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Tail event-based sovereign credit risk transmission network during COVID-19 pandemic

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ARTICLE INFO

JEL classification:
G01
G15
C1

Keywords:
Sovereign credit risk
Credit default swap
Tail event
Network risk
COVID-19 pandemic

ABSTRACT

This paper investigates the interconnectedness between sovereign credit risk based on the tail event and network dynamics technique. Specifically, we examine the interdependence in upper tails of sovereign credit default swap in the case of fifteen most COVID-19 affected countries. Empirical findings indicate that connectedness among SCDS spreads changed over time and is higher during the COVID19 outbreak. Russia, Brazil, and China are the most credit risk emitter and receiver during the COVID-19 pandemic.

1. Introduction

After the recent global financial crisis, large credit markets worldwide have become more interconnected. The ongoing COVID-19 pandemic and the uncertainty in global financial markets have increased the credit markets’ systemic vulnerability. Systemic risk is the extensive failure of financial institutions or capital markets, which affect the financial stability and the real global economy. Additional to systemic risk, systemic tail risk in global financial and credit markets emerges from financial markets’ turmoil. Harris et al. (2019) propose two systematic tail risk measures: the extreme downside correlation (EDC) and the extreme downside hedge (EDH). Ahelegbey et al. (2021) extend EDC and EDH measures and propose a multivariate network modeling framework methodology taking into account systematic tail risk and systemic tail risk. Cerchiello et al. (2017) present a systemic risk measure using graphical Gaussian models, including information from the financial market and big data from financial tweets. Härdle et al. (2016) propose a Tail-Event driven Network to assess the systemic risk of financial institutions conditional to their market capitalization and interconnectedness in tails.

The economic impact of the ongoing COVID-19 pandemic and the alarming increase of the credit default swap (hereafter CDS) spreads in the credit markets have renewed interest in investigating the spillover and connectedness between sovereign credit risk. A CDS is a financial contract principally traded in over-the-counter (OTC) derivatives markets. The CDS premium represents the cost for protection against a “credit event.” The buyer of the CDS (protection buyer) makes a series of fee payments to the protection seller and,

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https://doi.org/10.1016/j.frl.2021.102182
Received 16 August 2020; Received in revised form 12 April 2021; Accepted 26 May 2021
Available online 30 May 2021
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in exchange, receives the face value of the underlying asset in the occurrence of the credit event. A sovereign credit default swap (hereafter SCDS) is a financial contract where the reference entity is a government. This contract is developed to compensate international investors in the event of a sovereign default. A borrower country may default either due to a lack of economic resources for its debt repayments or a lack of willingness to fulfill its obligations (Yu, 2016). The spread in sovereign CDSs indicates sovereign credit risk. Therefore, SCDS is also a useful hedging tool to offset the sovereign credit risk and improve financial stability.

Most of the current studies focus on SCDS to explain dynamics of sovereign credit risk with country-specific variables (e.g., Aizenman et al. (2013), Beirne and Fratzscher (2013), Eysell et al. (2013), and Jeaneret (2018), among others). Other studies explain the dynamics of sovereign credit risk with macroeconomic variables and risk factors (e.g., Pan and Singleton (2008), Wang and Moore (2012), and Ang and Longstaff (2013), among others). A growing body of research investigates the impact of uncertainty variables and commodity markets on sovereign credit risk (e.g., Bouri et al. (2017), Bouri et al. (2018), and Naifar et al. (2020), among others). Notably, none of the available studies investigate the interconnectedness between SCDS during the COVID-19 pandemic. In this paper, three facts have motivated us to explore the tail event interdependencies among the most affected countries’ sovereign credit risk by the COVID-19 pandemic. The first fact relates to the unprecedented increase in the sovereign CDS spreads with the rise of COVID-19 infected cases. The SCDS indices are trading at their highest levels during the coronavirus epidemic. The second fact relates to the different reactions of SCDS spreads to the increase of global COVID-19 infected cases. According to Moody’s Analytics report (April 2020), Italy’s sovereign credit risk increased quicker and earlier during the COVID-19 pandemic than other countries (USA, China, UK, Germany, South Korea, Japan, France, and Spain). However, China’s credit risk is the least impacted compared to other countries.1 The third fact admits that there are no in-depth empirical studies that explain the interconnectedness between sovereign credit risk based on the tail event and network dynamics.

