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ORIGINAL PAPER

Cultural values and the global financial crisis: a missing link?

Adem Baltaci[1] · **Raif Cergibozan**[2] · **Ali Ari**[3]

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Abstract

We empirically investigate the role of cultural values on the occurrence of the global financial crisis. We use data based on Hofstede (Culture's consequences: comparing values, behaviors, institutions and organizations across nations, 2001) cultural values indexes and employ two econometric approaches, the self-organizing maps and logit, in a panel set of 38 developed and developing countries. We find that culture has a statistically and economically significant effect on the occurrence of the global financial crisis of 2007–2009. The relationship between cultural factors and the crisis occurrence remains strong when we consider control variables representing different sectors of the economy.

Keywords Culture · Financial crisis · Self-organizing maps · Logit

JEL Classification C35 · C45 · G01 · Z1

✉ Ali Ari
ali.ari@marmara.edu.tr

Adem Baltaci
adem.baltaci@medeniyet.edu.tr

Raif Cergibozan
raif.cergibozan@klu.edu.tr

1 Department of Business Administration, Istanbul Medeniyet University, D-100 Karayolu No: 98, 34000 Istanbul, Turkey

2 Department of Economics, Kirklareli University, Kayali Kampüsü B-Blok, 39000 Kirklareli, Turkey

3 Department of Political Science and Public Administration, Marmara University, Anadoluhisari Yerleskesi, 34820 Istanbul, Turkey

1 Introduction

The world economy faced a severe financial crisis that started in the US banking system in late 2007 and turned into global following the failure of Lehman Brothers in September 2008. Despite expansionist monetary and fiscal policies, and bank rescue plans, the "Great Recession" deeply affected the world economy. Several empirical studies (i.e., Obstfeld et al. 2009; Siebert 2010; Lane and Milesi-Ferretti 2011; Frankel and Saravelos 2012; Feldkircher 2014 among others) were then conducted to explain the occurrence and the severity of the global crisis across countries.

In general, these papers focus on the impact of macroeconomic and financial vulnerability on the outbreak of the global financial crisis. Contrary to previous studies, we do not only consider macro and micro variables, but also the impact of investors' decisions on the occurrence of the crisis. Because we argue that economic and financial outcomes are the consequences of economic agents' decisions. These decisions in turn are affected by culture. North (1990) describes culture as "intergenerational transmission of shared values and preferences that influence individuals' behavior and choices". Beugelsdijk and Maseland (2011) emphasize that culture matters for behavior as it channels actions, guides preferences, and shapes the process of decision-making. Besides, Elias (2004) and Rupert (2003) underline the fact that markets are embedded within a social context, thus, the economic spaces are shaped by structured relations of social power. Therefore, the present paper aims to examine whether cultural values may bring further clarifications on the occurrence of the global financial crisis. To do that, we employ two different econometric approaches, namely self-organizing maps (SOM) and logistic regression model, in a panel set of 38 countries. We consider cultural values indexes proposed by Hofstede (2001) who differentiates countries according to some specific social and cultural characteristics which are individualism, masculinity, power distance, and uncertainty avoidance.

In the literature, there exists a few descriptive papers on the relationship between cultural factors and crises. For instance, Griffin (2012) argues that individualistic and masculine structure of capitalist system make the economy more prone to crises. Mixa and Vaiman (2015) affirm that individualistic societies were affected much more from the global financial crisis than collectivist countries. On the other hand, there are few empirical works on the impact of cultural values on the risk-taking behavior of banks. Kanagaretnam et al. (2011) indicate that banks in high individualism, high masculinity, and low uncertainty avoidance societies tend to take higher risks to manage earnings to just-meet-or-beat the prior year's earnings. Similarly, Ashraf et al. (2016) find evidence that bank risk-taking is higher in countries which have high individualism, low uncertainty avoidance, and low power distance cultural values. These results, thus, suggest that countries where this risk-taking behavior is encouraged experienced more bank troubles during the global crisis. Berger et al. (2021) is the only study which empirically examines the impact of cultural values on individual bank failures using bank-level data. They find that individualism increases the probability of bank failure as managers in individualist countries have higher risk-taking incentives. Their results also indicate that masculinity augments the risk of bank failure since authorities in masculine countries allow banks to operate with less liquidity and capital.

We empirically estimate the impact of cultural values on the occurrence of the global financial crisis. Contrary to Berger et al. (2021), we focus on systemic banking crises and use aggregate banking data. Moreover, using the novel SOM approach to reduce the complexity of multidimensional datasets is another contribution of our study. Besides, we use a hierarchical estimation approach that allows us to avoid correlation problem among variables and selection bias, frequently encountered in econometric models. To be more precise, we first run a nonparametric cluster analysis through the SOM with 21 explanatory variables representing both cultural values and different sectors of the economy, we then estimate a panel logit model with variables found to be significant in the SOM model.

Empirical findings obtained from the SOM analysis indicate that the probability to be in crisis in the period of 2007–2009 was higher for countries with lower power distance and higher individualism. Logit results confirm the SOM findings as individualism and power distance are correctly signed and statistically significant. Our results are in general robust to the introduction of different control variables such as budget deficits, trade openness, credit growth, and currency appreciation.

The paper is organized as follows. In Sect. 2, we discuss the data and methodology used in our empirical analysis. Section 3 presents empirical results. Section 4 concludes.

2 Model

2.1 Data

Our sample covers the period from 2007 to 2009 and consists of 38 countries for which Hofstede (2001) provided cultural values indexes (see Table 6 for countries included into the empirical analysis). We cover a limited period in which the crisis severely hit the world economy. Moreover, as early empirical papers on the global financial crisis mostly considered those years, focusing on the same period would allow us to compare our results with those of early studies. Besides, as the global crisis affected many countries contrary to previous recent crisis episodes, focusing only on the global crisis would allow us to observe the impact of cultural values on the crisis occurrence across countries. Furthermore, data on cultural variables cannot be found as time series. As data on cultural values do very slowly change over time, repeated numbers in the model estimation could be problematic.

Data for macroeconomic and financial variables are gathered from World Bank—World Development Indicators (WDI) and IMF—International Financial Statistics (IFS) datasets.[1] Dependent crisis variable is taken from Laeven and

[1] The data is available upon request.

