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Embeddedness of Hungarian pig prices in the European pork market: a volatility spillover and partial wavelet coherence study

Compared to most of the agricultural commodity markets in the European Union (EU), the pig market is less regulated and EU pig prices can be regarded as free market prices. It is thus an ideal economic research opportunity to investigate agricultural market integration and spatial price transmission mechanisms in the EU in the different Member States (MS). Depending on the geographical location, the decoupling of production costs from prices paid to pig farmers can jeopardise the fragile market balance between producers and processors. To retrospectively identify price setting trends, this paper examines how price return trends in the Hungarian pig sector are reflected in dynamic Diebold–Yilmaz spillover indices between 2007 and 2021. The results show that Hungary was mostly a net spillover receiver throughout the investigated period. Pairwise comparison of price spillovers to and from other MSs indicated that the German pig market had the strongest effect on the price forecast error variance in the Hungarian market, but transient interaction with other MS markets was also detected. To obtain a detailed time domain representation of the multivariate relationship between different MS's price returns, our method considers an improved partial wavelet coherence (pwc) approach, which – to our knowledge – has not yet been used for analysing agricultural commodity prices. It was concluded that despite similarities, the German price and the EU average price affected the Hungarian market at distinct time scales. Collectively, our results indicate that the Hungarian pig producer prices underwent markedly different market regimes in the last decade due to shifting patterns of intra-European spatial connectedness of pig markets, which shall provide a reference for future modelling studies.

Keywords: Pig Producer Price, Price Transmission, Diebold–Yilmaz Spillover Index, Partial Wavelet Coherence.

JEL classifications: Q11, Q13

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Received: 9 December 2022; Revised: 20 February 2023; Accepted: 22 February 2023.

Introduction

In the European Union, financial subsidies paid to producers of products which were not eligible for direct payments (e.g. fruits, vegetables, poultry, pork and processed products thereof; Brockmeier and Salamon, 2003) came under intense scrutiny during the series of trade talks under the umbrella of the Doha Development Round between 2001 and 2008. These negotiations marked the end of the 'protectionist' approach of the Common Agricultural Policy (CAP), which was considered back then as a vestige of trade logic from Cold War times. Nowadays, a private storage scheme for EU pork producers is offered by the European Commission, aiming to balance the pig market, provide hedging opportunities and stabilise pig prices under abnormal market conditions (EU regulation 1308/2013; Clop-Gallart *et al.,* 2021). In 2004, and then in 2007, 10+2 countries joined the European Union, where pig production had evolved very differently from the old MS's. As a result, structural differences between the pig industry of the old and new MS surfaced immediately (Baráth *et al.,* 2021; Utnik-Banaś, 2022). In this study, we take a retrospective look at how the Hungarian pig price evolved after this transition period.

Customarily, many of the Hungarian pig farms and slaughterhouses abstained from entering into long-term contractual commitments (Marczin *et al.,* 2020). Over the past few years this situation has changed, and today many of the major processors apply a pre-fixed price or a price formula based on the wholesale prices of valuable meat parts. The most popular contract for determining producer price has become the price formula based on the largest pig producer European countries. In parallel, cost-based pricing or performance-based incentives have almost disappeared in purchase agreements (unpublished results). Undoubtedly, these measures adversely affected producers' market positions in the long run. A questionnaire launched by the Hungarian Institute of Agricultural Economics (AKI) and the Association of Hungarian Pig Breeders and Pig Farmers (MSTSZ) in 2018 asked Hungarian pig farmers about their contractual relationships with slaughterhouses/processors (unpublished results). The survey indicated that the prevalence of trading on spot markets (unnegotiated sales) were at ca. 40%, while contract durations with < 1 year, 1-5 years, or >5 years were at 50%, 10% or 20%, respectively (excluding holding companies).

The concept of the present study emerged from a discussion between MSTSZ and AKI. As a stakeholder organisation, MSTSZ tasked AKI to identify shortcomings in the existing price setting methods on the pork market in Hungary, which would gather the different market players under a common flag in order to better understand the rationale of pork price volatility. To grasp the drivers of fluctuation in commodity price returns has been at the forefront of scientific curiosity for a long time. The pork cycle was among the first described economic supply models in history (Szűcs and Vida, 2017), and its price variability has a well-known seasonal component (Utnik-Banaś, 2022).

Over time it became clear that pricing based on benchmark markets is no longer satisfactory for market agents, so we resorted to dynamic comparisons in our research.

We estimate here the spillover effect that helps to differentiate the forecast error variance in one market from the shocks in other markets (Szenderák *et al.,* 2018; Szenderák, 2018; Szenderák *et al.,* 2019; Abdallah *et al.,* 2020; Just and Echaust, 2022). The algorithm developed by Diebold and Yilmaz (2009, 2012) emerged after the global financial crisis and became an established methodology in financial interconnectedness analyses. Its popularity can be ascribed to melding of econometric modelling and Big Data approaches (Diebold and Yilmaz, 2023). It measures association between variables based on generalised vector autoregressions generated forecast error variance decompositions (Pesaran and Shin, 1998), in which forecast error variance decompositions is invariant to variable ordering. This method evaluates what percentage of the error variance of a variable's prediction is influenced by the effect of another variable. It captures both total and directional components, which ultimately answers the question of what the origin of the price fluctuation and its spillover effect is.

Using the Diebold and Yilmaz approach, meat was found to be one of the most significant net pairwise receivers of connectedness at all time periods among the investigated agricultural commodities (Kang *et al.,* 2019). In addition, tails price risk spillover analyses of the U.S. pork and beef sectors revealed that pork industry had a lower price risk connectedness between 1980 and 2020 (Fousekis and Tzaferi, 2021). The Diebold and Yilmaz method was used to reveal that geopolitical events can result in a closer connection of the agricultural markets (Just and Echaust, 2022; Gong and Xu, 2022), during which oil can play a net receiving role against food and agricultural raw materials (Dahl *et al.,* 2020).