The simplest way to implement the systemic risk is the Marginal Expected Shortfall (MES), proposed by Acharya et al. (2010). However, the marginal approach has the significant inconvenience that it ignores for the level of the firm’s characteristics. Brownlees and Engle (2012) expanded the MES to “SRISK” by taking into account the leverage and the size of the financial institution. The “SRISK” measures the capital shortfall of a financial institution during a crisis period in the entire financial system. The main advantage of “SRISK” that it can be computed at a higher frequency with no cost. However, it assumes that the liabilities of the firm are constant over the crisis period. Banulescu and Dumitrescu (2015) propose a measure called Component Expected Shortfall (CES), which addresses the main weaknesses of MES and “SRISK”. The CES of a financial institution measures the firm’s ‘absolute’ contribution to the financial system’s Expected Shortfall.

This paper contributes to the existing literature in three ways: First, we investigate the systemic interconnectedness between sovereign credit risk based on the tail event and network dynamics technique. We use a Tail-Event driven Network (hereafter TENET) risk technique proposed by Härdle et al. (2016). This technique allows us to rank credit risk receivers and credit risk emitters among countries. We examine the dependence among SCDS spreads using the TENET based on quantile regressions augmented with non-linearity and variable selection in a high dimensional time series setting. This work belongs to the quantitative group of literature that includes linear bivariate model by Adrian and Brunnermeier (2016) (from here on abbreviation as AB), Acharya et al. (2012), Brownlees and Engle (2017), and Abedifar et al. (2017). Although used as a starting point, the CoVaR approach of AB focuses on the bivariate measurement of tail risk. In contrast, the TENET approach assesses the risk contribution of SCDS spread of each country conditional on its upper tail interconnectedness with the relevant other countries in our sample. Here, a challenge is to select the set of relevant drivers for each SCDS spread which is achieved, statistically, by employing a variable selection method in the context of single-index model (SIM) for generalized quantile regressions, e.g., for quantiles and expectiles (Härdle et al., 2016) which is further extended to a time series variable selection context in high dimensions. The semi-parametric framework due to the SIM allows investigating possible non-linearities in tail interconnectedness. Hence, the SCDS network consisting of spillover effects among them is based on identified relevant risk drivers.

Second, we examine the tail event-driven interconnectedness in the case of fifteen of the most affected countries by the COVID-19 pandemic, which is of the USA, China, Brazil, Germany, the UK, Spain, France, Russia, Italy, Turkey, Mexico, India, Peru, Poland, and Colombia. Third, we construct a network and identify the most credit risk receivers and emitters during the COVID-19 pandemic. This paper is the first study that explores the sovereign credit risk transmission network during the COVID-19 pandemic by combining tail event and network dynamics to the best of our knowledge.

The rest of this study is organized as follows. Section 2 describes the methodology. Section 3 presents the data. Section 4 discusses the empirical findings. Section 5 concludes the paper.