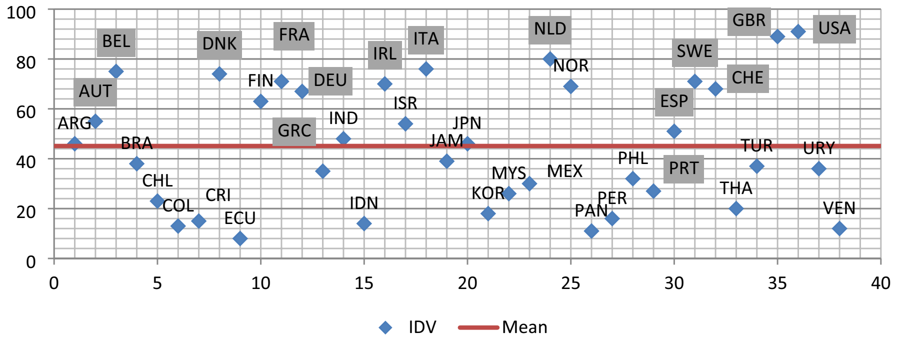

Fig. 1 Individualism scores.
Source: Authors' calculations based on Hofstede (2001)'s cultural values indexes and Laeven and Valencia (2013)'s systemic banking crises database

Valencia (2013) that present a comprehensive database on financial crises during the period of 1970–2011. Cultural indicators are obtained from Hofstede (2001). Hofstede's study consists of survey data about the values of people and help to differentiate and classify nations. This data is widely used in research on culture and economics because of its simplicity and comprehensibility. It also covers a large sample of countries. Hofstede developed a set of four cultural dimensions: individualism (vs. collectivism), masculinity (vs. femininity), power distance, and uncertainty avoidance.

Individualism refers to societies where ties between individuals are loose and the role of the individual is relatively emphasized as opposed to that of the group (Hofstede, 2001). High individualistic cultures praise individual achievements, self-orientation, and autonomy, while group cohesion and collective interests are given priority in collectivist countries. Given that pursuing profit or utility maximization is the most typical behavior pattern in individualistic cultures that may engender negative externalities. For example, seeking higher short-term benefits lead managers to take excessive risks that may endanger long-run growth performance of financial or nonfinancial institutions. This generalized behavior pattern could then deteriorate some key economic and financial indicators. Hence, our first hypothesis is that individualistic societies are prone to financial crises. Figure 1 presents individualism scores of 38 countries included into the sample. Grey-colored country codes indicate that these countries suffered from a financial crisis during the 2007–2009 period. As seen in Fig. 1, there seems to be a correlation between individualism and the incidence of financial crisis.

Masculinity refers to the extent to which a society emphasizes masculine values such as competitiveness, assertiveness, achievement, power, and ambition as opposed to feminine values such as quality of life, warm personal relationships, and care for the weak (Beugelsdijk & Maseland, 2011). Given that the acquisition of money and other material possessions praised in masculine cultures may result in more aggressive risk-seeking activities that reduce the quality of investments and lower return on investments. Hence, our second hypothesis is that societies

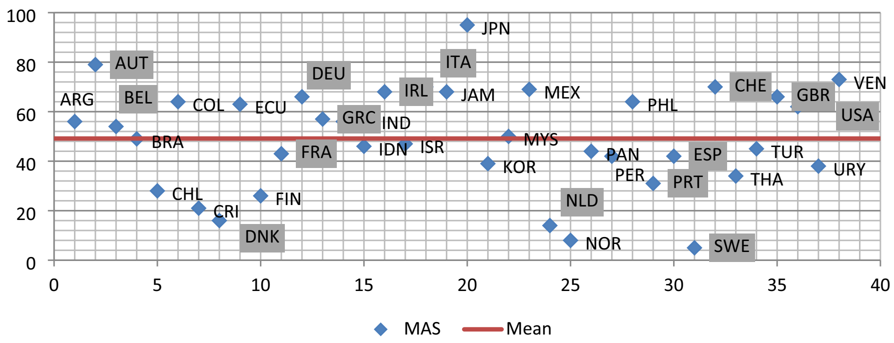

Fig. 2 Masculinity scores.
Source: Authors' calculations based on Hofstede (2001)'s cultural values indexes and Laeven and Valencia (2013)'s systemic banking crises database

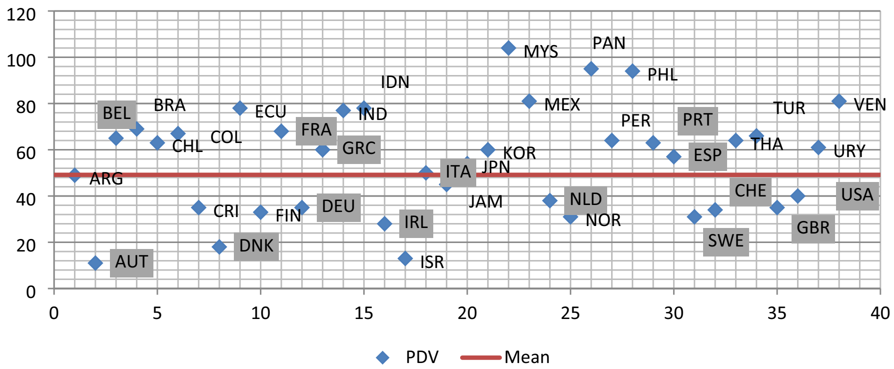

Fig. 3 Power distance scores.
Source: Authors' calculations based on Hofstede (2001)'s cultural values indexes and Laeven and Valencia (2013)'s systemic banking crises database

with higher masculinity values are likely to experience a financial crisis. Figure 2 indicates a partial correlation between these two variables.

Power distance measures the extent to which members with less power within a society accept and expect an unequal distribution of power (Hofstede, 2001). In countries with higher power distance, there exists a more hierarchical structure where people with less power tend to have respect and obedience towards people with more power. Hence, this hierarchical structure enables authorities to orient and manage economic agents' expectations. This can increase the efficiency of economic policies implemented by the policy makers in uncertain and extraordinary situations like crisis periods where social support for the implemented policies is much needed. However, on the other hand, unquestioned policies implemented by policymakers could also lower optimal allocation of resources in an economy leading to economic inefficiency. Although it is difficult to estimate the impact of power distance on the occurrence of crisis episodes, our third hypothesis is that societies with lower power distance values are likely to experience a

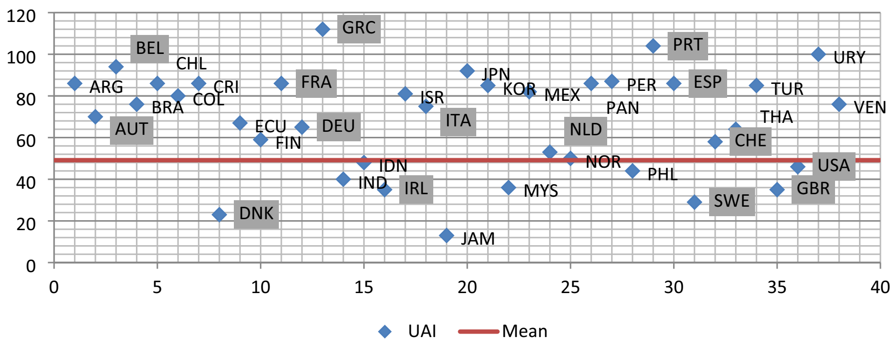

Fig. 4 Uncertainty avoidance scores.
Source: Authors' calculations based on Hofstede (2001)'s cultural values indexes and Laeven and Valencia (2013)'s systemic banking crises database

financial crisis. Figure 3 indicates a partial correlation between the occurrence of the crisis and power distance.