A complementary method to uncover time-dependent coupling between time series is entirely model-free (Torrence and Compo, 1998). Unlike other econometric techniques, wavelet does not estimate volatility. Instead, wavelet extracts volatility information using frequency-dependent windowing without having any assumption on the statistical properties of the underlying data. Wavelets are particularly effective at detecting signals that last for only a limited time and show nonlinear dependence in different time periods. It has proved to be a valuable tool in helping to decipher hidden dynamics in raw data in a wide range of disciplines e.g., climatology, psychology, neuroscience, and finance (e.g. Grinsted *et al.,* 2004; Hu *et al.,* 2017; Ng and Chan, 2018). To date, only a limited number of papers applied wavelet methods in the study of volatility transmission between markets (e.g. Albulescu *et al.,* 2017). To our knowledge, this is the first report that complements volatility spillover results with the recently revised partial wavelet coherence method (Hu and Shi, 2021).

A systematic description of the agricultural market interdependence in European settings is still far from complete in the literature. Accession to the European Union increased the speed of price transmission between the old MSs and the newly joined countries, and pork price is an exemplary model among the major agricultural commodities that has experienced a great deal of turmoil since then. The aim of this paper is thus twofold. We identify and retrospectively analyse the dominant factors shaping pig producer prices in Hungary. Along those lines, we also uncover how transmission of market information can be deduced from the volatility of pig prices, thereby identifying the direction of interlinkage between each actor.

Our results indicate that one of Europe's largest pig producer country, Germany – which has long played a key role in global pig output – has had a tangible effect on pig producer prices in Hungary since at least 2015. Germany's mounting influence can not only be tracked down at individual MS prices but on the average European price as well. This however does not imply that Germany has a unilateral influence on the composite European price, as our approach unveils different periods when German and European prices differed. In a Central and Eastern European context, the influence of national markets bordering Hungary is also evident, but their impact is more subdued.

Methodology

The time series used in our study spans over 14 years of weekly updated entry price to the slaughterhouse (pig producer price; without VAT and transport costs) from the beginning of 2007 until the end of 2021. Missing data were filled in by linear interpolation. Prices were recalculated for Hungarian currency (HUF) at daily exchange rate. Chicago Mercantile Exchange (CME) Lean Hog front month futures contract quotes were used as the US pig price. The time series were transformed to log returns due to the possible multimodal/non-normal distribution, which can be interpreted as percentage changes for small values (transformation into a record of percentiles as per Grinsted et al. (2004) did not change results; data not shown). The absolute values of the logarithmic returns were used as a proxy for volatility.

The Diebold –Yilmaz (DY) spillover index

The Diebold and Yilmaz (2009, 2012, 2023) spillover index is based on a variance decomposition from an *n*-variable *p* order covariance stationary difference vector autoregression model (DVAR) model:

$$x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t \qquad (1)$$

The variable x_t denotes the analysed price series in time t, Φ_i is the parameter matrix, while ε_t is the error vector term, which is assumed to be independently and identically distributed with zero mean, thus $\varepsilon_t \sim IN(0, \Sigma)$. During the calculations, the forecast error variance can be decomposed to own and cross variance shares. The spillover index simply measures the ratio of the own and the cross variance share to the total forecast error variance, expressed in percentages. The variance decomposition is dependent on the ordering of variables, which is introduced by the Cholesky decomposition, which is a precondition to achieve orthogonal innovations. As a significant improvement, Diebold and Yilmaz (2012) modified the index based on Pesaran and Shin (1998) and Koop (1996) generalised variance decomposition. Using this method, variance decompositions are invariant to the ordering. Furthermore, not only the total connectedness, but also directional connectedness is considered. Let us denote the forecast error variance decomposition (VD) of the H-period forecast by $\theta_{ij}^{g}(H)$ in case of $H=1, 2\ldots$:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i^{'} A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i^{'} A_h \Sigma A_h^{'} e_i\right)} \quad (2)$$

Here, σ_{jj} denotes the standard deviation of the j^{th} equation's error, Σ is the variance-covariance matrix of the error vector ε_t, while e_i is a simple selection vector with 1 in the i^{th} position and 0 otherwise. The matrix A_h follows from the moving average representation of the VAR model. Each entry of the variance decomposition matrix is normalised by the row sum as:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} * 100 \quad (3)$$

Here, $\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = N$ by construction. The rest of the indices can be calculated as the following. The *total spillover index* shows the share of the forecast error variance resulting from the cross-volatility effects. Therefore, it is an indicator of the average connectedness among the variables:

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} * 100 \quad (4)$$

The *directional spillover* measures the spillovers received by market i from all other markets j, and the spillovers transmitted by market i to all other markets j as:

$$S_{i*}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} * 100 \quad (5)$$

$$S_{*i}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum_{j=1}^{N} \tilde{\theta}_{ji}^{g}(H)} * 100 \quad (6)$$

The *net spillover index* implies whether a variable is a net transmitter or a net receiver of volatility spillovers (it is simply the difference between the transmitted and received gross volatility spillovers). If the net figure is positive, the variable i influences all the other markets more than being influenced by them:

$$S_{i}^{g}(H) = S_{*i}^{g}(H) - S_{i*}^{g}(H) \quad (7)$$

The *pairwise spillover index* measures the spillover effect among two market, i and j, as the difference between the gross spillovers transmitted from market i to market j and those transmitted from j to i:

$$S_{ij}^{g}(H) = \left(\frac{\tilde{\theta}_{ij}^{g}(H)}{\sum_{k=1}^{N} \tilde{\theta}_{ik}^{g}(H)} - \frac{\tilde{\theta}_{ji}^{g}(H)}{\sum_{k=1}^{N} \tilde{\theta}_{jk}^{g}(H)}\right) * 100 \quad (8)$$

The spillover measurement becomes dynamic by using a rolling window method with an arbitrarily chosen time-window and forecast period.

