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WHAT ARE THE MACROECONOMIC DRIVERS OF THE ASSET RETURNS OF TURKISH BANKS?

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Abstract. The aim of this paper is to investigate the effects of the macroeconomic factors to the movements of the asset returns of the banks in Turkey in terms of systemic risk from 2005 to 2018. In the study, Independent Component Analysis is applied for extracting driving factors of the asset returns of Turkish banks by decomposing the returns into its components. After examining the relationship between the independent components and the macroeconomic variables, the results conclude that one component shows strong similarities with the well-known stock market index of Turkey, namely the BIST100. Besides, the BIST100 is observed as the most important macroeconomic indicator affecting the movements of the asset returns. From systemic risk perspective, the BIST100 and the exchange rate from US dollar to Turkish lira are interpreted as two macro factors that contribute to the systemic risk of Turkish banks. When it is reviewed the regression results of the estimated independent components with the macroeconomic variables, it is found that while the BIST100 affects the asset returns of Turkish banks on its own, three macroeconomic factors (the credit default swap spreads of Turkey, the exchange rate and volatility) jointly affect the banks by creating a chain effect.

Keywords: independent component analysis, asset returns, macroeconomic factors, systemic risk, exchange rate, banks, BIST100, credit default swap.

JEL Classification: C14, C31, C50, C58, C80, C83, E02, G21.

Introduction

Asset returns are affected by financial movements in markets, especially during times of financial distress. As one of the leading indicators of financial markets, asset prices and thus asset returns play a crucial role in financial stability and monetary policy frameworks (Bank for International Settlements [BIS], 2007). It is known that financial crises have a large impact on asset returns. There is a general opinion that any abnormal movements in

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asset returns can be used as an early warning signal for financial crises. In the literature, the correlation between asset returns and financial crisis has been extensively researched. For example, Chaudhury (2014) investigates the effect of the crisis on daily stock returns for 31 non-financial and financial stocks in the US and the S&P 500 from January 2007 to December 2008. He finds that the value-at-risk of the stock portfolios rise sharply during the crisis. In the study of Christensen et al. (2015), they examine the effects of a financial disaster on two important properties of stock index yields in the US, i.e., the leverage effect and the risk & return impact during the period from 1926 to 2010. The results show that the fiscal effects enlarge substantially throughout crises period. The risk-return status is largely affirmative over financial disasters and unimportant during financial stability times, while the leverage has adverse effect during the period. Vila (2000) examines the relationship between stock market collapses and banking system crises for 14 developed countries over the period 1970 to 1999. The empirical results do not allow to extract a conclusion that the dramatic increases in equity price cause problems in both equity markets and the banking sector. Moreover, Hartmann et al. (2004) study the connection between treasury bond and stock exchange markets. They investigate the return linkages between asset markets during crisis periods using extreme value analysis. The results show non-negligible cross-asset market relations during distress times. Binici et al. (2013) examine the systemic risk status of the Turkish banking sector during the last two decades running a new systemic risk indicator which is defined as co-movement of banks' stock returns. In the study, the daily share prices of the seventeen banks quoted on the Turkish stock market are used between 1990 and 2011. The results indicate the correlation in 2000s almost double compared to 1990s. However, it is concluded that the correlation starts to decrease after 2002 and increases shortly after the financial crises in 2007.

In this paper, we investigate the impact of the main macroeconomic factors to the asset returns of Turkish banks over the period from 2005 through 2018. During the study period, there was a global financial crisis started in the late of 2007 that hit the global economy and brought about a systemic crisis over the global markets. The general thought is that financial crisis and systemic risk affect stock returns negatively. In recent years, it has been observed unusual fluctuations in asset returns such as boomed before the crises. However, the financial crises caused fire sales of assets. As a result, to understand which macroeconomic indicators such as inflation, exchange rate or interest rate can affect the movements in stock returns and hence asset returns including systemic crises effects has drawn more attention, notably in the studies of Fama (1981, 1990), Chen et al. (1986), Humpe and Macmillan (2009), Muradoglu et al. (2001), Rapach et al. (2005) and Tripathy (2011). These studies confirm the linkages. Moreover, BIS (2017) emphasizes on the linkages between asset prices and macroeconomic results by reviewing the literature on this topic. It claims that distress in financial markets can adversely affect asset prices and thus results in more fluctuations on macroeconomic factors. According to Rapach et al. (2005), the interest rate is the most predominant variable that influences on stock returns with a negative correlation. In terms of influence on banking, Paul and Mallik (2003) examine having a long-run linkage between stock prices in the finance and banking sector in Australia and macroeconomic indicators. They find that while interest rates have negatively impacted on stock prices, the growth of real economic activity has positively impacted on them, and inflation has no remarkable effect, consistent with the studies of Fama (1981), Chen et al. (1986) and Fifield et al. (2002).

In the study, the method introduced by Adrian and Brunnermeier (2016) has been used for the calculation of asset returns of a bank. Adrian and Brunnermeier (2016) advanced a new systemic risk measurement method, namely conditional value at risk (CoVaR). It is defined as the estimation of the value-at-risk of an institution, or the financial system given that another institution falls in trouble. They employ the CoVaR method to measure the contribution of an institution to the systemic risk of the financial system or vice versa. They associate CoVaR with systemic risk, and they claim that the higher CoVaR causes to increase the systemic risk contribution of the institution. Therefore, the contribution of our study is to bring a new perspective to find the key driving factors of the asset returns of Turkish banks using a different calculation method for the asset returns of a bank which is generally used for CoVaR. In this regard of this calculation method, the aim of the study is to determine the main macroeconomic factors that affect the asset returns and thus systemic risks of Turkish banks. This paper applies the technique of Independent Component Analysis (ICA) for extracting the factors driving the changes in the asset returns of banks. ICA is a technique of deducing hidden factors from a linear mixture of original signals by maximizing the independence of the components statistically (Westra et al., 2008). ICA is generally preferred when supposing a linear mixture of random variables that have non-gaussian distribution (Cortes et al., 2019). When the existing literature was reviewed, we couldn't find any research related to the application of ICA focused on the banks' stock returns in Turkey and their systemic risk, so this paper fills this research gap. Consequently, the objective of the study concentrates on exploring the answer to the following question: Does there exist an inherent association between the co-movement dynamics of asset returns of the Turkish banks and macroeconomic factors? We can construct the research hypothesis in this direction as follows: There is an intrinsic connection between the co-movement dynamics of the Turkish banks' asset returns and macroeconomic variables.

In exploring the linkage, it can be obtained which macroeconomic indicator(s) can create a systemic effect on the banks in Turkey. Thus, it is possible to identify the factor(s) that result in increasing the vulnerability of the Turkish banks during a financial crisis. The banking sector in Turkey dominate the financial sector (83% in 2018), and hence play an important market stabilization role for the whole Turkish economy (The Banks Association of Turkey [TBB], 2019). Thus, in this paper, we intend to find the main macro indicators that help for keeping the stabilization of the Turkish financial sector. Moreover, the results of the study can provide information about the factors affecting the returns of banks for investors in the Turkish stock market. Also, the study outcomes can be helpful for forecasting the stock price and thus asset returns of the Turkish banks by considering the significant factors.

