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Spillovers and diversification potential of bank equity returns from developed and emerging America

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\begin{abstract}
We examine the network spillovers, portfolio allocation characteristics and diversification potential of bank returns from developed and emerging America. We draw our results by applying a directional spillover index, the tail-event driven network (TENET) and nonlinear portfolio optimization methods on bank returns. We find that the spillovers and connectedness among banks from emerging America are noticeably smaller than those among banks from developed America. The largest emerging market spillover transmitters and receivers are the banks from Brazil, followed by the banks from Chile. The largest developed market spillover transmitter is JP Morgan Chase. The connectedness among banks from developed America is dominated by the banks from the USA, relative to those from Canada. The total connectedness of the emerging market banks is more intensified than that of the banks from developed America due to the effect of the COVID-19 pandemic. The portfolio optimization shows that in developed America, the largest banks from the USA are the largest risk contributors to total portfolio risk, whereas the banks from Canada contribute the least risk. In emerging America, the banks from Brazil contribute the most risk to total portfolio risk while the banks from Peru and one bank from Colombia contribute the least risk. The portfolio of banks from emerging America offers greater diversification potential and lower total portfolio allocation risk.
\end{abstract}

1. Introduction

The banking sector plays an important role in determining the performance of the financial sector and is a key factor, through intermediation in financial transactions, in shaping the functioning of economies. From the perspectives of investment and portfolio management, the banking sector is important to investors because of the close relationship among banks from the same country and across regions of the world, which could lead to contagion risk and to a reduction in diversification potential. Investors are often interested in knowing how banks interdepend (spillover) on one another and in the extent to which they affect and are affected by the performance of the financial sector. Hence, understanding the network structure of interdependence among banks and the financial

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sector is crucial to portfolio investors and risk managers, as this can help them design investment strategies that will reduce dependence risk and increase diversification. Investors are also often interested in identifying the banks that contribute the most (least) risk to their investment positions so that they are considered with caution in their investable portfolios, particularly during times of financial turmoil.

Our study, aware of the above issues and concerns of investors in relation to the banking sector, investigates the spillovers (the network structure of interdependence), risk profile and diversification potential of bank returns from developed and emerging America. Our motivation for modelling bank returns from developed and emerging America is that we are interested in establishing a comparison between banks from those regions of the world in terms of spillover and investment risks. In addition to that little or no research has been conducted about the spillover and portfolio risk characteristics of banks from those regions of the world.

We draw our empirical results by applying a directional spillover index, the tail-event driven network (TENET) and nonlinear portfolio optimization methods on bank returns. The research questions motivating our study are as follows: Are the spillovers among banks from developed America larger than those among banks from emerging America? What banks from developed and emerging America are the largest (smallest) spillover transmitters (receivers)? What banks most largely spillover onto and receive spillovers from the financial sector? What banks from developed and emerging America contribute the most (least) risk to total portfolio risk? Do banks from developed America offer greater diversification benefits than banks from emerging America?

Our main contribution to the relevant literature stems from the obtained empirical and original results which indicate that the spillovers and connectedness among banks from emerging America are noticeably smaller than those among banks from developed America. The largest emerging market spillover transmitters and receivers are the banks from Brazil, followed by the banks from Chile. The largest developed market spillover transmitter is JP Morgan Chase. The connectedness among banks from developed America is dominated by the banks from the USA, relative to those from Canada. The total connectedness of the emerging market banks is more intensified than that of the banks from developed America due to the effect of the COVID-19 pandemic. The portfolio optimization shows that in developed America, the largest banks from the USA are the largest risk contributors to total portfolio risk, whereas the banks from Canada contribute the least risk. In emerging America, the banks from Brazil contribute the most risk to total portfolio risk while the banks from Peru and one bank from Colombia contribute the least risk. The portfolio of banks from emerging America offers greater diversification potential and lower total portfolio allocation risk.

The implications of the results suggest that banks from developed and emerging America with large risk contributions to total portfolio risk should be taken with caution when designing investable portfolios and investment strategy. The low diversification potential exhibited by the portfolio of banks from developed America calls for investors interested in the banking sector to broaden their investment horizons in relation to which countries and economic sectors to invest in. Banks from emerging and developed America acting as the largest spillover transmitters could serve as performance benchmarks for banks that act as spillover receptors. Accordingly, our study appeals to portfolio investors and risk managers who are in search of diversification benefits and risk hedging advantages in the domain of the banking sector.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature. Section 3 explains the analytics of the modelling frameworks implemented. Section 4 presents a list of the banks selected, their ticker codes and the descriptive statistics of the bank returns. Section 5 states and discusses the obtained empirical results. Section 6 concludes the analysis.

2. Literature review

The large-scale breakdown of large banks and financial institutions after the global financial crisis of 2008 had major economic and social costs. Maintaining and controlling financial stability is therefore one of the main responsibilities of financial market regulators and central banks throughout the world. There is some important academic and institutional debate on the optimal level of financial interconnectedness. In this context, two major arguments oppose each other from a theoretical point of view.

The first view highlights the domino effects of networks and states that highly interconnected banking and financial networks can serve as a shock amplifier. Many studies argue that interbank networks may fail to allocate liquidity efficiently due to frictions, such as asymmetric information on bank assets (Flannery, 1996; Freixas & Jorge, 2008), bank free-riding on other banks’ liquidity and imperfect risk-sharing (Bryant, 1980; Bhattacharya & Gale, 1987), bank free-riding on the central bank’s liquidity due to selecting an insufficient liquidity buffer (Repullo, 2005), and frictions brought about by market power (Donaldson, 1992; Acharya, Gromb, & Yorulmazer, 2012). Among others, Dasgupta (2004) argues that contagion may occur with positive probability in a banking system as a result of balance sheet connections across institutions. Diamond and Rajan (2005) examined how the liquidity shortages and solvency problems of banks interact and how each can cause the other. Nier, Yang, Yorulmazer, and Alentorn (2007) analysed how the structure of the financial system affects systemic risk. Caballero and Símsek (2009) proposed a model for capturing what appears to be a central feature of financial panic. Gai and Kapadia (2010) explored how the probability and potential impacts of contagion are influenced by aggregate and idiosyncratic shocks, changes in network structure, and asset market liquidity. Blume, Easley, Kleinberg, and Kleinberg (2013) modelled interbank contagion as an epidemic. Zawadowski (2013) proposed a model of an entangled financial system in which banks hedge their portfolio risk using over-the-counter (OTC) contracts. The author argues that inefficiency arises when banks shift risk through the network externalities created by OTC contracts. Elliott, Golub, and Jackson (2014) studied cascades of failures occurring in financial networks using a model with equity share cross-ownership. Cabrales, Gottardi, and Vega-Redondo (2017) investigated how the capacity of an economic system to absorb shocks depends on the specific patterns of interconnections established among financial firms.

The second view focuses on insurance effects of networks and argues that bank networks can serve as shock-absorber systems. Some studies argue for the mutual monitoring and insurance effects of interbank networks. For example, Allen and Gale (2000)
studied how the banking system responds to contagion when banks are connected under different network structures. These authors showed that incomplete network structures are more prone to contagion than complete network structures and that more densely interconnected networks are more resilient because the proportion of losses in one bank’s portfolio is divided among several creditors, reducing the impact of negative shocks from an individual bank on other banks within the network. Freixas, Parigi, and Rochet (2000) argue that more interbank connections enhance the resilience of a system to the insolvency of a particular bank. Babus (2007, 2016) investigates whether banks can commit ex ante to mutually insure each other when contagion risk is present in the financial system.

Empirical studies usually focus on the networks and interdependence of banks in European countries. For example, Abbassi, Brownlee, Hans, and Podlich (2017, Germany), Becher, Millard, and Soramäki (2008, UK), Boss, Elsinger, Summer, and Thurner (2004, Austria), Cocco, Gomes, and Martins (2009, Portugal), Degryse and Nguyen (2007, Belgium), Diebold and Yilmaz (2014, U.S.), Elsinger, Lehár, and Summer (2006, Austria), Fournel, Heam, Salakhova, and Tavolaro (2013, France), Furfine (2003, U.S.), Langfeld, Liu, and Ota (2014, UK), Mistrulli (2011, Italy), Philippas, Koutelidakis, and Leontitis (2015, Europe and UK), Sheldon and Maurer (1998, Switzerland), Toivanen (2013, Finland), Upper and Worms (2004, Germany) and Wells (2004, UK) studied the financial networks of developed European countries. Aldasoro and Alves (2018), Brunetti, Harris, Mankad, and Michailidis (2015), Glasserman and Young (2015) and Kleinow and Moreira (2016) studied contagion in the financial network using data from the European interbank market. Fries, Raiser, and Stern (1999), Darvas and Szapáry (2000), Gelos and Sahay (2001), Weller and Morzuch (2000), and Betz, Hautsch, Peltonen, and Schienle (2016) analysed the bank networks of European Union (EU) and central and eastern European (CEE) countries.