In this study, the AIC and BIC information criteria indicated that the Vector Autoregression model gave a good approximation with a 1-week delay (not shown). Calculation of the DY spillover index on volatility values (absolute log returns) was done with a time window of 100-week and a 4-week forecast period. The model itself consists of the Hungarian pig producer price as the dependent variable and the respective MS data as the independent variable (Denmark, Germany, Spain, France, the Netherlands, Austria, Poland, Romania and the Hungarian imported pig price (IM)). Sensitivity test for the forecast and model lags indicated that the model was not sensitive to the changes of these parameters (not shown). *FrequencyConnectedness* and *testcorr* packages were used to calculate spillover indices and robust correlation in R (Baruník and Křehlík, 2018).

Continuous wavelet power spectrum (wt)

Wavelet theory and its mathematical treatise is described elsewhere (e.g. Torrence and Compo, 1998; Grinsted *et al.,* 2004). The *wt* measures the power of the spectrum of a single time series variable and enables examining local features of a signal, even in the presence of large amounts of noise. As the continuous wavelet transform does not completely deals with boundary conditions on a finite length dataset, a cone of influence (COI) was drawn to demarcate area where the algorithm encountered edge effects and correct data interpretation was impossible (highlighted as semi-transparent area on the graphs). We used Morlet wavelet, as it is widely used for financial applications and it provides both real and imaginary parts, construed as intensity and phase information. The sampling interval was one week.

Bivariate wavelet coherence (wtc)

For studying nonlinear relationships between a data set and a potentially influencing factor, *wtc* was calculated (for the equations of wavelet coefficients see e.g. Grinsted *et al.,* 2004; Hu and Si, 2021). It approximates how coherent two signals are in time–frequency space by examining the intermittent correlation of two oscillatory phenomena based on wavelet amplitudes. The *wtc* can find correlation even in the absence of high common power, and it allows to test for significance of the relationship between the two processes. It is to note, however, that correlation results do not necessarily imply causality. Having no *a priori* knowledge of distribution for the wavelet coherence, statistical significance was tested using the Monte Carlo methods included in the package.

Relative phase differences are shown by arrows on the wavelet coherence plots, which provide details about the delays in the oscillation (cycles) between the two time series under study. The arrows point to the right (left) when the time series are in-phase (anti-phase) or are positively (negatively) correlated. Arrows pointing up (down) means that the first time series leads (lags) the second one by $\pi/2$ radians of the local period read off the ordinate scale. Accordingly, directions deviating from perpendicular are considered to show mixed type of behaviour of the two processes.

Partial Wavelet Coherence (pwc)

Any correlation (coherence) between response and predictor variable may be misleading if a third, excluding data set shows significant correlation with the response variable. Partial correlation measures the association between two variables, while it adjusts for the presence of one or more confounding (excluding) variable. Its wavelet application was first proposed by Mihanović *et al.* (2009), generalised by Ng and Chan (2012), and extended to more than one excluding data set by Hu and Si (2021). Previous code implementation based on the real part of the complex bivariate coherence was corrected by Hu and Si (2021).

In analogy to the partial coherency of multivariate spectra (Koopmans, 1974), the modified *PWC* method is defined as the localised correlation in the time-frequency domain. According to Hu and Si (2021), for an arbitrary number of excluding variable the complex *pwc* is defined at scale *s* and location τ as

$$\rho_{y,x\cdot Z}^{2} = \frac{|1-R_{y,x,Z}^{2}(s,\tau)|^{2}\, R_{y,x}^{2}(s,\tau)}{(1-R_{y,Z}^{2}(s,\tau))\,(1-R_{x,Z}^{2}(s,\tau))} \tag{9}$$

where *y* is the response, *x* is the predictor and Z is the excluding variable ($Z = Z_1, Z_2,...,Z_q$), while $R_{y,Z}^2(s,\tau)$ and $R_{x,Z}^2(s,\tau)$ are the squared bivariate wavelet coherences between *y* and *Z* and *x* and *Z*, respectively (Hu and Si, 2021).

During the analysis, *wtc* was regularly checked on each variable pairs of a *pwc*, because *pwc* is prone to produce false positive correlation close to the COI (Hu and Si, 2021). The correlation was ignored, if high local correlation appeared after excluding one or more data sets by partial correlation relative to the bivariate correlation.

Results

Even though the European Union acts as a single market, noticeable differences exist between the different MSs. The time series of weekly pig prices show significant interannual variability from 2007 to present (not shown). A closer look at the sampled markets showed intermittent variability on top of interdecadal dynamics. As a preliminary step, we divided the logarithmic return time series of each MS's price quotation (H-Hungarian, E-average European, A-Austria, D-Danish, G-German, F-French, N-Dutch, P-Polish, R-Romanian, S-Spanish pig prices) into equidistant periods in time (2007-2009, 2010-2012, 2013-2015, 2016-2018, 2019-2021). Robust correlation values (Dalla *et al.,* 2020) were calculated for the entire period between 2007-2021 and for each of the triennials to examine the significance of cross-correlation in bivariate time series. These measures are robust against random variables characterised by different types of finite time-varying variances (heteroscedasticity), and against dependencies in the time series or in relation to each other.

Pig producer prices are defined as the slaughterhouse entry price of pigs. The Hungarian pig producer price (denoted here as H) was used as a proxy for the Hungarian pig industry and was used as the central dependent variable in subsequent analyses. For the entire 2007-2021 period, the correlation value (r) of the pig producer price in the major European Union producer countries with the Hungarian price ranged between 0.34 and 0.63 (correlation data are not shown). The value of the correlation with the pig producer price in Germany (G) was medium (r = 0.55), and between 0.54 and 0.63 for the pig producer price in Austria (A) and the Netherlands (N). For prices in Romania (R), France (F), Denmark (D) and Spain (S), the same value varied between 0.34 and 0.39. During the entire 2007-2021 period, the influence of individual MSs on prices in Hungary (H) changed continuously, while the evolution of the EU average price (E) was less sensitive to these changes, so the correlation with the EU27 average (E) became decisive over the entire length of time (r = 0.66).

