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On interaction between carbon spot prices and Czech steel industry

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ABSTRACT
Environmental policy in the European Union is a frequent topic when speaking about a strategic development of national economies, their sectors, or companies. This paper is focused on transmissions between the European carbon market and the Czech steel industry. This relationship is worth exploring for two main reasons – first, iron and steel industry is responsible for a substantial part of CO_2 pollution covered by the European Union emissions trading system (EU ETS) and, second, this sector is a traditional and vital industry in the Czech Republic. We use the dynamic Factor Augmented Vector Autoregression (FAVAR) model and Granger causality analysis to identify and assess the interactions between the factors of the EU ETS (prices of emission allowances and grandfathering), and factors of the steel industry like prices and amounts of production. To the best of our knowledge, this is the first application of the FAVAR model to analyse an industrial sector, and it is also the first analysis of the given topic where so many influencing factors are involved (this is allowed by the FAVAR model). The main results show that steel companies in the Czech Republic pass through the emission costs to customers.

KEYWORDS
Emissions trading; pass-through effect; FAVAR; Granger causality; Impulse Response Function; EUA

SUBJECT CLASSIFICATION CODES
C51

Q1 Introduction

Environmental policy in the European Union and its impact on the industry is a hot topic. Emissions trading is one of the main tools of this policy. This paper is devoted to a specific interaction between the European Union Trading Scheme (EU ETS), Czech iron and steel market and the macroeconomic environment in the Czech Republic for the period 2008 to 2016.

The aim of the EU ETS system is to reduce the total amount of emissions released by the included sectors by 20% compared to the level of 1990 until 2020, and by 43% compared to the level of 2005 [1, 2]. The EU ETS is a cap-and-trade system forcing industrial companies to cover their CO_2 emissions by allowances – EUAs (European Union Allowances), and CERs (Certified Emission Reductions). Companies doing their business in selected industries get a part of necessary allowances for free, which is called grandfathering. The remaining required allowances must be purchased, so they increase the total production costs. The EU ETS has been launched in 2005, and it has been split into the trading phases: Phase I (2005-2007) was a pilot phase characterized by overallocation of grandfathered allowances; Phase 2 (2008-2012) involved also the aviation sector into the system, and still suffered from overallocation; Phase 3 (2013-2020) brought several important changes, e.g. national governments cannot influence the number of grandfathered allowances any more, and the system is not so generous regarding the grandfathering (the electricity sector does not receive any allowances for free since this phase).

Iron and steel industry, which is explored in this study, is specific among the other sectors. It belongs to the group of energy intensive sectors as it produces large volumes of CO_2. The steel production is also included in the *carbon leakage* list involving the industries with high expected emissions, for which there is a high potential risk of transferring their business to companies outside the EU, where environmental constraints are laxer, see [2, 3]. To prevent the carbon leakage effect, companies from the carbon leakage group receive a compensation through grandfathering, mentioned above (a full compensation was applied in the first two EU ETS phases, whilst, in Phase III, the number of grandfathered allowances decreases linearly each year). Last but not least, the European steel producers are influenced by the competition of non-EU (particularly Asian) producers. Therefore,

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a high sensitivity to changes in macro environment can be expected in this sector [4]. The statistics of the World Steel Association [5] reveals that the growth of steel production was substantially higher outside the EU (48%) than in the EU member countries (10.2%) between 1993 and 2014 (but, e.g. the production in China increased by 818.6% during the same time period). For all these reasons, the research of the interactions between the EU ETS, macro environment, and the steel industry is very important.

In the Czech Republic, the iron and steel industry has a very strong tradition since the nineteenth century. And still, it is extremely important for the Czech economy. Based on the data of the Czech Statistical Office, the share of sales from iron and steel final products on GDP is between 4% and 5% in the last years [6].

The aim of this paper is to study the relationship between the iron and steel market in the Czech Republic and the EU ETS system from 2008 to 2016. The mutual interactions between the selected factors of the steel industry and prices of emission allowances are explored using a dynamic FAVAR (Factor-Augmented Vector AutoRegressive) model, Granger causality and Impulse response functions analysis (IRF). This paper is innovative from two points of view. It presents the first use of the FAVAR model in the given field, and, this is the first research focused on interactions between Czech steel market and emissions trading system. Moreover, the results of the FAVAR model and the IRF analysis allows to analyse the influence of shocks to the whole system.

The absence of any FAVAR application for analysis of a single economic sector does not mean that the FAVAR method is not suitable for this purpose. In general, if a proposed model has too many explanatory variables, it is more convenient to aggregate them into several factors in order to ensure a higher explanatory power of the results. And this is what the FAVAR model does unlike regular vector autoregressive (VAR) models.

In cooperation with two experts in the steel industry, we identified a set of variables, which can be potentially important for our analysis. Namely, the European carbon market is represented by the prices of EUA and CER prices, and the volumes of grandfathered allowances to the Czech steel sector. The Czech steel industry is described using amounts of production of various types of commodities, and prices of these products, new contracts for the products, and the crucial inputs for steel production (coal, gas, electricity, and iron ore). The last group of indicators describes macro environment in the Czech Republic - interest rates, economic sentiment indicator, industrial production index, rate of unemployment, government bond portfolio yields, and price indices (industrial producer price index and consumer price index).

The paper is organized as follows. This introduction is followed by Section the state of the art focused on the state-of-the-art analysis. In Section the factor-augmented var model and granger causality, a theoretical background for a FAVAR model and Granger causality is provided. Section data is devoted to the input data and their preprocessing. The results of the econometric analysis and the sensitivity analysis exploring the robustness of the obtained results are provided in Section results. Section discussion and recommendations for policy makers presents final recommendations for policy makers. In Section conclusion, main implications of the performed study are summarized.

The state of the art

The EU ETS system has already been analysed from many points of view. A special attention was paid to determinants of prices of emission allowances [1, 7], the dependencies between different types of allowances [8], the influence of prices of allowances on particular industrial companies [9], forecasting of allowance prices [10], or dependencies between spots and futures of allowances [11].

The influence of the European environmental policy and climate change policy on steel industry has already been analysed too. According to Flues et al. [12], the effect of the energy policy on the steel industry is worth analysing because this sector is very carbon-intensive. The studies of Okereke and McDaniels [4] and Santamaría et al. [13] explored the influence of several factors of the European environmental policy on steel companies like free allocation of emission allowances to the companies. According to Chevallier [1], European steel production is influenced also by the prices of inputs and energy, by information and availability of modern technologies, and by market demand and national supranational policy, including the environmental policy.

A great effort has also been paid to explore two closely related effects influencing the competitiveness of the EU steel industry under emissions trading – the carbon leakage effect, which has been already mentioned in the introduction, and the pass-through effect, i.e. the ability to pass the costs implied by emissions trading to customers. The studies devoted to the pass-through effect, performed by Reinaud [14], Boutabba and Lardic [15], McKinsey [16], or de Bruyn et al. [17], were based on different approaches, different input data, and subsequently led also to different results. Overall, no consensus exists even about the existence of carbon leakage and the pass-through effect in the steel industry, let alone their potential power.

Despite the FAVAR model has never been used to analyse only a single economic sector, its application related to EU ETS exists. Namely, Chevallier [8] explored the transmissions of international shocks to prices of EUA and CER spots and futures using 115 macroeconomic, financial and commodity indicators (based on daily data from 04/2008 to 01/2010). Using a FAVAR model, the results of this analysis suggest that carbon prices respond negatively to the impulses induced by exogenous shocks of global economic indicators, and that this response varies with types of allowances (CER futures are influenced more when comparing to EUA spots and futures).