Uncertainty avoidance represents a feeling of discomfort in unstructured or unusual circumstances (Hofstede, 2001). Given that in countries with higher uncertainty avoidance, unusual circumstances such as crisis incidence may lead to irrational decisions of economic agents which may then deepen the crisis. Moreover, the measures taken by policymakers to prevent the crisis occurrence and/or alleviate its negative impact may not bring the expected positive result. Hence, our fourth hypothesis is that societies with higher uncertainty avoidance values are likely to experience a financial crisis. Figure 4 indicates a partial correlation between the occurrence of the crisis and uncertainty avoidance.

Table 1 presents dependent and independent variables with their descriptive statistics. The study examines the impact of 17 explanatory variables representing different sectors of the economy and of 4 cultural variables on the occurrence of the global financial crisis.

2.2 Methodology

We use two different methods, namely SOM and multivariate logit model, to estimate main determinants of the global financial crisis across 38 countries. To be more precise, we first run a nonparametric cluster analysis through the SOM with 21 explanatory variables and then the logit model with variables found to be significant in the SOM analysis. This stepwise approach allows us to avoid correlation problem among variables frequently encountered in econometric estimations.

The SOM is an effective tool which is used to analyze existing patterns in high-dimensional datasets. The SOM basically provides the graphical visuality of the similarity among the input data and offers important advantages to analysts by supplying low-dimensional images of high-dimensional data. In other words, the SOM can provide a visual, easily interpretable, distribution-free, and nonlinear description

Table 1 Descriptive statistics

Indicator	Abbrev	Obs	Mis. val	Mean	Std. dev	Min	Max
Real effective exchange rate index	REER	87	27 (23.68%)	96.88	8.80	60.58	125.71
GDP growth (annual %)	GDP growth	114	0 (0%)	1.84	4.14	− 8.27	15.32
Trade (% of GDP)	Trade/GDP	114	0 (0%)	74.66	35.81	22.11	192.47
Inflation, consumer prices (annual %)	Inflation	114	0 (0%)	4.97	5.53	− 1.35	31.44
Deposit interest rate (%)	Interest rate	75	39 (34.21%)	5.98	4.85	0.08	22.91
Budget surplus/deficit (% of GDP)	Budget/GDP	94	20 (17.54%)	− 2.29	5.26	− 17.9	18.90
Short-term debt/GDP (%)	Sdebt/GDP	99	15 (13.16%)	394.89	1652.53	0.00	11,530.78
Total debt/GDP (%)	Total debt/GDP	99	15 (13.16%)	713.04	2621.83	0.07	17,695.85
Total reserves minus gold (%)	Reserves	111	3 (2.63%)	19.59	30.07	− 39.05	122.80
Broad money (% of GDP)	Broad Money/GDP	80	34 (29.82%)	77.39	46.92	23.39	227.02
Foreign direct investment, net inflows (% of GDP)	FDI/GDP	114	0 (0%)	4.92	9.32	− 3.51	87.44
Portfolio investments (% of GDP)	Portfolio/GDP	111	3 (2.63%)	− 0.54	5.51	− 15.52	24.33
Bank nonperforming loans to total gross loans (%)	NPL/TL	105	9 (7.89%)	2.80	1.75	0.08	9.45
Domestic credit to private sector (% of GDP)	CPS/GDP	111	3 (2.63%)	85.14	55.87	12.26	206.30
Bank liquid reserves to bank assets (%)	Reserves/assets	57	57 (50%)	17.33	12.67	0.25	52.92
Bank capital to bank assets (%)	Capital/asset	105	9 (7.89%)	7.86	2.87	3.22	14.24
Power distance index	PDI	114	0 (0%)	55.13	22.62	11	104
Uncertainty avoidance index	UAI	114	0 (0%)	67.89	24.09	13	112
Individualism versus collectivism	IDV	114	0 (0%)	45.11	24.54	8	91
Masculinity versus femininity	MAS	114	0 (0%)	49.16	20.49	5	95
Index of financial fragility (Laeven & Valencia, 2013)	IFF	114	0 (0%)	0.28	0.45	0	1

Abbrev. abbreviation, *Obs.* observations, *Mis. Val.* missing value, *Mean* mean, *Std. Dev.* standard deviation, *Min. and Max.* minimum and maximum, respectively

World Bank (World Development Indicators), IMF (International Financial Statistics), Hofstede (2001), and Laeven and Valencia (2013)

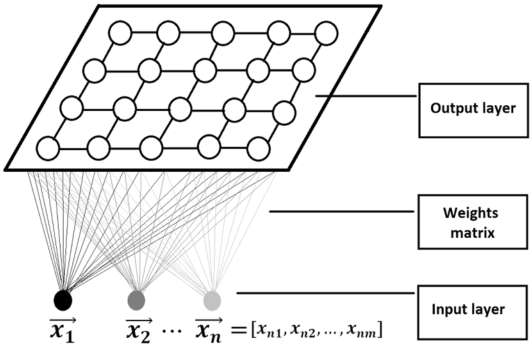

Fig. 5 Topology of the SOM network. Source: Mostafa (2010)

of the multidimensional data distribution without losing the topological relationships of data and sight of individual indicators (Sarlin, 2011; Sarlin & Peltonen, 2013).

