 32	2.9% / -0.026	61.7% / 62 ***	31.1% / 7.7e-05 **	2.4% / 5.3e-05	12.1% / 0.00073 #	21.6% / 0.00012 *	24.4% / 0.89 *	18.6% / 1.6 *	2.1% / -0.048
Al	29.8% / 0.018 **	0.1% / -0.41	1.4% / -0.012	31.5% / 7 **	44.8% / 2.3e-08 ***	7.0% / -7.5e-08	17.1% / 1.6e-07 *	2.0% / -8.7e-08	34.1% / 0.68 **	28.0% / 1.2 **	2.1% / 0.031
As	32.3% / -0.018 **		8.3% / 0.027		21.0% / -1.0e-05 *	51.9% / 2.3e-05 ***		0.8% / 5.0e-05	34.6% / -0.65 **	29.7% / -1.2 **	0.5% / -0.014
Au	22.0% / 0.02 *	0.0% / -0.026	10.7% / -0.042	5.9% / -1.3	0.0% / -1.9e-05	0.3% / -1.7e-05	22.4% / 0.0096 *		22.5% / 0.72 *	18.1% / 1.3 *	1.8% / -0.038
B	72.5% / -0.018 ***	75.2% / 1.9 ***	61.5% / 0.049 ***	74.0% / 1.6 ***	30.6% / -1.0e-07 **	13.3% / -6.8e-07 #			70.8% / -0.62 ***	75.3% / -1.3 ***	18.2% / 0.058 *
Be	18.9% / -0.028 *		16.8% / 0.079 *		38.3% / 0.0037 ***	21.7% / 0.0028 *		11.3% / 0.0032 #	19.6% / -1 *	15.8% / -1.8 *	1.1% / 0.045
Bi	14.6% / 0.021 #		0.0% / 0.00019		43.0% / 0.0002 ***	0.0% / 1.7e-05		1.7% / -0.00052	16.6% / 0.8 *	11.5% / 1.4 #	0.1% / 0.012
Br	7.9% / 0.0056		0.1% / -0.0019		19.4% / 7.9e-07 *	10.2% / 1.2e-06			9.1% / 0.21	7.3% / 0.39	0.1% / -0.003
Cd	8.7% / -0.04		15.8% / 0.16 *		14.3% / 0.0004 #	6.9% / 0.00022		47.7% / -0.0015 ***	7.0% / -1.3	10.6% / -3.1	27.4% / 0.46 **
Co	27.7% / 0.032 **	30.5% / -3 **	16.6% / -0.074 *	12.4% / -2.1 #	0.1% / -6.7e-07	10.9% / 9.0e-05 #	20.8% / 0.00029 *	47.0% / -0.00019 ***	26.0% / 1.1 **	29.5% / 2.4 **	7.3% / -0.11
Cr	45.3% / 0.036 ***	0.0% / 0.28	15.4% / -0.062 *	5.6% / -3.7	76.9% / 3.0e-07 ***	9.3% / -1.1e-06	13.7% / -7.8e-06 #	25.6% / -4.3e-06 **	47.6% / 1.3 ***	41.5% / 2.5 ***	0.5% / -0.024
Cu	40.6% / 0.04 ***	3.0% / 20	10.5% / -0.061	16.2% / 6.6 *	35.8% / 1.0e-07 **	15.8% / -5.2e-07 *	33.6% / -1.8e-06 **	18.8% / -8.0e-07 *	43.4% / 1.5 ***	37.9% / 2.8 ***	0.0% / 0.0017
Fe	25.8% / 0.023 **	6.9% / 6.7	8.0% / -0.038	28.9% / 11 **	29.9% / -2.4e-08 **	64.3% / -2.7e-08 ***		46.9% / -2.4e-08 ***	26.0% / 0.81 **	20.7% / 1.5 *	4.7% / -0.065
Ga	9.9% / 0.0074		0.0% / -0.0016		25.2% / 0.0042 **	34.1% / 0.013 **		3.1% / 0.025	11.7% / 0.29 #	9.5% / 0.52	0.1% / -0.0059
Ge	4.6% / -0.0097		17.8% / 0.057 *		0.3% / 0.00082	5.0% / 0.0077		5.0% / 0.0034	4.5% / -0.34	4.0% / -0.65	1.0% / 0.03
Hg	11.5% / 0.022 #	25.0% / -3.3 **	0.8% / -0.018	25.0% / -3.3 **	0.6% / 1.8e-05	15.4% / 0.00042 *	0.4% / -0.00047	2.4% / 0.00044	12.6% / 0.83 #	8.3% / 1.4	0.4% / 0.029
I	25.9% / 0.02 **		0.9% / -0.011		35.9% / 3.5e-05 **	3.4% / 5.1e-05			29.0% / 0.76 **	22.7% / 1.4 *	1.7% / -0.034
In	41.4% / 0.061 ***		10.9% / -0.093 #		46.2% / 0.0025 ***	41.8% / 0.012 ***		6.1% / 0.37	43.9% / 2.2 ***	40.7% / 4.3 ***	0.1% / -0.018
K	23.0% / 0.016 *	3.2% / 1.3	9.4% / -0.031	28.6% / -6.1 **	0.3% / -3.8e-09	8.7% / -1.0e-07		0.1% / -1.6e-07	22.6% / 0.57 *	21.4% / 1.1 *	3.9% / -0.044
Li	11.3% / -0.018 #		13.2% / 0.057 #	15.4% / 1.4 *	10.7% / -1.5e-06	37.4% / 0.00048 ***			11.7% / -0.63 #	10.5% / -1.2	0.7% / 0.028
Mg	5.0% / 0.0066		0.9% / -0.0085	0.0% / -0.079	12.6% / 5.8e-07 #	0.6% / 7.3e-07	3.1% / -9.6e-06	0.8% / -3.9e-06	5.0% / 0.23	4.1% / 0.43	0.9% / -0.018
Mn	51.7% / 0.039 ***	3.0% / 2.7	30.4% / -0.09 **	13.6% / -3.4 #	45.4% / 1.6e-07 ***	13.9% / 1.1e-06 #		57.2% / -5.5e-07 ***	52.9% / 1.4 ***	49.7% / 2.8 ***	1.3% / -0.04