Looking at the development of the producer price of Hungarian pig producer price (H) for the shorter period of 2007-2009, its correlation with the EU market (E) was generally weak (0.3), but with the pig producer price in Poland (P) was the highest (r = 0.34). The producer price in Germany (G) did not correlate with the Hungarian price (r = 0.13), unlike the German piglet price (Gpig) that reached 0.33.

From the start of the decade (2010-2012) the most important pig producing MSs began to play an increasing role in setting the Hungarian pig producer price (H). Supply chain integration improved in Hungary and leading Hungarian slaughterhouses started to base their pricing on the German ZMP base price (Marczin *et al.,* 2020). Despite these events, German base price (G) did not yet have an impact on the correlation data at this time (r = 0.44). However, the correlation value of the pig producer price in Poland (P) rose from 0.34 measured in the previous three years to 0.69, implying its co-movement with H.

The 2013-2015 period brought about the full market integration of the Hungarian pig producer price (H) with the EU market. The correlation coefficients were typically already above 0.8, at which point the pig producer price in Austria and the Netherlands showed the closest correlation with the price in Hungary, while the average price in Poland and the EU did not lag far behind this value either.

The period starting in 2019 was strongly influenced by the hectic market conditions. The German pig producer price (G) reached a high of 0.66 among the correlation coefficients for the producer price of Hungarian pigs, followed by the German piglet price (Gpig; r = 0.63). Both were, however, surpassed by the EU average pig price (E; r = 0.70). The corresponding values of pig producer price in Poland (P) and Austria (A) were slightly less (r = 0.59 and 0.61, respectively) than the price in Germany (G) in this recent period.

To summarise, the overall connectedness of the pig markets in our analysis increased considerably over the last two decades. Taking into account the correlation results, we can tentatively distinguish at this point two main periods of market drivers affecting the Hungarian pig supply (H): an early period characterised by more balanced bilateral ties until around 2014 and a later one with a dominant pan-European (mainly German) impact.

The correlation results provided evidence of strong dependence in the different commodities but were unable to capture the time-varying pattern of price changes over

Figure 1: Total volatility spillover index of the Hungarian pig producer price (in percent).

Source: Own composition

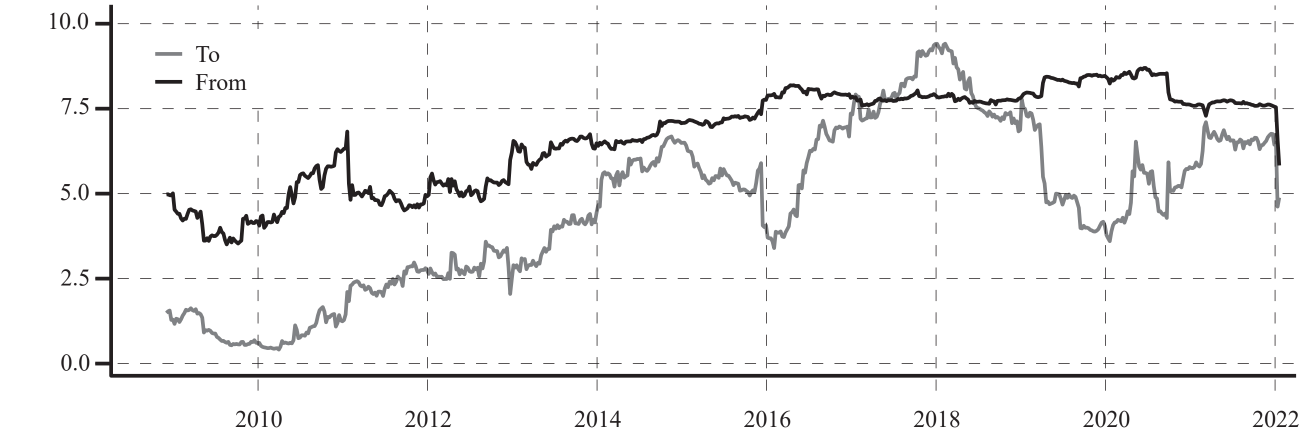

Figure 2: Directional volatility spillover index of Hungarian pig producer price (transmitted and received).

Note: 'To' shows how much spillover effect is directed by the Hungarian market to all the other MS markets, whereas 'From' can be interpreted as how much it received from the others.

Source: Own composition

time, so we turned to a more dynamic approach to detect country-wise connectedness. The concept of spillover effects stems from the recognition of econometrics that the volatility of financial markets increases during crises and spreads onto other markets. In our analysis, we used the modified volatility spillover method from Diebold and Yilmaz (2012) to measure the extent to which price fluctuations of a given market affect the volatility perceived in other markets.

A full-sample dynamic analysis of volatility spillovers was performed between the Hungarian (H) and the different MS markets. Analysing volatility spillovers over time helped us to identify connectivity patterns with high confidence in the constantly evolving European pig market landscape. Because of the applied 100 week-long rolling window sampling, data are plotted only from 2008.

First, we calculated the total, and directional volatility spillovers for the Hungarian pig producer price (H) using the standard VAR estimate (Figure 1). The level of volatility spillover was relatively low at the onset of the observed period and fluctuated between 45% to 50% for the first two years. After 2010, the evolution of the Diebold-Yilmaz total spillover index remained unsettled (Figure 1), followed by a minimum after 2014.

ASF virus entered the territory of the European Union in 2014, which caused great economic damage and had a lasting negative impact on the pork trade due to restrictions imposed on the import of pork from infected areas. It first appeared in Poland in February 2014, and for this reason Russia, which was one of the major export markets at that time introduced an import ban on live pigs and pork from the entire territory of the European Union. Due to strict environmental protection rules affecting animal farmers, pork production in China decreased by 4 percent in 2016 compared to the previous year, which generated huge demand for imports from mid-2016 and caused a price increase on the EU market for slaughter pigs. Given this international exposure, the Hungarian pig producer price (H) surged to a record high by 2018. The ASF virus was first detected in wild boar in Hungary in April 2018, and since then, around 33 countries have restricted the import of pork and meat products from Hungary, most of them – including China, Japan, South Korea and Taiwan – for the entire territory of the country. Since then, only a slow regression of the volatility spillover index has been noted, thus the index continues to be higher compared to the first half of the decade.