Moreover, the SOM can determine the importance of variables in the occurrence of financial crises. Hence, it allows us to avoid selection bias since the explanatory variables estimated in the logit model first pass through the SOM filter before being included into the logit model. Because the SOM technique is robust when dealing with highly correlated variables in large datasets. Furthermore, the SOM is robust when dealing with missing observations, since it gives enough information for the organization process by solely considering the indicators that are available (Kohonen, 2001; Sarlin, 2011). This is quite important for us since, since some explanatory variables are missing a small fraction of data (see Table 1). Hence, we can comfortably include variables with missing values that may play a role in the occurrence of the financial crisis during the period of 2007–2009. This approach allows us, thus, to avoid omitted variable bias frequently encountered in empirical analysis. Unlike many other analysis techniques, the SOM is a nonlinear and nonparametric method and is not based on strict assumptions. However, the SOM has also some negative aspects. The disadvantages of SOM are that the algorithm is time consuming, and the number of neurons affects the algorithm performance.

The SOM—also known as Kohonen Map—is an unsupervised competitive learning methodology, introduced in the literature of the Artificial Neural Networks by Kohonen (1982). The topology of the SOM network is shown in Fig. 5. The SOM network consists of two layers node; input and output. The important point here is that each output layer has one coordinate and enables to easily calculate the distances between output layers. Thus, they are in a two-dimensional topographic grid (map) according to the similarity of each output layer weight. Neurons having similar weight locate themselves closely, while dissimilar neurons are away from each other.

Self-organizing process involves four basic elements: initialization, competition, cooperation, and adaptation (Sarlin, 2011; Vesanto et al., 2000):

Step 1. Initialization: All connections are provided with an initial weight.

Step 2. Competition: The algorithm, using Euclidean distance, compares each input vector x_j with each output vector m_j and finds the best match m_c. The winning node is commonly called as Best Matching Unit (BMU).

$$\left\| x - m_c \right\| = \min_i \left\| x - m_i \right\| \tag{1}$$

Here, the smallest Euclidean distance might be defined as the best match point.

Step 3. Cooperation and Adaptation: In the input space, the BMU and its topological neighbors are closely located to the input vector. The update rule for the prototype vector of unit i is;

$$m_i(t+1) = m_i(t) + \alpha(t)h_{bi}(t)[x(t) - m_i(t)] \tag{2}$$

where t is time, $\alpha(t)$ is adaptation coefficient, and $h_{bi}(t)$ is neighborhood Kernel centered on the winner unit. Neighborhood is often calculated by using Gaussian neighborhood function.

$$h_{ic(j)} = \exp\left(-\frac{\left\| r_c - r_i \right\|}{2\sigma^2(t)}\right) \tag{3}$$

where r_c and r_i are two-dimensional coordinates of the reference vectors, m_c and m_i, respectively, and the radius of the neighborhood $\sigma(t)$ is a monotonically decreasing learning factor at time t.

Step 4. Repeat from step 2 for sufficient iteration for convergence.

Step 5. By using K-means clustering method, gather the nodes into a small number of clusters.

As highlighted by Mostafa (2010), Unified Distance Matrix (U-Matrix) is frequently used to see the structure of the clusters. But due to the lack of clarity of clusters' visuality obtained through U-Matrix, clustering becomes quite difficult. Hence, we opt for K-means clustering method to avoid such a problem. Note also that we employ the SOM Toolbox package developed by Vesanto et al. (2000) for SOM calculations. In their SOM codes, the optimal number of nodes is determined endogenously.

Note that there is no consensus on how to determine the importance of variables in SOM method, although there exist some techniques used in natural sciences. These are structuring index (SI), relative importance index (RI), cluster description index (CD), and Spearman rank correlation index (SRC). However, these methods can give quite different order of importance in estimates. In other words, while a variable is found to be important for an index, it may have a lower significance for other indexes. This inconsistency poses problems in interpreting the empirical results. Hence, we use all four techniques mentioned above, namely SI, RI, CD, and SRC following the literature. Then, as in Demir and Cergibozan (2018) we calculate an overall index to avoid any contradictory results as follows[2]:

[2] Note that this is a method used in the literature to construct currency crisis indicators. See Ari (2012) and Ari and Cergibozan (2016) for a detailed analysis.

$$Overall\,Index = \frac{SI - \mu_{SI}}{\sigma_{SI}} + \frac{RI - \mu_{RI}}{\sigma_{RI}} + \frac{CD - \mu_{CD}}{\sigma_{CD}} + \frac{SRC - \mu_{SRC}}{\sigma_{SRC}} \tag{4}$$

where σ_{SI}, σ_{RI}, σ_{CD}, and σ_{SRC} denote standard deviation of SI, RI, CD, and SRC, respectively, while μ_{SI}, μ_{RI}, μ_{CD}, and μ_{SRC} indicate mean of SI, RI, CD, and SRC, respectively.

On the other hand, the estimated logit model takes the following form:

$$\text{Prob}\left(C_t \middle| X_{t-k}\beta\right) = F\left(X_{t-k}\beta\right) \tag{5}$$

where the probability of a crisis $C_t = 1$ is estimated k step before the occurrence of a crisis, conditional on a given set of explanatory variables X_{t-k}. β is the vector of coefficients and F is logistic distribution function. The right-hand side of the equation is constrained to 0 or 1 and is compared to the observed value of the binary crisis variable C_t.

Equation 5 shows that the explanatory variables have a nonlinear effect on the probability that a crisis occurs. This characteristic makes the model well-suited to deal with financial crises (Bussiere & Fratzscher, 2006). Besides, the logit approach directly evaluates the conditional probability of a crisis given a set of indicators and lends itself to standard statistical tests that evaluate the robustness of the estimation results (Abiad, 2003).

Moreover, we also assess the forecast power of the logit model at different threshold levels (0.5, 0.25, and 0.20). In fact, the forecast performance of a model is measured through its ability to correctly predict actual crisis episodes. To this aim, one compares the predicted probability of a crisis produced by the model with the actual crisis probability. As the predicted probability is a continuous factor, a necessary step consists in specifying a probability level (cut-off or threshold), above which the predicted probability sends a crisis signal (Bussiere, 2013). However, setting a threshold level is problematic. Because a lower threshold value raises the number of correctly predicted crises, but at the expense of increasing the number of false alarms (Type II errors). On the other hand, a higher threshold value reduces the number of false alarms, but to the detriment of increasing the number of missed crises (Type I errors). One may solve this trade-off problem by defining a threshold probability according to the relative importance given to Type I versus Type II errors. The modeler may naturally choose a threshold of 0.5. However, as underlined in Esquivel and Larrain (2000), the sample is relatively unbalanced in favor of non-crisis periods. Therefore, a threshold set at 0.5 would underestimate the predictive power of the model. This leads us to consider two other threshold values (0.25 and 0.2) to evaluate the forecast performance of our models.