Mo	50.3% / 0.082 ***	5.0% / -3.2	17.2% / -0.14 *	8.7% / -5.6	73.6% / 2.0e-05 ***	60.9% / 7.8e-05 ***		51.5% / -0.00014 ***	52.1% / 3 ***	46.0% / 5.6 ***	1.7% / -0.1
Na	29.2% / 0.013 **		10.9% / -0.024 #		44.9% / 2.4e-08 ***	30.0% / -2.9e-07 **			29.5% / 0.47 **	26.7% / 0.91 **	2.6% / -0.026
Ni	41.8% / 0.048 ***	0.1% / -1.3	7.9% / -0.062	37.6% / -26 ***	55.8% / 1.7e-06 ***	9.1% / 7.1e-06	33.9% / 1.5e-05 **	24.9% / -1.4e-05 **	46.4% / 1.8 ***	39.1% / 3.3 ***	1.0% / 0.048
P	54.9% / 0.042 ***		33.7% / -0.097 **	0.7% / 2.3	17.0% / 1.3e-08 *	50.1% / -6.8e-08 ***			53.3% / 1.5 ***	50.0% / 2.8 ***	23.4% / -0.18 *
Pa	52.0% / 0.054 ***			4.1% / -1.3	50.6% / 0.00019 ***	62.6% / 0.0002 ***	16.3% / 0.00044 *	0.1% / 2.3e-05	52.4% / 5.3e-05 ***	52.0% / 0.00067 ***	10.9% / -0.16 #
Pb	73.9% / 0.05 ***	0.5% / -0.36	26.8% / -0.089 **	72.5% / 8.2 ***	28.1% / 7.8e-07 **	26.6% / 1.2e-06 **	64.7% / 1.8e-06 ***	59.2% / -1.1e-05 ***	76.8% / 1.8 ***	72.0% / 3.5 ***	4.0% / -0.076
Pt	54.8% / 0.045 ***	0.0% / -0.36	25.5% / -0.091 **	0.2% / 0.39	42.8% / 0.0074 ***	56.5% / 0.00019 ***	83.3% / 0.00082 ***		57.5% / 1.6 ***	49.4% / 3 ***	2.9% / -0.067
Re	47.1% / 0.037 ***		31.4% / -0.089 **		69.3% / 0.032 ***	37.4% / 0.022 ***			49.6% / 1.3 ***	45.7% / 2.6 ***	1.9% / -0.048
Rh	6.9% / 0.03		0.3% / -0.018	2.2% / 1.7	4.1% / 0.00094	13.8% / 0.0013 #	17.2% / 0.0052 *		9.3% / 1.2	5.6% / 1.9	12.0% / 0.26 #
S	31.1% / -0.07 **		34.6% / 0.22 **		7.6% / -4.5e-08	11.9% / 3.1e-07 #		29.1% / 6.1e-07 **	27.2% / -2.3 **	32.3% / -5.1 **	54.7% / 0.61 ***
Sb	12.1% / 0.021 #	22.7% / 24 *	3.2% / -0.033		16.7% / 4.3e-06 *	39.3% / -3.8e-05 ***	14.1% / -3.0e-05 #	33.0% / -8.1e-05 **	11.8% / 0.75 #	9.4% / 1.4	1.0% / -0.04
Si	47.5% / 0.019 ***		26.7% / -0.043 **		40.0% / 1.1e-07 ***	4.7% / -4.3e-07		50.8% / -6.9e-06 ***	47.5% / 0.67 ***	47.3% / 1.4 ***	6.1% / -0.045
Sn	1.5% / 0.0043	20.1% / -5.5 *	0.6% / 0.008		2.9% / 1.1e-06	8.6% / -1.3e-05	25.4% / 5.8e-05 **	2.4% / -1.6e-05	1.8% / 0.16	0.5% / 0.18	1.4% / 0.027
Sr	75.4% / 0.035 ***		34.1% / -0.07 **		68.5% / 1.8e-06 ***	3.0% / -5.9e-06			77.2% / 1.3 ***	77.1% / 2.5 ***	13.8% / -0.099 #
Ta	5.3% / 0.013	3.1% / 0.55	0.5% / 0.012	1.2% / 0.33	10.2% / 0.00033	11.7% / 0.001 #	22.0% / 0.0071 *		6.4% / 0.5	5.8% / 0.96	2.1% / 0.053
Ti	28.7% / 0.018 **	0.6% / 1.1	2.3% / -0.015	0.5% / 0.64	45.3% / 0.00051 ***	25.2% / 2.4e-05 **		11.7% / 2.4e-05 #	31.4% / 0.67 **	25.7% / 1.2 **	0.3% / 0.013
V	10.5% / 0.027		0.0% / -0.0021	5.3% / -3.8	25.6% / 2.0e-05 **			0.1% / -2.6e-05	11.9% / 1 #	8.0% / 1.7	2.3% / 0.084
W	47.9% / 0.049 ***		10.8% / -0.07	5.0% / 0.65	42.4% / 3.8e-05 ***	24.5% / 0.00012 *	23.5% / 0.0002 *	22.8% / -0.00018 *	49.8% / 1.8 ***	43.4% / 3.4 ***	0.7% / -0.039
Zn	23.0% / 0.023 *	3.0% / 18	0.0% / -0.0016	32.1% / 12 **	30.8% / 1.3e-07 **	0.8% / -2.5e-07	18.8% / 5.5e-06 *	25.4% / -1.2e-06 **	26.6% / 0.88 **	21.3% / 1.6 *	2.4% / 0.049
Zr	79.9% / 0.05 ***	0.5% / -1.1	34.5% / -0.097 **	70.8% / -8.2 ***	63.8% / 1.8e-06 ***	5.5% / 5.1e-06			81.8% / 1.8 ***	78.7% / 3.5 ***	6.7% / -0.094
Average	31.6% / 0.02 33x	10.0% / 4.3 5x	13.5% / -0.021 19x	21.5% / 2 14x	31.0% / 0.0013 32x	20.9% / 0.0015 24x	24.6% / 0.0013 16x	21.0% / 0.014 17x	32.8% / 0.71 35x	29.8% / 1.3 30x	5.4% / 0.0096 7x

