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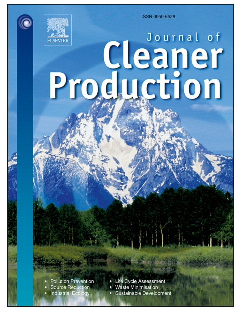

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CRediT authorship contribution statement

Matthias Buyle: Conceptualization, Methodology, Investigation, Data curation, Writing – original draft.

Amaryllis Audenaert: Supervision, Conceptualization, Writing – review & editing.

Jan Brusselaers: Supervision, Conceptualization, Methodology, Writing – review & editing.

Steven Van Passel: Supervision, Conceptualization, Writing – review & editing.

Rebound effects following technological advancement? The case of a global shock in ferrochrome supply

Matthias Buyle[1,2,3*], Amaryllis Audenaert[1], Jan Brusselaers[2,4], Steven Van Passel[3,5]

1. *Energy and Materials in Infrastructure and Buildings (EMIB), University of Antwerp, 2020 Antwerp, Belgium*
2. *Unit Sustainable Materials Management, Flemish Institute for Technological Research (VITO), 2400 Mol, Belgium*
3. *VCCM, Flanders Make, Belgium*
4. *Institute for Environmental Studies, Vrije Universiteit Amsterdam, 1081 HV, Amsterdam, Netherlands*
5. *Department of Engineering Management, University of Antwerp, 2000 Antwerp Belgium*

** Correspondence: matthias.buyle@uantwerpen.be, matti.buyle@vito.be*

Abstract

Novel recycling technologies aim at increasing material efficiency by turning former waste products into valuable reclaimed resources. A key question is whether such technologies really reduce primary resource consumption or instead stimulate aggregated market demand. In this study the consequences of a positive shock in ferrochrome supply to the global stainless steel value chain is assessed quantitatively. This new source might be unlocked by technology under development for the recovery of chromium from carbon and stainless steel slags. The aim of this study is to quantitatively assess the income and substitution effects of reclaimed ferrochrome along a part of the stainless steel value chain. The impact of the supply shock is analysed by means of a vector autoregression (VAR), a dynamic model where lagged values of all included variables estimate current state of the system. Additionally, the VAR model is extended to a structural vector autoregression (SVAR) to account for contemporary effects as well. Both the VAR and SVAR model indicate that additional ferrochrome supply leads to an increase in aggregated supply of stainless steel, in combination with a substitution effect between ferrochrome and nickel. The extended SVAR model additionally highlights that contemporaneous effects do play an important role as well to capture the direct rebound effect in the ferrochrome market when working with quarterly data. In other words, an additional supply of reclaimed ferrochrome triggers a complex combination of interactions and consequences, yet it does not necessarily lead to a lower overall material consumption. The main contributions of this paper are the assessment of direct rebound effects of supplying reclaimed metals along the value chain and the demonstration that quantifying the effects of circular strategies is feasible.

Highlights

- Emerging technologies have the potential to unlock new source of ferrochrome
- Analysis of a shock in ferrochrome supply to the global stainless steel market
- Vector autoregression to quantify income and substitution effects along value chain
- Additional ferrochrome leads to a structural increase in supply of stainless steel
- Substitution effects between ferrochrome and nickel are observed

Keywords

Emerging technology, rebound effect; by-product valorisation; vector autoregression, chromium recovery

1. Introduction

One of the core ideas of the circular economy is that technological development can assist in increasing material efficiency by turning former waste products into valuable reclaimed resources (Ellen

MacArthur Foundation, 2015). But do such emerging technologies really reduce primary resource consumption and corresponding environmental impact, or do they stimulate aggregated market demand instead? For example, in recent years there has been a growing interest for valorising valuable properties of carbon and stainless steel slag. To date, although these slag types are no longer considered as waste, they usually end up in low quality applications that ignore the value of the entrapped residual metals (Singh and Ordoñez, 2016). Recently, research has been done on how to increase the value of carbon and stainless steel slag after treatment. Three strategies can be distinguished in literature: high-quality matrix valorisation, metal recovery and alternative use outside the steel industry. The goal of the first strategy is to create high quality construction products like carbonated building blocks (Di Maria et al., 2018), the second aims at recovering entrapped valuable metals such as vanadium and chromium (Wang et al., 2019), while the use of slag in wastewater treatment applications is an example of the last strategy (Ahmad et al., 2020). The current study builds on previous research efforts that go beyond the state of the art by combining the first two strategies, thus valorising the full potential of the carbon and stainless steel slags (Buyle et al., 2021). The main goal of this technology under development is the recovery of chromium, while the metal-free residual matrix material can serve as an input for carbonated building blocks. Currently this technology has a low technology readiness level (TRL). But after further technical and economic optimization, two new types of reclaimed products may enter the market in the future, namely chrome compounds and carbonated bricks. In the rest of this study, the focus will be on the recovered chrome, assessing its global market potential and influence on the stainless steel market by means of an econometric model. This model will clarify the pricing mechanisms that play a role in parts of the simulated value chain of stainless steel. The starting point is the assumption that further R&D efforts will enable the recovery of chromium as ferrochrome (FeCr) in an economically viable way (Buyle et al., 2021; CHROMIC, 2021).

Chromium is one of the key elements of stainless steel. It is typically added in the form of ferrochrome, and it is essential to harden steel and increase resistance to corrosion (Kropschot and Doebrich, 2010). At the moment, around 80% of global ferrochrome production is consumed in stainless steel products (Wolfe, 2018). However, to date there is no market for recovered ferrochrome as there are currently no separating technologies commercially available. Chromium is only indirectly recycled, as part of (stainless) steel scrap that is recycled. This way, a recycling rate of 40 to 75% is achieved depending on the region and the steel grade (Daigo et al., 2010; Nakamura et al., 2017), while the potential global indirect end-of-life recycling rate is estimated at 70% for all steel grades (Henckens, 2021). In this context, it is unclear what might happen if a new source of reclaimed ferrochrome enters the market, which will be available for direct use. Such a new source is complementary to scrap recycling but competes with primary ferrochrome production. Given its importance in the stainless steel value chain, a proper evaluation of ferrochrome supply needs to involve stainless steel production. So, both the ferrochrome and the stainless steel markets have to be considered if one is interested in the (indirect) effect of additional ferrochrome supply.