Some studies have examined the bank networks of developed American countries. Among others, Furfine (2003) examined U.S. Fedwire data. Billio, Getmansky, Lo, and Pelizzon (2012) proposed several econometric measures of connectedness based on a principal-components analysis and Granger-causality networks and applied them to the monthly equity returns of hedge funds, banks, broker/dealers, and insurance companies in the U.S. Diebold and Yilmaz (2014) identified the time-varying connectedness of major U.S. financial institutions’ stock returns and volatilities. Cai, Eidam, Saunders, and Steffen (2018) analysed the interconnectedness of banks in U.S. loan syndication. Kreis and Leisen (2018) introduced a systemic risk measure based on the default frequency of the banking sector and estimated loadings of the U.S. banking system. Minoiu and Reyes (2019) explored properties of the global banking network, including those of U.S. and Canadian banks. Kanno (2015) assessed systemic risk in the global banking system by studying seven Canadian banks. Tonzer (2015) studied spillover risks in cross-border interbank networks including U.S. and Canadian banks.

Relatively few studies have examined bank networks of emerging American countries. Cont and Moussa (2010) presented a quantitative methodology for analysing the potential for contagion and systemic risk in a financial network and applied the methodology to a dataset from Brazil. De Souza, Tabak, Silva, and Guerra (2015) modelled and analysed contagion in interbank networks using a dataset for the Brazilian financial system. De Souza (2016) simulated the effects of credit risk, changes in capital requirements and price shocks on the Brazilian banking system. Silva, de Souza, and Tabak (2016) investigated how the structure of financial networks can affect bank efficiency in the Brazilian financial network. Silva, Guerra, Tabak, and Miranda (2016) analysed the roles of financial institutions within the Brazilian interbank market by using a network-based approach to assess how compliant networks serve as perfect core-periphery structures. Silva, de Souza, & Tabak (2018) simulated shocks to the real sector and evaluated how the financial system reacts to and amplifies these events using Brazilian loan-level data. Martínez-Jaramillo, Alexandrova-Kabadjova, Bravo-Benítez, and Solórzano-Margain (2014) examined topological properties of interbank exposure and payment system networks to measure and monitor systemic risk in the Mexican banking system. Poledna, Molina-Borboa, Martínez-Jaramillo, van der Leij, and Thurner (2015) developed a multi-layer network approach to quantify systemic risk and applied it to a dataset from the Mexican financial system. Berndsen, León, and Renneboog (2018) also analysed the multiplex (i.e., multi-layered) network comprising the large-value payment system, sovereign securities settlement system, and spot market foreign exchange settlement system of the Colombian financial system. León, Machado, and Sarmiento (2018) modelled the allocation of central bank liquidity among participants of the Colombian interbank market.

All of the above studies focused on data from only one country and did not consider connections between banks from several American countries. In this regard, as far as we know, our study is the first to investigate the financial networks of banks from developed and emerging American countries, although economic activity among these countries is very closely linked in terms of trade and finance.

Banks and other financial institutions are closely linked through networks of different types of financial contracts and connections. Thus, most empirical studies aim to identify the interconnectedness of the financial system using a network approach. In these research studies, several kinds of connectivity and transmission channels have been identified as links or measures of interconnectedness in the interbank network.

Most researchers have analysed physical trading networks based on direct contractual agreements, such as those stemming from interbank transfers of assets and liabilities (i.e., interbank lending and borrowing) (Affinito & Pozzolo, 2017; Allen and Babus, 2009; Babus, 2016; Barroso, Silva, & de Souza, 2018; Betz et al., 2016; Brunetti et al., 2015; Cocco et al., 2009; Degryse & Nguyen, 2007; Elsinger et al., 2006; Furfine, 2003; Glasserman & Young, 2015; Sheldon & Maurer, 1998; Silva, de Souza, et al., 2016, Silva, Guerra, et al., 2016, Silva et al., 2018; Sun & Chan-Lau, 2017; Toivanen, 2013; Upper & Worms, 2004), credit default swap (CDS) contracts (Ballester, Casu, & González-Urteaga, 2016; Gandy & Veraart, 2019; Kanno, 2019; Peltonen, Scheicher, & Vuillemey, 2014), and equity share cross-ownership (Cao, Gregory-Smith, & Montagnoli, 2018; Dastkhan & Gharneh, 2016, 2018; Elliott et al., 2014; Elsinger, 2009). However, bank networks are defined in our study based on economic connections identified from stock market price data (i.e., correlation networks of stock returns) as in Billio et al. (2012), Diebold and Yilmaz (2014), Brunetti et al. (2015) and Candelon, Ferrara, and Joëts (2018). The latter view is generally accepted in the literature as strong correlations in the bank equity
sector are the main source of systemic risk among financial institutions, and interconnectedness is driven by common features of the portfolio asset holdings of banks and mutual funds.\(^1\) On the sectoral level Balli, Balli, and Louis (2013) following Bekaert and Harvey (1997), Ng (2000), and Bekaert, Harvey, and Ng (2005), and by focusing on the return, volatility and trend spillover effects of global and local shocks, investigated the spillovers among Euro-wide sector indices and how integrated sector equity indices from the Euro area and USA are. With respect to spillovers among Euro-wide sectors they find that once the Euro was introduced global shock derived spillovers declined. In the same line they also find that the aggregate Euro index affects in different degrees the sectoral equity indices, most noticeably those from the financial services industry. In relation to integration among Euro and USA sector equity indices they find that when the trend is considered in the analysis of volatility spillovers some sector equity indices from both regions of the world have a similar response to global and local shocks, and that integration across equity sectors is not uniform. Balli, Bashir, and Louis (2013) also using the spillover models proposed by Bekaert and Harvey (1997), Ng (2000), and Bekaert et al. (2005) studied how global and local shocks impacted the sector equity returns from Gulf Cooperation Council (GCC) countries. Their findings indicate asynchronous and heterogeneous (in terms of magnitude) effects of regional and global shocks on GCC-wide sector equity returns. These shocks have a weaker impact on utility, telecom and basic material sectors, compared to other sectors, and there has been a reduction in the effect global shocks have on GCC sector returns. Lastly, they also find that national GCC equity market portfolios perform less better than portfolios diversified across GCC-wide sectors. Balli, Balli, and Luu (2014) by means of univariate AR-GARCH and trend spillover models analyse the impact of global and local shocks on the sector and national returns of South East Asian Nations (ASEAN). They also analyse the resource allocation characteristics of ASEAN-wide sector and national portfolios using mean–variance portfolio optimization. Their findings indicate a sector dependent effect from market shocks, with local shocks being the primary drivers of most ASEAN-wide sector and national returns. Moreover, a decreasing impact on most ASEAN-wide sector returns from global and regional shocks is observed. Lastly, the efficient frontier of portfolios consisting of only ASEAN national returns is better than that corresponding to portfolios comprised by ASEAN-wide sector returns.

In this study, to examine the direction and strength of spillover effects among the network structure of banks we use the directional spillover index approach of Diebold and Yilmaz (2009, 2014, 2015), which has been applied in several financial studies. For example, this approach has been used to investigate spillover effects among U.S. stock markets (Barunik, Kočenda, & Vácha, 2016); emerging and developed stock markets (Yarovalya, Brzeszczyński, & Lau, 2016); Latin American stock markets (Gamba-Santamaria, Gomez-Gonzalez, Hurtado-Guarín, & Melo-Velandia, 2017); and developed, emerging, and frontier stock markets (Baumohl, Kočenda, Lyócsa, & Výrost, 2018). Louzis (2015) measured directional spillover effects in financial markets of the Euro area, including the money, stock, foreign exchange, and bond markets. Balli, Uddin, Mudassar, and Yoon (2017) and Kang and Yoon (2018) examined the spillover effects of economic policy uncertainty in several countries.

Our study also uses the conditional value-at-risk (CVaR) measure and a non-convex portfolio optimization method to investigate the risk contributions of a single bank to total portfolio risk. The CVaR initially proposed by Rockafellar and Uryasev (2000) has been widely used in financial risk modelling because it can alleviate the well-known limitations of the VaR measure, such as the lack of sub-additivity and convexity (Artzner et al., 1997, 1999). Although both the CVaR and VaR use threshold values to determine the loss function in the negative tail of the distribution, the CVaR is less optimistic because it models these values in the negative tail exceeding the VaR threshold. Thus, the VaR may underestimate portfolio risk. When the VaR denotes the loss that will not be exceeded at a certain confidence level for a certain time period, the CVaR aims to estimate the loss that could exceed the VaR at a certain confidence level and for the time horizon. The CVaR is known to be a more conservative measure of market risk exposure (Szegő, 2002; Uryasev, 2000).

3. Models

3.1. Directional spillover index

In analysing spillover effects across bank returns of developed and emerging America, we use the spillover index methodology of Diebold and Yilmaz (2009, 2014, 2015), which fits a generalized VAR (GVAR) approach and incorporates the variance decomposition matrix. This spillover approach provides estimates of total, net and directional spillover effects among series of bank equity returns. The evolution of bank equity return series is assumed to follow a covariance stationary VAR(\(p\)) of the following form:

\[
x_t = \sum_{i=1}^{p} \psi_i x_{t-i} + \varepsilon_t
\]

The variable \(x_t\) is an \(N \times 1\) vector of bank equity returns, and \(\psi_i\) is an \(N \times N\) matrix of autoregressive coefficients denoting the effect of past bank returns on the evolution of \(x_t\), the predicted returns. The term \(\varepsilon_t\) is an error term that accounts for the effect of variables not considered in the evolution of the process. This term is assumed to be serially uncorrelated. A moving average representation of Eq. (1) is \(x_t = \sum_{i=0}^{\infty} \Theta_i \varepsilon_{t-i}\) where \(\Theta_i = \psi_1 \cdots \psi_i \Theta_{t-i} + \cdots + \psi_i \Theta_{t-p}\). In applying the GVAR, the effects of variable \(j\) on the \(H\)-step-ahead generalized forecast error variance of variable \(i\) can be expressed as follows:

\[
c_{ij}(H) = \frac{\sigma_{ij}^2 \sum_{h=0}^{H-1} (c_i \Theta_h \Sigma \theta_{h+1} c_j)^2}{\sum_{h=0}^{H-1} (c_i \Theta_h \Sigma \theta_{h+1} c_j)}
\]

\(^{1}\) For more details, see Elsinger et al. (2006), Brunetti et al. (2015), and Braverman and Minca (2018) among others.
where the term $\Sigma$ is a non-orthogonalized covariance matrix of errors corresponding to the VAR system. The term $\sigma_j$ is a vector of standard deviations of the error term for the $j^{th}$ equation, and $\epsilon_i$ is an $N \times 1$ vector taking a value of one as the $i^{th}$ element and a value of zero otherwise. The term $\Theta_h$ accounts for coefficients that scale the $h$-lagged error in the infinite moving-average representation of VAR.