show better performance, the USGS data generate better results for stocks, again. Surprisingly, the global ILZSG data on zinc lead to lesser R^2 and significance for every (significant) indicator, which could be explained by the high importance of U.S. figures for the global market. Lastly, the IMF time series data on iron ore prices shows superior results in comparison with the USGS time series data on

Table 10
Single regression results with different data sources.
This table lists regression results with different data sources (iron ore: IMF, copper: ICSG, lead and zinc: ILZSG). The format is just as in Table 9.

	Time	HHI_comp	Interest	HHI_Country	MineProd	AppConsum	X2Prod	Stocks	ln_GDP	ln_POP	US_Infla
Cu	40.6% 0.04 ***	3.0% 20	10.5% -0.061	16.2% 6.6 *	35.8% 0.00011 **	41.9% 0.00011 ***	35.7% 0.00078 **	3.8% -0.00021	43.4% 1.5 ***	37.9% 2.8 ***	0.0% 0.0017
Fe	51.7% 0.055 ***	22.8% 21 *	27.7% -0.12 **	13.7% 13 #	24.1% -3.6e-08 *	68.1% -4.7e-08 ***		60.0% -4.7e-08 ***	51.5% 2 ***	46.6% 3.8 ***	10.1% -0.16
Pb	64.3% 0.047 ***	3.6% -0.76	10.7% -0.053	70.0% 7.1 ***	79.7% 0.0003 ***	4.8% 5.2e-07	80.0% 0.00038 ***	50.2% -0.0025 ***	68.5% 1.7 ***	60.5% 3.4 ***	3.8% -0.062
Zn	11.2% 0.019	0.0% -1.6	4.9% 0.035	25.6% 11 *	16.9% 8.9e-05 #	8.3% -8.1e-07	0.9% 0.00024	24.9% -0.0006 *	14.8% 0.78 #	9.1% 1.3	4.3% 0.064

prices. With the exception of *HHI_Country* and mine production, all indicators perform better for the IMF prices, which could reflect the high degree of market regulation for iron ore and steel in the U.S.

To test the robustness of the multiple regression models, an out-of-sample test for the past five years was conducted (see Table 6). On an average, the calculated raw material price was about 6% lower than the actual price development. Only 11 raw material price models out of 42 show differences above 10%. The greatest discrepancy is found for platinum (36%), palladium (19%), cobalt (−14%), and iron ore (−13%). It is interesting to observe that the platinum-group metals are actually cheaper than the model with the reduced dataset estimated. A reason could be that especially the platinum price declined by 60% during the economic crisis in 2008 and did not recover enough within the observed time range, which ended in 2009. As roughly three quarters of the prices calculated by the reduced model are lower than the prices calculated by the full model, there is some indication that there has been a structural change in commodity markets making commodities more expensive in relation to the factors indicating their price. This is in line with the common observation that the commodity markets are getting more susceptible to price jumps within the previous years. Nevertheless, due to these moderate and plausible deviations, from an overall perspective, the out-of-sample test confirms the robustness of our multiple regression model.

Discussion

All in all, our results show that prices of raw materials are in fact significantly influenced by a number of material specific and general economic indicators. Thus, these prices are not just random walks, but are at least partially driven by fundamental factors. This can be used for the supply side and the economic scarcity aspects of criticality indicators, as a commodity is basically the more critical, the more its prices are increasing. Moreover, as some indicators show predictive qualities, this information does not seem to have been fully included in the price, which additionally increases their value.