When evaluating the burdens and benefits of new recycling technologies, for example by means of an environmental life cycle assessment (LCA), it is typically assumed that recovered materials can replace primary ones on the market at a 1:1 ratio as long as both meet the same technical or functional requirements (European Commission - Joint Research Centre - Institute for Environment and Sustainability, 2010; Weidema et al., 2009). However, this assumption overlooks the market dynamics with its direct and indirect rebound effects, which could lead to over-optimistic conclusions. For example, Greening et al. (2000) identify four types of rebound effect in the context of increasing energy efficiency, namely direct rebound, secondary, economy-wide, and transformational rebound effects. Direct rebound effects can be considered as pure price effects and decomposed in a substitution and income effect, while secondary effects result from increases in demand for other goods and services.

Economy-wide effects capture price and quantity readjustments as well, often in a general equilibrium context (Brockway et al., 2021; Sorrell, 2007). Transformational effects refer to changes in consumers' preferences and the alteration of social institutions. However, incomplete substitution beyond energy services has been acknowledged in literature as well (Ekvall, 2000; Zink et al., 2016). The integration of economic models in environmental studies is one of the proposed approaches to take into account market dynamics, such as price, income and substitution effects. A distinction can be made between theoretical work and more empirical solutions, e.g. (partial) equilibrium or (environmentally extended) input-output models, whether or not combined with LCA or other environmental assessment methods. Dealing with direct and secondary rebound effects from a theoretical point of view, according to (Zink and Geyer, 2017) an additional supply of circular products on the market should be evaluated by applying the following criteria: are circular products really substitutes for their linear counterparts and if so, first do they increase aggregated demand and second is the environmental impact of reclaimed products or resources lower compared to primary ones. Figge and Thorpe (2019) build on work of Zink and Geyer and they emphasize the importance of producers in the context of a (circular) rebound effect, in addition to the classic consumer-producer approach. So, from a theoretical point of view, it is clear that the rebound effect of new circular strategies must be taken into account. However, it remains unclear how the put this in practice. Economic models are useful tools to complete policy assessments because they rely on actual data about the current structure of an economy, combined with a set of equations based on economic theory. These equations allow modelling the behaviour of economic agents and hence to analyse the impact of demand, supply and policy shocks. Such models have already been applied in the agri-food sector (Chalmers et al., 2015), in (bio)energy systems (Beaussier et al., 2022; Earles et al., 2013; Menten et al., 2015), in agriculture (Vázquez-Rowe et al., 2013) and when dealing with metals (Ekvall and Andrae, 2006). More recently, efforts have been made to capture economy-wide rebound effects by linking LCA to integrated assessment models (IAM). IAMs aim to model the global economy, considering economy-wide interactions between regions, sectors and policy goals (e.g. climate targets). An example of a prospective IAM is Premise (Sacchi et al., 2022). However, despite the benefits of a consistent economy-wide model, the drawback of IAMS is their coarse technological resolution. In literature there is a strong focus on behavioural changes (direct and secondary) as a consequence of increased energy efficiency (Cansino et al., 2022; Sorrell and Dimitropoulos, 2008). However, very little research exists on the empirical assessment of the economic impact of supplying reclaimed materials to the market. Zink et al. (2018) analysed the effect of a sustained shock of additional supply of recycled aluminium to the US market with a simultaneous equation model (SEM). They concluded that recycled aluminium only replaces 10 to 20% of primary aluminium, but that more research is needed to evaluate whether additional supply leads to increased industrial material consumption or to substitution by other materials such as steel or plastics.

In the light of the increasing attention for the circular economy and material efficiency in general, it is key to properly assess the consequences of actions aimed at increasing circularity and improving sustainability. However, when it comes to empirically estimating the impact of marketing recovered materials, very little information is available. Zink et al. (2018) is one of the exceptions and studies the production of recovered aluminium. Moreover, despite the importance of the (stainless) steel industry, there is very little empirical research available that focuses on a larger part of the value chain. Studies often have a narrow focus, for example the issue of China's excess steelmaking capacity (Ahn, 2016). In this context, the aim of this study is to quantitatively assess the effect of a positive shock in the supply of ferrochrome to the global stainless steel value chain. This will be achieved through the following three objectives: an analysis of the structure of the global stainless steel and ferrochrome market in order to develop a theoretical model (1), and an estimation of the consequences of a shock in ferrochrome supply by means of a Vector Autoregression (VAR) model (2). A VAR is a dynamic model in which one estimates the current state of the system via lagged values of all included variables. However, it is not unlikely that interactions will occur within the current period. So, the last objective is to find out whether such contemporary effects do indeed play a role, by extending the initial VAR to a Structural Vector Autoregression (SVAR) model (3). Two hypotheses will be tested with the VAR and SVAR models. Both are based on economic theory and involve the quantification of direct rebound effects. The first hypothesis is that an additional supply in ferrochrome can lead to lower prices, which reduces the production cost of stainless steel, which in turn can lead to greater aggregated demand for stainless steel. The second hypothesis is that a lower price of one of the inputs in the production of stainless steel can lead to a substitution effect, namely between ferrochrome and nickel.

This work makes three important contributions. First, to the authors' knowledge this is the first study to assess rebound effects of reclaimed metals along (a part of) the value chain. By applying a VAR and a SVAR, all actors within the model are treated endogenously, so that interaction between multiple markets can be estimated dynamically based on real data. The big advantage is that in this way, both direct (substitution) and indirect (income) effects can be analysed quantitatively. Second, this research will show that it is feasible to quantify the effect of circular strategies, such as waste valorisation and recycling. By focusing on empirical data and econometric modelling, the gap between environmental and economic models can be bridged, reducing the need for generic guidelines and the use of rules of thumb. This approach is exemplified for low TRL slag treatment technologies, highlighting the benefit for econometric evaluations at early design stages in specific. Third, the concept of direct rebound effects is applied to the supply side in a non-energy related context.

2. Material and methods

2.1 Literature review

A schematic representation of the stainless steel making process is shown in Figure 1. In modern manufacturing applications, inputs are melted in an electric arc furnace (EAF). These inputs are stainless steel scrap and other types of ferrous scrap, pig iron from blast furnace (BF) production and other alloying metals such as chromium, nickel, molybdenum and vanadium. Thereafter, excess carbon is removed in an argon oxygen decarburization (AOD) system and given the desired shape as the metal begins to cool. In the following paragraphs, the most important inputs and their market context are analysed more in detail.