Pairwise directional spillovers from $j^{th}$ bank returns to $i^{th}$ bank returns are estimated as follows:

$$C_{ij}^H = C_{ij}^\theta (H)$$

(3)

All directional spillovers from all other banks to the $i^{th}$ bank are calculated as the sum of off-diagonal values from the resulting connectedness matrix as follows:

$$C_{i..}^H = \sum_{j \neq i} C_{ij}^\theta (H).$$

(4)

The total and off-diagonal sums of columns represent the total directional connectedness between all other banks and the $j^{th}$ bank as follows:

$$C_{..j}^H = \sum_{j \neq i} C_{ij}^\theta (H).$$

(5)

We can also define net total directional connectedness as follows:

$$C_{i}^H = C_{i..}^H - C_{i..}^H.$$  

(6)

Finally, the total connectedness (system-wide connectedness) is the ratio of the sum of to-others (from-others) elements of the variance decomposition matrix to the sum of all elements:

$$C^H = \frac{1}{N} \sum_{j \neq i} C_{ij}^\theta (H).$$

(7)

To develop the network topology of market connectedness, Diebold and Yilmaz (2014, 2015) interpret the variance decomposition matrix as the adjacency matrix of a weighted directed network. The elements of the adjacency matrix include pairwise directional connectedness, $C_{ij}^H$; row sums of the adjacency matrix (node in-degrees) denote total directional connectedness “from,” $C_{i..}^H$; and column sums of the adjacency matrix (node out-degrees) denote total directional connectedness “to,” $C_{..j}^H$.

3.2. TENET model

The so-called tail-event driven network (TENET) was proposed by Härdle, Wang, and Yu (2016). The TENET is constructed by combining systemic interconnectedness among banks based on tail-event spillover effects and a single-index model (SIM) for quantile regressions in a high dimensional framework. The TENET can be estimated in three steps.

In the first step, we measure VaR for each bank by employing linear quantile regression. The VaR of a bank $i$ at quantile level $\tau \in (0, 1)$ is defined as follow:

$$P(X_{i,t} \leq \text{VaR}_{i,t}) \equiv \tau$$

(8)

$$X_{i,t} = \alpha_i + \gamma_i M_{-1,t} + \tilde{\epsilon}_{i,t}$$

(9)

$$\text{VaR}_{i,t} = \tilde{\alpha}_i + \tilde{\gamma}_i M_{-1}$$

(10)

where $X_{i,t}$ is the log returns of bank $i$ at time $t$ and $M_{-1}$ includes the macro state variables.

In the second step, TENET estimates the non-linear linkage between banks, and contains more banks into the research to measure the tail-driven risk interdependencies. Accordingly, we have:

$$X_{i,t} = g(\hat{\beta}_{i,j}^T R_{i,t}) + \epsilon_{i,t}$$

(11)

$$\text{CoVaR}_{i,j,t}^{\text{TENET}} \equiv \frac{\partial g(\hat{\beta}_{i,j}^T R_{i,t})}{\partial R_{j,t}} R_{j,t} = \hat{\beta}_{ij}^T R_{j,t}$$

(12)

$$\hat{\beta}_{ij} = \left| \frac{\partial g(\hat{\beta}_{j}^T R_{j,t})}{\partial R_{j,t}} \right| R_{j,t} = g'(\hat{\beta}_{j}^T R_{j,t}) \hat{\beta}_{ij}$$

(13)

where $R_{j,t} \equiv \{X_{j,t-1}, M_{-1,j}, B_{j,-1}\}$ is the information set. Also, here $X_{j,t} \equiv \{X_{j,t}, X_{j,t}, \ldots, X_{k,t}\}$ is the set of $(k-1)$ independent variables such as the log returns of the banks apart from a bank $j$, $k$ is the number of banks. The term $B_{j,t-1}$ accounts for the internal factors of bank $j$. The term $\hat{\beta}_{ij} = \{\hat{\beta}_{ij}, \hat{\beta}_{iM}, \hat{\beta}_{jM}\}$ are the parameters.
The CoVaR\textsuperscript{TENET} stands for tail-event driven network risk using SIM model and is estimated by plugging in VaR of bank $i$ at level $r$ estimated in Eq. (10) into the Eq. (11). The terms $\hat{\theta}_{j|i}$, $\hat{\theta}_{j|i|}$, $\hat{\theta}_{j|i}$, and $R_{j|i}$ are $\{VAR_{j|i}, M_{j|i-1}, B_{j|i-1}\}$. $\hat{\cdot}$ represent the non-linear linkage between them. The parameter $\hat{D}_{j|i}$ is the gradient measuring the marginal effect of covariates evaluated, and the component-wise expression is $\hat{D}_{j|i} \equiv [\hat{D}_{j|i}, \hat{D}_{j|i|}, \hat{D}_{j|i}]^T$. We centralize spillover effects among banks, so our study only considers the partial derivatives of bank $j$ on the other banks (i.e. $\hat{D}_{j|i}$) in our tail network analysis. We apply moving window estimation to estimate the parameters. Let $\hat{D}_{j|i}$ be one element in $\hat{D}_{j|i}$ at the $s^{th}$ window, where $j$ stands for the bank as before, $i$ represents another bank that is one element in the other banks set $- j$. It means that $\hat{D}_{j|i}$ is the impact from bank $i$ to bank $j$ at estimation window $s$.

And, let $G(V, E)$ be the TENET, where $V = \{1, 2, \ldots, k\}$ is a set of nodes (banks) and $E$ is the set of directed edges between them. The weighted adjacency matrix $A$ of the TENET at the $s^{th}$ window is to be $A_s = (|\hat{D}_{j|i}|)_{h \times k}$, where $|\hat{D}_{j|i}|$ is defined as the connectedness across banks.

In the third step, TENET explains how to measure systemic risk measures. The SIM quantile regression (without variable selection) is used again to regress a predefined system returns on bank $j$ with controlling all the risk contributors for bank $j$ selected in Step 2, then the systemic risk contribution can be measured as follows:

$$X_{i,t} = g(B_{i|j}, F_{j,t}) + \epsilon_{i,t}$$

(14)

$$\text{CoVaR}^{\text{SYSTEM}} \equiv \text{CoVaR}^{\text{SIM}} = \hat{\cdot}(\hat{B}_{j|i} F_{j,t})$$

(15)

$$\hat{D}_{j|i} \equiv \frac{d\hat{g}}{dF_{j,t}|_{F_{j,t}}} = \hat{g}^\prime(\hat{B}_{j|i} F_{j,t})$$

(16)

where $X_{i,t}$ is a weighted sum of the log returns of the banks' system. Also, $F_{j,t} \equiv \{X_{j,t}, C_{j,t}\}$ and $C_{j,t} \equiv \{X_{j,t}, M_{j,t-1}, B_{j,t-1}\}$, with the star symbol '*' denoting that only those variables which are selected to be relevant for bank $j$ by the variable choice procedure are included, i.e. the log returns of selected bank except for bank $j$, the selected macro state variables and the selected bank characteristics $\hat{B}_{j|i} \equiv [\hat{B}_{j|i}, \hat{B}_{j|i|}]^T$. We also have that $F_{j,t} \equiv [VAR_{j,i}, C_{j,t}]$ and $C_{j,t} \equiv [VAR_{j,t-1}, M_{j,t-1}, B_{j,t-1}]$, i.e. the measured VaRs of selected banks except for bank $j$, the selected macro state variables and selected bank characteristics are included in $C_{j,t}$. Moreover, $\hat{B}_{j|i} \equiv [\hat{B}_{j|i}, \hat{B}_{j|i|}]^T$, and $\hat{B}_{j|i} \equiv [\hat{B}_{j|i}, \hat{B}_{j|i|}]^T$ is the partial derivatives of system CoVaR with respect to the variables in $F_{j,t}$ evaluated at level $F_{j,t} = F_{j,t}$. The term $\hat{D}_{j|i}$ is the partial derivative of system CoVaR with respect to bank $j$. In terms of identification of the system risk contributions, we focus here on $\hat{D}_{j|i}$.