However, as our database is limited to 26 years, it could be the case that some effects are just coincidence, or that we missed to observe some other correlation not included in the data. In addition, due to the absolute values used in the process, it is possible that indicators canceling each other out (i.e. the mostly falling inflation and the mostly rising GDP) gain an unduly large proportion. In particular, this effect can emerge from highly correlated indicators, which is why we excluded the indicator *population*, which highly correlates with the GDP.

Nevertheless, many of our results show a considerable significance, so that it would be improbable for all results to be just a result of coincidence. Therefore, even taking into account the limitations of classical regressions, the presented results are still valid, and because of the broad number of different indicators and metals they can be considered as robust. This conclusion is supported by the out-of-sample test that shows an overall fit with the original model despite some minor discrepancies.

In the end, we have identified three central conclusions of our results in contrast to the literature: first, based on our results we think that from an empirical point of view, arbitrarily chosen percentages for supply risk and scarcity aspects of criticality are not justified. Secondly, we are convinced that generic weights assigned to all materials are highly error-prone, as different materials show highly different cor-relations with each indicator. This thesis is also supported by Chen (2010), who found out that most metal price volatility is commodity-specific. Thirdly, a fixed selection of indicators for every metal is inadequate, as some indicators show a high correlation with the price of some raw materials, but no correlation at all with the price of others. Therefore, a criticality index should – at least for the scarcity and supply risk aspects – incorporate a specific and empirically determined weighting for every specific metal based on a specific set of indicators to give a significant statement on raw material supply risks. This result suggests an adaption of methods presented by, for instance, the Department of Energy Bauer et al. (2010), the European Commission (2010) or the IZT (Behrent et al., 2011). These methods could therefore be revised with an individual weighting factors for each element in order to come to reliable conclusions.

However, some systematic limitations have to be pointed out: first of all, our results, e.g. the percentages from the multiple regression, do not directly correspond to the percentages of criticality, as they only represent the percentages to which the respective indicator explains the price in the same period.

Nevertheless, the market price to a certain degree is an aggregate of geological and economic scarcity. Following this line of argument, our results can to some extent be interpreted as weights of different factors for the total economic scarcity. And as criticality indicators have – among others – take into account economic factors, we believe that these results can be transferred to some degree to criticality studies as well, at least regarding the economic aspects. From a general point of view, while our approach has a number of limitations, it provides some empirical means to determine specific wei-ghts of specific influencing factors, while many current appro-aches do not use empirically determined values at all. Therefore, we regard our approach as a first step towards a more empirically substantiated weighting of factors of scarcity and to some degree of criticality, while there is certainly much room for further work in this area.

One more limitation is the fact that our regression is only linear (however with logarithmic/exponential extensions). This reduces the amount of possible correlations that we can detect, however the correlations we *can* detect are valid nonetheless. In addition, as our model is purely quantitative, no qualitative effects can be observed beyond the quantitative dataset. And, of course, as we use the current logarithmic price as dependent variable for the regression, our model only explains the current price. The theory of efficient markets would claim that all known and predictable future risks (and therefore in a way a metal's criticality) are included in the current price, but the results of the Granger causality test show that in several cases there is reason to doubt perfectly efficient markets in this domain. This result quantitatively confirms what already a qualitative analysis of the imperfect market structure in many mineral product markets suggests. Moreover many social or environmental aspects are not inclu-ded in the market price at all. Furthermore, our results do not deter-mine the actual chain of causation underlying the observed

Table 11
Multiple regression results.

The table shows the results of the multiple regression for the metals in the respective rows with the respective beta values and their significance for each independent variable in the respective column. There, each cell shows the relative weight ($weight_{\beta_i^{norm}}$) of the respective independent variable for the total model (as bar on the left side and as percentage on the right side) and presents the normalized β_i^{norm}, indicating the direction and strength of the linear dependence, supplemented by its significance on the bottom right. To improve readability, the significance also determines the brightness of the text color in the respective cell, while black stands for maximum (***) significance and white for no ($p > 0.1$) significance. The right column presents the total adjusted R^2 of the multiple regression as bar and as percentage. While in this case, there is no beta-value, the significance of the total model is presented on the bottom right. Instead of a significance value, the last row shows the number of significant ($p≤0.1$) models for each variable and the average values for all other key figures. (#⇔$p≤0.1$, *⇔$p≤0.05$, **⇔$p≤0.01$, **⇔$p≤0.001$).