Around 80% of the ferrochrome is consumed by the stainless steel sector (Wolfe, 2018). Any change in the ferrochrome supply must therefore be analysed together with the stainless steel sector. The steel market – and by extension the stainless steel market – is a global one (Bucur et al., 2017; Wolfe, 2018), where prices converge in the long run (Giuliodori and Rodriguez, 2015). Global stainless steel production has grown exponentially in the last two decades, with output nearly tripling from 19 Mt in 2000 to 52.2 Mt in 2019 (ISSF, 2020). China is the main driver of this growth: China's share of Asian stainless steel slab production has increased dramatically from 4% (0.25 Mt) in 2000, to 71% (22 Mt) by 2017 (Chan-wook, 2018). For the entire stainless steel market, China's share was 56%, followed by the European Union (13%), India (8%), Japan (6%) and the US (5%) (ISSF, 2020). In response to the exploding domestic demand, Chinese stainless steelmaking capacity has expanded substantially over the past two decades. However, the slowdown in Chinese economic growth at the start of the second decade - described by the Chinese authorities as the "new normal"– led to substantial overcapacity in the Chinese steel sector (Ahn, 2016). Due to the declining domestic demand, steelmakers sought export markets to alleviate domestic oversupply, impacting global steel prices (Ahn, 2016). In summary, the stainless steel market can be considered as a global market, with China as a major player influencing global prices and output. Smaller markets such as the EU and US can be considered price takers, although import tariffs have been introduced on Chinese steel (products) in recent years (Aperam, 2020).

There are substantial regional differences in the key drivers of stainless steel demand (Pariser et al., 2018). For example, in Japan demand is driven by architecture, buildings and construction, along with the automotive sector, while the main application in Europe is machinery and equipment. Nevertheless, stainless steel is a versatile material that is used in many economic sectors. So depending on the application there may be substitutes (International Energy Agency, 2020). For example, a shift to electric vehicles (EV) could reduce the use of stainless steel in favour of lighter materials, like aluminium or carbon fibre. Nevertheless, stainless steel remains the most suitable and cheapest option for many applications and as a result, despite the differences between regions, demand usually follows general economic activity (Giuliodori and Rodriguez, 2015).

The main inputs to stainless steel production - and the driver of supply - that determine production costs are chromium, nickel and energy prices. The chromium content in stainless steel is 10.5% or more (typically around 18%) to ensure corrosion resistance (Kropschot and Doebrich, 2010; Pariser et al., 2018), while nickel (6 to 26%) is usually added to improve the formability and ductility of stainless steel (Nickel Development Institute, 1993). Even more than chromium, nickel is a dominant determinant of the price of stainless steel (Aperam, 2020). Both chromium and nickel can be added in primary form or embedded in steel scrap. Nevertheless, since the alloying element content of scrap is variable, primary alloying elements are still needed to get the desired grade (Pariser et al., 2018). However, unlike chromium and nickel, the scrap market does not follow regular economic cycles, as it mainly relies on scrap collection (Pariser et al., 2018). Because suppliers can easily switch between steel grades, chromium and nickel are – to some extent – substitutes in production. Nonetheless, most of the output is distributed over a limited number of grades (Giuliodori and Rodriguez, 2015). The importance of the alloying elements can be demonstrated by the stainless steel pricing in Europe and the US, where the price is composed of a base price and a monthly updated alloy surcharge. The former is quite stable since 2000, while the latter is much more volatile (Aperam, 2020; Outokumpu, 2021; Pariser et al., 2018).

In addition to the overall supply and demand drivers, it is important to consider China's role in the global stainless steel market. In the last decade, a trend of fiscal decentralizing along with the promotion system by which government officials strive for GDP growth, has given local governments strong incentives to excessively support the (stainless) steel market, e.g. provide preferential tax, provide cheap land, etc. (Yu and Shen, 2020), resulting in oversupply in China's steel market. Despite the central government's goal of cutting back steelmaking capacity and reducing supply, in reality the opposite is happening. An additional problem is that such a market disequilibrium cannot be solved by market mechanisms alone, so government measures are required here (Yu and Shen, 2020). To tackle overcapacity, companies are looking for new foreign markets, putting pressure on the global stainless steel market (Ahn, 2016). An additional complexity is the heterogeneity of the Chinese steel market: while some of the larger companies are subject to (some degree of) governmental control, many of the smaller ones are not. So to conclude, China certainly has some market power, driven by GDP targets leading to excess steelmaking capacity, yet it cannot be considered a mono- or oligopolist (Sourisseau, 2018).

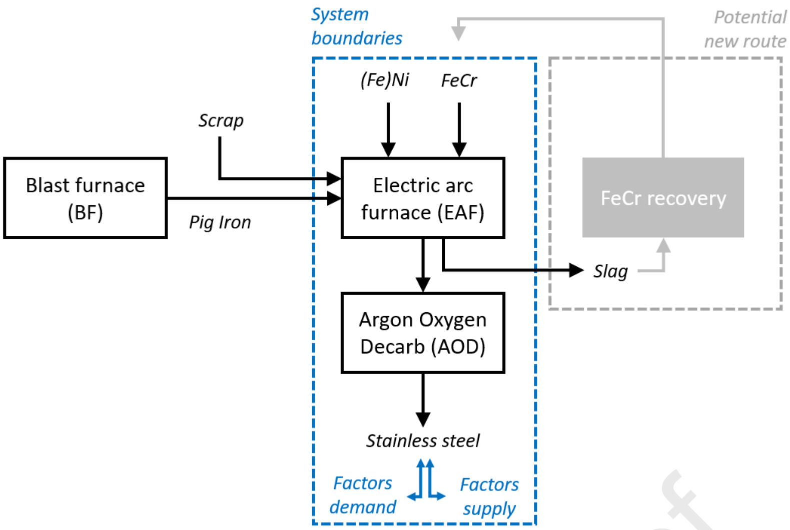

Figure 1. Schematic representation of the stainless steel making process. The blue dotted rectangle defines the system boundaries based on the literature review. The grey dotted rectangle represents the potential new route for ferrochrome recovery.

2.2 Empirical framework

In order to answer the second and third research question, an econometric model must dynamically capture the interaction between different markets and other drivers of supply and demand identified in the previous section. In this research, a vector autoregression (VAR) model is applied. A VAR is a multivariate linear time series model where the endogenous variables in the system are linear functions of the lagged values of all endogenous variables (Lütkepohl, 2005). One of the advantages of VAR models is that they are atheoretical, eliminating the need for structural equations assumptions. In this way, VAR models can describe the underlying process better than, for example, simultaneous equation models (SEM), which are subject to the risk of misspecification of structural equations and the requirement of an a priori division between endogenous and exogenous variables (Chan and Chung, 1995; Manera, 2006). On the other hand, a disadvantage of VAR models is that they only contain lagged variables, unlike SEMs.