2. Methodology

In this paper, we use the TENET methodology to investigate the systemic interconnectedness between sovereign credit risks. The first step of the TENET is the estimation of the Value at Risk (VaR). The VaR of a financial system \( i \) at the quantile \( \tau \) is defined as follow:

\[
P(X_{i,t} \leq \text{VaR}_i^{\tau}) = \tau
\]

(1)

Where \( X_{i,t} \) represent the loss of the financial system \( i \) at time \( t \). Following AB, the Conditional Value at Risk (CoVaR) of a financial system \( j \) given on some event of financial system \( i \) (\( X_{i,t} \)), at the quantile \( \tau \) can be defined as follows:

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1 https://www.moodysanalytics.com/articles/2020/coronavirus-assessing-the-impact-on-corporate-credit-risk
\[ P(X_{it} \leq \text{CoVaR}_{i,t}^{(\alpha_i)} / l_{it}) = \tau \]  

(2)

Where \( l_{it} \) indicates the information set which covers the event of \( X_{it} = \text{VaR}_{i,t}^{(\alpha_i)} \) and \( M_t = 1 \). The variable \( M_t = 1 \) represents a vector of common global variables replicating the overall state of the economy. We estimate the VaR for each financial system \( i \) by using linear quantile regression:

\[ X_{it} = \alpha_i + \gamma_i M_{t-1} + e_{it} \]  

(3)

\[ \widehat{\text{VaR}}_{i,t}^{\alpha_i} = \tilde{\alpha}_i + \tilde{\gamma}_i M_{t-1} \]  

(4)

\[ \text{CoVaR}_{i,t}^{(\alpha_i)} = \tilde{\alpha}_{ji} + \tilde{\gamma}_{ji} M_{t-1} + \tilde{\beta}_{ji} \text{VaR}_{j,t}^{\alpha_j} \]  

(5)

The VaR is estimated by the linear quantile regression (Eq. (3)) of the log-return of an SCDS spreads \( i \) on macro state variables. The risk of a financial system \( j \) is calculated via global variables and a VaR of a financial system \( i \).

The vital element of the network analysis is the calculation of the CoVaR. Eq. (2) shows that the CoVaR of the financial system \( j \) is estimated by conditioning on its information set \( (l_{it}) \). This information set contains the SCDS returns of other countries, the global variables used in the earlier step, and the country’s stock market index, which shows country-specific characteristics. After that, a systemic risk network is constructed. The TENET captures nonlinear dependency, and it is based on a single index quantile variable selection method. More specifically:

\[ X_{it} = g(\tilde{\beta}_{ji} l_{it}) + e_{it} \]  

(6)

\[ \text{CoVaR}^{\text{TENET}}_{j,t} = \tilde{g}(\tilde{\beta}_{ji} l_{it}) \]  

(7)

\[ \tilde{D}_{ji} = g(\tilde{\beta}_{ji} l_{it}) \tilde{\beta}_{ji} \]  

(8)

With \( l_{it} = (X_{-jt}, M_t = 1, S_{it} = 1) \) represents the information set, including \( p \) variables. \( X_{-jt} \) represent the log-returns of all SCDS, excluding the SCDS for the country \( j \). \( S_{it} = 1 \) is the country’s stock market index (the country’s specific factor). From Eq. (7), we note that CoVaR includes the effects of all SCDS (excluding SCDS of country \( j \)) and provides non-linearity revealed from the link function \( g \) (●). Consequently, \( \text{CoVaR}^{\text{TENET}} \) stands for Tail-Event driven NETwork risk (Härdle et al. (2016)). From Eq. (8), \( \tilde{D}_{ji} \) indicates the slope assessing the marginal effect of covariates at \( l_{it} = \bar{l}_{ij} \). Particularly, \( \tilde{D}_{ji} \) permits to measure spillover across the SCDS and describe their dynamic by a network. The total connectedness matrix \((\text{TC}_w)\) for the SCDS is represented as follow:

\[
\text{TC}_w = \begin{pmatrix}
0 & \ldots & |\tilde{D}_{1/w}|
\vdots & \ddots & \vdots
|\tilde{D}_{w/1}|
& \ldots & 0
\end{pmatrix}
\]  

(9)

The total connectedness matrix (or the weighted adjacency matrix) contains the absolute value of \( \tilde{D}_{1/w} \) at the upper triangular matrix and \( \tilde{D}_{w/1} \) at the lower triangular matrix. The factor \( \tilde{D}_{1/w} \) measure the impact of sovereign credit risk \( i \) (represented by SCDS) to sovereign credit risk \( j \) and \( \tilde{D}_{w/1} \) measure the impact of SCDS \( j \) to SCDS \( i \) at estimation window “w”.