3.3. Non-convex portfolio optimization

When implementing non-convex portfolio optimization, the underlying differential evolution method uses a floating-point encoding of the marginal distribution, along with arithmetic operators and alterations, to select and develop potentially feasible optimization solutions. Non-convex problems are generally more difficult to solve by regular optimization methods and generally involve making numerical approximations. In this regard, the differential evolution optimization method is an iterative process that systematically converges to an optimal solution through the application of transformations (or differential mutations) on vector parameters extracted from the marginal distributions or from the distribution of financial variables modelled in our study (see Ardia, Boudt, Carl, Mullen, and Peterson (2011) for further details). The method is employed for risk minimization purposes and can be expressed analytically as follows. Let NP represent the number of vector parameters $x \in \mathbb{R}^d$ of the population where $d$ accounts for dimensions. The first generation of parameters is obtained by estimating random values falling between predefined upper and lower boundaries. Each generation involves the creation of a new population from existing population members $\{x_i; i = 1, \ldots, NP\}$ where $i$ indicates the vectors that make up the population. The creation of new populations is carried out via differential mutations of the population members as follows. Suppose that $x_{i,d}$ stands for a certain population with $d$ vectors of parameters and $g$ generations. The first transform or mutated vector of parameter $\omega_{i,g}$ is produced by randomly selecting three population members $n_{i,g}, n_{i,g}, r_{i,g}$ or:

$$v_{i,g} = x_{i,d} + F(x_{i,d} - x_{r_{i,g}})$$

(17)

where $F$ is a positive scale factor taking values greater than zero and less than one (Ardia et al., 2011). The conditional value-at-risk contribution percentage of each developed and emerging American bank is estimated as follows (Boudt, Carl, & Peterson, 2012):

$$w_i \left[ -\mu_i + \left( \frac{1}{w} \sum w \phi(z_{i,d}) \right) \right]$$

$$-w_i \mu + \sqrt{w} \sum w \phi(z_{i,d})$$

(18)

where $w = (w_1, \ldots, w_j)$ is a transpose vector of weights and $\mu = (\mu_1, \ldots, \mu_j)$ is a transpose mean vector. The covariance matrix is represented by sigma parameter $\Sigma$. The parameter $z_{i,d}$ stands for the $\alpha$-quantile of the standard normal distribution. The parameter $\phi(\cdot)$ denotes a standard normal density function. In the optimization problem, we apply $\alpha = 5\%$.

The second form of portfolio optimization we use to examine total portfolio allocation risk and diversification potential uses the conditional Value-at-Risk as the risk measure. The CVaR measure introduced by Rockafellar and Uryasev (2000) as a way to
compensate for the inadequacies of the VaR (e.g., it assumes a normal return distribution). The risk measure captures the return distribution in the negative tail by employing probabilities in the forecasting of a portfolio’s losses. In this respect, the risk measure provides a probabilistic approximation of the loss that will exceed the VaR where the VaR estimate is a negative tail threshold risk value of the portfolio. The CVaR is considered to be more in tune with the loss function of the negative tails’ return distribution because it is less optimistic than the VaR (Szegö, 2002; Uryasev, 2000). In this case, the optimization problem to be solved is as follows (Ghalanos, 2013):

$$\min_{w,d,v} \sum_{i=1}^{n} d_i + v$$

Subject to:

$$\sum_{j=1}^{m} w_j r_{ij} + v \geq -d_i, \forall i \in \{1, \ldots, n\},$$

(20)

$$\sum_{j=1}^{m} w_j \mu_j = \mu_P,$$

(21)

$$\sum_{j=1}^{m} w_j = 1,$$

(22)

$$w_j \geq 0, \forall j \in \{1, \ldots, m\},$$

(23)

$$d_i \geq 0, \forall i \in \{1, \ldots, n\},$$

(24)

where $v$ represents the VaR at the-coverage rate and $d_i$ accounts for deviation values below the VaR. The CVaR portfolio optimization we implement considers a 1-day time horizon and a 95% confidence level. This consideration means that with 95% probability, the loss of the portfolio will not exceed the 1-day VaR.

4. Data

The data sample considered for the analysis of directional spillovers and portfolio optimization of banks from developed and emerging America consist of daily frequency price series spanning from January 11, 2011 to January 10, 2019, accounting for a total of 2013 observations. For the analysis of network connectedness and spillovers between banks using the TENET method we employ weekly frequency price series of banks spanning from April 2, 2010 to March 20, 2020. We opt for the usage of weekly data to apply the TENET method because the modelling is more adequate with that type of data according to previous studies (Härdle et al., 2016). Also, as part of the TENET modelling we consider variables such as the implied CBOE volatility index (VIX), the TED spread which is the difference between the 3-month treasury bill and the 3-month LIBOR based in US dollars, the T10Y3M which represents the 10-year treasury constant maturity minus 3-month treasury constant maturity, and the Western Texas Intermediate crude oil. These datasets also span from April 2, 2010 to March 20, 2020. The price series of listed banks from emerging America include banks from the U. S. and Canada. The price series of listed banks from emerging America include banks from Brazil, Chile, Mexico, Colombia and Peru. Using the price series of bank equity, we estimate logarithmic returns on which we implement our modelling frameworks. One additional variable we consider in our analysis is the MSCI ACWI Financials Index in order to investigate the impact (spillovers) banks have on it and vice versa. This global financial index captures large and midcap representations across 23 developed markets and 24 emerging markets, including the largest banks and financial institutions from the U. S. and Canada and from all of the emerging American countries under consideration. All banks selected for our analysis are the largest capitalized from each country. All price series have been downloaded from Eikon Thompson Reuters. Table 1 displays the names and ticker codes of the considered banks from developed and emerging America.

Table 2 displays descriptive statistics for the bank returns and other variables considered. It can be observed that all banks’ historical returns are in the range of zero. In developed America all banks’ returns display negative skewness. In emerging America with the exception of the three banks from Brazil (BBAS3, BBDC4, SANB4) all other bank returns display negative skewness. All volatilities are in the range of zero for all banks from developed and emerging America. The kurtosis for all banks is positive and larger than 3 indicating the absence of the normal distribution. In terms of risk (standard deviation) and return trade-offs, the banks from emerging America appear to be the better choice.

5. Empirical results

5.1. Spillover index results

Table 3 displays the spillovers among banks from emerging America. It can be observed that the largest spillover transmitters and receivers are the banks from Brazil, followed by the banks from Chile. Spillovers between pairs of emerging market banks are larger between banks from the same country, compared with banks from different countries. Specifically, the Banco do Brasil (BBAS3) largely spillovers on Banco Bradesco (BBDC4) from the same country (34.90, 34.88), with the spillover transmission of the former
Table 1
Names and ticker codes of banks from developed and emerging America.

| Stock codes of banks in developed America | Stock names of banks in developed America | Stock codes of banks in emerging America | Stock names of banks in emerging America |
|------------------------------------------|------------------------------------------|-----------------------------------------|------------------------------------------|
| JPM                                     | JP Morgan Chase                           | BBAS3                                   | Banco do Brasil                          |
| BRKs                                    | Berkshire Hathaway                        | BBDC4                                   | Banco Bradesco                           |
| BAC                                     | Bank of America                           | SANB4                                   | Banco Santander Brasil                   |
| WFC                                     | Wells Fargo                               | BSANTANDER                              | Banco Santander Chile                    |
| C                                        | Citigroup                                 | CHILE                                   | Banco de Chile                           |
| GS                                      | Goldman Sachs                             | BCI                                     | Banco de Credito e Inversiones          |
| MS                                      | Morgan Stanley                            | GFNORTEO                                | Grupo Financiero Banorte                 |
| RY                                      | Royal Bank of Canada                      | GFINBURO                                | Grupo Financiero Inbursa                 |
| TD                                      | Toronto-Dominion Bank                     | BBO                                     | Banco de Bogota                          |
| BMO                                     | Bank of Montreal                          | BIC                                     | Bancolombia                              |
| BNS                                     | Bank of Nova Scotia                       | DVI,p                                   | Banco Davivienda                         |
| CM                                      | Canadian Imperial Bank of Commerce        | CREDITC1                                | Banco de Credito del Peru                |
| NA                                      | National Bank of Canada                   | BBVAC1                                  | Banco BBVA Peru                          |

Notes: This table displays the ticker codes and names of banks from developed and emerging America considered. Banks from developed America correspond to those operating in the U.S. and Canada and banks from emerging America correspond to those operating in Brazil, Chile, Mexico, Colombia and Peru.