By plotting the value of spillovers received (*from*) and transmitted (*to*) by the dependent variable (Figure 2), we obtained the directional components of the volatility spillovers for the Hungarian pig producer price (H). Except for a short interruption in 2017, the Hungarian price (H) was always a net receiver in terms of inter-MS spillovers.

So far, we focused on the gross directional spillover effects. Below, we calculate net spillovers for the Hungarian pig producer price (H) to show how much spillover it transmitted and received from all the MS included in this study. When the value of a particular asset lies above the baseline, the commodity transmits more volatility to the others than it receives from them in that particular year. In such a case, that commodity is called a net spillover transmitter. Negative values correspond to net spillover that a commodity receives from the others and thus the asset acts as a net spillover receiver.

Figure 3 shows net spillover results of the different MSs and demonstrates that all of them can take both positive and negative values at some point. The index of the Hungarian pig producer price (H) remained mostly in the negative range, which implies that this variable mainly played a net volatility spillover receiver role under the market conditions prevailing throughout the entire period. Qualitatively the same result applies to imported slaughter pigs in Hungary, albeit at a reduced level.

Breaking down the net (transmitted-received) spillovers by country, the pig producer price in Germany (G) has been a net volatility transmitter since 2013. Increasingly, the same price in Poland (P) and Austria (A) have also started to play a transmitter role in the European pig market since 2017. However, net spillover has weakened in all three cases due to the pandemic and the outbreak of African swine fever disease. In contrast, the cross-border spillover effects of Dutch (N) and – to a lesser extent – the Romanian prices (R) dominated the first half of the analysed period, indicating that a large-scale reshuffle has taken place in the intra-EU market around 2015.

In volatility spillover plots, timescales are aggregated, so the exact conditions under which a net receiver position turns into a net transmitter position (or vice versa) remains elusive. For an accurate picture of interdependence between national pig prices, we mapped the dependence structure, structural break points and the lead–lag relationships between the individual variables. To unmask these relationships, a wavelet-based approach was chosen because

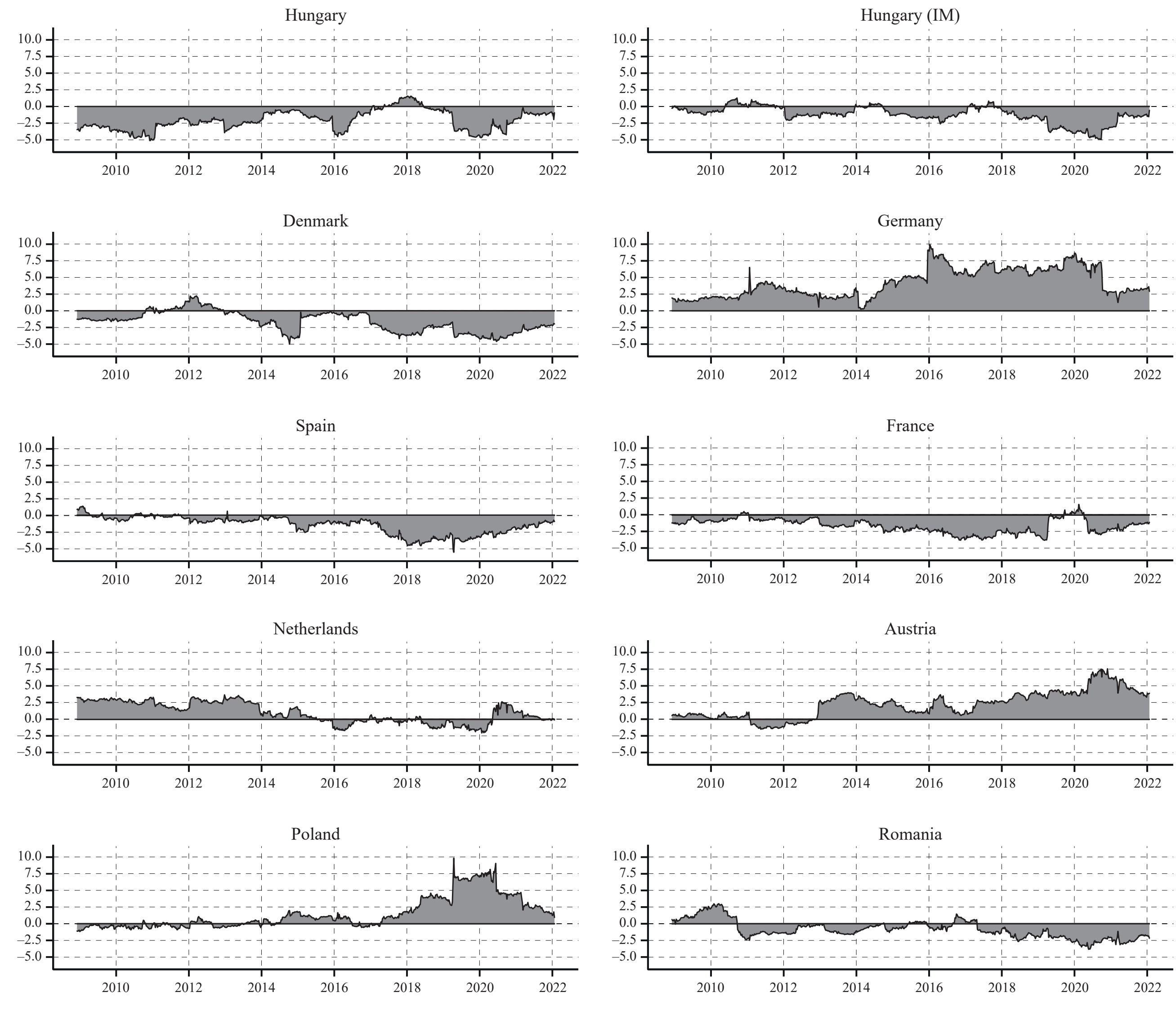

Figure 3: Net pairwise volatility spillovers of the indicated country's pork price with Hungarian pig producer price.
Source: Own composition