The general formula for a VAR(*p*) model is as follows, with *p* the number of lags, *k* the set of explanatory variables and *t* the time index:

$$y_t = c + A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t \qquad \text{Eq. 1}$$

Where $y_t = [y_{1t} \;\; y_{2t} \;\; \dots \;\; y_{kt}]'$ is a random (*k×1*) vector, $c = [c_1 \;\; c_2 \;\; \dots \;\; c_k]'$ a fixed time-invariant (*k×1*) vector, A_i are fixed time-invariant (*kxk*) coefficient matrices and $u_t = [u_{1t} \;\; u_{2t} \;\; \dots \;\; u_{kt}]'$ is a (*k×1*) vector of error terms (Lütkepohl, 2005). All effects of omitted variables and contemporaneous interaction are assumed to be included in the error term, in the literature often referred to as innovations.

However, it is not clear from theory whether instantaneous interaction can occur. SVAR studies of other metal markets indicate significant instantaneous effects, by using monthly (Wang and Wang, 2019) or quarterly data (Chen and Yang, 2021). Quarterly data is used for this study (see section 2.3) so it is not unlikely that some agents will respond to available information within a period. To take this into account, the initial VAR model is extended to a structural VAR (SVAR) as a sensitivity analysis. In a VAR, the vector of error terms u_t captures both the variances of the error terms and the contemporaneous effects. In contrast in a SVAR, the covariance matrix u_t is assumed to be diagonal and to contain only variances of the error term, while the contemporaneous relationships are described in one or two additional matrices. Therefore, with a SVAR analysis, it is possible to examine both dynamic interactions and immediate correlations between variables. In this study a SVAR with short term restrictions is implemented in its most general form, namely with the AB-model (AB-SVAR) (Lütkepohl, 2005). The general formula is presented in Eq. 2, where A_0 is the invertible contemporaneous correlation matrix of endogenous variables and B_0 is the matrix characterizing the structural relationships of errors. In this case, a set of simultaneous equations is specified for the errors of the reduced form model instead of for the observable variables directly. Thereby the model accounts for the shift from specifying direct relations for the observable variables to formulating relations for the error terms (Gao et al., 2018; Lütkepohl, 2005).

$$A_0 y_t = c + A_1 y_{t-1} + \cdots + A_p y_{t-p} + B_0 e_t \qquad \text{with} \quad A_0 u_t = B_0 e_t \quad \text{and} \quad e_t \sim (0, I_k) \qquad \textit{Eq. 2}$$

Both A_0 and B_0 contain *kxk* elements. However, to obtain a unique solution to the system of equations, a total of $2k^2 - k(k+1)/2$ restrictions must be specified, even if the diagonal elements of A_0 are set to one. Usually, this is done by choosing a specific shape for A_0 and B_0 that sets zero constraints, as illustrated in Eq. 3 and Eq. 4. In addition, specifying the restrictions should not be done using sample data, but should come from sources outside the model (Lütkepohl, 2005). The assumptions about the possible contemporaneous interactions should be made based on literature or economic theory. More specifically, the AB-model requires a hierarchy to be defined where the highest level does not respond to contemporaneous information, while the lowest level responds simultaneously to all other variables. For example, variable 1 (a_{11}) can affect variables 2 to k (a_{21}, …, a_{k1}) but does not respond to these variables, variable 2 (a_{21}) can affect variables 3 to k (a_{32}, …, a_{k2}) but will respond only to variable 1, and so on.

$$A_0 = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ a_{21} & 1 & & 0 \\ \vdots & & \ddots & \vdots \\ a_{k1} & a_{k2} & \cdots & 1 \end{bmatrix} \qquad \textit{Eq. 3}$$

$$B_0 = \begin{bmatrix} b_{11} & 0 & \cdots & 0 \\ 0 & b_{22} & & 0 \\ \vdots & & \ddots & \vdots \\ 0 & 0 & \cdots & b_{kk} \end{bmatrix} \qquad \textit{Eq. 4}$$

2.3 Variable description & model specification

Both the VAR and SVAR models rely on the same dataset of quarterly data from 2010-Q1 until 2019-Q4 (n=40). The selection of quarterly data is mainly due to the limited availability of higher resolution production data. A higher sampling rate would have been desirable, nonetheless the quarterly data is detailed enough to capture seasonal effects in the model.

Based on the literature review in section 2.1, seven essential variables have been identified. An overview of them is presented in Table 1. Central to the model is the stainless steel market, with lnQss representing the global crude stainless steel production volume as reported by the (ISSF, 2020) and lnPss representing the global market price for stainless steel. The latter is approximated by the weighted average unit price for EU hot rolled coils (HRC) of stainless steel. Unit prices are derived from the Eurostat Comext database, for which imports to the EU are accounted for but intra-EU trade is excluded (Eurostat, 2022) (See Appendix 1 for more details). The global ferrochrome market is the second market to appear in the model. LnQfecr represents the global ferrochrome production volume, approximated by South African chromite production (Statistics South Africa, 2022). The rationale of this proxy is that chromite is almost entirely used in the production of ferrochrome and that South Africa is responsible for more than 50% of global production (Wolfe, 2018). Therefore, trends in South African chromite production are believed to reflect global ferrochrome production movements. For the global market price for ferrochrome, lnPfecr, an identical approach is followed as for LnPss, based on weighted average unit prices for ferrochrome (Eurostat, 2022). Nickel is an important factor of production and affects the production cost of stainless steel. lnPni represents the global nickel market price, including all types of nickel compounds (World Bank, 2022). Two other relevant variables were identified from the literature review. First, the global stainless steel market is affected by China's excess production capacity and capacity utilization rate. Due to the lack of data, the latter is approximated by the export value of China's stainless steel exports, lnEXPVAL (Trading Economics, 2022). Fluctuations in export value are believed to reflect excess production volume as it is mainly driven by policy goals and exported. Second, global demand follows the general economic cycles. The OECD Industrial production index (lnINDPROD) has been selected as indicator for demand(OECD, 2022a). Nominal prices are deflated by applying the OECD Producer Price Indices (PPI) with 2015 as the reference year (OECD, 2022b). All variables in this model are logarithmically processed to eliminate possible heteroscedasticity and facilitate interpretation of the outcome.