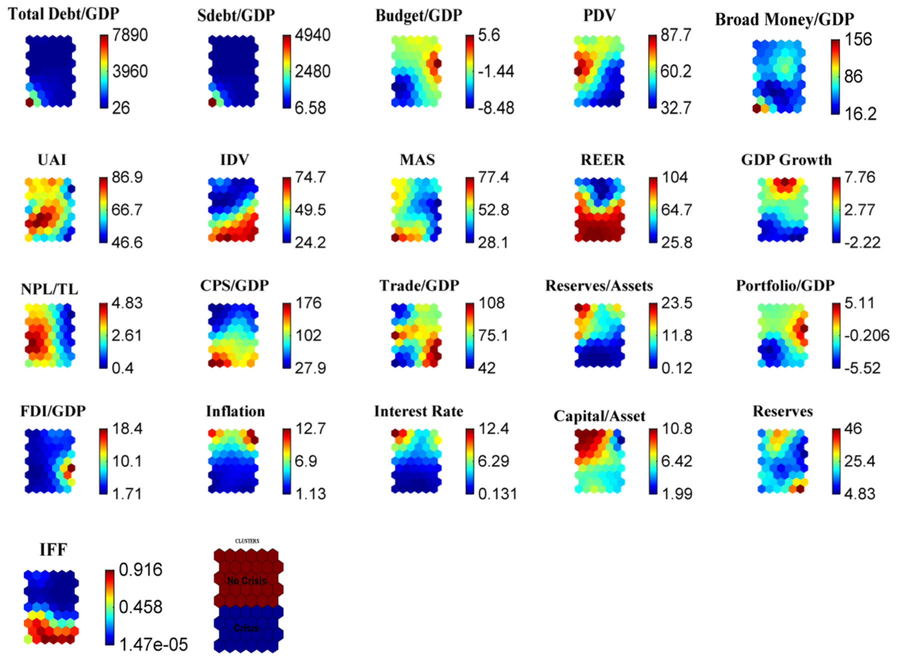

Fig. 6 SOM results

3 Empirical results

3.1 SOM results

We first analyze results obtained from the SOM model. Each graph in Fig. 6 represents values for different neurons of the variables using a color code ranging from dark blue (low values) to dark red (high values). Empirical findings presented in Fig. 6 show there are two different clusters: cluster 1 with red color indicates noncrisis episodes, while cluster 2 with blue color represents crisis episodes. As seen in Fig. 6, each variable has its own component matrix with two-dimensional visuality. One can then easily observe, via temperature maps and component matrix (the scale on the right-hand side of each graph), the value that each variable takes in crisis and noncrisis periods. Note that divergence between two clusters (crisis and noncrisis periods) is better visualized for some variables (see the graph of individualism) while it is not the case for others. Hence, to correctly interpret empirical results, one should also consider Table 2 that presents means and standard deviations of explanatory variables both during crisis and noncrisis periods.

Empirical findings first indicate that the probability to be in crisis in the period of 2007–2009 was higher for countries with lower power distance and higher individualism. The impact of masculinity and uncertainty avoidance is not clear-cut. On the other hand, appreciation of domestic currency, deterioration of budget balance over GDP, an increase in trade volume to GDP, low ratio of portfolio investments

Table 2 Sample statistics for clusters

Indicator	No crisis (mean)	Crisis (mean)	No crisis (Std. Dev.)	Crisis (Std. Dev.)
Real effective exchange rate index	92.32	100.96	8.87	6.48
GDP growth (annual %)	3.40	– 0.46	3.98	3.21
Trade (% of GDP)	73.60	76.22	37.01	34.28
Inflation, consumer prices (annual %)	7.15	1.77	6.18	1.49
Deposit interest rate (%)	6.74	1.96	4.89	1.54
Budget surplus/deficit (% of GDP)	– 0.50	– 4.15	5.51	4.29
Short-term debt/GDP (%)	39.00	804.94	88.83	2370.18
Total Debt/GDP (%)	111.89	1405.67	210.84	3742.01
Total reserves minus gold (%)	18.40	21.47	28.59	32.55
Broad money (% of GDP)	65.01	120.03	35.40	57.00
Foreign direct investment, net inflows (% of GDP)	3.59	6.87	2.63	14.19
Portfolio investments (% of GDP)	0.92	– 2.59	4.18	6.48
Bank nonperforming loans to total gross loans (%)	2.84	2.74	1.61	1.93
Domestic credit to private sector (% of GDP)	51.95	132.03	34.74	45.56
Bank liquid reserves to bank assets ratio (%)	20.01	3.02	12.02	1.45
Bank capital to assets ratio (%)	9.58	5.56	2.28	1.75
Power distance index	62.87	43.70	22.88	16.78
Uncertainty avoidance Index	67.60	68.33	22.38	26.66
Individualism versus collectivism	31.63	65.02	18.47	18.01
Masculinity versus femininity	48.06	50.78	16.70	25.19
Index of financial fragility (Laeven & Valencia, 2013)	0.03	0.65	0.17	0.48

Table 3 Ranking of explanatory variables

Rank	SI	Values	RI	Values	CD	Values	SRC	Values	Overall index	Values
1	NPL/TL	620.381	CPS/GDP	18.623	MAS	2.044	IDV	0.575***	CPS/GDP	0.931
2	IDV	573.500	Broad money/GDP	17.860	UAI	2.036	Sdebt/GDP	0.552***	REER	0.877
3	PDI	557.127	REER	12.487	Reserves	2.033	Total debt/GDP	0.551***	Broad money/GDP	0.841
4	CPS/GDP	548.102	Trade/GDP	9.316	NPL/TL	2.029	REER	0.516***	IDV	0.596
5	Budget/GDP	531.522	IDV	7.329	Trade/GDP	1.991	CPS/GDP	0.483***	NPL/TL	0.545
6	Capital/asset	523.326	MAS	6.659	Broad money/GDP	1.969	GDP growth	– 0.466***	MAS	0.476
7	REER	518.109	UAI	6.569	Portfolio/GDP	1.935	Capital/Asset	– 0.460***	Trade/GDP	0.451
8	GDP growth	475.100	PDI	5.491	Budget/GDP	1.865	Portfolio/GDP	– 0.395***	UAI	0.107
9	MAS	470.611	Reserves	3.744	FDI/GDP	1.805	Inflation	– 0.369***	PDI	0.068
10	Interest rate	461.533	Reserves/assets	2.779	PDI	1.753	Budget/GDP	– 0.368***	Budget/GDP	– 0.088
11	Trade/GDP	445.538	FDI/GDP	1.575	REER	1.745	PDI	– 0.367***	Reserves	– 0.110
12	FDI/GDP	423.373	Interest rate	1.267	GDP growth	1.738	Broad money/GDP	0.251**	FDI/GDP	– 0.181
13	Reserves/assets	408.145	Budget/GDP	1.135	Total Debt/GDP	1.508	Interest rate	– 0.174	Portfolio/GDP	– 0.381
14	Inflation	407.753	Portfolio/GDP	1.123	Sdebt/GDP	1.488	Reserves/assets	– 0.146	GDP growth	– 0.408
15	Broad Money/GDP	392.916	Inflation	0.973	IDV	1.487	Reserves	0.138	Total debt/GDP	– 0.448
16	Portfolio/GDP	384.913	GDP growth	0.746	CPS/GDP	1.437	UAI	– 0.126	Sdebt/GDP	– 0.513
17	UAI	376.002	Capital/asset	0.734	Capital/asset	1.404	NPL/TL	0.106	Interest rate	– 0.570
18	Reserves	258.150	Total debt/GDP	0.705	Inflation	1.387	FDI/GDP	– 0.094	Capital/asset	– 0.579
19	Total debt/GDP	242.567	NPL/TL	0.456	Interest rate	1.326	MAS	0.086	Inflation	– 0.785
20	Sdebt/GDP	226.437	Sdebt/GDP	0.430	Reserves/assets	1.063	Trade/GDP	0.027	Reserves/assets	– 0.830