This paper is organized into five sections apart from the introduction part. The first section presents the literature review. Section 2 provides a review on methodological explanation of ICA. Section 3 explains the data, and the details of the empirical analyses and the results are given in Section 4. The last section draws some conclusions.

1. Literature review

The literature consists of numerous studies concentrate on investigating the impact of macroeconomic factors on the Turkish banks. However, a large amount of the studies especially focuses on the profitability of banks. For instance, Alper and Anbar (2011) explore the profitability of ten Turkish commercial banks from 2002 to 2010. They reveal the positive impact of bank size on profitability. In terms of macroeconomic factors, they find interest rates having a profound effect on bank profitability. Dagidir (2010) identify interest rate as a proxy for the bank profitability and finds a negative linkage between interest rate and inflation, see also Muradoglu et al. (2000), Aysan and Ceyhan (2008), Baltaci (2014), Akbas (2012) and Ayaydin and Karaaslan (2014). On the other hand, there are few studies that focus on examining the impact of macroeconomic indicators on bank stock returns, such as Altay (2005), Kucukkocaoglu et al. (2013), Pekkurnaz and Elitas (2015), and Civan et al. (2020).

The well-known stock market index of Turkey is known as the Borsa Istanbul 100 return index (the BIST100). The BIST100 and the equity volatility index are used in many studies as the two significant macro variables directly related to the Turkish stock market. Bajo-Rubio et al. (2017) can be cited as an example for using the BIST100 as the main Turkish stock index. They investigate the spillover effects of both stock return and volatility in Turkey together with the impact of commodity markets and exchange rate and calculate the volatility of the indices from the period 1999 to 2015. Besides, Diebold and Yilmaz (2009) propose a new method for measuring the interdependence of asset returns and return volatilities from 1992 to 2007 for nineteen countries including Turkey. They select the BIST100 as the main indicator of the Turkish stock market. Kucukkocaoglu et al. (2013) focus on measuring the reaction of several banks' stock yields to Turkish monetary policy. They use the BIST100 as a proxy of the Turkish stock market. Similarly, Akkoc and Civcir (2019) examine the dynamic correlation between gold, oil and stock market returns in Turkey. They focus on the spillover effects of volatility from oil and gold to the Borsa Istanbul index after the 2008 financial crises. In the study of Sensoy and Sobaci (2014), they examine the dynamic linkages between three key indicators of economic and financial performance of Turkey from 2003 to 2013: interest rate, the stock market index and exchange rate. They use the daily BIST100 data as the benchmark stock market index of Turkey as in the other studies such as Altay and Calgici (2019). It is known that credit default swap markets and stock markets tend to incorporate credit risk information of a country or companies (Longstaff et al., 2011; Chau et al., 2018). Augustin (2018) examines the maturity structure of the spreads of credit default swap obtained from 44 countries including Turkey. He observes that the maturity structure of sovereign credit default swap spreads includes helpful information on the significance of domestic and global risks for the dynamics of sovereign credit risk. In the study of Chau et al. (2018) that investigate the drivers of credit risk between stock and credit default swap markets in the US, they find the economic condition and funding cost as important potential factors of credit risk discovery. Moreover, Markose et al. (2012) examine the market of credit default swap in a different angle that is the role of financial contagion and systemic risk. They propose a systemic risk ratio for concentration risk in this market. In the existing literature, it is observed that exchange rate and inflation are closely related to stock returns.

For example, Pavlova and Rigobon (2007) find that the foreign exchange market serves as a propagation channel from one stock to another. Their model specifies relationship between foreign-exchange, stock, and bond markets, see also Bajo-Rubio et al. (2017) and Sensoy and Sobaci (2014). In the study of Asprem (1989), he examines the linkages between macro variables, asset portfolios and stock indices in ten countries selected from Europe. The results show that inflation, employment, interest rates and imports negatively affect stock prices. Sathyanarayana and Gargesa (2018) focus on the correlation between inflation and stock yields of the selected global stock markets including Turkey. They find important correlation between inflation and the stock markets. In this regard of the previous studies, stock market indices, equity volatility index, credit default swap spreads, consumer price index and exchange rates reflect the main features of the Turkish stock market, and hence they are used as the key macro indicators for empirical analyses in this study.

In all these studies regarding the influence of macroeconomic factors to the Turkish financial market, it is usually applied panel data analysis, Granger causality test and co-integration test, autoregressive conditional heteroscedasticity (ARCH) type models and factor analysis. We couldn't find studies running the ICA method. ICA is developed for signal processing and data analysis in the beginning, but later it is the most widely used method in different areas such as feature extraction, telecommunications, financial data analysis, brain activity, biomedical signals, vision procession (Dogan & Akinci, 2013) and so on. In the financial sector, ICA reveals the driving factors behind the enormous data. The ICA model is more appropriate for the analysis of asset returns since ICA does not require observed variables having normal distribution. The number of works which apply ICA in different fields of finance has been continued to increase in recent years. The first empirical study of ICA in finance is presented by Back and Weigend (1997). They employ this method to the 3-years of daily yields of the 28 Japanese stocks, and comparing the outcomes gained from the technique of ICA with the results of principal component analysis (PCA). They express ICA as a strong method of extracting driving latent factors of data in financial markets. Then, many researchers have enhanced its implementation in their studies following Back and Weigend (1997). For example, Fabozzi et al. (2015) apply ICA to investigate the factors hiding behind the spreads of Eurozone credit default swap after the global financial crises in 2008. Kumiega et al. (2011) explore the impact of commodity price movements on returns and realized volatilities of equity indices over the period from 2007 to 2010. They conclude that the extracted factors from ICA are compatible with the major economic issues over the period. In similar to the study of Cha and Chan (2002) that aims to extract the components and the features of securities in the factor model of the returns of 7 stocks in China, Chen et al. (2007) implement ICA for extraction of original signals. As a result, they retrieve out of a high dimensional value-at-risk calculations. Moreover, Xian et al. (2020) integrate ICA into the method of ensemble empirical mode decomposition to find the hidden factors of single financial time series using the crude oil prices. They find the 5-major independent components such as the US-dollar index and the volatility of crude oil prices. All components found are consistent with the major economic principles. However, Chen and Khashanah (2015) employ ICA to examine the financial warnings for systemic risk in the US-stock market by introducing a systemic risk indicator. They reveal that the US financial market is more interconnected and more fragile during financial distress times. Miettinen et al. (2020) employ the ICA method for combining linear and quadratic autocorrelations on the basis of the time series data of exchange rates of seven currencies to US dollar. In the current studies, some researchers also combine ICA with neural networks methods for data mining. Lu et al. (2009), for instance, proposes an integration of ICA with support vector regression for forecasting of the Nikkei 225 opening index and TAIEX closing index, see also Liu and Wang (2011) and Chowdhury et al. (2018). Moreover, Moneta and Pallante (2020) compare the performance of different ICA estimators within the field of structural vector autoregressive (SVAR) method on the US government spending and tax cuts data. Ceffer et al. (2019) predict and model the future value of financial time series applying SVAR with ICA for pre-processing data. Liu et al. (2019), on the other hand, apply performance-relevant kernel ICA for non-linear and non-Gaussian processes on the comprehensive economic index data. There are insufficient studies on the applications of ICA for the Turkish financial market. Therefore, this paper specifically contributes to the literature by examining the impact of macroeconomic variables on the Turkish banks from the perspective of systemic risk by implementing, at the first time, a new data mining method, i.e., ICA.