The Factor-Augmented VAR model and granger causality

A FAVAR model, originally introduced by Bernanke et al. [18], is used for our analysis. An idea of the FAVAR approach is that, first, a set of considered informational variables is transformed into aggregated factors. Second, the factors are used to estimate the coefficients of a dynamic VAR model [19]. In this way, more information can be included into the VAR model without the necessity to estimate a large number of parameters because the estimates of the factors are used in the structured VAR model instead of the original variables. Estimates of the factors can be used in a structured VAR model. As with the usual VAR models, consequences of shocks in the involved factors may be explored by means of response functions.

The FAVAR model is built on a dynamic factor model structure, formulated in a state-space form [20]. Let $\boldsymbol{Y}_t \in \mathbb{R}^{m\times 1}$ be the vector of time series of observed variables (t is a time index, $t = 1, 2, \ldots, T$), and $\boldsymbol{F}_t \in \mathbb{R}^{k\times 1}$ (where k is small) be a vector of unobserved factors. Let us assume that joint dynamics of $(\boldsymbol{F}_t, \boldsymbol{Y}_t)'$ are given by the following transmission equation:

$$\begin{pmatrix} \boldsymbol{F}_t \\ \boldsymbol{Y}_t \end{pmatrix} = \sim\Phi_1 \begin{pmatrix} \boldsymbol{F}_{t-1} \\ \boldsymbol{Y}_{t-1} \end{pmatrix} + \sim\Phi_2 \begin{pmatrix} \boldsymbol{F}_{t-2} \\ \boldsymbol{Y}_{t-2} \end{pmatrix} + \ldots + \sim\Phi_p \begin{pmatrix} \boldsymbol{F}_{t-p} \\ \boldsymbol{Y}_{t-p} \end{pmatrix} + \sim\varepsilon_t^f \quad (1)$$

where $\sim\Phi_l, l = 1, 2, \ldots, p$ are estimated coefficients of lagged variables. The error term $\sim\varepsilon_t^f$ is i.i.d. with $N(0, \Sigma^f)$. The equation (1) defines a FAVAR model with lag p (FAVAR(p)). Eq. (1) cannot be estimated directly within one stage due to the fact that $\boldsymbol{F}_t$ are unknown.

Let $\boldsymbol{X}_t \in \mathbb{R}^{n\times 1}$ $(k + m \ll n)$ be the vector of informational time series, fulfilling

$$\boldsymbol{X}_t = \Lambda^F \boldsymbol{F}_t + \Lambda^Y \boldsymbol{Y}_t + \boldsymbol{v}_t \quad (2)$$

where $\Lambda^F \in \mathbb{R}^{n\times k}$ is a matrix of factor loadings, $\Lambda^Y \in \mathbb{R}^{n\times m}$ is a matrix of coefficients of particular observed variable $Y_{i,t}$ and $\boldsymbol{v}_t \in \mathbb{R}^{n\times 1}$ is a vector of i.i.d. error terms with zero mean. Eq. (2) is used to generate factors $\boldsymbol{F}$. The principal components analysis (PCA) may be used to estimate its parameters (alternatively, maximum likelihood can be used), see Bernanke et al. [18]. In our paper, we consider a two-step principal components approach - a non-parametric approach of uncovering the space spanned by the common components $(\boldsymbol{F}'_t, \boldsymbol{Y}'_t)$ in (2), see Bernanke et al. [18].

Within the first step, $\boldsymbol{F}_t$ is estimated using the PCA to $\boldsymbol{X}_t$. It is worth noting that this first step does not take into account the vector of time series of observed variables $\boldsymbol{Y}_t$ at all, whereas, in the second step, the FAVAR equation (1) is estimated by standard methods [21].

In this paper, the changes in EUA and CER prices stand in the place of the observed variables $\boldsymbol{Y}$. The set of 26 informational variables $\boldsymbol{X}$, which describe the Czech (and generally European) steel sector and its related environment, are used (see their complete list and description in Section data).

As an additional tool for analysing the system, the Granger causality test is used in this paper to explore to what extent the current values of the factors and observed variables can be explained by past values of other factors and observed variables in the model, i.e. what is an ability of the model to predict future values of a time series using its past, see Granger [22]. Let $c_t = (F_{1,t}, \ldots, F_{k,t}, Y_{1,t}, \ldots, Y_{m,t})'$ be the vector of all the variables of the FAVAR model, i.e. $c_{i,t}$ is either one of the extracted factors F_t or observed variables Y_t. The set of equations for the Granger causality test is as follows:

$$c_{i,t} = \alpha_0 + \alpha_1 c_{i,t-1} + \ldots + \alpha_l c_{i,t-l} + \beta_1 c_{i,t-1}$$

$$+ \ldots + \beta_l c_{i,t-l} + \omega_{i,t} c_{j,t} = \alpha_0 + \alpha_1 c_{j,t-1}$$
$$+ \ldots + \alpha_l c_{j,t-l} + \beta_1 c_{j,t-1} + \ldots + \beta_l c_{j,t-l} + \omega_{j,t} \quad (3)$$

for all $i \neq j$ and all possible pairs of $c_{i,t}$ and $c_{j,t}$ series. The Wald statistics for joint hypothesis has the null hypothesis that $c_{j,t}$ does not Granger-cause $c_{i,t}$ in the second regression in (3):

$$H_0 : \beta_1 = \beta_2 = \ldots = \beta_l = 0 \quad (4)$$

for each equation in (3). We will use this Granger test for investigation of causal relationships time series in the vector.

The third econometric method used in this paper is the Impulse Response Function analysis (IRF), which usually plays an important role in the FAVAR analysis. This method explores the impact of shocks in the observed variables $\boldsymbol{Y}$ on the factors $\boldsymbol{F}$ derived within the FAVAR method, and vice-versa. Namely, we analyse how strong the response is, how quickly it occurs and disappears. A thorough mathematical description of this method is provided by Bernanke et al. [18].

Data

This section provides a description of the data used in this paper. We consider two observed variables $\boldsymbol{Y}_t$ - EUA and CER spot prices (daily prices of the SENDECO2 market [23]), and 26 informational variables $\boldsymbol{X}_t$ related to the iron and steel sector in the Czech Republic, which are candidates to determinants of the carbon prices. The informational variables taken into consideration are listed in Table 1. Next, we justify their inclusion.

Variables determining volumes of production (production of raw iron, steel, final long and flat steel products and semi-finished products in the Czech Republic, industrial production index in the Czech Republic, and new contracts on final long and flat products and semi-finished products in the Czech Republic). For each production-oriented field, volumes and other properties of production are crucial. Moreover, according to Reinaud [14], the steel industry is mainly driven by demand, and steel companies rarely produce to stock. Therefore, the level of production and new contracts provide a reasonably good approximation of the market demand. Moreover, the analysis of Nera [24] recommends to include some variable, which captures the market share of modeled companies; and the market share is closely related with the new contracts, which we include. According to Zhang et al. [25], a mutual impact between the production and the prices of allowances is possible. By economic intuitions the higher production, the higher demand for allowances, and thus the higher price of allowance. Other way around, if the price of allowances increases enough, the production will be too expensive, and companies will be forced to restrict the production [9]. The data on these indicators are daily, and they were taken from Czech Steel Union's commercial database [26].