this mathematical tool is ideal to expand the data content from the time domain into different layers of frequency representation. Splitting non-stationary and complex time-series up into different frequency components allows us to look at long-term movements and high-frequency details at the same time, as economic decisions and actions are often realised at overlapping timescales. As a reference for subsequent discussions, we consider investors on pig market to be heterogenous with respect to the time horizon they trade (or conclude their purchase agreements). Accordingly, we make a distinction between short-term relationship up to 16 wk, medium-term between 16-64 wk, and long-term above 64 wk period bands on the scalograms.

First, we evaluated for each of the time series to define the dominant modes of local variance (Appendix 1., first column). The continuous wavelet power spectrum of each standardised weekly price series showed that the dominant scale of price fluctuation was very similar (shown for A, G, P, R, E and CME; from wt::A to wt::CME). Local variance of the signal was high in the medium-term range (32-64 wk) between 2013–2018, but other high variability, non-significant regions were also present over the entire timeframe (in the 8-64 wk band).

Wavelet coherence is helpful for elucidating which of the multiple input variables (predictor or independent variable) contributes the most to the response variable (Appendix 1, second column). Pairwise comparison from bivariate wavelet coherence (wtc::H~G) detected a very high degree of coherence between the Hungarian pig producer price (H) and the German price (G). Strong coherence was present between the two variables, particularly over an investor's time horizon of more than one year, which agrees well with the net spillover results discussed previously. Only on the spot market was the relationship erratic (short-term, < 4 wk period band). We found qualitatively the same result, when the Hungarian pig producer price (H) was compared to EU average (E) price (wtc::H~E).

On the graph, the in-phase relationship of Hungarian (H) and German (G) (or European: E) prices is demonstrated by the large number of phase arrows pointing right (wtc::H~G and wtc::H~E). However, as the period decreases on top of the scalogram arrows start increasingly to point upwards, indicating that German (G) (or European: E) price not only co-moved but led the Hungarian price (H) on spot markets by ca. half cycle (1 wk). A similar 1 wk lag was indicated by vector autoregressive model (VAR) calculations (not shown; Szenderák et al., 2019). Albeit at a slightly reduced level than previously shown, the Hungarian price (H) also showed an extensive correlation with the Austrian (A) and Polish prices (P) (wtc::H~A and wtc::H~P). A gap appeared in 2014 on both graphs in the 16 wk band that resolved after 2015, which is probably related to the market turmoil caused by the first report on ASFV incidents in the EU.

The bivariate coherence results demonstrate that most MSs' pig prices correlate extensively with the Hungarian price (H). This implies that some, so far unknown external factors (excluding variables) might influence both the Hungarian (H) (response variable) as well as the chosen MS's pig price (predictor variable) at the same time. If an excluding variable is indeed present, this could lead to an overestimation of the predictor variable's effect on response variable. Hence, we used an improved partial wavelet coherence method (*pwc*; Hu and Shi, 2021) to overcome congruence after excluding one or more common dependent variables (Appendix 1, third and subsequent column). For example, when an additional time series was removed from the H-G relationship (e.g. Austria; see pwc::H~G-A), the reliability of the test improved, but a large swathe of the previously significant region disappeared. Furthermore, if we excluded the effect of more than one data set (e.g. Austria, Poland and Romania; pwc::H~G-[A+P+R]) the resulting plot explained even less amount of variations. One likely explanation is that these excluded variables already contained a large amount of variance from the German time series and themselves were influenced by the German price. Again, the pattern for the European price was very similar to the German price (pwc::H~E-[A+P+R]), underlying the dominating role of E and G in setting the MS prices.

On all previous graphs, G and E showed very similar pairwise or multivariate coherence patterns (e.g. wtc::H~G and wtc::H~E). This raises the question if the average European price serves just as a proxy of the German price, or it shows some distinguishing features. To answer this we compared their partial wavelet coherence with H by switching the order of the predictor and excluding variables between G and E. Comparing the partial coherence pattern of pwc::H~E-G with the complementary pwc::H~G-E, a large band was present from 2014 onwards. When the E was the predictor variable, significant coherence was limited only within period-scales of about 32-64 wks, whereas G being the predictor variable, the band shifted to 64-128 wks. Obviously, H was affected by G and E at different time scale (or period) when the effect of another variable was excluded. This observation underlines the importance of taking care of the period information and implies that after 2014 European price changes were adapted more quickly in Hungarian pig supply contracts than the German price changes.

Other Central and Eastern European producers have a less obvious impact on the Hungarian price (H), such as from Romania (R) (wtc::H~R). Here, there was a stable positive correlation in the medium-term period (32-64 wk) band over the entire time length. On top of it appeared a transient "bulge" in 2017 in the Hungarian - Romanian time series at around 16 wks. If we removed the confounding effect of the German price (pwc::H~R-G) from the Hungarian-Romanian relationship, we could uncover a transient, in-phase association of Hungarian (H) and Romanian (R) prices around 2017. This is perhaps due to the increased Romanian demand for live pigs and pork from Hungary in 2017, as ASF outbreak on Romanian smallholders' live pig output caused a bottleneck in domestic supply at that time (Popescu, 2020). The wavelet result compares well with DY volatility spillover calculations. As demonstrated in Figure 2, Hungary's 'transmitted' spillover surpassed its 'received' position only during this time period.