	HHI_comp	Interest	HHI_Country	MineProd	AppConsum	X2Prod	Stocks	ln_GDP	Total
Ag	-0.11 (3.1%)	0.01 (0.2%)	0.47 (13.6%) *	0.05 (1.5%)	-0.5 (14.4%) #	0.43 (12.4%) #	0.37 (10.5%)	0.29 (8.3%)	- (64.1%) ***
Al	-0.12 (2.5%)	0.32 (6.5%)	0.62 (12.7%)	0.46 (9.4%)	-0.17 (3.5%)	0.41 (8.5%)	-0.55 (11.4%) *	-0.3 (6.3%)	- (60.8%) **
As		-0.32 (9.0%)		0.2 (5.6%)	0.69 (19.7%) **		0.18 (5.2%)	-0.5 (14.3%) #	- (53.8%) ***
Au	-0.05 (1.1%)	-0.11 (2.4%)	-0.4 (8.7%)	-1.48 (32.4%) ***	-0.41 (8.9%) **	0.13 (2.9%)		1.38 (30.1%) **	- (86.5%) ***
B	0.53 (26.9%) *	0.12 (6.3%)	0.1 (4.9%)	0.38 (19.4%) *	-0.05 (2.4%)			-0.54 (27.5%) **	- (87.5%) ***
Be		-0.22 (4.3%)		0.97 (19.0%) *	0.13 (2.5%)		-0.17 (3.4%)	0.13 (2.5%)	- (31.7%) *
Bi		0.75 (21.1%) ***		0.93 (26.0%) ***	-0.03 (0.7%)		0.29 (8.2%) #	0.42 (11.7%)	- (67.7%) ***
Br		0.29 (2.1%)		0.52 (3.7%)	-0.32 (2.3%)			0.47 (3.4%)	- (11.5%)
Cd		-0.03 (1.1%)		0.29 (12.8%)	0.13 (5.5%)		-0.66 (28.7%) ***	-0.02 (1.1%)	- (49.1%) **
Co	0.25 (2.7%)	0.39 (4.2%)	0.13 (1.4%)	-0.59 (6.4%)	-0.03 (0.3%)	-0.52 (5.6%)	-0.9 (9.7%)	1.12 (12.0%)	- (42.4%) *
Cr	-0.13 (5.2%)	-0.16 (6.3%)	-0.12 (4.8%)	0.85 (33.2%) **	-0.02 (0.7%)	-0.17 (6.8%)	0.41 (16.1%)	0.29 (11.3%)	- (84.3%) ***
Cu	-0.1 (2.0%)	0.44 (8.9%) ***	-0.4 (8.0%)	-0.85 (17.0%)	-0.3 (6.0%) *	-0.02 (0.4%)	-0.31 (6.3%) ***	2.32 (46.6%) ***	- (95.1%) ***
Fe	-0.26 (7.0%)	0.49 (13.0%) #		0.55 (14.6%) *	-1.39 (37.1%) ***		-0.25 (6.5%)	0.2 (5.3%)	- (83.6%) ***
Ga		0.43 (7.9%)		0.22 (4.0%)	0.48 (8.6%)		-0.22 (4.0%)	0.28 (5.1%)	- (29.6%) *
Ge		0.32 (5.1%)		0.11 (1.7%)	0.48 (7.5%)		0.59 (9.2%) *	-0.09 (1.4%)	- (24.9%) #
Hg	-7.96 (30.6%)	0.16 (0.6%)	7.46 (28.7%)	0.65 (2.5%)	0.16 (0.6%)	0.27 (1.0%) #	0.3 (1.1%) #	1.19 (4.6%) ***	- (69.8%) ***
I		0.7 (18.3%) **		0.71 (18.5%) #	-0.11 (2.8%)			0.48 (12.4%)	- (52.1%) ***
In		0.45 (10.1%) #		-0.02 (0.4%)	-0.34 (7.7%)		0.48 (10.9%) **	1.44 (32.7%) *	- (61.8%) ***
K	-1.53 (15.5%) **	0.3 (3.1%)	-0.02 (0.2%)	-0.55 (5.5%) *	0.23 (2.3%)			2.15 (21.7%) **	- (48.3%) **
Li		-0.21 (3.5%)	0.21 (3.5%)	-0.51 (8.6%)	0.72 (12.2%) **			0.39 (6.7%)	- (34.6%) *
Mg		-0.56 (0.3%)	0.35 (0.2%)	1.46 (0.9%)	0.39 (0.2%)	0.36 (0.2%)	-0.06 (0.0%)	-1.08 (0.6%)	- (2.5%)
Mn	0.21 (4.2%)	-0.17 (3.5%)	-0.48 (9.5%)	0.73 (14.7%) *	-0.09 (1.8%)		-0.65 (13.0%)	-0.74 (14.7%)	- (61.4%) ***