Prices in the Czech steel sector (prices of flat and long steel products and steel scrap, industrial producer price index, consumer price index). The prices of steel commodities are driving factors of companies' profit, and thus their competitiveness too. The data on these indicators are daily, and they were taken from [6, 26, 27].

Exchange rates (CZK/EUR, CZK/GBP, CZK/USD)**.** Due to the fact that most final products are exported out of the Czech Republic, and raw materials are purchased abroad, and most final products are exported out of the Czech Republic, the exchange rates are very important for Czech steel producers. The data on exchange rates were taken from the ARAD database of the Czech National Bank [28].

Interest rates and yields of Czech government bonds. These two factors play an important role in investments. Companies can decrease the impact of EU ETS if they reduce their emissions through investments in new (green) technologies, see Zhang et al. [25]. The lower interest rates, the higher motivation for investment. The data on exchange rates were taken from the ARAD database of the Czech National Bank [28].

Rate of unemployment in the Czech Republic. The steel industry is very labor-intensive. Oberndorfer et al. [29] showed in their analysis that unemployment and the allowance price are correlated in labor-intensive sectors. The data on exchange rates were taken from the ARAD database of the Czech National Bank [28]. The data on unemployment rate are available in the database of the Czech Statistical Office [6].

Market indices (Industrial producer index, Consumer price index, Sentiment index for the Czech economy). The mechanisms of potential correspondence of Industrial producer index and Consumer price index are similar to level of steel production and prices of steel products, respectively. They take into consideration not only the steel industry, but the Czech economy as a whole. Sentiment index for the Czech economy provides insight into the market's mood to stake-holders.

Table 1. List of included variables (TC = transformation code).

No.	Name	TC	Description of the observed var. ***Y*** (before transformation)
1	TEUA	3	EUA spot price [EUR/pc]
2	TCER	3	CER spot price [EUR/pc]
No.	Name	TC	Description of the informational var. ***X*** (before transformation)
3	TFL1	2	Production of steel in the Czech Rep. [t]
4	TFL2	2	Production of raw iron in the Czech Rep. [t]
5	TFL3	2	Prod. of steel semi-finished products in the Czech Rep. [t]
6	TFL4	2	Prod. of long steel products in the Czech Rep. [t]
7	TFL5	2	Prod. of flat steel products in the Czech Rep. [t]
8	TNC1	2	New contracts on semi-finished products in the CR [t]
9	TNC2	2	New contracts on long steel products in the CR [t]
10	TNC3	2	New contracts on flat steel products in the CR [t]
11	TLONGP	3	Price of long steel products [USD/t]
12	TFLATP	3	Price of flat steel products [USD/t]
13	TP1	3	Price of steel scrap [GBP/t]
14	TPPI	3	Industrial producer price index ($ø_{2005}$ =100)
15	TCPI	3	Consumer price index ($ø_{2005}$ =100)
16	TCZKEUR	3	Exchange rate CZK/EUR
17	TCZKGBP	3	Exchange rate CZK/GBP
18	TCZKUSD	3	Exchange rate CZK/USD
19	TBOND10	1	Yields of CR government bonds with ø maturity of 10 yrs [%]
20	TIR	1	Interest rate [%]
21	TUR1*	1	Rate of unemployment [%]
22	TPROD*	3	Industrial production index in the CR (2005 = 100)
23	TSENTIM*	3	Sentiment index for the Czech economy (2005 = 100)
24	TGASP	3	Price of gas [EUR/KWh]
25	TELECTP	3	Price of electricity [EUR/KWh]
26	TIRONP	3	Price of raw iron [EUR/t]
27	TCOALP	3	Price of coal [EUR/t]
28	TALGR	1	Number of allocated allowances to the steel sector for free

The data on exchange rates were taken from the ARAD database of the Czech National Bank [28], and the data on the Sentiment index were derived from the database of the Czech Statistical Office [6].

Prices of inputs (iron ore, coal, electricity, gas). All the studies exploring the mutual influence between EU ETS and the steel industry, which were mentioned in Section the state of the art, consider prices of inputs. The data on these indicators were taken from Czech Steel Union's commercial database [26].

Amounts of grandfathered allowances to the Czech steel industry. According to Okereke and McDaniels [4], free allocation of emission allowances to companies plays a crucial role when assessing the impact of the trading system on companies. The more allocated allowances, the less additional allowances must be purchased, and thus the lower costs of emissions trading. The data were taken from the Carbon Market Data database [30].

Due to different periodicity of the original time series, firstly, they had to be transformed to monthly time series. Namely, the prices of the inputs were interpolated to get monthly values from quarterly and biannual data, and the number of grandfathered allowances each year were simply split equally among all 12 months for each year. We used the data available from 01/2008 to 12/2016.

- TC = 1 (see Table 1): no transformation with a variable $var_{i,t}$ is done
- ($Tvar_{i,t} = var_{i,t}$);
- TC = 2 (see Table 1): first difference ($Tvar_{i,t} = var_{i,t} - var_{i,t-1}$);
- TC = 3 (see Table 1): first difference of logarithms ($Tvar_{i,t} = \log(var_{i,t}) - \log(var_{i,t-1})$).

Some pre-processing was made before the actual FAVAR. First, all the time series were seasonally adjusted using Census X-13 filter [31]. Second, all the time series were tested for stationarity, which is required by the FAVAR's estimation procedure [20]. Namely, Augmented Dickey-Fuller (ADF) and Phillips-Peron tests were used to check the stationarity. When the tests rejected stationarity, the data were differentiated. In the case that this step did not lead to stationarity, the transformation by first difference of logarithms was used instead, see the description below Table 1. To distinguish the names of variables, in particular steps of the analysis, a prefix "*T-*" was added to the original labels when the time series was transformed ($var_{i,t} \rightarrow Tvar_{i,t}$). As the last pre-processing step, the transformed time series were standardized, which was indicated by adding another prefix "*Z-*" to the variable names $Tvar_{i,t} \rightarrow ZTvar_{i,t}$).

The authors confirm that the data supporting the findings of this study are available at https://github.com/zaplef/CarbonManagementInputs.

Results

This section is divided into four subsections containing the results of the individual analyses. In the first one, Subsection estimation, the principal component analysis is used to identify the factors ***F*** and then the FAVAR model is estimated. Subsection Granger causality is focused on the causality between the factors and observed variables based on the results of the Granger causality test. Subsection impulse response analysis is devoted to the responses of the factors ***F***, and prices of EUA and CER to shocks in the values of these variables. The last subsection, Subsection sensitivity analysis provides the sensitivity analysis exploring the robustness of the obtained results for different time periods.

Estimation

As written in Section the factor-augmented var model and granger causality, the procedure of the FAVAR is split into two steps. New factors are identified from the standardized informational variables ***X*** (No. 3-28 listed in Table 1) using the Principal Component Analysis (PCA). As the second step, the coefficients of the FAVAR equation (1) are estimated.

Before the factors are identified, it is necessary to test, to what extent the data are suitable to be represented by factors. In particular, we used the Kaiser-Meyer-Olkin Measure of Sampling Adequacy, see Figure 1. The value of this measure is equal to 0.55 (i.e. 55% of variance is covered by the variables) and because it is greater than a threshold 0.5, it can be concluded that the factor analysis can be used.