The last step consists of the determination of the systemic credit risk contribution. The Systemic Credit Risk Receiver (SCRR) Index for a financial system (country) \( j \) is defined as follows:

\[ \text{SCRR}_{j,w} = \sum_{i \in K^{w}_j} \left( |\tilde{D}_{ij}^w| \right) \]  

(10)

The Systemic Credit Risk Emitter (SCRE) Index for a country \( j \) is defined as follows:

\[ \text{SCRE}_{j,w} = \sum_{i \in K^{\text{OS}}_w} \left( |\tilde{D}_{ij}^w| \right) \]  

(11)

Where \( K^{w}_w \) and \( K^{\text{OS}}_w \) represents the groups of SCDS connected with SCDS \( j \) by incoming and outgoing links at window “w” respectively, \( |\tilde{D}_{ij}^w| \) and \( |\tilde{D}_{ij}^w| \) derived from Eq. (9), which represents raw (incoming) and column (outgoing) direction connectedness of SCDS \( j \) as described in Eq. (11).
3. Data description and preliminary analysis

3.1. Data description

This paper’s sample consists of daily SCDS data with a 5-year maturity from January 2, 2019, to November 18, 2020. We calculated the daily log-returns of the SCDS mid-spreads. We selected fifteen of the most COVID-19 affected countries: the USA, China, Brazil, Germany, the UK, Spain, France, Russia, Italy, Turkey, India, Colombia, Mexico, Peru, and Poland. To capture the effect of country-specific characteristics, we used the stock index returns for each country (e.g., when we use the US CDS spread, we use the US stock market index). The country’s stock market reflects the micro and macroeconomic conditions, and a stable stock market transfers a positive message to local and international investors on the country’s economic conditions.

To capture the effect of macro-state variables that characterize the general state of the financial system, we used the following variables: (i) the VIX index (frequently referred to as the “Fear Index”), which measures global financial uncertainty. (ii) The Merrill Lynch Option Volatility Estimate (MOVE) Index measures uncertainty in the global bond market. (iii) The Crude Oil Volatility Index (OVX) index which measures the oil market uncertainty. (iv) The CBOE Gold ETF Volatility (GVZ) Index, which measures the gold market uncertainty. (v) The (EPU) index measures the global economic policy uncertainty. Many recent empirical studies suggest the relationship between the macro-state variables and SCDS spreads dynamics (e.g., Shahzad et al. (2017); Bouri et al. (2018); Naifar et al. (2020); among others). Table 1 summarizes the variables of the study.

3.2. Preliminary analysis

The objective of this study is to show that spillover across countries’ SCDS spreads rose as the COVID19 hit them. Fig. 1 shows the time trends of the SCDS spreads during the period of the study.

Fig. 1 shows that SCDS spreads exhibit a remarkable rise starting during March 2020, which corresponds to the announcement of COVID-19 as a global epidemic by the World Health Organization. Fig. 2 illustrates the time trends of the SCDS spread and government stringency index for the USA’s case.

Notes. This figure shows sovereign CDS (SCDS) spread (red line) and government stringency index (blue line) from January 1, 2020, until November 18, 2020. We only show the figure for the USA to save space. Figures of other countries are available on request. Source: Oxford COVID-19 Government Response Tracker. More at: bsg.ox.ac.uk/covidtracker or github.com/OxCGRT/covid-policy-tracker.

Fig. 1 and Fig. 2 demonstrate that the COVID-19 pandemic increases all the study countries’ sovereign credit risk. A natural next step is to investigate a spillover among SCDS and construct a financial network of sovereign credit risk spillover effects across countries.