Table 1. Variables and data sources

Variable	Description	Units untransformed data	Source
lnQss	Global crude stainless steel production volume	kton	(ISSF, 2020)
lnPss	Global stainless steel market price	Euro/ton	(Eurostat, 2022)
lnQfecr	Global ferrochrome production volume	index with 2015 as base year	(Statistics South Africa, 2022)
lnPfecr	Global ferrochrome market price	Euro/ton	(Eurostat, 2022)
lnPni	Global nickel market price	$/mton	(World Bank, 2022)
lnEXPVAL	Export value of Chinese stainless steel export	1000$	(Trading Economics, 2022)
lnINDPROD	OECD Industrial production index	index with 2015 as base year	(OECD, 2022a)

An AB-SVAR model is included in this study, which takes into account short-term constraints in the form of zero-restrictions in A_0 and B_0. A brief literature review was conducted on SVAR studies targeting steel and other metals to identify hierarchical relationships between variables. The least restrictions are placed on global macroeconomic trends, with indicators such as GDP (Ehrlich, 2018; Hammoudeh et al., 2015; Stürmer, 2013). Specifically for metals, both (Stürmer, 2013) and (Ehrlich, 2018) argue that production quantity influences prices within a given period. But change in production takes time and the effects are expected to occur in later periods. This is also supported by (Gao et al., 2018; Zhong et al., 2019) who argue that the more flexible an agent is, the more likely a contemporary response becomes. In a SVAR context this means that the flexible agents are lower in the hierarchy. Translating these observations to the seven variables of interest, it becomes clear that lnINDPROD is the most general and aggregated indicator. So the assumption is that all other variables can respond within a period (a_{21} to a_{71}). lnEXPVAL is also a macroeconomic indicator, but only for China. The first restriction is therefore the assumption that lnINDPROD does not affect lnEXPVAL (a_{12} = 0). Next are the two production variables, with ferrochrome being less flexible (Wolfe, 2018). The last three are the price variables, ordered by their position in the value chain, assuming that production inputs directly influence the price of the final output. The identified relationships and hierarchy are summarized in Eq. 5, which is the empirical operationalization of the conceptual formulas Eq. 2 to Eq. 4.

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 & 0 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 & 0 & 0 & 0 \\ a_{41} & a_{42} & a_{43} & 1 & 0 & 0 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & 1 & 0 & 0 \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & 1 & 0 \\ a_{71} & a_{72} & a_{73} & a_{74} & a_{75} & a_{76} & 1 \end{bmatrix} \begin{bmatrix} u_{\mathrm{lnINDPROD}} \\ u_{\mathrm{lnEXPVAL}} \\ u_{\mathrm{lnQfecr}} \\ u_{\mathrm{lnQss}} \\ u_{\mathrm{lnPni}} \\ u_{\mathrm{lnPfecr}} \\ u_{\mathrm{lnPss}} \end{bmatrix} = \begin{bmatrix} b_{11} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & b_{22} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & b_{33} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & b_{44} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & b_{55} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & b_{66} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & b_{77} \end{bmatrix} \begin{bmatrix} e_{\mathrm{lnINDPROD}} \\ e_{\mathrm{lnEXPVAL}} \\ e_{\mathrm{lnQfecr}} \\ e_{\mathrm{lnQss}} \\ e_{\mathrm{lnPni}} \\ e_{\mathrm{lnPfecr}} \\ e_{\mathrm{lnPss}} \end{bmatrix} \qquad \textit{Eq. 5}$$

3. Results & discussion

3.1 Descriptive statistics & data analysis

Summary statistics and graphs of the seven variables are presented in Table 2 and Figure 2 (see Appendix 2 for untransformed variables). These graphs clearly show that all variables except lnPfecr are trending to some degree. Prices tend to fall, while output, export value and the OECD industrial production index are rising. The short-term fluctuations indicate the possibility of seasonal effects. The seasonal effects are indeed confirmed through a decomposition analysis (see Appendix 3).

To derive meaningful results from an econometric analysis, it is important that the data is predictable to some degree, meaning that the data is stationary. A time series is stationary if its probability distribution does not change over time (Stock and Watson, 2020). A time series that is not stationary is said to have a unit root, which can be converted to stationary time series by differencing the original time series. Variables that exhibit this behaviour are also referred to as 'integrated of order n' with n the number of times the series is differenced. To test for unit roots, both an Augmented Dickey Fuller (ADF) test (Dickey and Fuller, 1979; Fuller, 1973) and a Phillips and Perron (PP) test (Phillips and Perron, 1988) were performed. The null hypothesis in both tests is that a unit root is present in a time series sample. In addition, a Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test (Kwiatkowski et al., 1992) is included as well. In this case, the null hypothesis is the opposite, which is that the time series is stationary around a deterministic trend, so no unit root is present. The p-values of the three tests are listed in Table 2. According to the KPSS test, trend stationarity cannot be rejected for all variables. A unit root can be rejected for all variables for at least one test (ADF or PP) except for lnPni. An option would be to take first differences of lnPni. However, given the relatively small sample size and the low power of the stationarity tests, it is relevant to look at literature as well (Arltová and Fedorová, 2016). In this context, (Ahrens and Sharma, 1997) found that nickel price series appear to be generated by a trend stationary process without a unit root. It was therefore decided to continue with lnPni without differencing, but assuming a deterministic trend in the model.

*Table 2. Summary statistics and p-values from ADF, PP and KPSS stationarity tests. (note: for ADF & PP $p < 0.05$ means reject non-stationarity, while for KPSS $p < 0.05$ means reject stationarity). Superscripts ***, **, * indicate significance at 1%, 5% and 10% respectively*

Variable	Mean	Min	Max	Std. dev.	Skewness	Kurtosis	ADF(1)	PP	KPSS
lnQss	9.23	8.92	9.52	0.18	-0.15	-1.17	0.01 ***	0.01 ***	0.10
lnPss	7.52	7.24	7.87	0.16	0.31	-0.87	0.05 **	0.04 **	0.09
lnPni	9.57	9.07	10.22	0.31	0.28	-0.89	0.63	0.69	0.10
lnPfecr	6.89	6.72	7.19	0.11	0.71	0.39	0.05 *	0.11	0.10
lnQfecr	-0.10	-0.58	0.18	0.19	-0.47	-0.50	0.01 ***	0.01 ***	0.10
lnEXPVAL	16.15	15.46	16.56	0.21	-0.91	1.88	0.43	0.02 **	0.10
lnINDPROD	-0.006	-0.097	0.055	0.039	-0.12	-0.73	0.54	0.08 **	0.10

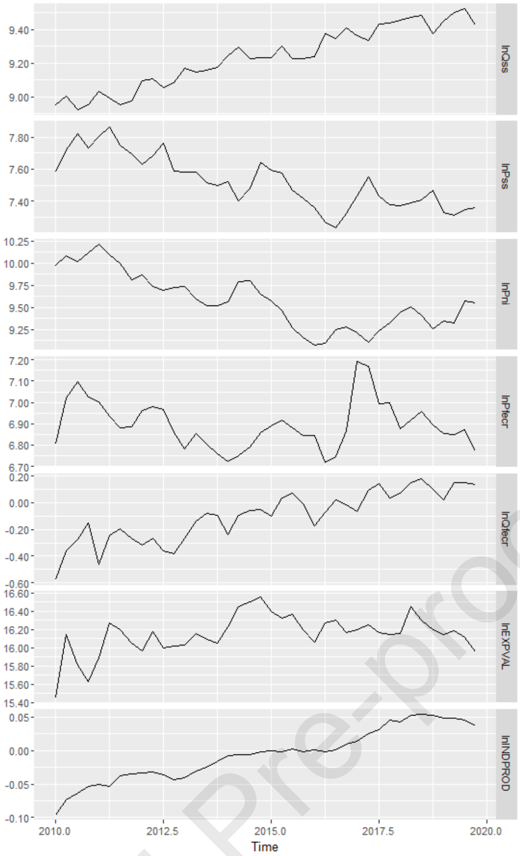

Figure 2. Plot of the time series of the log transformed seven variables of interest