The result of the Kaiser-Meyer-Olkin test is also confirmed by the Barlett's test of sphericity. We reject the null hypothesis that our correlation matrix is an identity matrix. Thus, our variables are related enough, implying that the structure of the variables is suitable for extraction at the 5% level of significance.

Overall 6 factors $\boldsymbol{F} = (F1, F2, F3, F4, F5, F6)$ were extracted using the PCA from the set of informational variables; in line with the usual practice, the number of factors was set equal to a number of eigenvalues greater than 1. The rotated factors were generated after seven iterations by the Varimax method for PCA available in SPSS software, see the resulting rotated component matrix in Figure 2 [32]. The factors were named according to their relationship with particular informational variables

$F1 - F6$, see Table 2. The first factor ($F1$) "Prices in the steel industry" includes the price level of steel products, prices of inputs (gas and electricity) and indices (Industrial Producer Price index and Consumer Price Index), and covers 12.3% of the variance. The second factor $F2$ - "exchange rates" covers almost 10.3% of the variance and includes the exchange rates between CZK and EUR/GBP/USD. The next factor, $F3$ "Production of long steel products, raw iron, and steel" describes almost 9.5% of the variance. Factor $F4$ associates grandfathered allowances and macroeconomic factors (interest rates, unemployment and sentiment), and explains about 8.9% of variance. Similarly to $F3$, $F5$ also includes indicators of production, namely, production of flat steel products and semi-finished products. This factor explains about 7.4% of variance. The last factor ($F6$) involves new contracts on steel products in the Czech Republic (including

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,578
Bartlett's Test of Sphericity	Approx. Chi-Square	1181,589
	Df	325
	Sig.	,000

Figure 1. The tests of suitability of the set of variables for a factors extraction (Processed using SPSS 24 software).

Rotated Component Matrix[a]

	Component					
	F1	F2	F3	F4	F5	F6
ztgasp	0,836					
ztelectp	0,749					
ztlongp	0,734					
ztflatp	0,722					
ztppi	0,658					
ztcpi	0,407					
ztczkeur		0,842				
ztczkusd		0,798				
ztczkgbp		0,768				
ztsentim		-0,473		-0,435		
ztfl1			0,914			
ztfl2			0,879			
ztfl4			0,679			
Ztalgr				-0,826		
ztir				0,732		
ztur				0,610		
Ztironp				0,436		
Ztcoalp						
ztfl5					0,769	
ztfl3					-0,625	
ztp1					0,475	
ztnc1						0,647
ztnc2						0,561
ztprod						
ztbond10						
ztnc3						

Extraction Method: Principal Component Analysis.
a. Rotation converged in 7 iterations.

Figure 2. Rotated component matrix using the Varimax method.

Table 2. List of extracted factors.

No.	Name	Variability explained [%]
*F*1	Prices in the steel industry	12.33%
*F*2	Exchange rates	10.29%
*F*3	Production of long steel products, raw iron, and steel	9.94%
*F*4	Number of grandfathered allowances and macroeconomic factors	8.93%
*F*5	New contracts on steel products	7.36%
*F*6	Industrial market factor	6.22%
	In total:	55.09%

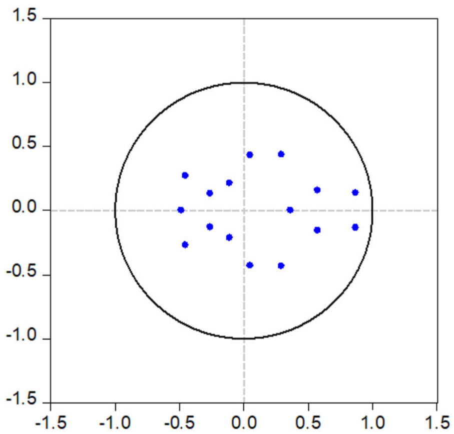

Figure 3. Inverse roots of AR characteristic polynomial.

export contracts), and covers about 6.2% of variance in informational variables $\boldsymbol{X}$.

Time series for the identified factors $F1 - F6$ can be found in Appendix A. The graphs suggest that all these time series are stationary.

Within the second step of the FAVAR procedure, transmission equations (1) are estimated using the standard OLS method for each equation [21]. Based on the Akaike criterion and Final prediction error, a lag length p was set to 2, see the results of the tests in Appendix B. The inverse roots of the characteristic AR polynomial in Figure 3 confirm that the estimated FAVAR is stable (stationary) because all the roots have modulus less than one and lie inside the unit circle.

The values of the estimates for the FAVAR model are shown in Table 3 (statistically significant estimated parameters are denoted by bold font).

Regarding the transmission channels between the steel sector and EU ETS, the FAVAR model does not identify any involved factor of the Czech steel industry to have an impact on EUA and CER prices. Despite many studies agree on the impact of industrial production on carbon prices [33], the Czech steel sector itself is not powerful enough to cause a noticeable change. This result is in line with [34].

As for the impact of EUA and CER prices on the considered six factors, two interactions occurred, see Table 4. First, changes in EUA prices with lag 1 and 2 months influence *F*1 factor, which includes the prices of final steel products and prices of inputs (electricity and gas). This means that the emissions costs are passed on from producers of emissions to customers. Second, prices of CERs affect new contracts on steel production (*F*6) with a lag of two months. The higher CER price, the less new contracts. This influence is significant at the 1% level; however, this effect is very weak due to very low levels of the CER price and its volatility too. Therefore, we do not pay more attention to this relationship in this paper.

Another factor, which is related to the EU ETS, is *F*4. A question arises, which variables, included in the factor are due to this influence: whether the grandfathered allowances or the macroeconomic factors. If it were the grandfathered allowances, then this effect would be counterintuitive: the less grandfathered allowances, the higher prices in the steel sector.[1] Therefore, the source of this relationship can be found rather among the macroeconomic factors (high unemployment and interest rate are signals of an economic recession accompanied with lower production and inflation rate). Anyway, as well as for the relationship between the CER price and *F*6, no further attention will be paid to this relationship in the rest of this paper.

Interested readers can explore further identified influences between the factors in Table 4. Since the aim of this paper is to study interactions between emissions trading and the steel sector, we do not discuss in detail the interactions not directly associated with the EU ETS, despite they can be very useful for other purposes.

Granger causality

In this section, Granger causality described by (3) is tested and the results of these tests are discussed and compared with the results of the FAVAR model, see Table 5.

The results of the Granger test for causal relationships confirmed the existence of the main interaction identified by the FAVAR model, i.e. the impact of the change in the EUA price on the *F*1 factor (prices in the steel industry).

The Granger causality test suggests that none of the factors $F1 - F6$ does Granger-cause changes in EUA or CER spot prices. This also confirms the results of the FAVAR model, i.e. these two observed variables are exogenous.

Detailed results of the test are provided in Appendix C.

Table 3. Estimated parameters of the FAVAR equations (at significance level of 1% (***), 5% (**)).