2. Independent component analysis

Independent component analysis is originally a signal processing technique which is aimed to find independent components from only observed data without any prior knowledge of the mixing mechanism (Cha & Chan, 2002). ICA associates with the method denoted by Blind Source Separation (BSS) (Herault & Jutten, 1986; Jutten & Herault, 1991). In ICA, an original signal, i.e., independent component, attributes an original source such as a speaker in a cocktail party. Blind referees having few information, and with the help of this information, the mixing matrix is tried to find. If we obtain the mixing matrix, then we make some assumptions on the original signals (Hyvarinen & Oja, 2000). ICA is mostly similar to the PCA but differs from the way of using second order statistics. While both of them separate the linearly observed signals into their components, ICA uses higher order moments such as kurtosis for defining the signals. In contrast to PCA which requires normal distribution, ICA applies to non-gaussian distribution. It is not possible to order the components in ICA on the contrary to PCA since ICA is only used for finding statistically independent sources (Back & Weigend, 1997).

It is assumed that there are n-observed mixture signals denoted by $x_i(t)$ formed by a linear mixture of unknown sources expressed as $s_j(t)$. Here, x_i is defined as the observed signals and t is the time index. It is known only the observed signals $x_i(t)$ that they can be used for estimating the original signals, i.e., $s_j(t)$. The basic linear equation of ICA model is given by (Hyvarinen & Oja, 2000):

$$x_i(t) = \sum_{j=1}^{n} a_{ij} s_j(t). \tag{1}$$

ICA indicates the process of decomposing the observed signal vectors, x, and estimating from them a new set of statistically independent vectors, y, called the independent components or the sources. In ICA, it is assumed that the observed variables come out of mainly the outcomes of an unknown mixing mechanism of some latent original sources. Using the vector-matrix notation, the main ICA model is obtained from the following model of X which is a linear mixture of n-dimensional independent components s(t) denoted by (Back & Weigend, 1997; Lu et al., 2009):

$$\mathrm{X} = \mathrm{AS}, \tag{2}$$

where S = $\left[s_1(t), s_2(t), \ldots.., s_q(t)\right]^T$ is a vector of q-independent random variables and X = $\left[x_1(t), x_2(t), \ldots.., x_j(t)\right]^T$ representing the observed variables. The matrix A and S are unknown, just the n-dimensional matrix X can be observed. The main objective is to estimate the mixing matrix A by maximizing independence between the sources, S, using the matrix of X. For achieving this goal, the key issue is to find W, the decomposing matrix, given by (Back & Weigend, 1997):

$$y(t) = \mathrm{W}x(t); \tag{3}$$

$$y(t) = \mathrm{WA}s(t). \tag{4}$$

Suppose that we have as many observed variables as we have sources, so A is a nxn-square matrix. If W = A^{-1}, then $y(t) = s(t)$ and de-mixing happens. To obtain a de-mixing matrix W, the below assumptions could be made (Back & Weigend, 1997; Tharwat, 2021):

1. The sources sj(t) are statistically independent.
2. The independent components must be non-gaussian, but it is allowed only one component being a normal distribution. In ICA, non-gaussianity is classically measured with kurtosis (Hyvarinen & Oja, 2000).
3. The signals are stationary. It is supposed that both the observed variables and the independent components have zero mean or have centered by subtracting the sample mean to make the model zero mean.

It is needed an algorithm for decomposing X into S by finding the matrix A such that sj is as independent from the other sj. There are several algorithms for finding A. The FastICA algorithm proposed by Hyvarinen et al. (2001) has been applied in this paper to estimate the statistically independent components (ICs) and to construct the mixing matrix. FastICA defines ICA by enabling the maximize of the non-gaussianity of independent components based on the fixed-point method. With FastICA, the data is at first centered and then whitened (Fabozzi et al., 2015). Consequently, it is possible to make a linear transformation from the observed signals into a new set of signals whose components are uncorrelated and their mean and variances are equal to zero and one (Kumiega et al., 2011).

3. Data

We analyzed the returns of the market value of total assets (in briefly "asset returns") of Turkish banks from January 2005 to December 2018 in this study. ICA was applied to data. The data was obtained from the quarterly consolidated financial statements of the banks published by the Banks Association of Turkey (TBB) and on the websites of the banks. We used the quarterly asset returns of twelve major Turkish banks out of totally 52 banks: 9 private banks, 1 state-development and 2 public banks. These banks constitute approximately

73% of the whole asset size of the Turkish banking sector. The sample of banks were selected in accordance with publicly available data since the share prices of stocks were required in addition to the banks' financial statements. To calculate the asset returns of a bank, it was needed publicly opened company. In Turkey, two public banks, Halkbank and Vakifbank, were initially public offered in 2005 and 2007, whereas the initial public offerings for many private banks were started before 2005. Consequently, the observation period from 2005 to 2018 was chosen based on data availability.

While calculating the stock returns of a bank according to the below expression, it was employed the logarithmic returns of the 2nd closing prices of stocks:

$$r = 100 * \left[\ln\left(p_{it}\right) - \ln\left(p_{it-1}\right)\right] / \ln(p_{it-1}). \tag{5}$$

The quarterly asset returns of a financial institution denoted by X^i was calculated applying the method introduced by Adrian and Brunnermeier (2016), which is carried out as follows:

$$X^i = \frac{ME_t^i.LEV_t^i - ME_{t-1}^i.LEV_{t-1}^i}{ME_{t-1}^i.LEV_{t-1}^i} = \frac{A_t^i - A_{t-1}^i}{A_{t-1}^i}; \tag{6}$$

$$A_t^i = ME_t^i.LEV_t^i = BA_t^i.\left(\frac{ME_t^i}{BE_t^i}\right), \tag{7}$$

where A_t^i indicates the market value of a bank's total assets in terms of the 2^{nd} session closing share prices of the bank, BA_t^i and BE_t^i shows the book value of a bank's total assets and total equity, ME_t^i shows the market value of a bank's total equity, $LEV_t^i = BA_t^i / BE_t^i$ represents the leverage ratio of a bank and t shows the quarterly time index.

The public offerings of Halkbank and Vakifbank were started in August 2005 and May 2007. Thus, there are missing share price quotations for the dates range from March 2005 to September 2005 for Vakifbank and from March 2005 to March 2007 for Halkbank. Moreover, TEB has no stock prices since June 2015 because of willingly unsubscribing from the Turkish stock market. The asset returns of these missing share price quotations were obtained with the assistance of using a banking sector index in the Borsa Istanbul Inc., namely XBANK, by following the method described in the study of Civan et al. (2020).