Table 2
Descriptive statistics of the returns of banks from developed and emerging America.

| Stock Codes | \( \mu \)  | \( \sigma \)  | \( K \)  | \( SK \) |
|-------------|------------|--------------|---------|---------|
| JPM         | 0.0013     | 0.0340       | 5.3401  | -0.5113 |
| BRKs        | 0.0015     | 0.0228       | 4.8011  | -0.2707 |
| BAC         | 0.0003     | 0.0437       | 5.0516  | -0.2439 |
| WFC         | -0.0002    | 0.0332       | 6.9202  | -0.5303 |
| C           | -0.0001    | 0.0437       | 5.5986  | -0.4810 |
| GS          | -0.0001    | 0.0365       | 4.4152  | -0.1585 |
| MS          | 0.0002     | 0.0448       | 4.6099  | -0.2791 |
| RY          | 0.0000     | 0.0267       | 5.9713  | -0.2702 |
| TD          | 0.0001     | 0.0261       | 5.1394  | -0.6145 |
| BMO         | -0.0006    | 0.0280       | 10.1751 | -1.4047 |
| BNS         | -0.0005    | 0.0270       | 6.0882  | -0.6283 |
| CM          | -0.0005    | 0.0274       | 7.9568  | -1.0217 |
| NA          | 0.0002     | 0.0304       | 6.7010  | -0.9885 |
| BBAS3       | -0.0006    | 0.0682       | 6.1607  | 0.2531  |
| BBDC4       | -0.0001    | 0.0535       | 5.7992  | 0.1279  |
| SANB4       | 0.0001     | 0.0607       | 3.9654  | 0.1198  |
| BSANTANDER  | -0.0003    | 0.0349       | 4.6346  | -0.2992 |
| CHILE       | 0.0006     | 0.0296       | 5.8492  | -0.6229 |
| BCI         | 0.0004     | 0.0367       | 5.0247  | -0.2452 |
| GFNORTEO    | 0.0001     | 0.0478       | 5.4060  | -0.3280 |
| GFINBURO    | -0.0014    | 0.0438       | 3.9217  | -0.0928 |
| BBO         | -0.0002    | 0.0312       | 7.7990  | -0.9007 |
| BIC         | -0.0013    | 0.0419       | 14.6656 | -1.4992 |
| DVI,p       | -0.0010    | 0.0384       | 14.9766 | -1.6837 |
| CREDITC1    | 0.0022     | 0.0307       | 7.3903  | 0.8412  |
| BBVAC1      | 0.0009     | 0.0332       | 6.8313  | -0.0325 |
| State variables                                      |                                           |                                           |                                           |
| Financials index                                     | 0.0001                                  | 0.0249                                  | 8.1209                                  | -0.9851 |
| WTI crude oil                                        | -0.0023                                 | 0.0411                                  | 16.1570                                 | -1.6918 |
| VIX                                                   | 17.0010                                 | 6.3599                                  | 19.8251                                 | 3.0239  |
| TED spread                                            | 0.2948                                  | 0.1132                                  | 5.1754                                  | 1.1518  |
| T10Y3M                                                | 1.7496                                  | 0.9130                                  | 2.6360                                  | -0.3150 |

Note: Abbreviations \( \mu \), \( \sigma \), \( K \) and \( SK \) denote the mean, standard deviation, kurtosis and skewness. The WTI abbreviation means Western Texas Intermediate, while VIX is the implied CBOE volatility index. The TED spread is the difference between the 3-month treasury bill and the 3-month LIBOR based in US dollars. The T10Y3M represents the 10-year treasury constant maturity minus 3-month treasury constant maturity.

bank being slightly larger than its spillover reception from the latter bank. Banco Santander Chile (BSANTANDER) largely spillovers on Banco de Chile (CHILE) (17.43, 17.13) and Banco de Credito e Inversiones (BCI) (13.50, 12.43) from the same country, with its spillover transmission to both banks being slightly larger than its spillover reception from them. Grupo Financiero Banorte
Table 3
Spillover index among banks from emerging America.

| From   | BBAS3 | BBDC4 | SANB4 | BSANTANDER | CHILE | BCI | GFNORTEO | GFINBURO | BBO | BIC | DVI_p | CREDITC1 | BBVAC1 | TO  | ALL  | Net  |
|--------|-------|-------|-------|------------|-------|-----|----------|----------|-----|-----|-------|----------|--------|-----|------|------|
| BBAS3  | 62.18 | 34.88 | 1.15  | 0.26       | 0.19  | 0.11| 0.25     | 0.27     | 0.09| 0.13| 0.20  | 0.19     | 0.13   | 37.8| 101.2 | 1.9  |
| BBDC4  | 34.90 | 62.35 | 1.34  | 0.29       | 0.21  | 0.07| 0.06     | 0.12     | 0.06| 0.19| 0.12  | 0.19     | 0.09   | 37.7| 103.1 | 3.1  |
| SANB4  | 2.36  | 3.44  | 91.28 | 0.16       | 0.24  | 0.35| 0.41     | 0.37     | 0.36| 0.15| 0.23  | 0.07     | 0.58   | 8.7 | 95.7  | 4.4  |
| BSANTANDER | 0.20  | 0.22  | 0.15  | 69.14      | 17.13 | 12.43| 0.06     | 0.07     | 0.20| 0.12| 0.04  | 0.07     | 0.04   | 30.9| 102.8 | 33.6 |
| CHILE  | 0.18  | 0.18  | 0.12  | 17.43      | 69.89 | 11.46| 0.08     | 0.19     | 0.04| 0.12| 0.07  | 0.22     | 0.03   | 30.1| 102.8 | 1.15 |
| BCI    | 0.36  | 0.39  | 0.07  | 13.50      | 12.40 | 71.99| 0.12     | 0.12     | 0.13| 0.12| 0.14  | 0.23     | 0.43   | 28.0| 102.1 | 13.8 |
| GFNORTEO| 0.15  | 0.35  | 0.12  | 0.06       | 0.16  | 0.12| 85.74    | 12.00     | 0.59| 0.05| 0.16  | 0.21     | 0.29   | 14.3| 103.1 | 2.7  |
| GFINBURO| 0.10  | 0.25  | 0.17  | 0.29       | 0.16  | 0.15| 11.94    | 85.85     | 0.10| 0.21| 0.21  | 0.28     | 0.30   | 14.2| 102.8 | 2.5  |
| BBO    | 0.12  | 0.22  | 0.29  | 0.29       | 0.13  | 0.07| 0.03     | 0.10     | 94.7| 1.34| 2.09  | 0.06     | 0.59   | 5.3 | 102.8 | 2.9  |
| BIC    | 0.32  | 0.19  | 0.29  | 0.54       | 0.56  | 0.39| 0.04     | 0.20     | 1.43| 89.99| 5.84  | 0.09     | 0.42   | 10.4| 102.8 | 1.0  |
| DVI_p  | 0.43  | 0.48  | 0.17  | 0.10       | 0.19  | 0.21| 0.23     | 0.14     | 2.10| 7.70| 87.07 | 0.22     | 0.95   | 12.9| 103.1 | 2.7  |
| CREDITC1| 0.18  | 0.07  | 0.26  | 0.11       | 0.67  | 0.36| 0.26     | 0.25     | 0.25| 0.10| 0.08  | 97.05     | 0.36   | 3.0 | 102.8 | 1.1  |
| BBVAC1 | 0.24  | 0.14  | 0.30  | 0.61       | 0.18  | 0.45| 0.31     | 0.28     | 0.64| 0.58| 0.35  | 0.21     | 95.70  | 4.3 | 103.1 | 4.4  |
| TO     | 39.7  | 40.8  | 4.4   | 33.6       | 32.2  | 26.1| 13.8     | 14.1     | 6.0 | 10.9| 9.6   | 2.0      | 4.2    | 237.5| 103.1 | 4.4  |
| ALL    | 101.8 | 103.1 | 95.7  | 102.8      | 102.1 | 98.1| 99.5     | 99.9     | 101.0| 100.5| 96.6  | 99.0     | 99.9   | 18.3%| 103.1 | 1.0  |
| Net    | 1.9   | 3.1   | −4.3  | 2.7        | 2.1   | −1.9| −0.5     | −0.1     | 0.7 | 0.5 | −3.3  | −1.0     | −0.1   | −1.0| 103.1 | 1.0  |

Notes: The table displays the spillovers occurring between banks from emerging America. The columns display the spillover transmission of each bank to other banks (“TO”) while the rows display the spillover receptions of each bank from other banks (“FROM”).
(GFNORTEO) from Mexico also largely spillovers on Grupo Financiero Inbursa (GFINBURO) (11.94, 12.00) from the same country, with its spillover transmission being smaller than its spillover reception from the latter bank. The largest spillovers between banks across different countries occur between CHILE-CREDITC1 (0.67, 0.22) from Chile and Peru, respectively, with the spillover transmission of the Chilean bank being larger than its spillover reception from the Peruvian bank; between BBO- BBVAC1 (0.64, 0.59) from Colombia and Peru, respectively, with the spillover transmission of the Colombian bank being larger than its spillover reception from the Peruvian bank; between BSANTANDER- BBVAC1 (0.61, 0.03), from Chile and Peru, respectively, with the spillover transmission of the Chilean bank with much larger than its spillover reception from the Peruvian bank; and between BIC-BBVAC1 (0.58, 0.43) from Colombia and Peru, respectively, with the spillover transmission of the Colombian bank being larger than its spillover reception from the Peruvian bank. Accordingly, the largest spillovers between banks across countries in emerging America take place between the banks from Chile and Colombia, and those from Peru, with the banks from the latter country being stronger receivers of spillovers than transmitters. On the contrary, the smallest spillovers across banks from emerging America happen between the Mexican and Colombian banks, specifically between GFNORTEO-BBO (0.03, 0.59), from Mexico and Colombia, respectively, with the spillover transmission of the Mexican bank being much smaller than its spillover reception from the Colombian bank; and between GFNORTEO-BIC (0.04, 0.12), with the spillover transmission of the Mexican bank being much smaller than its spillover reception from the Colombian bank. A comparison of spillover transmission and reception patterns between banks from emerging America and those from developed America reveals that spillovers among banks from emerging America are noticeably smaller.

The economic intuition behind the large spillovers between banks from the same country comes down to the higher level of cross bank transactions (i.e. daily transfers and deposits, overnight borrowing and lending, currency exchanges, trading, among others) and investment that normally take place between domestic or local banks. The largest spillovers identified between the banks from Chile and Colombia, and those from Peru can be explained mainly by three mechanism, the higher level of financial transactions and investment that occurs between the banks of those countries, the stronger penetration of domestic banks on foreign markets, and the higher level of trade between the economies of those banks’ countries. Furthermore, the larger size of spillovers between banks from developed America than between banks from emerging America can be explained by the proximity of the USA and Canadian economies and their trade linkages which are large. In this regard, Canada is the second largest trading partner of the USA. This type of strong trading partnership does not occur between economies from emerging America. Hence, we would expect more and larger size financial transactions (i.e. daily transfers and deposits, overnight borrowing and lending, currency exchanges, trading, among others) taking place between banks from the USA and Canada than between banks from emerging America.