	TEUA	TCER	F1	F2	F3	F4	F5	F6
Vector Autoregression Estimates								
Sample (adjusted): 3 105								
Included observations: 103 after adjustments								
TEUA(−1)	**0.228967****	0.028655	**1.382615****	0.150066	−0.727449	**0.982375***	−0.318094	0.340088
TEUA(−2)	**−0.195067***	−0.249295	**−1.639994****	−1.093265	−0.231841	0.790192	−0.602383	**1.982364***
TCER(−1)	**0.047537***	−0.010855	−0.059676	−0.168993	0.078812	0.034439	−0.405317	0.353224
TCER(−2)	−0.016633	0.062721	0.107536	−0.037278	0.294723	−0.106041	0.194413	**−0.87474*****
F1(−1)	0.019428	0.039006	**0.600780*****	−0.062039	−0.115031	−0.028686	0.096295	**−0.282393****
F1(−2)	−0.009108	−0.052757	**0.189375****	0.051763	−0.157107	0.014218	**−0.344478****	0.181381
F2(−1)	0.001825	0.013878	**−0.29928*****	0.212829**	**−0.190895****	−0.026479	**−0.169388***	**−0.25842*****
F2(−2)	0.008902	0.005950	0.093889	−0.156413	**−0.277299****	−0.046906	−0.140957	0.051296
F3(−1)	0.007030	−0.022265	**0.174808*****	−0.117737	**−0.225954****	**−0.11548*****	−0.044364	0.070443
F3(−2)	**0.018052***	−0.004350	−0.041991	**−0.296652****	**−0.166841***	**−0.12561*****	0.081415	0.063871
F4(−1)	0.003605	0.040965	**0.245626***	**−0.484751****	−0.129174	**0.377040*****	0.135338	−0.289277
F4(−2)	−0.015348	0.003250	**−0.337125****	**0.387879***	−0.193969	**0.476626*****	−0.105215	0.238780
F5(−1)	0.010586	−0.016998	**0.184650*****	−0.073718	**0.213160****	0.074086	**−0.26218*****	0.046454
F5(−2)	−0.013993	−0.015035	**0.128522****	0.160499	**0.275700*****	0.013959	−0.155185	0.073892
F6(−1)	0.005862	−0.017448	0.024278	−0.008116	0.139169	−0.072968	**−0.41074*****	**−0.34782*****
F6(−2)	−0.005546	0.023012	**0.156857****	−0.122967	**0.203068***	**−0.116403****	0.053074	−0.047329
C	−0.017878	**−0.100847***	0.084115	0.026928	**0.289286****	0.073890	−0.009566	−0.003489
R-squared	0.241136	0.051588	0.737677	0.190148	0.331806	0.849634	0.335601	0.397182
Adj. R-squared	0.089363	−0.138094	0.685212	0.028177	0.198167	0.819561	0.202721	0.276618
Sum sq. resids	0.713174	11.96207	26.29936	82.91465	69.23033	14.98494	69.05916	61.75241
S.E. equation	0.091598	0.375140	0.556241	0.987657	0.902482	0.419873	0.901366	0.852349
F-statistic	1.588795	0.271970	14.06047	1.173964	2.482857	28.25218	2.525595	3.294375
Log likelihood	109.9464	−35.27177	−75.84367	−134.9794	−125.6902	−46.87498	−125.5628	−119.8035
Akaike AIC	−1.785368	1.034403	1.822207	2.970474	2.790102	1.259708	2.787626	2.675796
Schwarz SC	−1.324929	1.494841	2.282645	3.430912	3.250540	1.720146	3.248064	3.136234
Mean dependent	−0.014796	−0.037263	−0.021005	0.017051	0.000376	−0.028341	0.001669	0.014105
S.D. dependent	0.095988	0.351645	0.991412	1.001873	1.007852	0.988445	1.009476	1.002152
Determinant resid covariance (dof adj.)		1.78E-05						
Determinant resid covariance		3.82E-06						
Log likelihood		−526.7075						
Akaike information criterion		13.02345						
Schwarz criterion		16.70695						

Table 4. The results of the FAVAR analysis - interactions between the factors (numbers in brackets stand for lags in months).

Influenced factors	Influencing factors
*F*1	+*TEUA*(−1), − *TEUA*(−2), + *F*1(−1), + *F*1(−2), −F2(−1), +F3(−1), −F4(−2), +F5(−1), +F5(−2), +F6(−2)
*F*2	+F2(−1), −F3(−2), −F4(−1)
*F*3	−*F*2(−1), − *F*2(−2), − *F*3(−1), + *F*5(−1), + *F*5(−2)
*F*4	−*F*3(−1), − *F*3(−2), + *F*4(−1), + *F*4(−2), + *F*6(−2)
*F*5	−*F*1(−2), − *F*5(−1), − *F*6(−1)
*F*6	−*F*1(−1), − *F*2(−1), − *F*6(−1), − *TCER*(−2)
TEUA	+*TEUA*(−1)
TCER	

Table 5. The results of VAR Granger causality (*** = 1%, ** = 5%, significance level; all = all variables together).

Influenced factors	Influencing factors
***F*1**	*TEUA***, *F*2***, *F*3***, *F*4**, *F*5***, all***
*F*2	*F*3**
*F*3	*F*1**, *F*2***, *F*5***, all***
***F*4**	*TEUA***, *F*3***, all***
*F*5	*F*1**, *F*2**, *F*6***, all***
*F*6	*TCER****, *F*2**, all***
TEUA	–
TCER	–

Impulse response analysis

This section is devoted to the impulse response functions' (IRF) analysis in the FAVAR model estimated in Subsection estimation. An idea of this analysis is the fact that a shock to an explaining factor affects the *i*-th variable not only directly, but also through the dynamic (lagged) structure of the FAVAR. An impulse response function traces the effect of a one-time shock in a single variable to current and future values of the variables $c_{i,t}$. This shock may impact other variables not only through the regression coefficients linking them, but also through the dynamics of the other variables and the correlations of the residua. Unfortunately, unlike the plain VAR models, an interpretation of the IRF analysis is not easy in FAVAR models when applied to the factors, as it is difficult to assess what a shock in a factor means. Sometimes, however, the factors changes may be interpreted, as we show below.

0.2%.[2] Using the last observed value of the steel prices (12/2016), this increase is equal to 1.2 EUR per tonne of steel products.

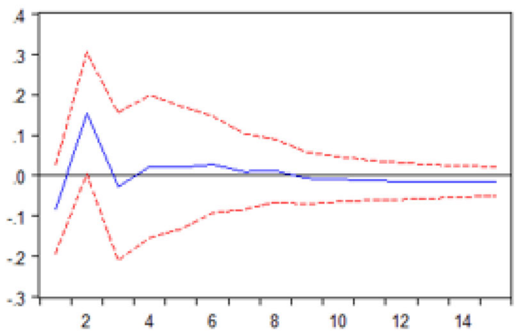

Figure 4. Response of *F*1 to the shock of 1 standard deviation to *TEUA*.

Sensitivity analysis

The results of our analysis reveal that the EU ETS has, through the EUA price, a considerable impact on the Czech steel sector. However, it is reasonable to ask if the system would not work completely different way under different conditions, for instance, with substantially different carbon price levels. Doubts are in place because, in the beginning of the involved time period (2008-2016), the EUA price was substantially higher than during the last years. To get stationary series, the prices were differenced, and the information about their absolute value was in fact lost. To address this issue, we re-run the model for two shortened time periods (2008-2010 and 2014-2016). Clearly, the explanatory power of the results with the shortened periods is lower. On the other hand, the purpose of this sensitivity analysis was only to get a hint, whether the discovered effects hold under different conditions, perhaps with less significance Q2 (Figure 4).