to GDP, high ratio of bank nonperforming loans to bank total loans, increases in domestic credit over GDP, decreases in bank liquid reserves to bank assets ratio, and low ratio of bank capital to bank assets are found to be significant macro-financial determinants of the crisis across countries.

The next step in the SOM analysis is to determine the importance of variables in the occurrence of the global financial crisis. Ranking explanatory variables according to their order of importance will also help in selecting variables to be included into the logit analysis. As mentioned above, there is no consensus on 'the best ranking technique' since different methods can give quite different order of importance in estimates. Hence, we also use the overall index to avoid any inconsistency problems in interpreting the empirical results. The inconsistent results presented in Table 3 clearly indicate why we needed to calculate the overall index. According to the overall index, CPS/GDP, REER, Broad Money/GDP, IDV, NPL/TL, MAS, Trade/GDP, UAI, PDI, and Budget/GDP are respectively the most important 10 variables in differentiating crisis and noncrisis clusters.

3.2 Logit results

Table 4 presents estimation results of seven different logit models. Model 1 is estimated only with core macro-financial variables, while following four models consist of one cultural variable along with core macro-financial indicators. Note also that Model 6 is estimated with all macro-financial and cultural variables, while Model 7 consists of only cultural variables. By following this approach, we aimed to assess the additional benefit of including cultural variables in crisis prediction.[3]

According to Model 1, all macro-financial explanatory variables are correctly signed and significant except for Trade/GDP. Estimation results indicate that an increase in credit to private sector over GDP, an increase in real effective exchange rate, and a decrease in budget balance over GDP augment the likelihood of the crisis during the period of 2007–2009. Interestingly, Trade/GDP representing trade openness becomes significant when we run models with cultural variables. On the other hand, estimation results of Models 2, 3, 4, and 5 indicate that individualism and power distance are correctly signed and statistically significant, contrary to masculinity and uncertainty avoidance. To be more specific, higher individualism and lower power distance increase the probability of crisis across countries during the 2007–2009 period. We can thus affirm that logit results perfectly confirm findings obtained from the SOM analysis. Note also that both SOM and logit estimation results partly validate our hypotheses on the impact of cultural values on the occurrence of the financial crises since two out of four cultural variables are statistically significant.

[3] Note that we exclude, from the logit estimation, two explanatory variables (Broad Money/GDP and NPL/TL) found to be significant in the SOM analysis, due to their high correlation with domestic credit to private sector over GDP (see Table 7 in Appendix).

Table 4 Logit estimation results

Variables	Dependent variable: IFF						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
CPS/GDP	0.024** (0.009)	0.038** (0.016)	0.024** (0.010)	0.023** (0.010)	0.025** (0.010)	0.042** (0.017)	
REER	0.266*** (0.092)	0.200* (0.104)	0.251*** (0.093)	0.264*** (0.092)	0.277*** (0.095)	0.216** (0.108)	
Budget/GDP	− 0.257** (0.101)	− 0.636*** (0.225)	− 0.388*** (0.142)	− 0.273** (0.112)	− 0.244** (0.103)	− 0.705*** (0.264)	
Trade/GDP	0.010 (0.009)	0.025* (0.014)	0.021* (0.012)	0.026* (0.015)	0.026* (0.014)	0.033* (0.017)	
IDV		0.109*** (0.038)				0.109*** (0.041)	0.087*** (0.020)
PDI			− 0.029** (0.014)			− 0.026 (0.024)	− 0.009 (0.017)
UAI				− 0.006 (0.018)		− 0.006 (0.018)	0.024 (0.015)
MAS					0.008 (0.016)	0.004 (0.020)	0.006 (0.012)
Constant	− 31.158*** (9.586)	− 35.064*** (13.112)	− 17.880*** (6.422)	− 30.371*** (10.041)	− 32.854*** (10.585)	− 37.492*** (13.850)	− 7.147*** (1.970)
Observations	74	74	74	74	74	74	114
Pseudo R^2	0.46	0.59	0.50	0.46	0.46	0.61	0.37
LR Stat	45.5***	59.4***	50.0***	45.6***	45.7***	61.0***	49.5***
Akaike Info	0.87	0.71	0.84	0.90	0.89	0.77	0.84

***, ** and * represent statistical significance at the 1%, 5% and 10% level, respectively

Moreover, it is interesting to observe the consistency between significant macro-financial variables and significant cultural variables. As expected, the countries with higher degree of individualism present higher probability to experience a crisis. This could be related to the aggressive risk-seeking behavior that may endanger long-run growth performance of financial and nonfinancial institutions.[4] The perfect example is excessive compensation practices frequently used before the outbreak of the global financial crisis. This generalized practice in most financial institutions that rewarded executives and traders based on short-term performance without considering market fundamentals and long-term earnings. Executives were given stock options and shares without cash-out restrictions, which they could manipulate to earn more money. The more an executive could increase company's stock price, the more money s/he would get. This compensation structure operated, therefore, as a powerful incentive to take risk (Benassy-Quere et al., 2009) which caused in parallel higher lending to private sector that led to bubbles in housing and stock markets, and higher financial leverage that increased financial system weaknesses. On the other hand, our results corroborate the arguments of Mixa and Vaiman (2015) about the higher crisis probability in the individualistic countries such as the US, the UK, and Iceland and the empirical results of Berger et al. (2021) who indicated higher individualism is associated with bank failures. Our findings are also consistent with the results of the early empirical studies since strong credit growth (Claessens et al. 2010; Lane & Milesi-Ferretti, 2011; Feldkircher, 2014), high leverage (Berkmen et al., 2012), and real appreciation (Frankel & Saravelos, 2012) were pointed out to be main determinants of the global crisis.