4. Empirical results and discussion

In the first step, we estimated the VaR as in Eq. (3) and (4). We regressed daily log-returns of each SCDS spreads on macro-state variables at the quantile level $\tau = 0.95$, window size $w = 200$ days, and the whole period $T = 475$ days. For example, when the SCDS for the USA is the dependent variable, the independent variables include (i) the USA stock market returns; (ii) SCDS returns of the other fourteen countries; (iii) five macro state variables, which are VIX, EPU, OVX, GVZ and MOVE indexes. In the second step, we estimated the CoVaR based risk network ($\text{CoVaR}_{T\text{NET}}$) by applying the single-index model with variable selection. To justify the use of the nonlinear model, we compare the estimated CoVaR based risk network with CoVaR based linear quantile LASSO ($\text{CoVaR}_L$). Fig. 3 illustrates the estimated $\text{VaR}$ (thinner red line), the estimated CoVaR based risk network $\text{CoVaR}_{T\text{NET}}$ (thicker blue line), and the estimated CoVaR based linear quantile for US SCDS log returns.

Notes. Log returns (black points), $\text{VaR}$ (thin red line), $\text{CoVaR}_{T\text{NET}}$ (thick blue line), and $\text{CoVaR}_L$ (thin green line), $\tau = 0.95$, window size $w = 200$ days, $T = 475$ days.

Fig. 3 demonstrates that the VaRs (95%) and CoVaRs (95%) significantly rose during COVID19 periods (specifically during March 2020, which corresponds to the announcement of COVID-19 as a global epidemic by the World Health Organization).

| Variables | Definition |
|-----------|------------|
| SCDSR     | 5-year sovereign CDS returns. |
| Country-specific variables | The return of the country stock index. |
| CSR       | The return of the country stock index. |
| macro-state variables | Implied volatility on S&P 500 index options. |
| VIX       | Implied volatility on S&P 500 index options. |
| MOVE      | Implied volatility on the global bond market. |
| OVX       | The market’s expectation of 30-day volatility of crude oil prices. |
| GVZ       | The market’s expectation of 30-day volatility of gold prices. |
| EPU       | The Global Economic Policy Uncertainty Index. |
Fig. 1. Time trend of the fifteen SCDS spreads.

Fig. 2. Sovereign CDS spread and government stringency index of USA.

Fig. 3. Log returns and CoVaR estimates for the USA.
The next step is the network analysis made by the CoVaR based risk network \((\text{CoVaR}^{\text{NET}})\). Fig. 4 illustrates the total connectedness between sovereign credit risks during the sample period. The overall level of risk is categorized by the overall connectedness of the sovereign credit risk and the averaged value lambda (\(\lambda\)) of the CoVaR estimations.

Notes. Total connectedness (solid blue line) and average lambda (dashed black line) of 15 countries’ sovereign CDS spreads from October 18, 2019 to November 18, 2020, \(\tau = 0.95\), window size (w) = 200 days, \(T = 475\) days.

The solid blue line of Fig. 4 represents the total connectedness, and the dashed black line represents the evolution of averaged lambda, which indicates the variation of the systemic risk. Fig. 4 shows a higher level of connectedness from March 2020, which corresponds to the announcement of COVID-19 as a global epidemic by the World Health Organization. After that, we observe a consistently high level of total connectedness among 15 SCDS spreads, and the averaged lambda began to increase. As the COVID-19 pandemic started spreading across the globe, the system’s collectively sovereign credit risk became more deeply interconnected and peaked in the mid of March 2020.

The pool connectedness based on the incoming links is defined as: \(CC_{\text{IN}}^{w} = \sum_{i=1}^{k} \sum_{j=1}^{p} \left| \hat{D}_{ij}^{w} \right| \) \(\text{where } p = 1, 2, \ldots 15 \text{ represents the fifteen SCDS of the most COVID-19 affected countries. The pool connectedness based on the outgoing links is defined as: } CC_{\text{OUT}}^{w} = \sum_{j=1}^{k} \sum_{i=1}^{p} \left| \hat{D}_{ji}^{w} \right| \). Fig. 5 illustrates the incoming links for all the SCDS.