Table 6 shows the comparison of the FAVAR results for all three settings (S1 with the original long period 2008-2016; S2 with the period 2008-2010 where the EUA price was higher; S3 with the period 2014-2016 with low EUA prices). The table replicates the original results (Table 4) plus with information, in which of the shortened analyses the effects were replicated. It can be seen that, under the settings S2 and S3, less relationships are identified in comparison with the original results, which could, however, be expected due to less information available. When focusing on the relationships between the EU ETS and the steel sector, only one of the original relationships is confirmed for both the additional analyses: the impact of the EUA price on *F*1 factor representing the prices in the steel industry, i.e. the pass-through effect, which is thus confirmed for all three considered time periods.

Table 6. The comparison of the FAVAR results for 3 different considered periods.

Influenced factors	Influencing factors
*F*1	+*TEUA* (**S2**, **S3**), + *F*1(**S2**, **S3**), -*F*2(**S2**), +F3, −F4, +F5, +F5, +F6
*F*2	+F2, −F3(**S2**), −F4(**S3**)
*F*3	−*F*2(**S2**), − *F*3(**S3**), + *F*5(**S2**)
*F*4	−*F*3(**S2**), + *F*4(**S3**), + *F*6(**S2**)
*F*5	−*F*1, − *F*5, − *F*6(**S3**)
*F*6	−*F*1, − *F*2, − *F*6(**S2**, **S3**), − *TCER*
TEUA	+*TEUA*
TCER	

The same analysis is done also for the Granger causality results, see Table 7. Similarly to the results of the FAVAR analysis above, less relationships are identified, and only one of them is confirmed for both shortened periods – again it is an effect of the EUA price on *F*1 factor, i.e. the prices in the steel industry.

Finally, we compared the Impulse Responses from the shortened analyses with the original one, namely the relationship between the EUA price and the prices in the steel industry as it has been confirmed in all the three cases. The result can be found in Figure 5.

The pattern for all three response functions is evidently very similar – after two months after the shock occurred, the prices in the steel industry (F1) substantially increase.

Summarized, the sensitivity analysis confirmed the existence of the pass-through effect for the steel industry.

Discussion and recommendations for policy makers

In this section, we provide a critical discussion of the results and we compare them with state of the art. At the end of this section, we formulate some recommendations for policy makers.

Discussion of the results

The analysis performed in this paper reveals an important relationship between the steel sector and the EU ETS: the impact of the EUA prices on the prices of steel products.

This identified channel provides an evidence of the pass-through effect in the steel industry. Even though this phenomenon was confirmed by [35] for electricity producers and energy intensive sectors during the first and the second EU ETS trading phases, its existence for the steel sector in the third phase has not been confirmed yet.

The pass-through effect in the steel industry and its power are largely disputed. According to

Table 7. **The results of VAR Granger causality (*** = 1%, ** = 5%, significance level; all = all variables together) for 3 different considered periods.**

Influenced factors	Influencing factors
***F*1**	$TEUA^{**}(\boldsymbol{S2}^{**}, \boldsymbol{S3}^{**})$, $F2^{***}(\boldsymbol{S3}^{**})$, $F3^{***}(\boldsymbol{S3}^{**})$, $F4^{**}(\boldsymbol{S3}^{**})$, $F5^{***}(\boldsymbol{S2}^{**})$, all***
*F*2	$F3^{**}(\boldsymbol{S2}^{*})$
*F*3	$F1^{**}(\boldsymbol{S2}^{**})$, $F2^{***}(\boldsymbol{S2}^{**})$, $F5^{***}(\boldsymbol{S2}^{**})$, all***
***F*4**	$TEUA^{**}$, $F3^{***}(\boldsymbol{S2}^{**})$, all***
*F*5	$F1^{**}(\boldsymbol{S2}^{**})$, $F2^{**}(\boldsymbol{S2}^{**})$, $F6^{***}(\boldsymbol{S2}^{***})$, all***
*F*6	$TCER^{***}(\boldsymbol{S3}^{***})$, $F2^{**}$, all***
TEUA	–

COLOR Online / B&W in Print

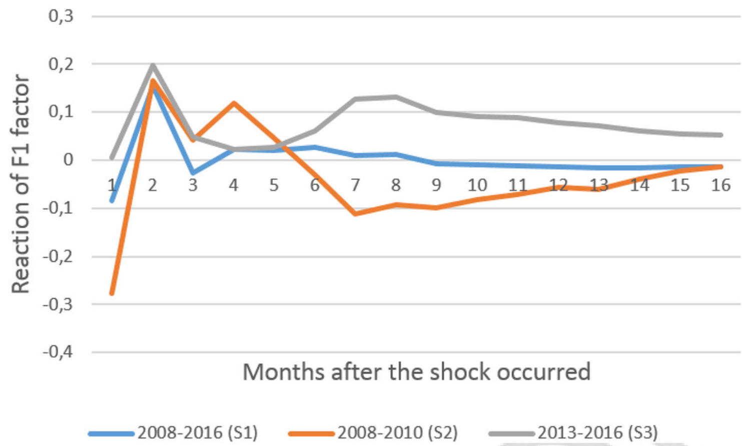

Figure 5. **Response of** $F1$ **to the shock of 1 standard deviation to** *TEUA* **for all 3 considered time periods.**

Reinaud [14], Boutabba and Lardic [15], and de Bruyn et al. [17], the pass-through effect is not likely in the steel-sector. They argue that (i) *the pass-through is more likely for companies with higher production capacity usage because the marginal costs of such companies increase more steeply.* Evidently, steel industry is not like that as it suffers from free capacities in the long term (according to data from Czech Steel Union, approximate capacities varied from 70% to 74% between 2008 and 2016), see [26]. Further, (ii) *Companies with unique (differentiated) product tend to use the pass-through more likely.* Steel products can be both, highly differentiated (top-quality steel and specialized products thereof), and homogeneous (standardized products made of not so high quality steel, semi-finished products, etc.); however, the Czech steel companies, manufacture rather homogeneous products (steel of ordinary quality manufactured using the basic oxygen furnace process, flat products – plates), thus have a weaker power of price-makers and it is more difficult for them to pass through the costs of emissions trading. Moreover, (iii) *despite the volumes of allowances allocated for free decreased between the trading phases, and they keep decreasing year by year in the current trading phase, the companies still receive vast majority of allowances for free. This keeps the effective carbon price for this sector very close to zero. Therefore, based on economic intuition, the steel companies should not incline to pass through the emission costs.* Here, all we have to do is to agree, even though the situation keeps changing, as the number of grandfathered allowances decreases each year; moreover, according to de Bruyn et al. [17], the companies can pass through not only real costs, but also the value of freely obtained allowances in order to increase their profit.

The pass-through effect is often denied by the leaders of the biggest steel producers. A manager at ThyssenKrupp proclaimed that the pass-through effect is a commercial secret [4]. A manager at ArcelorMittal proclaimed that this company cannot increase prices of steel products, even to pass on costs of emissions trading [4]. According to Reinaud [14], it was not clear if the steel companies decided to apply the pass-through effect in the first trading phase of the EU ETS.