For performing the subsequent analyses, the five macroeconomic variables are preferred as the key indicators of the Turkish financial market: the 2nd session closing value of the BIST100 and the equity volatility index based on 63 days of the BIST100 as the Turkish stock market indicators, the Turkey 5 years sovereign Credit Default Swap (CDS) spreads as a sovereign credit risk indicator, the consumer price index (CPI) of Turkey as an inflation indicator and the indicative exchange rate between the US dollar and the Turkish lira (USD to TRY) as a foreign exchange market indicator. We mainly focus on the quarterly changes of logarithmic returns of all the aforementioned macro variables denoted by bist100, volatility, CDS, CPI, USDTRY and the quarterly logarithmic asset returns of the banks denoted by logXi. It was obtained the volatility and the bist100 data from the Borsa Istanbul Inc., the Turkey 5 years CDS spreads from the Undersecretariat of Treasury, the CPI data from the Turkish Statistical Institute (TURKSTAT) website and the USDTRY data from the website of the Central Bank of the Republic of Turkey (CBRT).

For the process of estimating the independent components of Turkish banks, the asset returns of the banks were used for de-mixing its statistically independent components. Thus, the observed variables were defined as the banks' asset returns. Then, the estimated independent components were compared to the macro variables and the returns of banks.

4. Empirical results

We apply ICA to extract the independent components behind the data of Turkish banks using the FastICA algorithm (Hyvarinen, 1996; Hyvarinen & Oja, 2000) since FastICA performs well with financial data (Garcia-Ferrer et al., 2008, 2012). The estimated ICs are, further, compared to the selected five macroeconomic variables, and it is checked whether there are strong similarities between some of the ICs and the macro variables. We aim to identify, for each independent component, a resemble macroeconomic factor whose fluctuation looks like the independent component, and then to find which macroeconomic variable(s) has significant effects on which ICs. Consequently, it is tried to reveal which ICs and the macro variable(s) contribute to the movements of the asset returns. In the empirical analysis, we initially overview the data in terms of descriptive statistics and the data suitability for ICA; then decompose the asset returns into the main independent components. Finally, it is constructed quantile regression models with the macro variables using the estimated ICs.

4.1. Summary statistics

As of pre-processing the data, it was checked the assumptions explained in section 2. ICA requires the observed signals to be stationary, so it was transformed the nonstationary asset returns into stationary by taking the differences between successive values of the variables. In this way, it was obtained a new set of observed signals, and their components are independent, and their mean and variance are equal to zero and one. The algorithm in FastICA tries to find the weighting matrix and statistically independent components by maximizing the negentropy (Hyvarinen & Oja, 2000). For maximizing the negentropy, it should be maximized the non-gaussianity of the variables (Comon, 1994; Kumiega et al., 2011). Thus, we checked the univariate normality of each individual series, i.e., the asset returns of the banks using the kurtosis values of the observed values.

Table 1 shows the descriptive statistics of all the observed variables. The standard deviations of the banks' asset returns ranging from 0.169 to 0.371 show the high and low volatility in the asset returns. Moreover, it is observed that most of the asset returns have the high kurtosis values (higher than 3), which indicates tail heaviness property of the returns such as Halkbank, Vakifbank and TEB. According to the skewness and kurtosis values, the distributions of the banks' asset returns differ from those of the Gaussian distribution, thus they are not normally distributed except for Isbank, Finansbank, Sekerbank and Akbank. It is also applied the Jarque-Bera test for the univariate normality of all the banks. The results of the Jarque-Bera test are given in Table 1. The null hypothesis of normality is rejected at the 5% significance level for the banks except for Isbank, Finansbank, Sekerbank and Akbank since they are normally distributed. ICA allows only one variable to be normally distributed. Thus, it is decided to take out Akbank, Finansbank and Sekerbank from the list and to move on the study with the rest of nine banks.

In addition, it is performed the Mardia test for assessing the multivariate normality of the rest of nine banks. The test of Mardia is empirically based on the multivariate kurtosis and skewness values of the variables. According to the test results, the null hypothesis of multivariate normality for the asset returns is rejected at 1% significance level (the test statistic for multivariate skewness is 867.167 and p-value <0.0000, and for multivariate kurtosis is 23.655 and p-value <0.0000).

The descriptive statistics of the five macroeconomic variables are presented in Table 2. According to the table, the variables of volatility and CDS have the highest standard deviations, i.e., the highest volatilities. With respect to the skewness and kurtosis values, all the macro variables are not normally distributed.

The market value of the banks' asset returns from January 2005 to December 2018 were calculated based on the Eqs (6) and (7). The individual graphs of the banks are given in Appendix 1. It was observed that the asset returns of all the banks especially Isbank, Halkbank, Akbank, Garanti, TEB and Sekerbank were adversely affected from the financial crises of 2008. Their asset returns dramatically decreased in the first quarter of 2008 and then continued to decrease through 2008. They started to recover from 2009. When looking at the graphs of the macroeconomic variables presented in Appendix 2, it was revealed that the return of bist100 and volatility also sharply decreased in the beginning of 2008, and they

Table 1. The descriptive statistic of the logarithmic asset returns of the banks (2005–2018)

$LogX^i$	Obs.	Mean	Std.Dev.	Median	Max	Min	Skewness	Kurtosis	J.Bera	p-value
Halkbank	56	0.0832	0.3272	0.0372	2.0648	–0.3984	4.0034	25.2315	1302.80	0.0000
Vakifbank	56	0.0708	0.3312	0.0459	1.8047	–0.6203	2.2848	15.0807	389.25	0.0000
Isbank	56	0.0345	0.1723	0.0385	0.3460	–0.3642	–0.0638	2.5821	0.45	0.8003
Akbank	56	0.0374	0.1693	0.0380	0.4703	–0.3227	–0.0247	2.8515	0.06	0.9718
Garanti	56	0.0572	0.2021	0.0720	0.5615	–0.7357	–1.0851	6.6624	42.29	0.0000
Yapi Kredi	56	0.0294	0.2277	0.0606	0.5763	–0.8961	–1.3166	6.9617	52.80	0.0000
Denizbank	56	0.0893	0.3090	0.0301	1.2988	–0.4866	1.4271	6.3562	45.29	0.0000
TEB	56	0.0109	0.3715	0.0350	0.7669	–1.7654	–1.9277	10.8289	177.70	0.0000
TSKB	56	0.0417	0.2510	0.0516	0.8676	–0.6979	0.3554	5.2719	13.22	0.0013
Kalkinma	56	0.0932	0.3117	0.0403	1.3895	–0.6045	1.2469	7.5459	62.73	0.0000
Finansbank	56	0.0678	0.2005	0.0579	0.6588	–0.5338	0.0980	4.0773	2.80	0.2469
Sekerbank	56	0.0241	0.2406	0.0232	0.5476	–0.6019	–0.4296	3.6010	2.57	0.2773

Table 2. The descriptive statistics of the macro variables (2005–2018)

	Obs.	Mean	Std.Dev.	Medium	Max	Min	Skewness	Kurtosis
bist100	56	0.0232	0.1438	0.0299	0.3816	–0.4342	–0.7251	4.5638
volatility	565 56	–0.0014	0.2890	–0.0219	0.6543	–0.6201	0.1788	2.6926
CDS	56	0.0072	0.2384	–0.0326	0.6981	–0.4124	0.7609	3.6149
CPI	56	0.0221	0.0162	0.0170	0.0893	–0.0033	1.6224	7.0187
USDTRY	56	0.0245	0.0765	0.0146	0.2727	–0.1260	0.8587	4.0941

started to improve from 2009. While bist100 and volatility decreased during 2008, the CDS and USDTRY increased steadily through 2008 because of the adverse effects of the risk of global markets and started to improve in the early of 2009.