Fig. 5 shows the incoming links to all SCDS spread, and it indicates that China, Brazil, and Russia received the highest credit risk from the system. From December 2019 to January 2020, Spain received more credit risk compared to other markets. Notably, the incoming links do not change much over time and stay consistently high from March 2020 until the end of the sample period. The picture is different in the case of outgoing links. Fig. 6 illustrates the outgoing links for all the SCDS.

Fig. 6 demonstrates that Russia, Brazil, China, and Peru emit more credit risk to the financial system than the other countries. From October 2019 to the end of January 2020, China transmits more credit risk to the system. This finding may be explained by the bad news received from China regarding the identification of the ongoing coronavirus in December 2019. From March and June 2020, Russia, Brazil, and China emit more credit risk to the networked countries. From May onwards, Mexico is also a significant emitter of sovereign credit risk to the networked countries.

In the next step, we focus on the directional connectedness from \(\text{SCDS}_i\) to \(\text{SCDS}_j\). Fig. 7 illustrates the directional connectedness between the SCDS.

Note. This elliptical network representation is weighted adjacency matrices for the full sample from January 2, 2019, to November 18, 2020, \(\tau = 0.95\), window size \(w = 200\) days, \(T = 475\).

Fig. 7 shows a strong connection between the sovereign credit risk of Russia, Brazil, China, the USA, Spain, and Italy. Besides, a strong link is observed from France to the UK, from Mexico to Colombia, and from Russia to Turkey. Another association (with higher intensity) is observed from Russia to Germany. There are also weak connections from Italy to France and the UK. To make the links more detailed, we aggregated the directional connectedness between SCDS by the sum of the absolute value of \(\left| \hat{D}_{ij}^{w} \right|\) and \(\left| \hat{D}_{ji}^{w} \right|\) over a window size “w” = 200. Table 2 illustrates country ranking (credit risk transmitters and credit risk receivers) for the full sample.

Table 2 shows that the strongest spillover is from Russia, Brazil, and China. Simultaneously, these countries are also the highest spillover receivers, with China, Brazil, and Russia, respectively. Russia is the highest credit risk emitter to Brazil, China, and Turkey, and the total percentage of risk contribution to the system is 38.7%. We observe 11 out of 15 sovereign credit risk transmitters with different intensities. Overall, we see that China, Russia, and Brazil are the most significant risk transmitters and receivers in the selected sovereign credit risk network.

To further investigate the spillover across countries’ SCDS spreads before and during the COVID19 pandemic, we focus on the directional connectedness from \(\text{SCDS}_i\) to \(\text{SCDS}_j\) before and during the coronavirus period. Fig. 8 illustrates the network representation of a weighted adjacency matrix for the said two sub-samples. We selected March 12, 2020 (which corresponds to the announcement of the World Health Organization COVID-19 as a global pandemic) as the split date for two samples. Fig. 8a shows China is the most important credit risk emitter before the COVID-19 pandemic period, followed by Russia. We observe the strongest transmission of sovereign credit risk from China to Spain, the USA, Russia, Italy, and Germany. These findings are expected as China was the epicenter of the disease, and all the bad news was coming from there until it started spreading throughout the world. Spain was the second most severely hit at that time. During COVID-19, as shown in Fig. 8b, findings are similar to what we find in the full sample analysis. And this finding can be explained by various facts: (i) The increase in the USA’s affected cases. (ii) The attack of the USA president to the World Health Organization as a proxy for China. (iii) The US Bureau of Industry and Security (BIS) increases restrictions on technology exports to China in April 2020. (iv) The US exports to China fell during the coronavirus period. The previous facts increase pressure on supply chains and foreign investment in the USA. Fig. 8b also shows connections of sovereign credit risk emitted from Russia to Germany. The ongoing coronavirus intensely affects Germany’s export (mainly high-tech products and automotive engineering) to Russia.