Contrary to these arguments, our study proves the pass-through effect for the Czech steel companies, confirming the former results provided by [16, 17, 36, 37] for the first and the second trading phase (our data, being from 2008 to 2016, cover the first half of the third trading phase). The pass-through effect takes place despite grandfathering and the fact that the conditions for easy pass-through effect mentioned above are not met by the Czech steel industry. Besides the confirmation itself, our analysis helps to shed some new light on the origin of the effect, because, thanks to grouping into factors, our (FAVAR) model involves enough informational variables to be realistic; this way, we circumvented the problem, mentioned by Okereke and McDaniels [4], that it is very hard to assess the pass-through effect since it depends on many factors.

Studies confirming the pass-through effect are often questioned. Similarly to the steel producers, the European Steel Association denies the existence of the pass-through effect *via* the study performed by Nera [24], which strongly criticizes the studies [16, 17, 36, 37] showing the ability of steel companies to pass through the emissions costs. The main alleged drawbacks are the ignorance of a market share as an important variable, insufficient (or missing) analysis of robustness, and using wrong input data (some relevant missing data are replaced by the available, but not relevant, inputs).

To be specific, according to Nera [24], the market share is extremely important factor when assessing the pass-through effect: a possible reason why the studies confirmed the effect is that the European steel companies are significantly exposed to international trade, which pushes their profit margin down; thus, when the EUA price increases, these companies cannot bear the additional costs by themselves (resulting in negative margins) and are forced to pass through these costs to customers, sacrificing a part of their market share. However, this is not the case in our analysis as the market share is a part of our model, represented by new contracts amounts. If the pass-through effect were enforced by a market exposure and accompanied with a decrease in the market share, it would be revealed by the impulse response functions. Namely, the shock to the EUA price would influence the new contracts in the sector. This, however, does not happen in our analysis, se there is no evidence that the companies in the sector are enforced to pass through the emission costs and that the pass-through effect is an act of despair.

The remaining critical judgements of [24] do not apply to our analysis, too. Our results can be seen as reliable since our results were confirmed by the sensitivity analysis and the input data are strictly related with the steel industry, the macro environment and the EU ETS (moreover, these data are complete and from reliable sources).

As for the strength of the pass through effect, the results of the existing studies are rather inconsistent. This strength is usually expressed by so called pass-through rate (what share of the emission costs is passed through). The study by McKinsey [16], based on the expert judgements, report the rate of 60% for flat products and 66% for long products. De Bruyn et al. [17] estimate the rate to be up to 120% (for hot rolled products) using the ex-post econometric model (similar to our one). The authors of [37] used the ex-ante market model and concluded that the pass-through rate equals 75% for flat products and 80% for long products, respectively. In our study, the impulse response analysis (Section impulse response analysis) showed that a 1EUR shock to the EUA price leads to 0.2% increase in prices of steel products (the difference between the flat and long products is negligible). For the last available observation of the steel product prices, and for the levels of CO_2 emission intensity for flat and long products used by De Bruyn et al. [17], the resulting cost pass-through rate is approximately equal to 55% for flat products and 65% for long products. These rates are slightly lower compared with [16, 17, 36, 37].

Policy recommendations

In this paper, we showed that the prices in the Czech steel sector are influenced by the EUA prices. This indicates that Czech steel companies pass through the costs of emissions trading to customers. The existence of the pass-through effect has been already proven for the energy sector during the first two trading phases of the EU ETS by Sijm, Neuhoff and Chen [38], Lise, Sijm and Hobbs [39]. This finding resulted in the change in rules for energy producers: they do not receive any free allowances since 2013. Due to the fact that the steel sector is very energy-intensive, it is struck by the EU ETS twice. First, energy producers pass their emission costs to steel companies. Second, steel companies must cover the emission costs implied by own production.

Unlike the energy sector, where the existence of the pass-through effect is not disputed in the literature, there is no clear consensus regarding this effect in the steel industry in the literature. However, despite some typical symptoms of the pass-through effect are not observed in the Czech steel sectors, namely:

- most allowances are allocated to the sector for free, thus the impact of the EU ETS on this sector is reduced,
- steel products in the Czech Republic are rather homogeneous, thus the power of Czech steel companies to influence the prices of their

products should be weaker in comparison with the sectors with more differentiated product,
- the long-term production capacity usage in the sector ranges from 70% to 74% in the considered time period, therefore, one can expect that the marginal costs of an additional production do not increase steeply, and thus the pass-through effect is less likely,

the quantitative analysis performed in this paper suggests that Czech steel companies have a power to pass through the costs of emissions trading to customers. Therefore, by the argumentation given by [35], the carbon leakage effect is unlikely in this sector.

One can argue that the pass-through effect by steel companies can be partly caused by energy producers, who, according to Sijm, Neuhoff and Chen [38], or Lise, Sijm and Hobbs [39], pass through their emissions costs to steel producers. To explore this option, we ran the same model again, but without the prices of inputs; this additional analysis, however, exhibited the pass-through effect with a comparable statistical significance. Thus, it is likely that the pass-through effect is indeed caused by the steel producers.

The unequal rules for different industrial sectors are often targets of criticism. On the other hand, it is reasonable that the EU policy makers are very careful, and they do not want to threaten the competitiveness of companies. However, based on the results of our analysis, we recommend to reconsider listing the steel industry in the carbon leakage group, or at least the number of grandfathered allowances.

Conclusion

This paper was devoted to the transmission channels between Czech steel production, Czech steel prices, and changes in EUA and CER allowance prices. The interactions were analysed using the FAVAR model, which allowed to involve 26 informational variables playing potentially important roles in the Czech steel industry. Then, we extracted 6 factors using the principle component analysis. These factors covered almost 55% variability of the informational variables.

The transmission channels between the factors themselves, and between the factors and the prices of allowances were analysed using the estimated coefficients of the FAVAR model, Granger causality test and Impulse Response Analysis. The results can be summarized as follows.

The prices in the steel industry (i.e. the prices of final products and the prices of inputs) are found to be positively influenced by EUA prices suggesting the existence of the pass-through effect in the industry. The power of this effect is weaker in comparison with some existing studies (from 55% to 65%), on the other hand, this effect was confirmed by all the three statistical tools we used. Further, the sensitivity analysis brought evidence that the results are robust to the EUA price level. Moreover, the impulse response analysis showed that this pass-through effect is not accompanied by a decrease of the market share like some studies argue. Due to this fact, there is no signal that the steel sector is exposed to the risk of carbon leakage. Based on our evidence, we recommend to reconsider the rules for the steel industry. Of course, before such a fundamental intervention to the trading rules is done, an analysis similar to our one should be done for the whole European steel sector, based on a time series covering the entire third trading phase of the EU ETS (2013-2020).

This paper can be beneficial from several points of view. The FAVAR model has been usually used to explore interactions within national economies; its implementation to analyse a part of industry is unique. Further, the presented study is the first one dealing with the transmissions between the Czech steel industry and the prices of emission allowances. Moreover, our paper contributes to the discussion about the pass-through effect, suggesting that it occurs even in Czech steel companies during the second and the third phase of the EU ETS, despite the steel sector belongs to the group of sectors, which receive most allowances for free. Last but not least, the presented model can be used for forecasting the emission prices as well as the other involved variables.

Disclosure statement

No potential conflict of interest was reported by the author(s). Q3

Notes

1. Note that the coefficient of grandfathered amounts in F4 is negative. This counterintuitive direction may be caused by the special character of the variable **Ztalgr**, which is defined as a difference of log-grandfathered amounts, recalculated to months. As such, it is zero except for the turns of the years, where it is negative. Thus, it is possible that this variable in fact substitutes institutional changes other than

the grandfathering policy or discontinuities in reporting.