Table 3 reports the correlation matrix of the banks and the macroeconomic variables based on the spearman and pearson methods. The spearman correlation values are presented at the upper diagonal of the matrix. The matrix indicates that the highest spearman correlation with the banks belongs to the bist100. For example, Garanti, Yapikredi, Vakifbank and Isbank (in descending order) have the significant positive correlations with the bist100. In addition to the bist100, the CDS and the exchange rate of the US dollar to Turkish lira have the most effective macroeconomic variables on the asset returns. As expected, the bist100 positively effects the banks' asset returns, whereas both the CDS and the exchange rate negatively affect them. The pearson correlation values confirm these results, too. When it is looked at the spearman correlations among the macro variables, it is seen that the exchange rate has considerable correlations with the remaining four macro variables. The results confirm the common view that any change in exchange rate has a substantial impact on the CDS (69%) and the volatility (40%). In other words, an increase in the exchange rate of US dollar to Turkish lira directly increases the CDS spreads of Turkey and the volatility of the market. However, an increase in the exchange rate negatively affects the bist100 (–56%), i.e., decrease the stock return index. Furthermore, the bist100 has a relatively strong negative correlation with the CDS (–65%), as expected. Also, it is seeing a remarkable positive correlation between the volatility and the CDS (47%).

Table 3. The correlation matrix of the banks with the macro variables

$LogX^i$	isbank	vakifbank	Halkbank	garanti	yapikredi	denizbank	teb	tskb	kalkinma	bist100	CDS	CPI	Volatility	USDTRY
Isbank		0.80**	0.66**	0.66**	0.73**	0.12	0.60**	0.54**	0.21	0.76**	–0.52**	–0.28*	–0.09	–0.40**
Vakifbank	0.68**		0.68**	0.67**	0.74**	0.15	0.61**	0.52**	0.29*	0.80**	–0.56**	–0.25	–0.15	–0.45**
Halkbank	0.31*	0.24		0.65**	0.64**	0.03	0.46**	0.42**	0.31*	0.69**	–0.45**	–0.29*	–0.20	–0.49**
Garanti	0.60**	0.55**	0.47**		0.76**	0.14	0.56**	0.50**	0.16	0.81**	–0.51**	–0.10	–0.08	–0.50**
Yapikredi	0.73**	0.63**	0.34**	0.61**		0.03	0.50**	0.58**	0.17	0.81**	–0.49**	–0.31*	–0.07	–0.48**
Denizbank	0.04	0.14	–0.03	0.08	–0.07		0.18	0.16	0.15	0.23	–0.20	–0.01	–0.26	–0.12
Teb	0.43**	0.35**	0.19	0.32*	0.33*	0.13		0.59**	0.28*	0.66**	–0.55**	–0.16	–0.24	–0.44**
Tskb	0.56**	0.42**	0.15	0.43**	0.63**	0.06	0.45**		0.25	0.63**	–0.38*	–0.07	–0.06	–0.23
Kalkinma	0.09	0.12	0.04	0.16	0.06	0.20	0.18	0.28*		0.30*	–0.18	–0.28*	–0.01	–0.03
bist100	0.73**	0.61**	0.45**	0.69**	0.71**	0.20	0.47**	0.55**	0.19		–0.65**	–0.18	–0.19	–0.56**
CDS	–0.56**	–0.49**	–0.36**	–0.46**	–0.62**	–0.16	–0.49**	–0.44**	–0.06	–0.61**		0.07	0.47**	0.69**
CPI	–0.34**	–0.15	–0.20	–0.16	–0.35**	–0.04	–0.07	–0.15	0.13	–0.22	0.19		0.03	0.25
Volatility	–0.07	0.00	–0.16	0.02	–0.10	–0.32*	–0.30*	–0.08	0.14	–0.25	0.49**	0.02		0.40**
USDTRY	–0.41**	–0.33*	–0.36**	–0.32*	–0.46**	–0.17	–0.25	–0.23	0.06	–0.47**	0.68**	0.47**	0.32*	

Note: *p < 0.05, **p < 0.01.

4.2. Extracted independent components of the asset returns of banks

While performing the FastICA algorithm on the asset returns to estimate the ICs, it is assumed that the number of asset returns equals to the number of independent components. Thus, all the asset returns of nine banks were used as inputs in the algorithm. The descriptive statistics of the estimated nine independent components are given in Table 4. It is shown that all ICs have higher kurtosis values. For example, the kurtosis value of ICs_3 has almost 40 which describes the heavily tail risk in the returns of the banks. Furthermore, ICs_2 and ICs_9 have kurtosis values that exceeds 23. Thus, these results underly the significance of tail–heavy models for forecasting and modeling the returns.

Afterwards, it is analyzed the graph of each estimated independent component. The graphs are, further, compared to both the banks and the macroeconomic variables, respectively. Figure 1 presents the joint graph of nine ICs obtained from the algorithm. Here, it is tried to find the answer to the question of if ICA reveal useful information on the movements of the Turkish banks' asset returns based on the estimated ICs.

It is further checked the correlations of the macroeconomic variables with the ICs and threw out the independent components that had weak correlations with the macroeconomic variables. After this reduction, the algorithm is run again. It is examined with several numbers of ICs such as nine, six, five, four and two. In all trials, the empirical results are close to each other in terms of correlations. The empirical results based on the five estimated ICs are submitted in the following of the study. The descriptive statistics of the five ICs are given in Table 5, and Figure 2 shows the graph of them. According to the summary statistics, the five ICs have higher kurtosis values such as almost 34, which indicates the heavy tail risk similar to the estimated nine ICs.

Table 4. The descriptive statistics of the independent components (ICs)

ICs	Obs.	Median	Minimum	Maximum	Skewness	Kurtosis
ICs_1	56	–0.1545	–1.6168	5.4360	2.9638	16.6272
ICs_2	56	–0.0099	–1.5871	5.9591	3.6358	23.1306
ICs_3	56	0.0808	–6.8695	0.9877	–5.7327	39.8317
ICs_4	56	0.0335	–4.8059	1.8143	–2.2729	11.8256
ICs_5	56	–0.1579	–2.1783	4.5908	1.7883	9.5144
ICs_6	56	–0.0347	–4.1594	3.0708	–1.1747	8.9559
ICs_7	56	0.0292	–2.4459	4.9169	1.8047	11.8829
ICs_8	56	0.0480	–2.5561	3.5286	0.5766	5.0180
ICs_9	56	0.0032	–5.9429	3.4556	–2.9293	25.0103

