Resources Policy 52 (2017) 107–113

Contents lists available at ScienceDirect

Resources Policy

journal homepage: www.elsevier.com/locate/resourpol

Economic and social determinants of global physical flows of critical metals

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1. Introduction

Rare metals and rare earth metals (i.e., the 15 lanthanoid elements plus scandium and yttrium) are critical elements in high-tech industries. These elements have attracted considerable attention, not only for their economic value, but also because they are central to the future diffusion and adoption of clean energy technologies that are being developed to mitigate global warming (National Research Council, 2008; European Commission, 2010). Since the availability of these metal resources is limited by geopolitical constraints (Achzet and Helbig, 2013), environmental impact (Golev et al., 2014), price volatility (Fizaine, 2015; Maxwell, 2015), export regulations (Mancheri, 2015), and difficulty of substitution and recycling (Reck and Graedel, 2012; Binnemans et al., 2013), a stable supply of critical metals is becoming increasingly important (Massari and Ruberti, 2013; Suárez Sánchez et al., 2015; Barteková and Kemp, 2016) and the metal criticalities have been qualitatively assessed (Graedel et al., 2012, 2015; Hatayama and Tahara, 2015; Nansai et al., 2014, 2015, 2017; Nassar et al., 2015; Helbig et al., 2016; Nuss et al., 2016b).

Given this background, studies on the flows of critical metals (silver, cobalt, indium, lithium, selenium, platinum, gallium, germanium, tellurium, yttrium, nickel, chromium, molybdenum, rare earth metals, such as neodymium and dysprosium) (Reck et al., 2008; Daigo et al., 2010; Du and Graedel, 2011; Harper et al., 2012; Elshkaki, 2013; Elshkaki and Graedel, 2013; 2014; Kavlak and Graedel, 2013a, 2013b; Nakajima et al., 2013; Nansai et al., 2014; Seo and Morimoto, 2014, 2016; Guyonnet et al., 2015; Licht et al., 2015; Choi et al., 2016; Yano et al., 2016; Hao et al. 2017), as well as iron (Müller et al., 2006; Hatayama et al., 2010; Pauliuk et al., 2013; Pauliuk and Müller, 2014), aluminum (Hatayama et al., 2007; Chen and Graedel, 2012), copper (Graedel et al., 2004; Daigo et al., 2009; Elshkaki et al., 2016), lead (Elshkaki et al., 2005, 2009), zinc (Daigo et al., 2014) and other base metals and alloy elements (Ohno et al., 2014, 2015, 2016a) have been conducted by material flow analysis (MFA), substance flow analysis (SFA), and an IO-MFA modeling approach (Nakamura et al., 2007, 2014). More recently, network analysis studies have been used to analyze the complex network of metal flows (Chen et al., 2016; Ge et al., 2016b; Nuss et al., 2016a; Ohno et al., 2016b; Tokito et al., 2016). While most of these studies examined the flows of critical metals in their supply chains in specific years, some attempted to capture future critical metal demands (Elshkaki, 2013; Elshkaki and Graedel, 2013, 2014; Seo and Morimoto, 2014; Choi et al., 2016; Ge et al., 2016a; Yano et al., 2016), as such assessments are useful for developing resource policies that consider 'potential' procurement risks associated with critical metals. Regarding secondary materials, Elshkaki (2013) estimated future platinum demand and accumulation in mineral waste, soil, landfill sites, and construction materials using system dynamics modeling of intentional and non-intentional flows and stocks. Choi et al. (2016) also employed system dynamics modeling to forecast the supply and demand for indium under different energy and technology development scenarios, focusing on copper indium gallium selenide photovoltaics and light-emitting diode lighting. Elshkaki and Graedel (2013) modeled critical metal demands and stocks in renewable energy technologies, such as wind power and photovoltaic solar power, from 2010 to 2050. Both Elshkaki and Graedel (2014) and Seo and Morimoto (2014) projected the future demand for dysprosium, which is an important component of the permanent magnets used in clean technologies (e.g., wind power and hybrid electric vehicles). Ge et al. (2016a) constructed a dynamic computable equilibrium model to forecast the production, domestic supply, and export of China's rare earths in 2025. Yano et al. (2016) estimated the potential for recovery of rare earth metals from end-of-life hybrid electric transmissions and battery units in Japan between 2010 and 2030. These studies employed dynamic material flow analyses that specifically assessed the demand for end-of-life products and stock scenarios. Furthermore, Shigetomi et al. (2015) and Tisserant and Pauliuk (2016) adopted a multi-regional input-output (MRIO) model to estimate future demand-driven cobalt consumption (cobalt footprint of final demand). However, no studies have addressed the global trade patterns of critical metals, which would significantly affect future supply risks (Tisserant and Pauliuk, 2016). To estimate the structure of international critical metal flows, it is crucial to identify