2. To get this value, we used the fact that, by its construction, $F_1 = 0.734 \cdot log(ztlongp) + 0.722 \cdot \log(ztflatp) + rest$, where *rest* is a function of the past values of the steel prices and the other variables included in F_1. Thus, if *F1* increases by Δ and we assume that this is caused only by changing *ztlongp* and *ztflatp* to *ztlongp* $\cdot d$ and *ztflatp* $\cdot d$, respectively, we easily get that $d = e^{\frac{\Delta}{0,734+0,722}}$.

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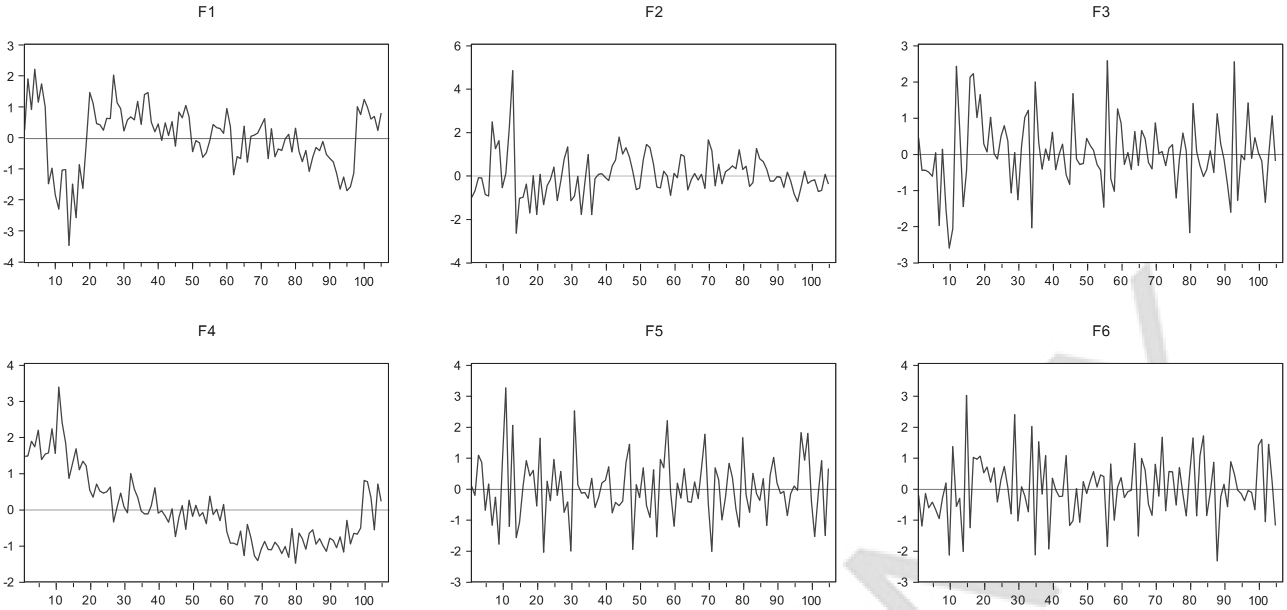
Appendix A: Adjusted and transformed time series on carbon prices and the extracted factors *F*1–*F*6



Appendix B: – the results of the Akaike criterion and final prediction error for the FAVAR model

VAR Lag Order Selection Criteria
Endogenous variables: TEUA TCER F1 F2 F3 F4 F5 F6
Exogenous variables: C
Date: 06/20/19 Time: 09:13
Sample: 1 107
Included observations: 101

Lag	LogL	LR	FPE	AIC	SC	HQ
0	−753.4376	NA	0.000572	15.23639	15.65066	15.40410
1	−598.5136	279.1701	9.50e-05	13.43591	15.50729*	14.27447*
2	−515.4666	136.4931*	6.68e-05*	13.05874*	16.78723	14.56814
3	−467.2317	71.63594	9.73e-05	13.37092	18.75652	15.55117
4	−425.3001	55.63197	0.000171	13.80792	20.85062	16.65901

* indicates lag order selected by the criterion.
LR: sequential modified LR test statistic (each test at 5% level).
FPE: Final prediction error.
AIC: Akaike information criterion.
SC: Schwarz information criterion.
HQ: Hannan-Quinn information criterion.

Appendix C: the results of VAR Granger causality

Dependent variable: F1

Excluded	Chi-sq	df	Prob.
TEUA**	8.224288	2	0.0164
TCER	0.565887	2	0.7536
F2***	25.30699	2	0.0000
F3***	9.906368	2	0.0071
F4**	6.510045	2	0.0386
F5***	10.59151	2	0.0050
F6*	5.609988	2	0.0605
All***	76.34160	14	0.0000

Dependent variable: F2

Excluded	Chi-sq	df	Prob.
TEUA	0.777538	2	0.6779
TCER	0.337269	2	0.8448
F1	0.141684	2	0.9316
F3**	8.888464	2	0.0117
F4	4.199250	2	0.1225
F5	2.964815	2	0.2271
F6	1.166070	2	0.5582
All	16.25049	14	0.2983

Dependent variable: F3

Excluded	Chi-sq	df	Prob.
TEUA	0.536425	2	0.7647
TCER	1.232451	2	0.5400
F1**	6.567256	2	0.0375
F2***	13.34700	2	0.0013
F4*	5.409254	2	0.0669
F5***	9.621783	2	0.0081
F6	3.515503	2	0.1724
All***	39.29469	14	0.0003

Dependent variable: F4

Excluded	Chi-sq	df	Prob.
TEUA**	7.084006	2	0.0290
TCER	0.804106	2	0.6689
F1	0.171549	2	0.9178
F2	1.516009	2	0.4686
F3***	13.74992	2	0.0010
F5	2.379100	2	0.3044
F6*	5.172827	2	0.0753
All***	35.12702	14	0.0014

Dependent variable: F5

Excluded	Chi-sq	df	Prob.
TEUA	0.431631	2	0.8059
TCER	2.894832	2	0.2352
F1**	8.879252	2	0.0118
F2**	6.226530	2	0.0445
F3	1.020543	2	0.6003
F4	0.393033	2	0.8216
F6***	19.13044	2	0.0001
All***	36.01993	14	0.0010

Dependent variable: F6

Excluded	Chi-sq	df	Prob.
TEUA	3.857387	2	0.1453
TCER***	13.99689	2	0.0009
F1	3.720264	2	0.1557
F2**	8.133292	2	0.0171
F3	1.039784	2	0.5946
F4	2.014226	2	0.3653
F5	0.688820	2	0.7086
All***	31.70309	14	0.0044

Dependent variable: TEUA

Excluded	Chi-sq	df	Prob.
TCER	3.495891	2	0.1741
F1	1.695379	2	0.4284
F2	0.756405	2	0.6851
F3	3.809982	2	0.1488
F4	0.901994	2	0.6370
F5	3.517119	2	0.1723
F6	0.900047	2	0.6376
All	18.33421	14	0.1920

Dependent variable: TCER

Excluded	Chi-sq	df	Prob.
TEUA	0.280806	2	0.8690
F1	0.799573	2	0.6705
F2	0.170823	2	0.9181
F3	0.324674	2	0.8502
F4	0.630804	2	0.7295
F5	0.234050	2	0.8896
F6	0.677746	2	0.7126
All	3.069334	14	0.9989