Table 5. The descriptive statistics of the five ICs

ICs	Obs.	Median	Minimum	Maximum	Skewness	Kurtosis
ICs_1	56	–0.0226	–3.6899	2.2256	–0.3576	5.4591
ICs_2	56	–0.1069	–2.5290	4.3644	1.2007	8.3617
ICs_3	56	–0.3243	–1.6323	4.2972	1.9056	7.8860
ICs_4	56	–0.0467	–2.1078	5.5920	2.9612	18.4518
ICs_5	56	0.2107	–6.5855	2.0634	–4.9224	33.9655

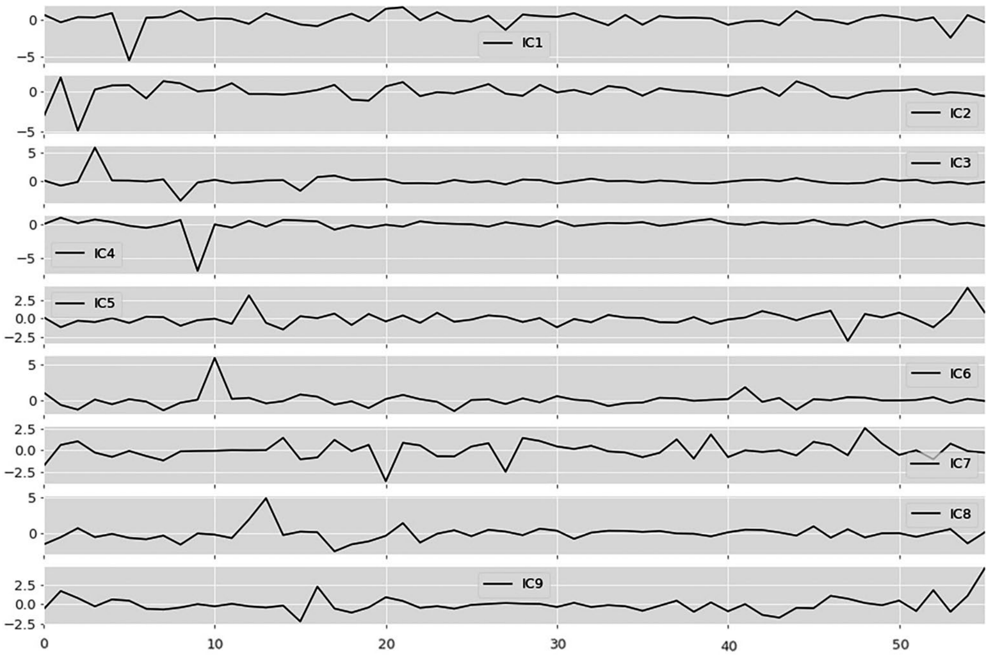

Figure 1. The graph of the estimated nine ICs

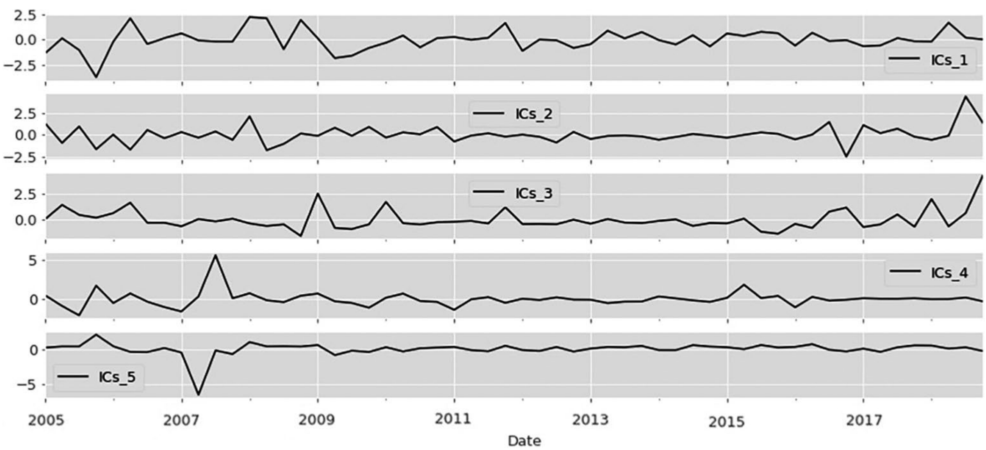

Figure 2. The graph of the estimated five ICs

Table 6 presents the spearman correlations (and also the Pearson correlations within parenthesis) between the five independent ICs and the macro variables. With respect to the correlation matrix based on the spearman method, the ICs_1 has a strong correlation with the bist100, the CDS and the USDTRY (especially with the bist100, 88%). However, we observe the remarkable correlations among ICs_4 and volatility and also between ICs_5 and the USDTRY.

Table 6. The correlation matrix between the five ICs and the macro variables

	IC_1	IC_2	IC_3	IC_4	IC_5
bist100	−0.88** (−0.80**)	0.07 (0.00)	−0.04 (−0.02)	−0.20 (−0.08)	−0.28* (−0.17)
CDS	0.62** (0.64**)	0.04 (0.11)	0.06 (0.04)	0.26* (0.19)	0.17 (0.12)
CPI	0.22 (0.23)	−0.27* (0.16)	0.04 (0.06)	0.12 (−0.06)	0.10 (0.12)
volatility	0.21 (0.11)	0.21 (0.24)	−0.13 (−0.22)	0.31* (0.31*)	0.17 (0.17)
USDTRY	0.49** (0.43**)	0.04 (0.18)	0.08 (−0.03)	0.26* (0.04)	0.33* (0.23)

Note: *$p < 0.05$, **$p < 0.01$.

4.3. Results of the quantile regression models

Here, it is investigated whether the estimated ICs are related to the macroeconomic variables. If it is found strong similarities between some macro variables and the ICs, in this case this IC(s) is interpreted as a representative of this macro variable and confirm the effects of the macroeconomic variable to the movements of the asset returns. For this, it is established a simple regression model. In the regression models, while the predictor variable is selected from out of the five macroeconomic variables, one of the independent components undertake the role of the dependent variable. We need a robust regression method because of the estimated ICs having non-normally distributed. Thus, it is applied the quantile regression as a robust regression method for the quantile levels of q = 5%, q = 50% and q = 95%.

The quantile regression results for the five ICs with each macro variable for q = 50% are respectively submitted in Table 7. According to the results, it is found that it might be a link between ICs_1 and all the macro variables except for the volatility and the CPI since the coefficients of the three macro variables in each regression model are significant. The R^2 values of the three regression models range from 8% to 51%. However, the highest determination coefficient among the median regression models set up for ICs_1 belongs to the bist100. The coefficients of the CDS and the USDTRY are also significant in the regression models generated for ICs_4. Thus, it is showed the importance of the CDS and the exchange rate along with the bist100.