The "bulge" disappeared entirely by removing the effect of G (pwc::H~R-G). Qualitatively the same result was obtained if we checked the association of R and G excluding the variable H (pwc::R~G-H). This time, however, phase arrows pointed up and left, indicating an anti-phase relationship where G leads R by approximately half a period (ca. 16 wks). The most likely explanation for these observations is that Hungary played a major role in relieving Romanian live pig shortage by expanding its export to Romania, while increasing imports from Germany, so the "bulge" disappears if either H or G is excluded from partial coherence.

Another conspicuous phenomenon is apparent on the partial coherence plot of H and R, controlling for P (pwc::H~R-P). From 2013, a statistically significant, high coherency band appeared that creeped diagonally on the scalogram, while its characteristic period continuously increased. When we included more than one excluding data set (e.g. pwc::H~E-[A+P+R]), the correlation result got more fragmented. Care must be taken in interpreting these results, as multiple (more than one) confounding variables might be present in our pig price system. Here, the German price (G) is definitely one of the major candidates that might have a marked influence on other MS's pork prices.

Despite the ongoing pig market integration within the EU, the United States – with a global market share of 12% – is also able to influence internal producer prices. The dependence on U.S. prices can best be understood, if we compare the Hungarian price (H) with U.S. hog prices published by the CME Group (wtc::H~CME). The bivariate comparison showed a significant level of correlation after 2014 in the midterm period band, where upward facing arrows indicate a prompt impact of U.S. price on H. This remained stable even if we exclude the effect U.S. dollar exchange rate (pwc::H~CME-USD), but diminished almost completely when the German price was excluded (pwc::H~CME-G). We regard this as an indication that Germany acts as a lever to convey world market impact on other MSs, like Hungary.

Market competitiveness requires streamlining supply chain. For the pork industry this translates – among others – to the need to detach piglet production from the fattening phase, with consequences on market dynamics. Submarket analysis of German piglet price on the Hungarian price (H) revealed a rather extensive coupling between the two. It was nonetheless only significant in the medium-term range (32-64 wk) between 2014-2017 (wtc::H~Gpig), when we compared it to the continuous wavelet transform of German piglet price (wt::Gpig). Omitting the German price (G) from the comparison of H and Gpig (pwc::H~Gpig-G), a strip appeared in the same period band that showed a counter-phase relationship between the two prices. Arguably, piglet price serves as an input in a product chain that influences swine stock size, ultimately affecting pig price as output.

Discussion and Conclusions

In this paper, we studied market connectedness of the Hungarian pig industry between 2007 and 2021. In the first part, we studied the volatility spillover behaviour of a set of national pig price time series (Diebold and Yilmaz, 2012) that represents each of the major European producer's net position. Based on the net volatility spillover results, we noted that the Hungarian price's association was the strongest with the German price. It was stable over the entire analysed period but declined somewhat in 2021 in the aftermath of the Covid-19 pandemics. Austria also transmitted a sizeable amount of spillover to Hungary starting from 2013. Polish market pressure built up only after 2018, reached a height in 2020 and subdued afterwards. Other competitors' (Romania, Denmark, the Netherlands) net spillover receiver or transmitter position remains less conclusive. It is to note that Romania, as a Black Sea basin country, has slightly different market access opportunities than the rest of the studied countries. Granger causality test indicated that there is a bidirectional causality-in-variance information flow between international and local pork prices in this country (Guo and Tanaka, 2022).

In the second part of our study, we extended our spillover study with wavelet analysis in order to study the gradual shift in geographical pattern and to better estimate the hierarchical structure of the drivers of price volatility. Pairwise wavelet coherence (*wtc*) of the various countries with the Hungarian pig price showed an almost homogenous wavelet coherence pattern. But removing the effect of each individual country one-by-one in partial coherence (*pwc*) revealed a different amplitude and phase relationships that was not apparent in the pairwise (*wtc*) results. As Holst and von Cramon-Taubadel (2013) pointed out, price transmission works even in the absence of physical trade. Unexpectedly, the German market's predominant correlation appreciably weakened when more than one excluding variable was used. One explanation could be that traders from Austria, Poland, and Romania, which are also active in Hungary, base their pricing on the German market price and this business practice partly offsets the German component observed in Hungary. The calculated average European pig price was even more predictive for the Hungarian price, than the German price. Our finding supports the view that the Hungarian price is coupled to the European price the most efficiently.

The limitations of this study are manifold. Pork meat is a cost-driven commodity in the international trade (Hoste, 2018) and its price is linked to inflation and business cycles. In a preliminary assessment (not shown), we explored several potential input factors affecting production costs or substitute product prices (e.g. chicken meat), but few of them had a notable effect on the Hungarian pig price. Pork prices also seem to be resilient to feed price variability (e.g. feed maize, oilseed). This may be related to the fact that deepening relationship between grain marketers and grower-integrator is already under way or on the agenda of many pork producers. The spot market of pig is thus expected to shrink in the long run.

Forward-pricing in futures market might be a tool for producers to alleviate risks traditionally associated with agricultural spot markets and to decrease volatility in prices (Wang *et al.,* 2021). A sizeable number of transactions must take place as a requisite, but in terms of capitalisation, the European futures market for live pig is minuscule compared to the U.S. hog market (Ziegelbäck and Kastner, 2013, Adämmer *et al.,* 2016). Instead, price swap was recently proposed as a remedy for pork meat producers that would force buyers to reveal their reservation price (Lievens *et al.,* 2021) and would put producers in a better position.

Another limitation of our study is related to the constraint of the sampling theorem for adequate data frequency. In fact, the finite number of samples in price time series poses a limit for the maximum attainable time resolution of a wavelet transformation, which – using the Morlet as a mother wavelet function – limited us to a couple of weeks in this study, severely underestimating fast market decisions.

From the many branches of animal husbandry, the European pig industry is remarkably vulnerable to shifting patterns of consumer behaviour, trade disputes, ASF occurrences and tightening regulatory standards. To tackle these challenges, the industry is on the verge of major changes (Faris and Rehder, 2019). Hence, further studies are needed to investigate how connectedness of pork markets across the European Union will change as a result of these measures.