To facilitate the model specification, the autocorrelation function (ACF) and partial ACF (PACF) were calculated for all variables. A very persistent ACF suggests the existence of a unit root, while a faster decreasing effect indicates an autoregressive component in the data. In contrast, significant lags in the PACF indicate a moving average component (Stock and Watson, 2020). All ACF and PACF plots are included in Appendix 4; only key findings are discussed in the manuscript. First, no significant lags were identified for all seven variables in the PACF. So, no moving average components are included in the model. Second, one to nine significant lags are identified in the ACF. These observations support the choice for the selection of an autoregressive model such as a (S)VAR, given the available data.

Based on the previous observations, the starting point will be a VAR(1) and SVAR(1) model, including a deterministic trend and seasonal dummies. However, according to the Akaike and Bayesian Information Criterion (AIC & BIC), the ideal lag length is four periods (see Appendix 5 for details). The problem that arises is that there are not enough observations to properly estimate a system with seven variables, four lags and some dummies. In addition, since the data is quarterly, four lags most likely only capture the seasonal effect. Therefore, in this research there has been opted to include only one lag, complemented with three seasonal dummies. The underlying rationale is that the AR(1) component absorbs the indirect effects of previous lags more parsimoniously. This is of course a limitation, so in future research efforts additional data should be collected to increase sample size.

3.2 VAR(1)

The reduced form of the VAR(1) was estimated consistently with ordinary least squares. The coefficients of the seven regression equations are included in Appendix 6. Own lagged variables are always significant, but it is important to note that in addition, all variables are significant at least once in the set of equations. However, because a VAR is a set of equations, a shock in one variable affects the entire system of equations. It is therefore difficult to interpret the individual coefficients and the analysis of the model is usually done via the orthogonal (cumulative) impulse response functions (IRF). IRFs describe how the model responds over time to structural shocks of a single variable. Before looking at the results, it is important to evaluate the model first. For the full model, the roots of the characteristic polynomial are less than one, so the model is robust and stable. Based on the asymptotic Portmanteau Test of the residuals, there is no serial correlation in the residuals. Moreover, there is also no heteroscedasticity in the residuals and no structural breaks occur either. Only the soft pre-requisite of normality is violated, but this does not affect the interpretation of the IRFs (Lütkepohl, 2005). So, the model withstands the most important diagnostics (full details are added in Appendix 5).

IRFs with a length of 50 periods are shown in Figure 3. In this manuscript, only the orthogonal cumulative IRFs of a one standard deviation shock of lnQfecr are analysed, as this is the driving variable to answer the research questions. In this study, the general research question relates to the aggregated market responses in the medium-term so the cumulative effects matter. Non-cumulative IRFs reflect changes from period to period and are easier to notice when convergence is achieved. In an exploratory preliminary evaluation of the results, convergence was analysed this way. All other IRFs are listed in Appendix 8. The IRFs also include the 90% confidence interval. According to (Lütkepohl, 2005), responses over time can be considered statistically significant if significance for at least one time period can be identified. Nevertheless, as other statistics, e.g. F-statistics and adjusted R^2, indicate that the model is relevant, all IRFs will be discussed. All variables are log transformed, meaning that the effects can be interpreted as percentage changes:

- The structural shock of one standard deviation of ferrochrome production corresponds to an additional supply of 5.7%. Then this rises to 7.4% after two periods, before converging to a value of 6.3%. In other words, the equilibrium situation is about 10% higher compared to the initial shock, indicating the existence of a rebound effect. As expected by economic theory, the extra supply of ferrochrome leads to a price decrease of 1.7% in the longer term.
- The drop in the nickel price suggests that nickel and ferrochrome are indeed substitutes to some extent. Even though they are not direct technical substitutes, a shift between steel grades can occur. When looking at the IRF after a shock of lnPni, the substitution between nickel and ferrochrome appears here as well (see Appendix 8, fig 17). The possibility of such a substitution was confirmed both by empirical evidence (Giuliodori and Rodriguez, 2015) and by long-term forecasts of the stainless steel market (Sverdrup and Olafsdottir, 2019). A final note on nickel prices is that convergence is achieved, but only after a very long time. Previous studies confirm the long-lasting effect of shocks on the nickel market, ranging from 9 to 18 years (Cashin and McDermott, 2001; Ehrlich, 2018).
- The stainless steel market is clearly affected by a shock in ferrochrome supply. If ferrochrome prices fall, possibly accompanied by a shift between steel grades, stainless steel prices are expected to decrease by 6%. The latter in turn leads to a 4.6% increase in total stainless steel demand in the long term. This observation endorses the central research question, namely the existence of a rebound effect after a ferrochrome shock.
- The supply indicator lnINDPROD is only affected to a very limited extent, which makes sense as this is a macroeconomic indicator that covers the entire OECD economy and not just the stainless steel sector.
- The only unexpected result is the large influence of lnQfecr on lnEXPVAL, which converges to 17.4%. One possible interpretation is that Chinese exports are responding to the growing aggregated demand for stainless steel. This would mean that GDP targets are not the only driver of Chinese exports. This is in line with Sourisseau's observation of a very heterogeneous Chinese steel sector (Sourisseau, 2018).