When it is reviewed all the regression results from Table 7, it is concluded that ICs_1 has a strong relation with the bist100, and considerable relations with the other macro variables. It is remembered that the bist100 has significant correlations with the asset returns of nine banks, and with the macro variables, especially negative correlations with the CDS and the exchange rate (see Table 4). Thus, it can be interpreted that ICs_1 is related to the bist100, and so ICs_1 can be described as a representative of the bist100. In fact, when looking at the graphs in Figure 3, it is found that ICs_1 shows strong similarities with the bist100 since the correlation between them is 88% over the whole period from 2005 to 2018. The values of ICs_1 is multiplied to (−1) to see the relationship clearly in Figure 3. It is clearly observed from Figure 3 that while the 2008 financial crises affect the ICs_1 likewise the bist100, that is, they started to fall down in the beginning of 2007, deepened in 2008 and began economic recovery after 2008, they were differently affected from the military coup attempt which was made on 15 July 2016 in Turkey. The bist100 fell dramatically in 2016 and its recovery started in the late of 2016, however, the ICs_1 was not impacted on this attempt as the same degree as the bist100 since ICs_1 is extracted from only the asset returns of the banks of Turkey. On the contrary to the ICs_1, the bist100 includes the share prices of the first hundred companies from different sectors of Turkey.

Afterwards, it is tried to set up new multiple quantile regression models adding more than one macroeconomic variable as predictors for each model of the ICs since some ICs can be a relation with more than one macroeconomic variable. After many trials of different combinations of the macro variables with each ICs for different quantiles, it is concluded that if the CDS and the volatility in addition to the bist100 are added to the regression model of ICs_1, the coefficients of each one of these three macroeconomic variables are significant for q = 5%. While the coefficients of the bist100, the CDS and the USDTRY are significant for q = 95%, all the macroeconomic variables are insignificant for median quantile except for the

Table 7. The quantile regression results of the ICs with the macro variables

Predictors	ICs_1		ICs_2		ICs_3		ICs_4		ICs_5	
	coefficient	R^2	coefficient	R^2	coefficient	R^2	coefficient	R^2	coefficient	R^2
bist100	–5.90***	0.51	–0.16	0.00	0.16	0.00	–0.94	0.03	–1.11	0.04
volatility	0.33	0.00	0.60	0.03	–0.13	0.00	0.48	0.03	0.29	0.02
CDS	3.11***	0.23	0.11	0.00	–0.07	0.00	0.69*	0.04	0.21	0.00
CPI	3.37	0.00	–6.94	0.01	9.43	0.00	3.73	0.02	0.55	0.00
USDTRY	5.30*	0.08	–0.33	0.00	0.22	0.00	1.53*	0.04	0.94	0.02

Note: 1) In the quantile regression model for q = 50%, the each one of the estimated five ICs are the dependent variable, regressed on each macro variable as a predictor, respectively. 2) In the multiple quantile regression model generated for the ICs_1 as a dependent variable along with the bist100, the CDS and the volatility as independent variables, the coefficients of the macro variables are –5.66***(bist100), 3.63***(CDS) and –1.88***(volatility) for q = 5%. The determination coefficient of this model, R^2, is 49%. For q = 95%, the coefficients of the macro variables in the model of ICs_1 are –6.46***(bist100), –4.35*(USDTRY) and 2.04*(CDS), and R^2 is 57%. 3) For q = 95%, the coefficients of the model set up for ICs_4 are 4.57(bist100), 7.56*(CDS) and –16.05*(USDTRY), and R^2 = 14%. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.

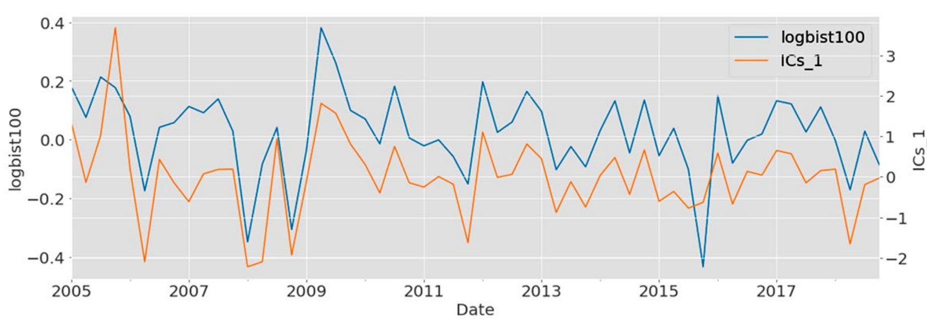

Figure 3. The graph of independent component ICs_1 and the bist100

bist100 in the regression model of ICs_1. It is shown that the determination coefficient of the model, R^2, increases to 57% at the quantile of 95%. Furthermore, out of the probable multiple quantile regression models set up for ICs_2, ICs_3 and ICs_4 based on several combinations of the macroeconomic variables as predictors, only the model for ICs_4 with the CDS and the USDTRY at q = 95% has the meaningful outcomes. The regression results for ICs_4 indicate the significance of the coefficients of the exchange rate and the CDS. As a result, we cannot reject the research hypothesis, that is, it is accepted to the co-movement of the asset returns of Turkish banks with the bist100, the exchange rate and CDS as the macroeconomic factors.

Lastly, it is added a dummy variable as a predictor to the quantile regression models for different quantiles (q = 5%, 50% and 95%). It is set up new models for each of the five ICs only with the dummy variable, respectively. Our purpose is to examine the effects of the financial crises in 2008 to the estimated five ICs. It is described the dummy variable as "1" for the time periods of 2008, and "0" for rather than 2008. With respect to the results, the coefficients of the dummy variable are significant in the models generated for ICs_1 for q = 50%, ICs_3 for q = 95% and ICs_4 for q = 5%. Thus, it is able to see the effects of the 2008 financial crises on the ICs_1, ICs_3 and ICs_4 for different quantiles.

Conclusions

This study has explored the application of ICA to the asset returns of Turkish banks. ICA seems to be more suitable technique for non-gaussian series especially financial data including the asset returns of financial institutions. It is investigated the behaviours of the asset returns of nine Turkish banks over the period from January 2005 to December 2018. It has been aimed to find interpretable factors that affects the movements of the banks' asset returns. It is found that two factors out of the estimated five ICs affects them. We find strong similarities between IC_1 and bist100, so the results indicated that the first component is related to the bist100. The graphs of ICs_1 and the bist100 also confirm this similarity. In addition, the ICs_4 can be related to the exchange rate from US dollar to Turkish lira based on their similarities. As a variable, the stock market index plays a pivotal role which directly effects the movements of the asset returns of the banks, consistent with Altay and Calgici (2019). The ICA technique reveals a fact that the movements of the bist100 and the exchange rate impact the mechanism behinds the data of the banks. This result is partly compatible with the study of Muradoglu et al. (2001) which indicates the significance of foreign currency. Moreover, we also find that inflation has no important effect, consistent with Fama (1981), Rapach et al. (2005) and Paul and Malik (2003). As a result, if it is aimed to establish a forecasting model for the returns of Turkish banks, the most valuable variable would be the bist100 as an indicator of the Turkish financial markets.

When it is looked at the graph of the bist100 and ICs_1 (see in Figure 3), it is found that the bist100 is adversely affected from the military coup attempt in 2016 in Turkey, but this attempt does not significantly impact on the ICs_1. While the bist100 sharply decreases in 2016, the ICs_1 falls off slowly, and stays steadily and starts to increase with the bist100 again. These results can be interpreted as the feature of the bist100 index since it is computed from the stock prices of the first hundred firms which are selected from different sectors of

Turkey including finance. Therefore, while the bist100 is influenced from the 2016 military attempt, the ICs_1 estimated from the asset returns of the banks is not affected as much as the bist100 since the Turkish banking sector has been strictly regulated by the government authorities such as the CBRT and the Undersecretariat of Treasury. These governmental institutions observe the capital requirements of the banks, their operating facilities, and their ratios like leverage ratio, capital requirements ratio, etc. Consequently, this study reveals that the Turkish banking sector has stronger than the other sectors of Turkey in the face of many difficulties including any event causing systemic risk.