Besides, our estimation results show that countries with lower power distance had higher probability to experience a crisis in the 2007–2009 period. This indicates that in countries with lower power distance, there exists a less hierarchical structure which prevents authorities to orient and manage investors' expectations. Hence, this may limit the efficiency of implemented economic policies. This result is quite intriguing, since it explains why and how governments could not prevent further collapses in the financial system despite an aggressive interest rate policy, substantial liquidity provisions to financial markets, extensive bank rescue and guarantee plans, and expansionist fiscal policies (Ait-Sahalia et al., 2010).

Table 5 presents the forecasts from estimated logit models. As seen in table, Models 2 (estimated with individualism and core macro-financial variables) and 6 (estimated with all cultural and core macro-financial variables) have the best performance in predicting crisis and noncrisis episodes at 0.2 and 0.5 threshold levels, respectively. This definitely shows the additional benefit of including cultural variables in crisis prediction. Note also that Model 7 (estimated only with cultural variables) predicts 92% of noncrises and 72% of crisis episodes at 0.5 and 0.25 cut-off values, respectively. As expected, a lower threshold value raises the number of correctly predicted crises, but at the expense of decreasing number of correctly predicted noncrisis episodes. On the other hand, a higher threshold value rises the

[4] There are other factors that may affect this risk-taking behavior such as legal, institutional, and social environment (see Aktaruzzaman and Farooq 2020).

Table 5 Forecasts of logit models

Cut-off level	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
C = 0.5							
% and number of Cor. predicted noncrises	86.36% (38/44)	88.64% (39/44)	84.09% (37/44)	80.00% (38/44)	88.64% (39/44)	90.91% (40/44)	92.68% (76/82)
% and number of Cor. predicted crises	83.33% (25/30)	83.33% (25/30)	80% (24/30)	80% (24/30)	76.67% (23/30)	83.33% (25/30)	56.25% (18/32)
C = 0.25							
% and number of Cor. predicted noncrises	65.91% (29/44)	77.27% (34/44)	68.18% (30/44)	65.91% (29/44)	65.91% (29/44)	77.27% (34/44)	71.95% (59/82)
% and number of Cor. predicted crises	93.33% (28/30)	96.67% (29/30)	93.33% (28/30)	93.33% (28/30)	93.33% (28/30)	96.67% (29/30)	87.50% (28/32)
C = 0.2							
% and number of Cor. predicted noncrises	61.36% (27/44)	75.00% (33/44)	65.91% (29/44)	63.64% (28/44)	61.36% (27/44)	72.73% (32/44)	68.29% (56/82)
% and number of Cor. predicted crises	93.33% (28/30)	100.00% (30/30)	96.67% (29/30)	93.33% (28/30)	93.33% (28/30)	100% (30/30)	87.50% (28/32)

number of correctly predicted noncrisis episodes, but to the detriment of increasing number of missed crises.

4 Conclusion

Contrary to early empirical papers which have generally focused on macroeconomic and financial factors as crisis determinants, this study aimed to empirically investigate the role of cultural values that shape decision-making of economic agents on the occurrence of the global financial crisis by using the SOM approach and logit model in a panel set of 38 countries. Empirical findings obtained from empirical analysis indicate that the probability to be in crisis in the period of 2007–2009 was higher for countries with lower power distance and higher individualism. This result validates our hypotheses on the impact of individualism and power distance on the occurrence of a crisis during the period of 2007–2009.

On the other hand, forecast performance of logit models was quite remarkable, since more than 85% of noncrisis (tranquil) and 90% crisis episodes are correctly predicted at 0.5 and 0.2 threshold values, respectively. However, the model estimations with cultural values had better performance in correctly predicting all crisis episodes than models estimated with only macro-financial variables. This result clearly indicates the additional value of including cultural variables in crisis prediction.

Besides, empirical results show that strong credit growth, increases in budget deficits and trade openness, and currency appreciation rose the crisis probability during the 2007–2009 period. These results are in line with the existing theoretical and empirical literature that analyze the global financial crisis, since credit growth (Claessens et al. 2010; Caprio et al. 2014), currency appreciation (Frankel & Saravelos, 2012), and budget deficits (Berkmen et al. 2012) were found to be statistically significant predictors of the global crisis.

This study contributes to the crisis literature in terms of both methodology (SOM) and approach (cultural variables). It might be, however, extended for further research, on the one hand, by expanding the sample period to examine other crisis episodes to reach more robust and reliable results, hence, to improve our understanding on why and how financial crises occur, on the other hand, by assessing the impact of cultural values on the crisis length or crisis severity. The study may also be expanded by considering other datasets measuring cultural differences such as World Values Survey.

Appendix

See Tables 6 and 7.

Table 6 Crisis dates

Country	Code	Crisis dates
Argentina	ARG	–
Austria	AUT	2008, 2009
Belgium	BEL	2008, 2009
Brazil	BRA	–
Chile	CHL	–
Colombia	COL	–
Costa Rica	CRI	–
Denmark	DNK	2008, 2009
Ecuador	ECU	–
Finland	FIN	–
France	FRA	2008, 2009
Germany	DEU	2008, 2009
Greece	GRC	2008, 2009
India	IND	–
Indonesia	IDN	–
Ireland	IRL	2008, 2009
Israel	ISR	–
Italy	ITA	2008, 2009
Jamaica	JAM	–
Japan	JPN	–
Korea, Rep	KOR	–
Malaysia	MYS	–
Mexico	MEX	–
Netherlands	NLD	2008, 2009
Norway	NOR	–
Panama	PAN	–
Peru	PER	–
Philippines	PHL	–
Portugal	PRT	2008, 2009
Spain	ESP	2008, 2009
Sweden	SWE	2008, 2009
Switzerland	CHE	2008, 2009
Thailand	THA	–
Turkey	TUR	–
United Kingdom	GBR	2007, 2008, 2009
United States	USA	2007, 2008, 2009
Uruguay	URY	–
Venezuela, RB	VEN	–

Source: Leaven and Valencia (2013)