Table 4 displays the spillovers among the banks from developed America. It can be observed that the largest spillover transmitters and receivers are the largest banks from the U.S. and not those from Canada. Here again, the largest spillovers occur between banks from the same country. Regarding spillovers between pairs of banks, the most pronounced occur between JP Morgan Chase (JPM) and the rest of the U.S. banks, with the spillover transmission of the former bank being larger than its spillover reception from all of the other banks. The banks receiving the largest spillovers from JP Morgan Chase (JPM) are Citigroup (C), Bank of America (BAC) and Goldman Sachs (GS). Spillovers occurring across banks from different countries are noticeable only between the Royal Bank of Canada (RY) and each of the U.S. banks, with the Canadian bank acting mainly as a large spillover receiver than as a transmitter. The U.S. banks that most largely spillover on the Royal Bank of Canada (RY) are Citigroup (C) and JP Morgan Chase (JPM). Other large spillovers between banks from the USA occur between BAC-C (14.00, 14.80), with the spillover transmission of BAC being smaller than its spillover reception; between GS-MS (14.06, 14.50), with the spillover transmission of GS being smaller than its spillover reception from MS; and between C-MS (13.86, 13.45), with the spillover transmission of C being larger than its spillover reception from MS. On the other hand, the smallest spillovers between banks from the USA take place between BRKas-BAC (8.51, 10.55), being the spillover transmission of BRKas smaller than its spillover reception from BAC; and between BRKa-C (8.47, 10.97), being the

| Table 4 |
| Spillover index for banks from developed America. |
| JPM | BRKa | BAC | WFC | C | GS | MS | RY | TD | BMO | BNS | CM | NA | From |
|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| JPM | 18.97 | 9.41 | 12.91 | 12.06 | 13.97 | 12.72 | 12.88 | 6.83 | 0.04 | 0.11 | 0.02 | 0.04 | 0.04 |
| BRKa | 12.27 | 24.71 | 10.55 | 11.92 | 10.97 | 11.04 | 10.89 | 7.26 | 0.08 | 0.17 | 0.05 | 0.05 | 75.3 |
| BAC | 13.68 | 8.51 | 20.25 | 11.49 | 14.80 | 11.88 | 13.04 | 5.96 | 0.11 | 0.10 | 0.02 | 0.10 | 0.04 |
| WFC | 13.47 | 10.18 | 12.10 | 21.48 | 12.60 | 11.19 | 11.45 | 7.34 | 0.01 | 0.10 | 0.02 | 0.03 | 0.04 |
| C | 14.06 | 8.47 | 14.00 | 11.32 | 19.19 | 12.17 | 13.45 | 7.02 | 0.07 | 0.10 | 0.02 | 0.08 | 0.04 |
| GS | 13.56 | 9.10 | 11.96 | 10.71 | 12.90 | 20.15 | 14.50 | 6.60 | 0.07 | 0.24 | 0.05 | 0.09 | 0.06 |
| MS | 13.29 | 8.65 | 12.69 | 10.62 | 13.86 | 14.06 | 19.70 | 6.65 | 0.06 | 0.19 | 0.04 | 0.10 | 0.08 |
| RY | 10.82 | 8.65 | 8.79 | 10.20 | 11.04 | 9.79 | 10.19 | 30.08 | 0.09 | 0.17 | 0.08 | 0.03 | 0.08 |
| TD | 0.74 | 0.25 | 0.82 | 0.73 | 0.61 | 0.65 | 0.45 | 1.47 | 32.84 | 16.48 | 17.73 | 15.49 | 11.73 |
| BMO | 1.21 | 0.64 | 1.17 | 1.34 | 1.23 | 1.14 | 0.96 | 2.30 | 16.21 | 32.07 | 15.23 | 14.28 | 12.61 |
| BNS | 0.75 | 0.29 | 0.77 | 0.75 | 0.77 | 0.61 | 0.52 | 1.87 | 17.57 | 15.27 | 32.13 | 15.10 | 13.59 |
| CM | 0.77 | 0.42 | 0.86 | 0.82 | 0.82 | 0.74 | 0.69 | 1.86 | 16.01 | 15.08 | 15.99 | 34.11 | 11.83 |
| NA | 11.9 | 0.65 | 1.06 | 1.23 | 1.22 | 1.04 | 0.86 | 2.99 | 12.94 | 13.74 | 15.14 | 12.50 | 35.44 |
| To | 95.8 | 65.2 | 87.7 | 83.2 | 94.8 | 87.0 | 89.9 | 58.1 | 63.3 | 61.8 | 64.4 | 57.9 | 49.8 |
| All | 114.8 | 89.9 | 107.9 | 104.7 | 114.0 | 107.2 | 109.6 | 88.2 | 96.1 | 93.8 | 96.5 | 92.0 | 85.2 |
| Net | 14.8 | -10.1 | 8.0 | 4.7 | 14.0 | 7.1 | 9.6 | -11.8 | -3.9 | -6.1 | -3.5 | -8.0 | -14.8 |

Notes: The table displays the spillovers occurring between banks from developed America. The columns display the spillover transmission of each bank to other banks (“TO”) and the rows display the spillover reception of each bank from other banks (“FROM”).
Table 5
Spillover index across banks of emerging America with the MSCI ACWI Financials index.

| From       | BBAS3 | BBDC4 | SANB4 | BSANTANDER | CHILE | BCI | GFINORTEO | GFINBURO | BBO | BIC | DVI_p | CREDITC1 | BBVAC1 | MSCI_ACWI_FIN |
|------------|-------|-------|-------|------------|-------|-----|-----------|----------|-----|-----|------|--------|--------|---------------|
| BBAS3      | 62.14 | 34.87 | 1.14  | 0.25       | 0.18  | 0.11| 0.25      | 0.27     | 0.09| 0.13| 0.20 | 0.18   | 0.13   | 0.06          |
| BBDC4      | 34.88 | 62.28 | 1.33  | 0.28       | 0.21  | 0.07| 0.07      | 0.12     | 0.06| 0.19| 0.12 | 0.19   | 0.09   | 0.12          |
| SANB4      | 2.35  | 3.43  | 91.21 | 0.16       | 0.24  | 0.35| 0.41      | 0.36     | 0.36| 0.16| 0.23 | 0.07   | 0.59   | 0.09          |
| BSANTANDER | 0.20  | 0.22  | 0.16  | 69.04      | 17.02 | 12.41| 0.06      | 0.06     | 0.21| 0.25| 0.07 | 0.04   | 0.03   | 0.23          |
| CHILE      | 0.18  | 0.18  | 0.12  | 17.34      | 69.78 | 11.46| 0.08      | 0.19     | 0.04| 0.12| 0.07 | 0.22   | 0.03   | 0.20          |
| BCI        | 0.36  | 0.39  | 0.07  | 13.47      | 12.38 | 71.87| 0.12      | 0.12     | 0.12| 0.12| 0.14 | 0.23   | 0.43   | 0.19          |
| GFINORTEO  | 0.15  | 0.35  | 0.12  | 0.05       | 0.16  | 0.13| 85.62     | 11.94    | 0.60| 0.05| 0.17 | 0.20   | 0.30   | 0.17          |
| GFINBURO   | 0.10  | 0.26  | 0.16  | 0.30       | 0.17  | 0.14| 11.87     | 85.75    | 0.10| 0.22| 0.21 | 0.27   | 0.31   | 0.15          |
| BBO        | 0.12  | 0.21  | 0.28  | 0.29       | 0.13  | 0.06| 0.03      | 0.09     | 94.60| 1.34| 2.11 | 0.06   | 0.60   | 0.07          |
| BIC        | 0.42  | 0.19  | 0.29  | 0.54       | 0.56  | 0.38| 0.04      | 0.21     | 1.43| 89.53| 5.79 | 0.09   | 0.42   | 0.13          |
| DVI_p      | 0.44  | 0.48  | 0.16  | 0.10       | 0.19  | 0.21| 0.23      | 0.14     | 2.12| 7.64 | 86.79 | 0.21   | 0.93   | 0.36          |
| CREDITC1   | 0.18  | 0.07  | 0.26  | 0.11       | 0.64  | 0.36| 0.25      | 0.25     | 0.25| 0.10| 0.08 | 96.87  | 0.36   | 0.22          |
| BBVAC1     | 0.25  | 0.14  | 0.31  | 0.61       | 0.19  | 0.43| 0.32      | 0.29     | 0.65| 0.57| 0.35 | 0.21   | 95.40  | 0.31          |
| MSCI_ACWI_FIN | 0.04 | 0.14  | 0.11  | 0.37       | 0.20  | 0.23| 0.45      | 0.17     | 0.10| 0.63| 0.29 | 0.37   | 0.33   | 96.57         |
| To         | 39.7  | 40.9  | 4.5   | 33.9       | 32.2  | 26.3| 14.2      | 14.2     | 6.1 | 11.5| 9.8  | 2.4    | 4.5    | 2.3           |
| All        | 101.8 | 103.2 | 95.7  | 102.9      | 102.0 | 98.2| 99.8      | 100.0    | 101.0| 101.1| 96.6 | 99.2   | 99.9   | 98.9          |
| Net        | 1.8   | 3.2   | -4.3  | 2.9        | 2.0   | -1.8| -0.2      | 0.0      | 0.7 | 1.0 | -3.4 | -0.7   | -0.1  | -1.1          |