While trying many possible multiple quantile regression model combinations of the macroeconomic variables with each one of the ICs, we are aware of that although the coefficient of the volatility is not solely significant in the regression models generated for each ICs, when the volatility along with the bist100 and the CDS are included in the model as predictors for the low quantile, $q = 5\%$, its coefficient turns into significant. It brings about increasing the determination coefficient of the model. Moreover, it is concluded that the exchange rate and the CDS together with the stock market index are significant in the models of ICs_1 and ICs_4 only for the high quantile, $q = 95\%$. It can be interpreted that when the CDS as a sovereign risk indicator spread of Turkey have fluctuated at a time; they bring about a trigger event on the bist100 and the exchange rate (or vice versa). Thus, this result can also be interpreted as the importance of the joint effect of the CDS, volatility and the exchange rate to the Turkish stock market. As a result, they impact on the asset returns of the banks as a part of a chain, however, the bist100 affects them on its own.

In this study, it is applied a different asset return calculation method which is used for CoVaR, one of the systemic risk measurement methods. The calculation method is based on the returns of the market valued of the Turkish banks' total assets. If some factors cause to decrease the returns of the market valued of the banks, it can be implied that they increase the systemic risk contributions of the banks. In this regard, when it is reviewed the empirical results from systemic risk perspective, the bist100 and the exchange rate impact on the returns of the market valued of the Turkish banks total assets. Thus, the stock market index and the exchange rate as the indicators of the Turkish financial market contribute to the systemic risk of the Turkish banks, consistent with the results of Binici et al. (2013) and Civan et al. (2020), and the study of Pavlova and Rigobon (2007). They reveal the importance of the foreign exchange market as a spillover tool. It is revealed that the bist100 is observed to be the most important factor to affect the returns of the banks and so to make the most contribution to the systemic risk of the banks. As a result, to understand what determines asset returns movements in the Turkish financial market has become more important for regulatory institutions to develop new policy frameworks for the financial stability in Turkey.

The study has a limitation of using only the five macroeconomic factors. Thus, future research can be developed for exploring the impact of different macroeconomic indicators on the Turkish financial sector to assist the Turkish regulatory authorities via shed light on which macroeconomic factors cause systemic risk. In addition, the study can be extended to different banks selected from global markets considering the importance of banking sector in financial markets and compare the results from the perspective of global systemic risk in the world.

Author contributions

Prof. Dr. Gulhayat Golbasi Simsek, Dr. Zehra Civan and Utku Kubilay Cinar conceived the study and were responsible for the design and development of the data analysis. They were responsible for data interpretation. Dr. Zehra Civan was responsible for data collection and wrote the article.

Disclosure statement

The authors declare that they do not have any competing financial, professional, or personal interests from other parties.

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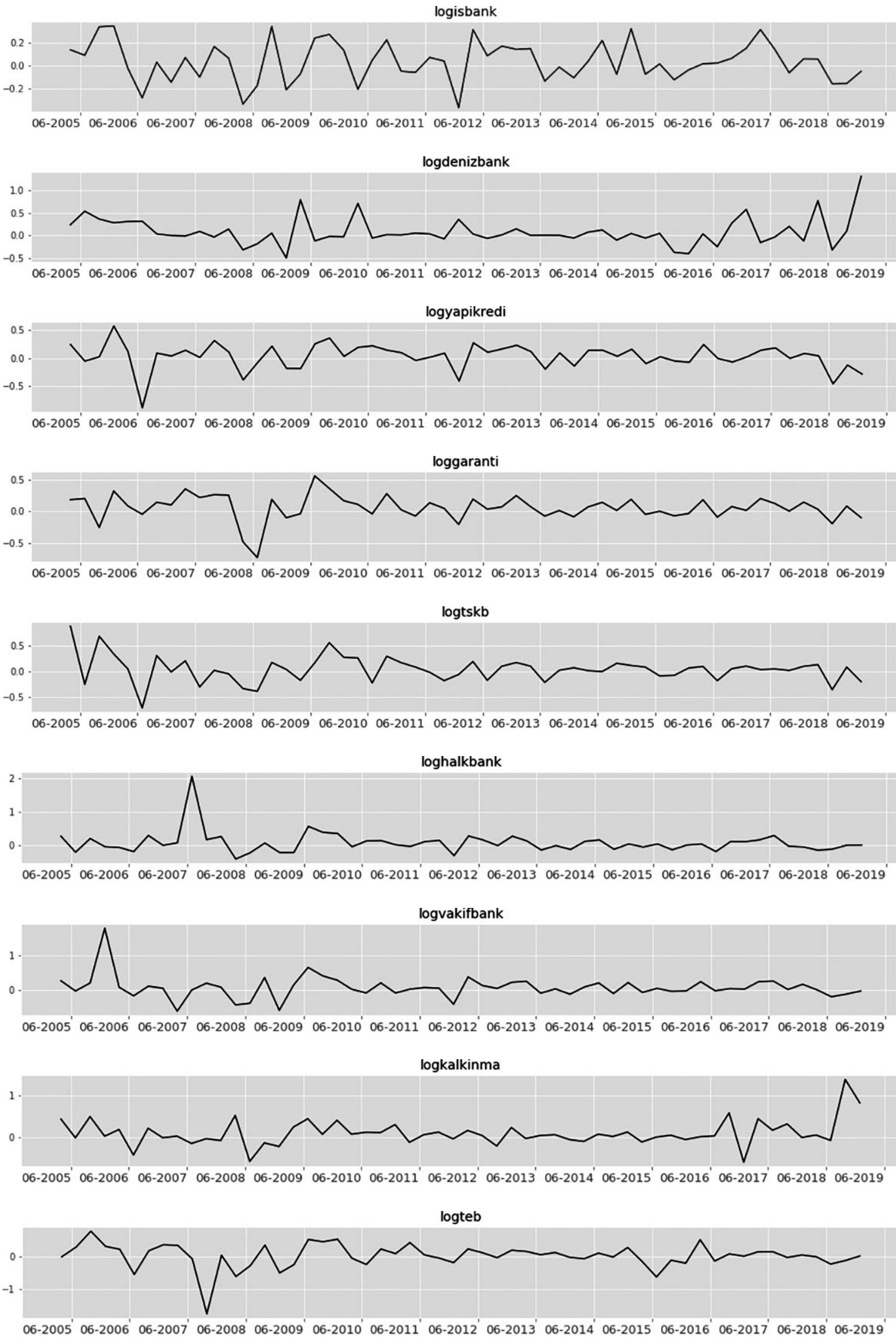
APPENDIX

1. The logarithmic asset returns of the banks (LogX^i)



2. The log-returns of the macroeconomic variables