Table 7 Correlation matrix

Probability	Correlation																			
	VAR1	VAR2	VAR3	VAR4	VAR5	VAR6	VAR7	VAR8	VAR9	VAR10	VAR11	VAR12	VAR13	VAR14	VAR15	VAR16	VAR17	VAR18	VAR19	VAR20
VAR1	1.00																			
P value	–																			
VAR2	− 0.41	1.00																		
P value	0.08	–																		
VAR3	0.05	0.34	1.00																	
P value	0.84	0.15	–																	
VAR4	− 0.14	0.45	0.53	1.00																
P value	0.56	0.06	0.02	–																
VAR5	− 0.13	0.40	− 0.18	0.44	1.00															
P value	0.59	0.09	0.45	0.06	–															
VAR6	− 0.11	0.59	0.48	0.38	0.23	1.00														
P value	0.66	0.01	0.04	0.10	0.35	–														
VAR7	0.00	− 0.60	− 0.44	− 0.57	− 0.55	− 0.29	1.00													
P value	0.99	0.01	0.06	0.01	0.01	0.24	–													
VAR8	− 0.03	− 0.59	− 0.44	− 0.57	− 0.56	− 0.28	1.00	1.00												
P value	0.92	0.01	0.06	0.01	0.01	0.25	0.00	–												
VAR9	− 0.13	− 0.55	− 0.56	− 0.60	− 0.45	− 0.27	0.97	0.97	1.00											
P value	0.60	0.01	0.01	0.01	0.05	0.26	0.00	0.00	–											
VAR10	0.10	− 0.49	− 0.26	− 0.70	− 0.67	− 0.24	0.81	0.82	0.82	1.00										
P value	0.67	0.03	0.29	0.00	0.00	0.32	0.00	0.00	0.00	–										
VAR11	0.17	0.54	0.74	0.57	0.17	0.60	− 0.66	− 0.67	− 0.75	− 0.63	1.00									
P value	0.49	0.02	0.00	0.01	0.48	0.01	0.00	0.00	0.00	0.00	–									

Table 7 (continued)

Probability	VAR1	VAR2	VAR3	VAR4	VAR5	VAR6	VAR7	VAR8	VAR9	VAR10	VAR11	VAR12	VAR13	VAR14	VAR15	VAR16	VAR17	VAR18	VAR19	VAR20
VAR12	0.57	− 0.23	0.24	− 0.24	− 0.42	0.31	0.20	0.19	0.07	0.18	0.30	1.00								
P value	0.01	0.33	0.32	0.32	0.07	0.20	0.41	0.43	0.78	0.47	0.22	–								
VAR13	− 0.01	− 0.30	− 0.66	− 0.14	0.42	− 0.55	− 0.03	− 0.04	0.04	− 0.26	− 0.39	− 0.32	1.00							
P value	0.98	0.21	0.00	0.56	0.07	0.01	0.89	0.88	0.88	0.29	0.10	0.18	–							
VAR14	0.12	− 0.60	− 0.26	− 0.64	− 0.62	− 0.12	0.90	0.90	0.88	0.86	− 0.48	0.37	− 0.21	1.00						
P value	0.62	0.01	0.28	0.00	0.00	0.63	0.00	0.00	0.00	0.00	0.04	0.12	0.38	–						
VAR15	− 0.28	0.40	0.07	0.53	0.37	0.13	− 0.54	− 0.54	− 0.50	− 0.65	0.31	− 0.26	0.13	− 0.72	1.00					
P value	0.24	0.09	0.77	0.02	0.12	0.60	0.02	0.02	0.03	0.00	0.20	0.28	0.61	0.00	–					
VAR16	− 0.31	0.45	0.15	0.64	0.61	− 0.03	− 0.65	− 0.65	− 0.63	− 0.77	0.30	− 0.58	0.41	− 0.81	0.46	1.00				
P value	0.20	0.05	0.53	0.00	0.01	0.90	0.00	0.00	0.00	0.00	0.21	0.01	0.08	0.00	0.05	–				
VAR17	− 0.05	− 0.04	− 0.60	− 0.01	0.47	0.08	0.08	0.08	0.14	− 0.36	− 0.02	0.05	0.50	0.00	0.22	0.08	1.00			
P value	0.85	0.87	0.01	0.97	0.04	0.74	0.75	0.75	0.56	0.13	0.93	0.84	0.03	1.00	0.37	0.75	–			
VAR18	− 0.09	− 0.07	0.16	0.03	− 0.59	0.13	0.40	0.40	0.28	0.15	0.11	0.40	− 0.32	0.29	0.18	− 0.35	0.06	1.00		
P value	0.70	0.78	0.51	0.92	0.01	0.60	0.09	0.09	0.24	0.55	0.65	0.09	0.18	0.23	0.46	0.14	0.80	–		
VAR19	0.00	− 0.11	− 0.30	− 0.60	− 0.45	− 0.19	0.38	0.38	0.45	0.74	− 0.51	− 0.04	− 0.16	0.38	− 0.16	− 0.56	− 0.39	0.05	1.00	
P value	0.99	0.66	0.21	0.01	0.05	0.43	0.11	0.10	0.06	0.00	0.03	0.86	0.51	0.11	0.52	0.01	0.10	0.85	–	
VAR20	− 0.05	− 0.45	− 0.74	− 0.67	− 0.35	− 0.50	0.83	0.84	0.87	0.72	− 0.82	− 0.08	0.26	0.69	− 0.54	− 0.44	0.17	0.12	0.48	1.00
P value	0.85	0.05	0.00	0.00	0.14	0.03	0.00	0.00	0.00	0.00	0.00	0.74	0.28	0.00	0.02	0.06	0.49	0.64	0.04	–

VAR1 real effective exchange rate index, *VAR2* GDP growth (annual %), *VAR3* trade (% of GDP), *VAR4* inflation, consumer prices (annual %), *VAR5* deposit interest rate (%), *VAR6* budget surplus/deficit (% of GDP), *VAR7* short-term debt/GDP (%), *VAR8* total debt/GDP (%), *VAR9* total reserves minus gold (%), *VAR10* broad money (% of GDP), *VAR11* foreign direct investment, net inflows (% of GDP), *VAR12* portfolio investments (% of GDP), *VAR13* bank nonperforming loans to total gross loans (%), *VAR14* domestic credit to private sector (% of GDP), *VAR15* bank liquid reserves to bank assets ratio (%), *VAR16* bank capital to assets ratio (%), *VAR17* power distance index, *VAR18* uncertainty avoidance index, *VAR19* individualism versus collectivism, *VAR20* masculinity versus femininity

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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