Notes: The table displays the spillovers occurring between the banks from emerging America and the MSCI ACWI Financials index. The columns display the spillover transmission of each bank to other banks ("TO") and the rows display the spillover reception of each bank from other banks ("FROM").
spillover transmission of BRKa smaller than its spillover reception from C. As to the banks from Canada, the largest spillovers occur between TD-BMO (16.21, 16.48), with the spillover transmission of TD being smaller than its spillover reception from BMO; and between TD-BNS (17.57, 17.73), being the spillover transmission of TD smaller than its spillover reception from BNS. The smallest spillovers between the banks from Canada take place between TD-RY (1.47, 0.09), being the spillover transmission of RY larger than its spillover reception from TD; and between RY-CM (1.86, 0.03), being the spillover transmission of RY larger than its spillover reception from CM. Lastly, the smallest spillovers between banks from the USA and those from Canada happen between BRKa-TD (0.25, 0.08), with the spillover transmission of BRKa being larger than its spillover reception from TD; and between BRKa-BNS (0.29, 0.05), being the spillover transmission of BRKa larger than its spillover reception from BNS.

As in the case of the banks from emerging America, the large spillovers between banks from the same country in developed America can be explained by the higher level of cross bank transactions and investment that commonly happens among domestic or local banks. On the other hand, the larger size of the spillovers between banks from the USA compared to the spillovers between banks from Canada could be explained by the stronger network and flow of transactions (i.e. daily transfers and deposits, overnight borrowing and lending, currency exchanges, trading, among others), as well as the size of those transactions, taking place between banks from the USA, relative to those taking place between banks from Canada. The USA economy is significantly much larger than the Canadian economy. The leading role of JP Morgan Chase (JPM) as spillover transmitter on all other US banks considered is no surprise as this bank is the largest in the USA in terms of total assets. Accordingly, most banks from the USA must have strong links through financial transactions and trading with JP Morgan Chase. The implication of this finding is that JPM is in a position to more easily trigger systemic risk in the USA financial sector and in the economy as a consequence. The largest spillovers identified between the USA banks and the Royal Bank of Canada (RY) can also be explained by the higher number and larger size of financial transactions the RY has with the USA banks, relative to other smaller banks from Canada. In this respect, it should be noted that RY is the largest bank in Canada in terms of total assets, making it very attractive to USA banks for investment, trading and borrowing, while having the most assets to make the largest transactions with USA banks. The largest and smallest spillovers between pairs of banks from the USA, and between pairs of banks from Canada can be understood in the light of the above rationale.

Table 5 displays the spillovers occurring between banks from emerging America and the MSCI ACWI Financials Index. The banks from emerging America that most largely spillover on the financial index are Bancolombia (BIC), followed by Grupo Financiero Banorte (GFNORTEO) from Mexico, and Banco Santander Chile (BSANTANDER). On the other hand, the banks receiving the largest spillovers from the MSCI ACWI Financials Index are Banco Davivienda (DIV_p) from Colombia, followed by Banco BBVA Peru (BBVAC1), and Banco Santander Chile (BSANTANDER). Table 6 displays the spillovers occurring between the banks from developed America and the MSCI ACWI Financials Index. The banks from developed America that most largely spillover on the financial index are the banks from the U.S., specifically Morgan Stanley (MS), followed by Goldman Sachs (GS) and Bank of America (BAC). On the other hand, the banks receiving the largest spillovers from the MSCI ACWI Financials Index are the banks from Canada, specifically, the Canadian Imperial Bank of Commerce (CM), followed by Bank of Nova Scotia (BNS), Bank of Montreal (BMO) and Toronto-Dominion Bank (TD). The largest spillovers exerted by the BIC, GFNORTEO and BSANTANDER banks from emerging America, and by the MS, GS and BAC banks from developed America, on the MSCI ACWI Financials Index could be explained by the fact that those banks are some of the largest (in terms of total assets) and have some of the largest financial transaction networks in the financial industry of emerging and developed America. Hence, when any of those banks is positively or negatively affected by local, regional or global market shocks their return and risk spillover ramifications are the strongest and the largest in the financial industry of the Americas.
Fig. 1 displays the net-pairwise connectedness between banks from emerging America and the MSCI ACWI Financial Index. In Panel A it can be observed that Banco Bradesco (BBDC4) from Brazil largely spillovers on Banco Santander Brasil (SANB4). We also observe large spillovers from Bancolombia (BIC) to Banco Davivienda (DVI_p) of the same country. The Banco do Brazil (BBAS3) has medium size spillovers on Banco Santander Brasil (SANB4). Other moderate spillovers occur from Banco Santander Chile (BSANTANDER) and Banco de Chile (CHILE) to Banco de Credito e Inversiones (BCI) of the same country. According to Panel B, most of the banks from emerging America spillover only marginally on the MSCI ACWI Financial index. The largest spillovers between banks are similar to those observed in the network structure of Panel A.

Fig. 2 displays the net-pairwise connectedness among banks from developed America. From Panel A, it can be observed that Goldman Sachs (GS) largely spillovers on the Royal Bank of Canada (RY). In fact, the latter bank acts as large and moderate spillover receiver from all banks from the U.S. considered. Another bank that acts as a moderate spillover receiver from various banks of the U.S. is Berkshire Hathaway (BRKa). By contrast, JP Morgan Chase (JPM) acts as moderate spillover transmitter. In Panel B, in which the MSCI ACWI Financial index is included, it can be observed that most of the banks from developed America spillover onto the index only marginally. The most pronounced spillovers between banks occur similarly to those observed in the network structure of Panel A.
5.2. TENET analysis

Following the TENET analysis of Härdle et al. (2016), firstly, we calculate the Tail Event VaR of all banks. Fig. 3 displays the log returns (black points) and estimated $\text{CoVaR}^{\text{TENET}}$ (thicker blue line) for J.P Morgan Chase (JPM) and Banco do Brasil (BBAS3), respectively. Secondly, we perform the NETwork analysis based on the SIM with variable selection. Fig. 4 shows the time evolution of the total connectedness (solid blue line) and the averaged $\lambda$ values (dashed black line) of the CoVaR estimates for each ban group (developed market banks and emerging market banks), respectively. In the beginning of 2012, the total connectedness and average $\lambda$ values of developed market banks are higher than those of emerging market banks whereas, in the early 2020, both developed and emerging market bank groups show similar level of total connectedness and average $\lambda$ values. In particular, the total connectedness of the emerging market bank group is more intensified due to COVID-19 pandemic than its counterpart.

In order to measure the risk channels and the relative role of each bank in the system network, we define three levels of connectedness: (i) the total connectedness of links; (ii) the total incoming links; (iii) the total outgoing links in the connectedness matrix. Fig. 5 illustrates the connectedness network of a weighted adjacency matrix in developed and emerging market banks, respectively. In Fig. 5(a), we see two clustering bank groups: Canadian banks (left) and US banks (right). There are a lot of strong mutual connections,
Fig. 3. Log returns and CoVaR estimates. Log returns (black points), \( \hat{\text{VaR}} \) (thinner red line), \( \text{CoVaR}^{\text{TENET}} \) (thicker blue line), and \( \text{CoVaR}^{\text{L}} \) (thinner green line), \( \tau = 0.05 \), window size \( n = 48 \), \( T = 473 \). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

**a). Developed market banks**

**b). Emerging market banks**

Note: Total connectedness (solid blue line) and average lambda (dashed black line) of 13 banks from April 2, 2010 to March 20, 2020, \( \tau = 0.05 \), window size \( n = 48 \), \( T = 473 \). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
a). Developed market banks

![Network representation of a weighted adjacency matrix for developed market banks](image)

**Note**: These elliptical network representations are of weighted adjacency matrices for the full sample from April 2, 2010 to March 20, 2020, \( t = 0.05 \), window size \( n = 48 \), \( T = 473 \).

b). Emerging market banks

![Network representation of a weighted adjacency matrix for emerging market banks](image)

**Note**: These elliptical network representations are of weighted adjacency matrices for the full sample from April 2, 2010 to March 20, 2020, \( t = 0.05 \), window size \( n = 48 \), \( T = 473 \).

BAC and NA to other banks. The connectedness among banks from developed markets is stronger than that between banks from emerging markets. The weak connectedness of banks from emerging markets occurs sporadically in Fig. 5(b). We also find some pairs of mutual connections between BBAS3 and BBDC4, between BIC and DVL_p, and between BCI and CHILE. Table 7 reports the rank of links for individual banks in developed and emerging markets, respectively. In developed market banks (Table 7(a)), BRKa has the highest rank of connections following by JPM, BAC, and WFC, while NA has the lowest contribution on connectedness. For BRKa, the strong incoming links come from MS, BAC, and C, the outgoing links go to MS, BAC, and JPM. In emerging market banks (Table 7(b)), we observe that BBDC4 is the largest contributor of incoming and outgoing links. For example, BBDC4 received links from BBAS3, SANB4, and BCI and transmitted links to BBAS3, SANB4, BSANTANDER.