In general, international trade moderates price fluctuations of commodities that experience cyclic production. Despite this, our results indicate that the intra-European pig market price fluctuates heavily, and this influences producers' margin and thereby farm income in Hungary. There does not seem to be an end in sight to the price volatility, as upcoming animal welfare regulations will likely further exacerbate the situation. The information presented here is intended for the actors in the pig industry to set their investment decision and price negotiation tactics accordingly.

Acknowledgements

We are grateful to Wei Hu (The New Zealand Institute for Plant and Food Research Limited) for giving insights on how partial wavelet coherence results should correctly be interpreted and A. Grinsted and Wei Hu for the free wavelet software packages. We thank Norbert Potori for insightful comments on the manuscript.

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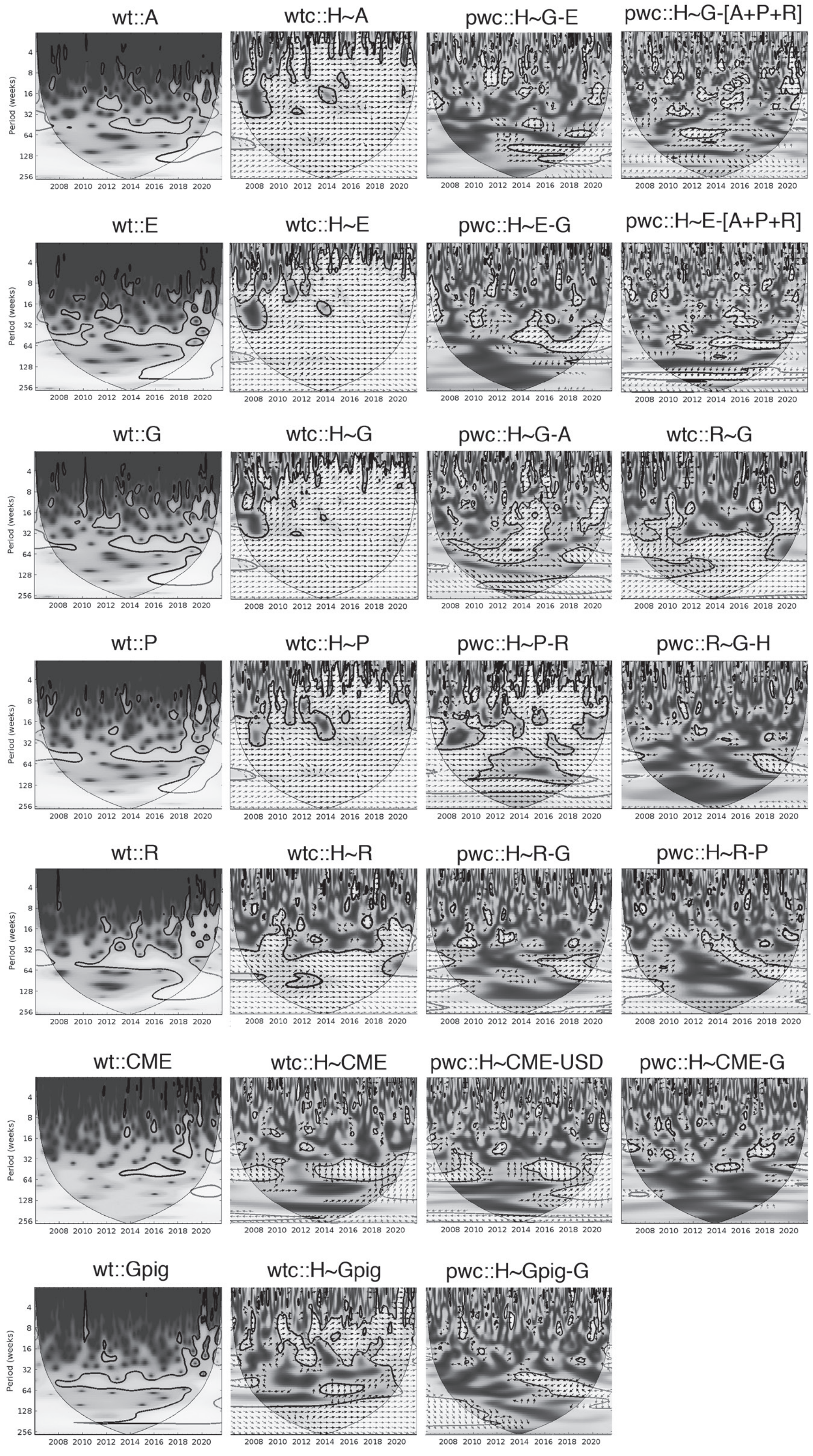
Appendix

Appendix 1: Continuous wavelet power spectra (wt, first column) of the indicated variable. Bivariate wavelet coherences (wtc, second column) between the response (1. position in graph title) and the predictor variable (2. position). Partial wavelet coherency (pwc, third and subsequent columns) of pig prices measured between the response (1. position) and the predictor variable (2. position), while excluding the effect of the confounding variable(s) (3. position).



Abbreviations: A: Austrian pig price (p. p.), CME: U.S. hog price, G: German p. p., Gpig: German piglet price, H: Hungarian p. p., P: Polish p. p., R: Romanian p. p.
The data are sampled weekly. Time (years) is shown on the horizontal axis of the scalogram, the vertical axis refers to the inverse of frequency (period in weeks), while local wavelet power (variance) is intensity-coded. Bivariate wavelet coherence plots highlight those areas in the time-frequency space where the two variables co-vary. The warmer the colour, the higher the coherence is (interpreted as correlation) at that position of the time-frequency plot. A bold line delineates statistically significant areas of coherence. Arrows correspond to the phase angles of the wavelet spectra. Cones of influence are shaded, and thick solid lines show the 95% confidence levels computed by Monte Carlo simulations.
Source: Own composition