Mo	0.08 (1.9%)	-0.5 (12.3%) *	0.41 (10.2%) **	0.93 (23.1%) ***	0.39 (9.8%) *		-0.33 (8.3%) *	-0.73 (18.2%) *	- (83.9%) ***
Na		0.21 (7.6%)		0.65 (24.0%)	-0.31 (11.4%)			-0.02 (0.7%)	- (43.7%) **
Ni	0.51 (9.3%) **	0.1 (1.9%)	-0.22 (4.0%)	1.27 (23.4%) *	-0.27 (4.9%)	0.75 (13.8%) #	1.02 (18.7%) **	-0.07 (1.2%)	- (77.2%) ***
P		-0.17 (9.2%)	0.18 (9.5%)	0.29 (15.4%) *	-0.34 (18.1%) *			0.46 (24.3%) *	- (76.6%) ***
Pa			0.27 (1.3%)	-5.21 (25.3%) *	5.54 (26.9%) *	-1.23 (6.0%) *	1.65 (8.0%) #	0.83 (4.0%)	- (71.5%) ***
Pb	0.12 (3.2%)	0.27 (7.0%)	-0.63 (16.4%) #	0.39 (10.3%) *	-0.21 (5.5%)	0.37 (9.6%)	-0.22 (5.7%) #	1.19 (31.1%)	- (88.7%) ***
Pt	0.11 (3.8%)	-0.13 (4.7%)	0.11 (4.0%)	-0.1 (3.7%)	0.18 (6.4%)	1.17 (42.1%) **		-0.44 (16.0%)	- (80.6%) ***
Re		-0.29 (11.3%)		1.04 (40.0%) ***				-0.43 (16.4%)	- (67.9%) ***
Rh		0.36 (3.0%)	-0.17 (1.4%)	-1.54 (12.9%) *	1.01 (8.5%)	1.23 (10.3%) #		-0.05 (0.4%)	- (36.5%) *
S		0.03 (0.7%)		0.79 (17.4%) *	0.71 (15.6%) ***		0.86 (19.1%) *	-0.32 (7.0%)	- (59.8%) ***
Sb	0.3 (2.9%)	-0.3 (2.9%)		1.36 (13.1%) *	-0.77 (7.4%) *	0.51 (4.9%)	0.2 (1.9%)	-1.0 (9.6%) #	- (42.8%) *
Si		0.07 (2.1%)		0.52 (15.3%)	0.29 (8.5%)		-0.58 (17.3%) #	-0.11 (3.2%)	- (46.3%) **
Sn	-0.42 (5.7%)	0.5 (6.9%)		-0.1 (1.3%)	-0.25 (3.4%)	0.2 (2.8%)	-0.45 (6.2%)	0.41 (5.6%)	- (31.8%) *
Sr		0.19 (10.2%)		0.15 (8.0%)	0.16 (8.5%)			0.93 (50.2%) **	- (76.8%) ***
Ta	-1.05 (10.9%) *	0.64 (6.7%) *	0.17 (1.7%)	0.99 (10.3%) *	-0.22 (2.3%)	0.91 (9.5%) **		0.17 (1.8%)	- (43.1%) *
Ti	-0.48 (7.1%)	0.51 (7.5%)	-0.25 (3.7%)	-0.28 (4.1%)	0.23 (3.3%)		-0.27 (3.9%)	1.74 (25.7%) **	- (55.4%) **
V		0.33 (4.1%)	-0.15 (1.8%)	0.1 (1.3%)			0.63 (7.8%) #	1.06 (13.1%) #	- (28.1%) *
W		0.24 (5.3%)	-0.58 (12.9%) **	0.21 (4.7%) #	-0.27 (6.1%)	0.09 (1.9%)	0.49 (10.8%) #	1.79 (39.9%) ***	- (81.6%) ***
Zn	-0.45 (4.6%) *	0.87 (8.7%) ***	0.84 (8.5%) #	-0.57 (5.7%)	-0.45 (4.5%) *	0.09 (0.9%)	1.52 (15.3%) #	2.83 (28.4%) **	- (76.6%) ***
Zr	0.07 (4.4%)	0.18 (10.7%) #	-0.37 (21.7%) **	0.26 (15.4%) **	-0.06 (3.7%)			0.6 (35.6%) **	- (91.5%) ***
Average	-0.5 (7.4%) 5x	0.16 (6.4%) 9x	0.29 (7.4%) 6x	0.15 (12.7%) 21x	0.12 (7.4%) 12x	0.28 (7.8%) 7x	0.12 (9.2%) 16x	0.43 (14.6%) 16x	0.028 (58.7%) 40x