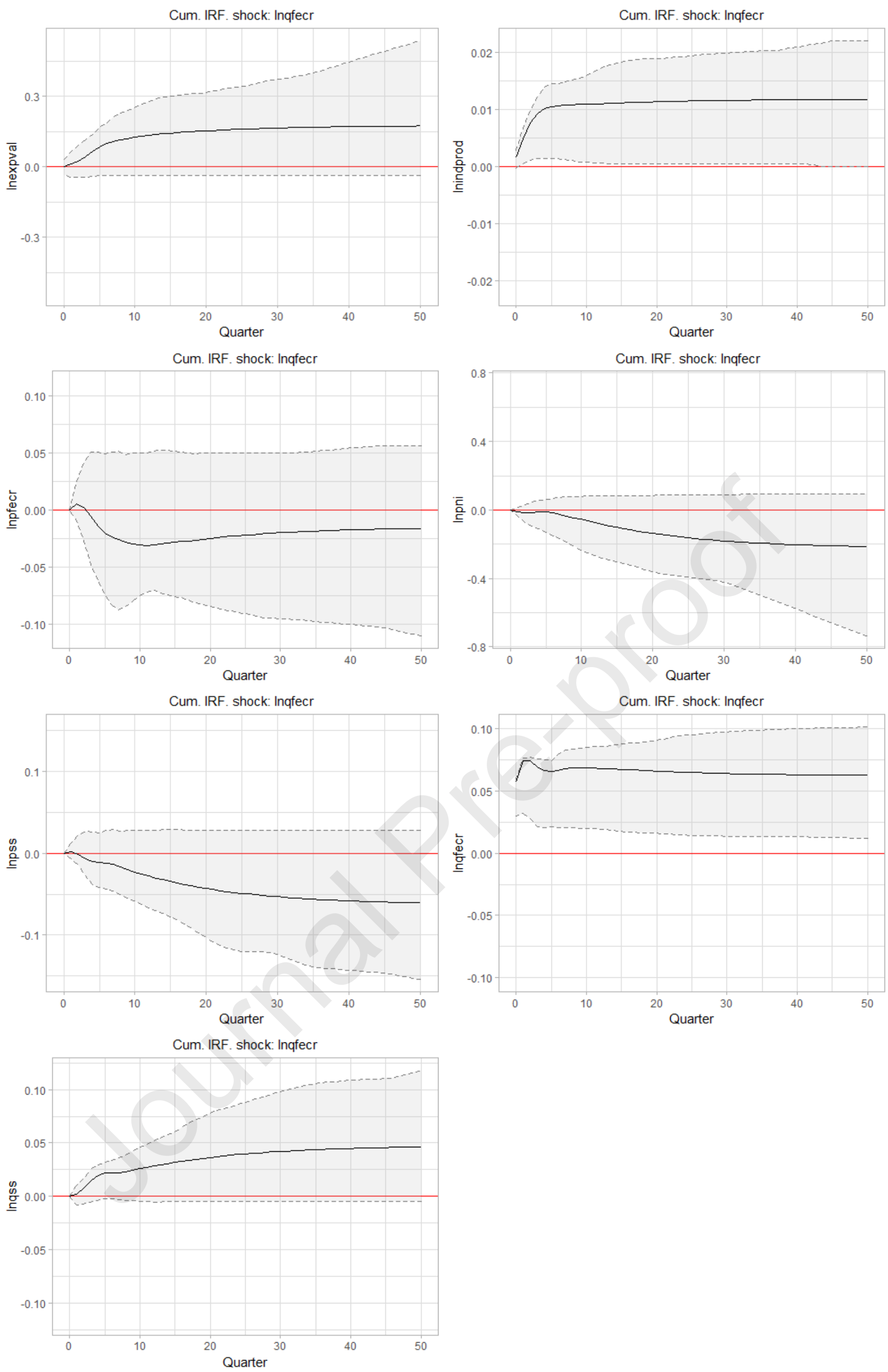

Figure 3. Cumulative IRF after a shock of lnQfecr of the VAR(1) model

3.3 SVAR(1)

In the second part of the analysis, the initial model is extended. Contemporaneous interaction is possible to some extent, but it is limited by the constraints defined by the shape of the A_0 and B_0 matrices (see Appendix 7). Again, only the IRFs of a shock in ferrochrome supply are shown (Figure 4); all the others are listed in Appendix 9. Comparing the results with the original VAR(1) model, it is clear that similar conclusions can be drawn. However, there are also some important differences to note.

First of all, the contemporaneous effects are not negligible. After a 6.13%[1] shock of lnQfecr, there are substantial price effects at t = 0: +1.6%, -2.1% and -2.0% for lnPni, lnPfecr and lnPss, respectively. LnQss

[1] This represents one standard deviation of lnQfecr based on the SVAR(1) model.

also reacts within the first period, but to a lesser extent (+0.7%). This also means that, given that the long-term equilibrium situation is quite similar, convergence is achieved at a faster rate compared to the initial VAR(1) model. Second, the bounds of the confidence intervals are slightly narrower. This is in particular true for the main variable of interest lnQss. So, allowing instantaneous interaction makes the conclusion of a rebound effect on the stainless steel market more robust. Third, lnQfecr converges to 7.96% after a shock of 6.13%, which is an increase of 29.8%. Thus, when contemporaneous interaction is taken into account, the direct rebound effect nearly triples (from 10.5% for VAR(1) to 19.8% for SVAR(1))