Note. These elliptical network representations were of weighted adjacency matrices for pre-covid19 and during covid19 periods, \(\tau\)

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2 Instead of showing network for different dates (because the limitation space), we have shown the network before COVID19 (until March 2020) and during COVID19 (from March 2020 until end of sample period.)
5. Conclusion

In this paper, we presented novel empirical evidence on the connectedness between sovereign credit risks in the case of fifteen most COVID-19 affected countries: USA, China, Brazil, Germany, the UK, Spain, France, Russia, Italy, Turkey, Mexico, India, Peru, Poland, and Colombia. We estimated each country’s sovereign credit risk contribution conditional on its upper tail interconnectedness with the relevant country’s financial system. We constructed a financial network consisting of sovereign credit risk spillover effects across countries. Empirical findings show that connectedness among SCDS spread changed over time and is higher during the COVID19 outbreak. Also, we presented a weighted adjacency matrix as a network, and we detected the sovereign credit risk transmitters and receivers during the coronavirus period. We find that China, Russia, and Brazil are the most credit risk emitter-receiver during the COVID-19 pandemic period. Understanding the dynamics and the connectedness of SCDS spread is vital for international investors seeking portfolio investments and foreign borrowers seeking credit risk management and hedging strategies.
Fig. 7. Network representation of a weighted adjacency matrix.

Table 2
Country ranking and top three links – full sample.

| Credit risk transmitters Rank | Country | Percentage | Outgoing links          | Credit risk receivers Rank | Country | Percentage | Incoming links          |
|-------------------------------|---------|------------|--------------------------|----------------------------|---------|------------|--------------------------|
| 1                             | Russia  | 38.7%      | Brazil; China; Turkey    | 1                          | China   | 14.2%      | Russia; Brazil            |
| 2                             | Brazil  | 19.3%      | Russia; China; Turkey    | 2                          | Brazil  | 12.8%      | Russia; China             |
| 3                             | China   | 18.0%      | Italy; USA; Russia       | 3                          | Russia  | 12.3%      | Brazil; China             |
| 4                             | Mexico  | 7.4%       | Colombia; Spain; Poland  | 4                          | France  | 9.4%       | Italy; Germany; Russia    |
| 5                             | Italy   | 5.1%       | France; UK; Germany      | 5                          | Colombia| 9.0%       | Mexico; Peru              |
| 6                             | France  | 4.4%       | UK; Germany              | 6                          | Turkey  | 7.7%       | Russia; Brazil; China     |
| 7                             | Peru    | 2.6%       | Colombia; Poland; India  | 7                          | Italy   | 7.2%       | China; Russia; Brazil     |
| 8                             | Colombia| 2.3%       | Poland; India            | 8                          | UK      | 6.8%       | France; Russia; Brazil    |
| 9                             | Germany | 2.2%       | France; UK; Poland       | 9                          | Germany | 6.5%       | Russia; China; France     |
| 10                            | Turkey  | 0.1%       | France                   | 10                         | USA     | 6.1%       | China; Russia; Brazil     |
| 11                            | UK      | 0.1%       | Germany                  | 11                         | Spain   | 5.4%       | China; Russia; Mexico     |
| 12                            | USA     | 0.0%       | –                        | 12                         | Poland  | 2.3%       | Colombia; Peru; Brazil    |
| 13                            | Spain   | 0.0%       | –                        | 13                         | India   | 0.2%       | Colombia; Peru; China     |
| 14                            | India   | 0.0%       | –                        | 14                         | Mexico  | 0.0%       | –                        |
| 15                            | Poland  | 0.0%       | –                        | 15                         | Peru    | 0.0%       | –                        |
Declaration of Competing Interest

None.

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