correlation. Thus, the resulting percentages just represent the external effects of some black box correlations, on whose inner workings our statis-tical method does not provide any interpretation.

A further issue is data reliability or quality. The data situation especially for trace metals like indium or gallium is highly non-trans-parent, and all data is often provided by a single source, only.

Table 12
Granger causality test results.
The first column presents the analyzed metals. Every subsequent column shows if there is a significant time-shifted correlation between the independent variable and the price of the respective metal. In particular, the three symbols indicate significant predictive qualities for one, two or three years. For instance, the notion -/*/- means that a certain independent variable has a significant predictive quality for two years, but not for one or three years. ($^{\#}\Leftrightarrow p \le 0.1$, $^{*}\Leftrightarrow p \le 0.05$, $^{**}\Leftrightarrow p \le 0.01$, $^{***}\Leftrightarrow p \le 0.001$).

	HHI_Country	MineProd	AppConsum	X2Prod	Stocks	LN_GDP	LN_Pop	US_Infla	HHI_Comp	Interest
Ag		*/-/-			*/*/-	**/-/-	**/-/-	*/-/-	-/-/*	***/*/*
Al		-/*/-								
As		*/**/*	**/**/*							
Au		*/-/-			*/*/-	**/-/-	**/-/-	*/-/-	*/-/-	***/*/*
B							-/*/*	-/*/*		
Be					-/**/**					
Bi										
Br		**/*/-								
Cd		*/-/-								
Co										
Cr		*/-/-				-/*/-				
Cu				*/-/-						
Fe			*/*/-		***/***/**	***/-/-	***/*/-		***/*/-	**/*/-
Ga			*/-/-							-/*/-
Ge										
Hg										*/*/**
I										
In			-/*/*		-/*/-					*/-/-
K		*/*/*	-/**/***							
Li	-/-/*									
Mg										
Mn		*/-/*	-/*/*		*/-/-		-/*/-			
Mo	*/-/-									**/*/-
Na		**/ ** /**				-/*/-				
Ni										
P										
Pb	*/*/*				**/*/*	*/*/-				-/*/-
Pd		**/*/*	***/ ** /**					*/-/-		
Pt	-/-/*		*/-/-				-/**/-			-/-/*
Re		*/*/-	*/-/-							
Rh										
S					**/-/-	**/-/-				**/-/-
Sb				-/*/-	*/-/-					*/-/-
Si					**/**/*	-/*/-	-/*/-			
Sn				-/*/-						
Sr						*/***/**	*/**/**			
Ta				-/**/**						
Ti										*/-/-
V	*/*/-		-/-/*							
W	**/-/-	*/-/-			*/*/-	*/*/*	*/-/-			-/*/-
Zn										
Zr		*/-/-				-/*/-	-/*/-			-/*/-
Lag 1:1	5	16	9	1	14	12	9	3	4	16
Lag 1:2	5	9	9	4	12	9	9	1	1	9
Lag 1:3	5	6	9	2	6	3	3	1	4	
Total	15	31	27	7	32	24	21	5	9	25

More-over, data on more common metals and minerals shows a num-ber of flaws, too. Our selective analysis of the influence of additional data sources (see Table 10) strongly suggests that the USGS database – while being a reasonable starting point – can be significantly improved by additional data sources, especially where global figures are concerned. It is therefore important to include this issue in future criticality assessments to make sure that scientifically obtained results are based on as a reliable database as possible.

Lastly, we do neither analyze the specific vulnerability of specific metals in specific sectors nor do we take into account different grades of the respective commodities we analyze. This has to be taken into account when applying our results. Our generalized results have to be complemented by an analysis of the metal specific vulnerability, by ecological, social or technical factors like substitutability and of course by the specific price of the desired grade of the relevant commodity.

Nevertheless, taken as a whole, in spite of the presented limitations, we hope that our results contribute to the clarification of some frequently discussed questions, especially on how which indicator actually influences the price, the scarcity and thus to some degree the criticality for what raw material. While the resulting values are certainly not a final result, we are convinced that it is now clear that fixed percentages over all raw materials are highly doubtful, and that material and indicator specific weights offer a much more valid base-line for scarcity and for the economic aspect of criticality indicators.

Outlook and conclusion

In this paper, we have presented an empirical approach to identify what part of commodity prices can be explained by which factors, providing an empirical basis for the weighting of factors for the supply risk and scarcity aspects of criticality. Therefore, after an introduction and motivation in the Introduction section, we have presented a selection of relevant literature in the Literature and theory section and identified 11 relevant quantitative factors for the supply risk part in criticality assessment methods. The influence of these factors on the price of 42 commodities within 26 years is analyzed by the linear regression method and a number of extensions, as described in the

Methodology section. The results and their evaluation (see Empirical results and Discussion sections) show that a number of common assumptions, for instance static and general percentages for different factors and metals, have to be questioned as outlined in our discussion. This section presents an outlook and concludes the paper.

From an overall perspective, our results show that modeling the supply risk and scarcity aspects of criticality of commodities based on their price and the price influencing indicators leads to interesting and relevant results for a many chemical elements. Our model can be helpful for a better understanding of possible price influencing factors and price development, which is relevant both for research and practice. It also contributes to answer the question which factors should be weighted how much. In addition, for a limited number of metals a price forecast is possible, making these factors even more interesting for long-term criticality assessment. By adjusting the price indicators element by element, even better results can be achieved.

However, even the extensive analysis we performed in this paper still does not exhaustively explain the inner workings on how commodity prices really develop. Therefore, as future work, an extended analysis taking into account additional (e.g. global) indicators and a longer period of time will certainly be worthwhile. Likewise, analyzing different forms and grades of the analyzed commodities might provide further useful insights. Moreover, it has to be questioned if there are other valid quantitative proxies for the scarcity and supply risk part of criticality in addition to the commodity price. Here, we plan to identify to which part the market price represents geological or economical scarcity, respectively. In addition, many studies use price changes instead of absolute prices, which – in spite of some less encouraging first tests we performed – deserves further study. It would also be interesting to analyze future prices as well, or even completely different measures for criticality, in order to identify what really makes a commodity critical from an empirical point of view. Finally, extended methods capturing the nonlinear dynamics of the correlation between prices and their indicators would certainly be worthwhile to gain additional insights.

In the meantime, there is a need for improved decision support methods that refrain from using across-the-board indicators and weights for every metal. For some elements, a purely quantitative approach is not properly working (e.g. tin, tantalum, rare earth elements). Here, solutions could be achieved by qualitative social-science methods such as expert surveys and interviews on the market or on the technological potential of different commodities. All in all, we hope that our approach can contribute to a more empirically substantiated view on the influence of different factors on the scarcity and supply risk aspects of criticality of commodities, although this topic still yields a large number of further questions to be answered by future research.

References

Achzet, B., Zepf, V., Meissner, S., Reller, A., 10-01 2010. Strategien für einen verantwortlichen Umgang mit Metallen und deren Ressourcen (Strategies for a Responsible Handling of Metals and their Resources). Chemie Ingenieur Technik 82 (10).