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http://dx.doi.org/10.1016/j.resourpol.2017.02.004
Received 14 December 2016; Received in revised form 14 February 2017; Accepted 14 February 2017
0301-4207/

the socio-economic drivers that affect these flows, and to clarify the relationship between the metals flows and the drivers.

By analyzing the relationships between the physical flows around the globe related to environmental burdens and socio-economic drivers, several studies have identified the important drivers of international waste flows (Kellenberg, 2012) and virtual water flows (D'Odorico et al., 2012; Fracasso, 2014; Tamea et al., 2014). Kellenberg (2012) examined 'international waste-haven' effects and how the environmental regulations of nations have stimulated the export of waste by-products from countries with stringent environmental regulations to countries with lax environmental regulations. D'Odorico et al. (2012) assessed how significant geographic and economic factors, such as distance, population and wealth, can contribute to global virtual water flows. Fracasso (2014) discussed the relationships between virtual water flows and various explanatory variables related to international trade at the regional and global scales. Tamea et al. (2014) identified the main economic drivers of virtual water flows as food demand and farmland, and related these to water resource consumption by using panel data on international virtual water trade for 1986–2010. These studies all employed the gravity model of trade proposed by Tinbergen (1962).

To the best of our knowledge, this is the first study to attempt to elucidate the various factors that have a strong effect on the international flow of critical metals using the gravity model approach. The critical metals targeted in this study were neodymium, cobalt, and platinum. These metals were selected to illustrate differences in analytical results, and because these metals are essential for the new energy technologies that are being adopted to mitigate greenhouse gas (GHG) emissions. Neodymium is used in the manufacture of the permanent magnets in automobile motors and wind-power turbines. Cobalt is used as a positive electrode material in the lithium secondary batteries used in electric and hybrid vehicles. Platinum is widely used as a catalyst in automobile exhaust systems and in electronic devices. The use of these metals, which are referred to as critical metals due to their associated supply risks and recycling restrictions imposed by United Nations Environment Programme and United Nations University: UNEP and UNU (2009), is expected to increase markedly in the future (Harper et al., 2012; Elshkaki, 2013; Elshkaki and Graedel, 2013; Tisserant and Pauliuk, 2016). Among the 62 critical metals in question, the criticalities associated with neodymium and cobalt are relatively high in terms of supply risk and vulnerability to supply restriction, while that of platinum is marked in terms of environmental implications and vulnerability to supply restrictions (Graedel et al., 2015).

The remainder of this paper is organized as follows: Section 2 describes the methodology and data, Section 3 presents the results and discussion, and Section 4 concludes the paper.