Next, we direct our attention to the impact of COVID-19 on the connectedness network in Fig. 6. Compared to Fig. 5(a), we observe a weaker connectedness network in developed market banks (Fig. 6(a)). Interestingly, there are unidirectional connections from JPM to BAC, from WFC to BAC, and from BAC to C, but not vice versa. We also find a couple of mutual connections between MS and C, and between BAC and C. In addition, in Fig. 6(b) for emerging market banks there are a lot of weak mutual connections, BBAS3 and BBDC4, BBDC4 and SANB4, BSANTANDER and CHILE, BSANTANDER and BCI in emerging banks. In Table 8 we present the
impact of COVID-19 on the rank of links in developed and emerging market banks. Unlike in Table 7, we observe fewer incoming and outgoing links, implying that the COVID-19 might cut off the complex links among developed and emerging market banks.

5.3. Non-convex portfolio optimization results

Table 9 displays results corresponding to the differential evolution optimization of the portfolios of banks from developed and emerging America. From the portfolio of banks from developed America, we observe that the largest risk contributors to total portfolio risk, for an equally weighted portfolio, are the three largest banks from North America, namely, Morgan Stanley (MS), followed by Bank of America (BAC) and Citigroup (C). The banks contributing the least risk to total portfolio risk are three of the largest banks from Canada, namely, the Canadian Imperial Bank of Commerce (CM), followed by the Bank of Montreal (BMO) and Toronto-Dominion Bank (TD). In general, it can be observed that the banks from the U.S., compared to those from Canada, contribute more risk to the portfolio. Additionally, a cross comparison between the optimal weights obtained for maximum risk contribution limit equal to 7.692%, and the risk contributions of each bank indicate that the largest amounts of financial resources are allocated to those banks that contribute the least risk to total portfolio risk. This result is observed for Canadian banks which are the least risk contributors among banks from developed America.

From the portfolio of banks from emerging America, we observe that the largest risk contributors to total portfolio risk are three banks from Brazil, namely, Banco Santander Brasil (SANB4) and Citigroup (C). The banks contributing the least risk to total portfolio risk are Banco do Credito del Peru (CREDITC1), followed by Banco de Bogota (BBO) and Banco BBVA Peru (BBVAC1). For this category of banks also the largest amounts of financial resources are allocated to banks that contribute the least risk to total portfolio risk. Compared with banks from developed America, the risk contribution values for banks from emerging America are larger.

Table 10 displays the CVaR portfolio optimization results. A broad analysis of the concentration of financial resources in both portfolios, for developed and emerging America, indicates that in the portfolio of developed banks from America, financial resources are allocated to a few banks. In the portfolio of banks from emerging America, financial resources are allocated across a larger number of banks. This information implies that the portfolio of banks from emerging America offers greater diversification potential. This portfolio also has a lower total CVaR value, implying that it is more desirable for investment compared to the portfolio of banks from developed America.
a). Developed market banks

b). Emerging market banks

Note: These elliptical network representations are of weighted adjacency matrices for the February 21, 2020 (COVID-19 hit the markets), $\tau = 0.05$, window size $n = 48$.

Fig. 6. Network representation of a weighted adjacency matrix on 21 February 2020 (COVID-19). a). Developed market banks. b). Emerging market banks. Note: These elliptical network representations are of weighted adjacency matrices for the February 21, 2020 (COVID-19 hit the markets), $\tau = 0.05$, window size $n = 48$.

from developed America.

In developed America, the banks most preferred for investment are those from Canada, namely, the Canadian Imperial Bank of Commerce (CM), the Royal Bank of Canada (RY), the Bank of Montreal (BMO), and the Bank of Nova Scotia (BNS). Most U.S. banks are allocated zero financial resources. The exception is Berkshire Hathaway (BRKa). In emerging America, the banks preferred for investment are those from Chile, followed by those from Colombia. Specifically, Banco Santander Chile (BSANTANDER), Banco de Chile (CHILE), Banco de Bogota (BBO), Bancolombia (BIC), and Banco Davivienda (DVI_p) are identified.

6. Conclusion

Understanding the interdependence among banks from the same country and from the same region of the world is of importance to portfolio investors and risk managers because investment strategy and diversification are dependent on banks being spillover transmitters or spillover receivers. Motivated by the importance of understanding banks interdependence this study examines the network structure of spillovers, the portfolio allocation characteristics and diversification potential of bank returns from developed and emerging America. We draw our empirical results by applying a directional spillover index, the tail-event driven network
and nonlinear portfolio optimization methods on bank returns. The obtained empirical results indicate that the spillovers and connectedness among banks from emerging America are noticeably smaller than those among banks from developed America. The largest emerging market spillover transmitters and receivers are the banks from Brazil, followed by the banks from Chile. The largest developed market spillover transmitter is JP Morgan Chase. The connectedness among banks from developed America is dominated by the banks from the USA, relative to those from Canada. The total connectedness of the emerging market banks is more intensified than that of the banks from developed America due to the effect of the COVID-19 pandemic. The portfolio optimization

Table 8
Banks ranking and top three links – on 21 February 2020 (COVID-19).

| Rank | Ticker | Received link from | Transmitted link to |
|------|--------|--------------------|--------------------|
| 1    | BRKa   | MS                 |                    |
| 2    | JPM    | BAC                |                    |
| 3    | BAC    | JPM, WFC, C        | C, MS, BAC         |
| 4    | WFC    |                    | BAC                |
| 5    | C      | BAC, MS            | MS, BAC            |
| 6    | RY     | RY                 | MS, TD             |
| 7    | MS     | GS, C, BRKa        | G, GS, BAC         |
| 8    | GS     |                    | MS                 |
| 10   | BNS    |                    | BAC, MS            |
| 11   | BMO    |                    | MS, BAC            |
| 12   | CM     |                    | MS                 |
| 13   | NA     |                    | BAC, MS            |

Table 9
Non-convex differential evolution optimization of bank portfolios from developed and emerging America.

| Bank codes for institutions in Developed America | OW Max-RC < 7.692% | RC-EW | Bank codes for institutions in Emerging America |
|-------------------------------------------------|--------------------|-------|-----------------------------------------------|
| JPM                                             | 4.867              | 11.372| BBAS3, SANB4, DVI_p                          |
| BRKa                                            | 8.258              | 6.459 | BBDC4, BBDC1, BBVAC1, SANB4                  |
| BAC                                             | 3.548              | 14.739| BIC, CREDITC1, BBVAC1, SANB4                 |
| WFC                                             | 5.385              | 9.819 | CHILE, BIC, SANB4                            |
| C                                               | 4.057              | 14.275| BSANTANDER, CHILE                           |
| GS                                              | 4.799              | 11.561| CREDITC1, BBVAC1, GFINBURO                  |
| MS                                              | 3.685              | 15.557| BBDC4, BAC, SANB4, BBVAC1, DVI_p            |
| RY                                              | 8.181              | 6.408 | BIC, CREDITC1, BBVAC1, GFINBURO             |
| TD                                              | 11.828             | 1.890 | BBO, BIC, BBVAC1                           |
| BMO                                             | 11.518             | 1.869 | BIC, SANB4                                   |
| BNS                                             | 11.015             | 2.082 | BBDC4, BBVAC1, DVI_p                        |
| CM                                              | 11.675             | 1.844 | BAC, MS                                      |
| NA                                              | 10.985             | 2.124 | BAC, MS                                      |

Note: The banks are ranked according to market capitalization (MC). The received links from other banks and transmitted links to other banks are shown. Only the first three most influential banks are listed for each ticker, n = 48.

Note: Abbreviations “OW Max-RC” and “RC-EW” stand for optimal weights subject to maximum risk contributions and to the risk contributions of an equally weighted portfolio.

(TENET) and nonlinear portfolio optimization methods on bank returns. The obtained empirical results indicate that the spillovers and connectedness among banks from emerging America are noticeably smaller than those among banks from developed America. The largest emerging market spillover transmitters and receivers are the banks from Brazil, followed by the banks from Chile. The largest developed market spillover transmitter is JP Morgan Chase. The connectedness among banks from developed America is dominated by the banks from the USA, relative to those from Canada. The total connectedness of the emerging market banks is more intensified than that of the banks from developed America due to the effect of the COVID-19 pandemic. The portfolio optimization
shows that in developed America, the largest banks from the USA are the largest risk contributors to total portfolio risk, whereas the banks from Canada contribute the least risk. In emerging America, the banks from Brazil contribute the most risk to total portfolio risk while the banks from Peru and one bank from Colombia contribute the least risk. The portfolio of banks from emerging America offers greater diversification potential and lower total portfolio allocation risk.

The implications of the results suggest that banks from developed and emerging America with the largest risk contributions should be taken with caution when constructing investable portfolios and designing investment strategy. The low diversification potential exhibited by the portfolios of banks from developed America calls for investors interested in the banking sector to broaden their investment horizon in relation to which countries and economic sectors to invest in. Banks from emerging and developed America with the largest spillovers could serve as performance benchmarks for banks that act as spillover receivers. Accordingly, our study appeals to portfolio investors and risk managers who are in search of diversification benefits and risk hedging advantages in the domain of the banking sector.

CRediT authorship contribution statement

Jose Arreola Hernandez: Conceptualization, Methodology, Data curation, Writing - original draft. Sang Hoon Kang: Investigation, Visualization, Software, Validation. Syed Jawad Hussain Shahzad: Investigation, Software. Seong-Min Yoon: Writing - review & editing, Supervision, Funding acquisition.

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Appendix A. Supplementary data

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