Angerer, G., Marscheider-Weidemann, F., Lüllmann, A., Erdmann, L., Scharp, M., Handke, V., Marwede, M., 2009. Raw Materials for Emerging Technologies—The Influence of sector-specific feedstock demand on future raw materials consumption in Material-Intensive Emerging Technologies. German Federal Ministry of Economics and Technology.

Bauer, D., Diamond, D., Li, J., Sandalow, D., Telleen, P., Wanner, B., 2010. Critical Materials Strategy. U.S. Department of Energy.

Behrendt, S., Scharp, M., Kahlenborn, W., Feil, M., Dereje, C., Bleischwitz, R., Delzeit, R., 2007. Seltene Metalle—Manahmen und Konzepte zur Lösung des Problems konfliktverschärfender Rohstoffausbeutung am Beispiel Coltan. Umweltbundesamt.

Behrent, S., Erdman, L., Feil, M., 2011. Kritische Rohstoffe für Deutschland—Identifikation aus Sicht deutscher Unternehmen wirtschaftlich bedeutsamer mineralischer Rohstoffe, deren Versorgungslage sich mittel-bis langfristig als kritisch erweisen könnte. KfW Bankengruppe.

Breusch, T.S., Pagan, A.R., 1979. A simple test for heteroscedasticity and random coefficient variation. Econometrica 47 (5), 1287.

Chambers, M.J., Bailey, R.E., 1996. A theory of commodity price fluctuations. Journal of Political Economy 104 (October (5)), 924–957.

Chen, M.-H., 2010. Understanding world metals prices—returns, volatility and diversification. Resources Policy 35 (September (3)), 127–140.

Bob Jaffe, Jon Price (Eds.), Critical Elements for New Energy Technologies. Massachusetts Institute of Technology, April 2010.

European Commission, 2010. Critical raw materials for the EU. Technical Report, June.

Geological Survey of Finland, 2010. Finland's Minerals Strategy. ⟨www.mineraalistrategia.fi⟩.

Graedel, T.E., Barr, R., Chandler, C., Chase, T., Choi, J., Christoffersen, L., Friedlander, E., Henly, C., Jun, C., Nassar, N.T., Schechner, D., Warren, S., Yang, M.Y., Zhu, C., 2012. Methodology of metal criticality determination. Environmental Science and Technology 46 (2), 1063–1070.

Granger, C.W.J., 1969. Investigating causal relations by econometric models and cross-spectral methods. Econometrica 37 (3), 424–438.

Hagelüken, C., Meskers, C.E.M., 2008. Mining our computers—opportunities and challenges to recover scarce and valuable metals from end-of-life electronic devices. In: Electronic Goes Green.

Hotelling, H., 1931. The economics of exhaustible resources. Journal of Political Economy 39 (April (2)), 137–175.

Jarque, C.M., Bera, A.K., 1980. Efficient tests for normality, homoscedasticity and serial independence of regression residuals. Economics Letters 6 (3), 255–259.

Kleinbaum, D.G., Kupper, L.L., Nizam, A., Muller, K.E., 2007. Applied Regression Analysis and Other Multivariate Methods, 4th edition Duxbury Press, Belmont, April.

Krautkraemer, J.A., 1998. Nonrenewable resource scarcity. Journal of Economic Literature 36 (4), 2065–2107.

Langhammer, D., 2010. An Empirical Analysis of structural forces in Refractory Metal Markets. Augsburg.

LME, 2012. London metal exchange market data.

Marquardt, D.W., 1970. Generalized inverses, ridge regression, biased linear estimation, and nonlinear estimation. Technometrics 12 (3), 591–612.

Meadows, D., Meadows, D., Randers, J., Behrens, W., 1974. The Limits to Growth: A Report for the Club of Rome's Project on the Predicament of Mankind. A Potomac Associates Book. Universe Books.

National Research Council, 2007. Minerals, Critical Minerals, and the U.S. Economy. The National Academies Press.

Rosenau-Tornow, D., Buchholz, P., Riemann, A., Wagner, M., 2009. Assessing the long-term supply risks for mineral raw materials—a combined evaluation of past and future trends. Resources Policy 34 (4), 161–175.

Savin, N.E., White, K.J., 1977. The Durbin–Watson test for serial correlation with extreme sample sizes or many regressors. Econometric 45 (November (8)), 1989–1996.

Smith, M., 2005. European strategic metals & industrial minerals—knowledge gaps risks and vulnerabilities. Gecko Environment.

Svedberg, P., Tilton, J.E., 2006. The real, real price of nonrenewable resources: copper 1870–2000. World Development 34 (March (3)), 501–519.

Tilton, J., 2003. On Borrowed Time?: Assessing the Threat of Mineral Depletion. Rff Press, Taylor & Francis.

U.S. Department of Defense, 2009. Reconfiguration of the national defense stockpile report to congress. Available at: ⟨https://www.dnsc.dla.mil/pdf/NDSReconfigurationReporttoCongress.pdf⟩ (accessed 11.12.12).

Waeger, P., Lang, D., Bleischwitz, R., Hagelüken, C., Meissner, S., Reller, A., Wittmer, D., 2010. Rare Metals—Raw Materials for Technologies of the Future. Swiss Academy of Engineering Sciences.

Wouters, H., Bol, D., 2009. Material Scarcity. Materials Innovation Institute, November.