2. Methods and data

2.1. The gravity model

The gravity model is among the most widely applied empirical models in economics (Anderson, 2011; Tayyab et al., 2012), and has been used to model a variety of flows, including migration (Simini et al., 2012), air travel (Grosche et al., 2007) and commodity trade flows (Silva and Tenreyro, 2006). The gravity model of trade expresses international trade between two regions analogously to Newton's law of universal gravitation equation, shown in Eq. (1):

$$F_{ij} = G\frac{M_i M_j}{D_{ij}^2} \tag{1}$$

In Eq. (1), F_{ij} is the bilateral flow from exporting country i to importing country j, and M_i and M_j are the economic scales of the respective regions; Gross Domestic Product (GDP) is typically used as a measure of economic scale. D_{ij} is the distance between countries i and j, and G is a constant. In general, the coefficients of interest are estimated using the ordinary least squares (OLS) after log-linearization of Eq. (1) and introduction of parameters and an error term, as shown in Eq. (2) (Silva and Tenreyro, 2006).

$$\ln F_{ij} = \beta_0 + \mathbf{x}_{ij}\boldsymbol{\beta} + \varepsilon_{ij}, \quad E(\varepsilon_{ij}|\mathbf{x}_{ij}) = 0 \tag{2}$$

where $\mathbf{x}_{ij}$ is the vector of explanatory variables, β_0 and $\boldsymbol{\beta}$ are the parameters to be estimated, and ε_{ij} is an error term.

The conventional gravity model uses the logarithm of the flows between two countries as the dependent variable and therefore excludes zero flows; however, using such a sub-sample makes estimator inconsistent (see Fracasso (2014); Kellenberg (2012); World Trade Organization: WTO (WTO) (2012)). This study therefore applied a Poisson pseudo-maximum likelihood (PPML) estimator to Eq. (3), which is considered to be well suited to avoiding the aforementioned inconsistency (Silva and Tenreyro, 2006).

$$E(F_{ij}|\mathbf{x}_{ij}) = \exp(\beta_0 + \mathbf{x}_{ij}\boldsymbol{\beta}) \tag{3}$$

This method allows us to utilize all observations, i.e., including zero flows, because taking the logarithms of the flows is not necessary. It is therefore regarded as an appropriate method for avoiding the problems associated with the scatter and/or unevenness that is frequently encountered in data related to international trade (Silva and Tenreyro, 2006). This PPML method was also used by Fracasso (2014) and Kellenberg (2012).

Each of the critical metal flows used in the analysis includes a considerable number of zero-value data (about 75% of the total number of flows), indicating the existence of not only non-existent bilateral flows, but also incomplete data. We therefore examined the significance of coefficients of the explanatory variables and their usefulness for estimating the value of the critical metal flows by the PPML method using the variables described in the next subsection.

2.2. Variables and dataset

This study analyzed the factors that determine the global flows of neodymium, cobalt, and platinum between countries or regions from four perspectives: (1) distance between the countries or regions, (2) economic scales, (3) technologies related to the use of metals in the countries or regions, and (4) supply related to the use of metals in the countries or regions. Technology- and supply-side variables likely to be affected by future increases in the consumption of critical metals were selected for analysis. Table 1 presents the explanatory and explained variables used for the analysis.

Table 1
Descriptive statistics: Cross-sectional data for 2005.

Variables	Obs.	Mean	Std. Dev.	Min.	Max.
Dependent					
Nd flow [t]	231	0.32	19.6	0	4047
Co flow [t]	231	2.88	76.6	0	7750
Pt flow [t]	231	0.008	0.31	0	35.5
Explanatory					
GDP per capita [US$]	197	9444	16970	0	126599
Population [million people]	204	31.4	128	0	1304
Motor vehicles [% of 100 people]	176	15.0	20.4	0	81.6
Cellular phone [% of 100 people]	203	38.8	37.7	0	166
Internet access [% of 100 people]	200	17.3	22.0	0	87.0
Industry, value added [% of GDP]	183	23.2	17.3	0	87.1
Renewable electricity output [% of total electricity]	159	25.1	32.3	0	100
Mining country of Nd [dummy]	231	0.017	0.13	0	1
Mining country of Co [dummy]	231	0.22	0.41	0	1
Mining country of Pt [dummy]	231	0.082	0.28	0	1
Distance [km]	53130	7946	4965	0	19951