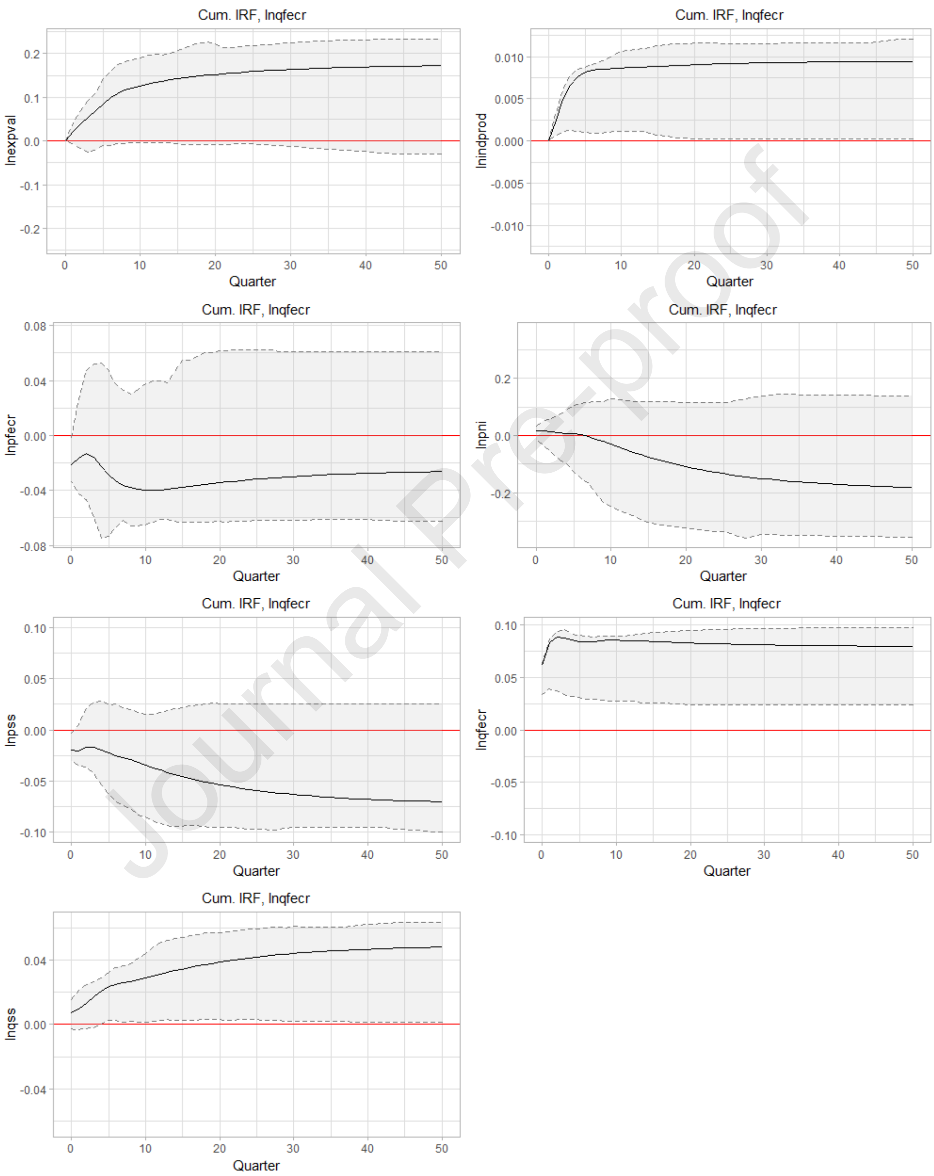

Figure 4. Cumulative IRF after a shock of lnQfecr of the SVAR(1) model

3.4 Model evaluation and limitations

To the best of the author's knowledge, the present study is the first to conduct VAR and SVAR to estimate the global impact of an additional supply of ferrochrome and its effect on related markets such as stainless steel. Validation by direct comparison with other studies was not possible as no clear benchmark studies could be identified. Only the work of (Zink et al., 2018) has a similar research question, focusing on recycled aluminium but applying the rather coarse simultaneous equation model (SEM). Nevertheless, as validation of the model, most of the results could be explained by economic theory or validated point by point with literature, such as the slow convergence of nickel prices (Cashin and McDermott, 2001; Ehrlich, 2018), the potential substitution between stainless steel grades (Giuliodori and Rodriguez, 2015; Sverdrup and Olafsdottir, 2019) or the existence of both a price and an income effect on the steel an nickel market (Fernandez, 2018).

In general, the results obtained confirm the initial hypotheses. However, this global model is highly aggregated. Future research efforts should focus on geographical disaggregation, as there are regional differences in consumption patterns, trade restrictions, import tariffs, transport costs, quality restrictions, etc. Such differences can lead to deviations from the global trends, due to the specific local or regional context. The model could also be extended to other determinants of the stainless steel supply chain, such as the stainless steel scrap and the energy market.

Another aspect is that the model is based on on historical data, so it does not account for possible changes. For example, nickel demand is expected to increase substantially in the future, driven by electric vehicle battery production (International Energy Agency, 2020). This trend is already happening today, with the supplier shifting to the production of battery-grade nickel (Pariser et al., 2018). Such a trend will affect the stainless steel market as well. Incorporating projections on the nickel and other markets in the model is another research opportunity.

Finally, it was found that an additional supply of ferrochrome resulted in an increase in the aggregate supply of stainless steel. However, the environmental impact is unclear. More steel will be produced, but given the assumption that the additional shocks are produced from (stainless) steel slag, which is expected to have a lower environmental impact in the long term compared to primary production, it is still unclear what the net effect will be.

4. Conclusion

This study deals with the assessment of the consequences of introducing additional supply of reclaimed raw materials, including the effect on the demand for downstream production. The method is applied to the ferrochrome and stainless steel market from a global perspective. Based on the results of the proposed model, the initial hypotheses could be confirmed: a shock in ferrochrome supply does lead to an increase in the aggregated supply of stainless steel, in combination with a substitution between ferrochrome and nickel. Additionally, the SVAR model highlights that contemporaneous effects also play an important role to capture the direct rebound effect in the ferrochrome market when working with quarterly data. In other words, an additional supply of reclaimed ferrochrome will cause a complex combination of interactions and consequences, but will not necessarily lead to a lower overall material consumption.

Based on the observations in this study, several policy recommendations can be formulated. First, to evaluate circular strategies such as recycling or reuse, indirect effects must be considered. A 1:1 substitution ratio between primary and secondary materials is highly unrealistic, given the existence of rebound, substitution and income effects across different markets. By recognizing and quantifying such effects, the development of greener technologies can be stimulated and unwanted side effects and externalities can be avoided. These can then be tackled more accurately with the appropriate policy instrument (e.g. bans, subsidy, tax, etc.). Second, when evaluating materials that can serve as inputs for other processes or materials, it is important to look beyond a single market and include a wider part of the value chain. In this study, an isolated evaluation of the ferrochrome market alone would have failed to capture several indirect effects. After all, the most important consequence of the shock analysed is the extra stainless steel production. Finally, the fact that indirect effects between markets have been identified does not prevent emerging (circular) technologies to play an important role. However, ambitions during technology development must be higher so that the benefits of recovery, recycling or reuse exceed the burdens caused by the increase in aggregated demand. Therefore, future research efforts on emerging circular technologies, should combine a thorough econometric assessment with the quantification of direct and indirect environmental impacts, to draw robust conclusions and guide further research efforts.

Abbreviations

VAR	Vector Auto Regression
SVAR	Structural Vector Auto Regression
SEM	Simultaneous Equation Model
TRL	Technology Readiness Level

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CRediT authorship contribution statement

Matthias Buyle: Conceptualization, Methodology, Investigation, Data curation, Writing – original draft.

Amaryllis Audenaert: Supervision, Conceptualization, Writing – review & editing.

Jan Brusselaers: Supervision, Conceptualization, Methodology, Writing – review & editing.

Steven Van Passel: Supervision, Conceptualization, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendices

1. Appendix 1: Market price estimation based on trade data
2. Appendix 2: Summary statistics untransformed variables
3. Appendix 3: Decomposition analysis
4. Appendix 4: Details ACF & PACF
5. Appendix 5: Model diagnostics VAR(1)
6. Appendix 6: Coefficients VAR(1)
7. Appendix 7: Coefficients A_0 and B_0 matrix SVAR(1)
8. Appendix 8: Impulse response functions VAR(1)
9. Appendix 9: Impulse response functions SVAR(1)
10. Appendix 10: Dataset
    a. *Dataset_VAR_Quarterly_import.xlsx*
11. Appendix 11: R-script
    a. *VAR-SVAR.R*

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Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: