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Contagion effect of migration fear in pre and European refugee's crisis period: evidence from multivariate GARCH and wavelet empirical analysis

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Abstract
To test the contagion effect of fear migration between countries, and to show its causality direction, our paper contributes to the economic literature by providing a new study based on migration fear indices quarterly data of France, Germany, United Kingdom and United States spanning period 1990–2019. Our empirical strategy is based on dynamic conditional correlation GARCH model and continuous wavelet transform analysis. Our results show a significant contagion effect of fear migration between the selected countries in pre and at the European Refugees crisis. The main findings of this work are changes level of conditional correlation in the two subsample periods, and changes in the arrow's directions in red space of the phase difference between each two fear migration series. These findings indicate that European Refugees crisis changes the relationship between European Union countries and USA, and the Brexit changes the European people behavior towards migrants and refugees. Our findings offer a new directions and tracks in the international relations to the policy makers, moreover it calls into question the various studies examining economic interdependence and the contagion effect of financial crises and policies events on the different markets.

Keywords: Fear migration, Contagion effect, Causality direction, European Refugees crisis, DCC-GARCH, Continuous wavelet transform

JEL Classification: C12, C22, F22, F52

Introduction
Poverty, political instability, violence, wars and civil wars, human rights violations, and genocide are the main factors of migration and asylum. Sine year 2000, the world is facing the highest levels of forced displacement since World War II. Currently, more than 65 million people are forcibly displaced by various conflicts around the world as refugees and internally displaced persons (IDPs) (Akesson & Badawi, 2017; Almustafa, 2021; Human Rights Watch, 2016). The earlier experience of Afghan and other refugees has shown that such displacements can last for three or more decades. In addition to

refugees seeking asylum outside their homeland, there also 6.6 million IDPs within Syria (Almustafa, 2021), many of these having been displaced many times as a result of changing tides in the civil war between the Syrian government and the many different kinds of rebels, ISIS fighters from various countries and from time to time interventions by Russians, Kurds, and others The Syrian crisis is now the world's biggest humanitarian crisis, with more than 4.9 million registered refugees and more than 7 million IDPs.

At the end of Arab Spring, refugee waves from the Middle East and North Africa are causing major problems in European countries. Fears of terror and crime arising as a result of such large flows of migration have significant impacts on economic policies and also on the behavior of the European people (Beerli & Peri, 2015; Boeri et al., 2015). The European countries create anxiety about the political, social and economic consequences of large population inflows (Halla et al., 2015). The Paris attacks on 13 November intensify security concerns and are likely to impede assimilation efforts (Gould & Klor, 2014). Fears about terrorism and crime add to traditional economic worries about the effects of large immigration flows on labor markets, housing markets, schooling, social services, and government spending (Borjas, 2003; Card, 2005). Major immigration policies, including the open border concept in the 26-country Schengen zone, are now in question (Pop, 2015).

In the United States, the attacks of September 11, 2001, transformed the landscape of global security, none more than borders and immigration. The topography of citizenship, belonging, and suspicion instantly changed for Arab and Muslim communities in the United States. They drew the sharp attention of U.S. law enforcement and intelligence services, and that continues. But the public's focus has swung south to scrutinize the U.S.-Mexican border as a source of insecurity. For the most part, the alarms about immigrants as threats are exaggerated. And the policy choices driven by these concerns, much larger border security measures are costly in a globalized economy and unnecessary for security in any case.

Given that European Union countries and United States of America are interdependent at the economic, financial and security level, they are largely sensitive to changes. Thus, vulnerability interdependence highlights the gains of cooperation and the potential losses of destabilizing relationships (Mansfield & Pollins, 2003). Indeed, high level in migration fear in a country positively influences the migration fear in the other linked countries. This positively relationships between time series of fear migration are explained as contagion effects.

The concept of contagion is studied in the financial framework to examine the effects of the financial crisis on stock market, banks, firms, and households (Adrian & Shin, 2010; Bernanke, 2010, 2015; Gertler & Gilchrist, 2018; Gertler et al., 2017; Gorton, 2010). Indeed, there are many studies examining the existence of contagion effect of various crises in the world. In this framework, different methodologies have been utilized to measure how shocks are transmitted internationally: cross-market correlation coefficients, ARCH and GARCH models, cointegration techniques, and direct estimation of specific transmission mechanisms.

This contagion of migration fear between countries is transmitted through geopolitical, economic, societal and financial channels. For the geopolitical risks channel, Czudaj (2018), Eckstein and Tsiddon (2004), Blomberg et al. (2004) argue that an increase in migration fear could lead the population to become hesitant on security issues and thus is related with the impact of geopolitical risks on economic variables.

The second is the financial channel. Global stock markets and especially those of Europe and the USA are integrated, the massive and sudden waves of migration increase the economic policy uncertainty which in turn negatively influences economic growth and stock markets returns (Arin et al., 2008; Brounen & Derwall, 2010; Karolyi & Martell, 2010) This lead to negatively influence the investor sentiment (increase of investor fear). In this case, if a stock market responses by decreasing investment, due to decline in returns, the others react in the same direction.

The third transmission channel of contagion effect of migration fear is economic and societal channel, the deterioration of the employment situation in the country of destination can affect the migrant's income and this leads to thefts and crimes which are the major sources of fear in European and American societies (Karolyi & Martell, 2010). Borjas (2003), Boeri et al. (2015) and Beerli et al. (2018) showed that immigrants shape the housing market and increase the employment rate. Therefore, immigration and economic conditions are closely intertwined, and immigration could affect fear sentiment to lose jobs, houses, security, … This fear sentiment is spreading mainly in the euro zone and united states by what is called neighbor effect and contagion effect.

Although there are many studies in the literature that examine the effects of the migration problem on the economy through macroeconomic variables (Furlanetto & Robstad, 2019; Kiguchi & Mountford, 2017; Liu, 2010), and also other studies on the impacts of migration on the stock markets (Chrétien & Coggins, 2009; Powell et al., 2009; Santa-Clara & Valkanov, 2003; Wong & McAleer, 2009), but there is no study analyzing the contagion effects of migration fear between countries.

Thanks to Baker et al. (2015, 2016) the migration fear is digitized. Indeed, they create migration fear indices for countries such as Germany, France, and UK by scanning newspaper articles from the term sets "migration" and "fear". From this point, it was easy to study the effect of migration fear on stock markets indices, unemployment, household's behavior, investment… In this context, under the assumption that exist contagion effect of migration fear, the principal aim of this study is to determine the relationship between the migration fear index and to study the causality direction of them for Germany, France, United states and the UK.

In this paper, we define contagion firstly as the co-movement showed by positive conditional and unconditional correlations given by DCC-GARCH model estimation. Secondly, contagion effect as explained by the phase differences which represented by arrows in the wavelet coherency plots. The contagion causality direction between fear migration series is defined by right pointing arrows, and the up and down directions signify respectively the leading and the lagging variables. To do this, we firstly determine the date break, based on Zivot–Andrews and Bai–Perron approaches, which expected coincides with European refugees' crisis. Then, we estimate the correlations coefficients in pre and at crisis period samples. The main hypothesis of the present study is to prove the existence of contagion effect of fear migration in the four selected countries. In addition, we show the direction causality of the founded contagion effect. Finally, we examine the effects of European Refugees crisis on contagion effect and its causality direction, and on relationships between countries.

This paper contributes to the economic literature, firstly, to our knowledge, by providing a pioneer study examining the contagion effect of migration fear based on Baker et al. (2015, 2016) Fear migration index series spanning 1990–2019 years. Secondly, by providing the first study on contagion effect based simultaneously on the DDC-GARCH model and continuous wavelet transform (CWT).

The rest of the paper is organized as follows. "Empirical framework" section presents the empirical framework. While "Empirical findings" section presents the empirical results and discussion, followed by concluding remarks and policy implication of our findings in "Conclusion" section.

Empirical framework

This section outlines the used methodology to study the contagion effect of migration fear. The appropriate empirical model we estimate such as multivariate GARCH and continuous wavelet transform. Finally, we present our data series with their descriptive statistics.

Methodology

To study the contagion effect of migration fear in our selected countries sample (France, Germany, United Kingdom, and United States), we start by determine the structural changes. Indeed, we use two approaches to make our results robust. So, we use the Zivot and Andrews (1992) (ZA) and Bai and Perron (1998) (BP) tests. The first tests the presence of unit root with one structural break. The second approach estimate L possible structural date breaks in each series. With the ZA estimated date break we divide our full sample into two subsamples. Then, we estimate our appropriate model (M-GARCH) in each subperiod. With DCC-GARCH model we obtain the conditional correlations which gives an idea for the contagion effect between countries fear migration. In addition, to support the results presented by the DCC- GARCH model and to determine the direction of the contagion effect, we use the continuous wavelet transform (CWT). The CWT analyze the dynamic relationship between Fear migration indices and shows coherency and phase difference.

DCC GARCH model

The DCC- GARCH model is given below:

$$H_t = D_t R_t D_t$$

where H_t is conditional variance matrix, D_t is a $k \times k$ diagonal matrix having conditional variance $\sqrt{H_t}$.

On it's diagonal and R_t is time-varying correlation matrix. The conditional variance h_{it} for return series are estimated using univariate GARCH.

$$h_{it} = a_i + \sum_{j=1}^{q_i} \alpha_{ij} e_{it-j}^2 + \sum_{k=1}^{p_i} \beta_{ik} h_{it-k}, \quad for\ i = 1, 2, \ldots, m$$

where a_i, α_{ij} and β_{ik} are non-negative and $\sum_{j=1}^{q_i} \alpha_{ij} + \sum_{k=1}^{p_i} \beta_{ik} < 1$, and m is the number of selected sectors.

If, the residual (e_t) and the conditional standard deviation ($\sqrt{h_{it}}$) are obtained, the conditional standard deviation is expressed by diagonal matrix D_t, which consists ($\sqrt{h_{it}}$) elements on its diagonals as shown as follow.

$$D_t = \begin{bmatrix} \sqrt{h_{11t}} & 0 & \cdots & 0 \\ 0 & \sqrt{h_{22t}} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sqrt{h_{mm,t}} \end{bmatrix}$$

The standardized residuals ε_t are used for estimating the symmetric and dynamic correlation matrix R_t.

$$R_t = \begin{bmatrix} 1 & \rho_{12,t} & \rho_{13,t} & \cdots & \rho_{1m,t} \\ \rho_{12,t} & 1 & \rho_{23,t} & \cdots & \rho_{2m,t} \\ \rho_{13,t} & \rho_{23,t} & 1 & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \rho_{m-1,m,t} \\ \rho_{1m,t} & \rho_{2m,t} & \cdots & \rho_{m-1,m,t} & 1 \end{bmatrix}$$

The element of $H_t = D_t R_t D_t$ is $[H_t]_{ij} = \sqrt{h_{it} h_{jt}} \rho_{ij}$, *where* $\rho_{11} = 1$

According to Engle (2000), Lim and Masih (2017) and Orskaug (2009), $R_t = Q_t^{*-1} Q_t Q_t^{*-1}$

where $Q_t^{*-1} = \begin{bmatrix} \sqrt{q_{11}} & 0 & \cdots & 0 \\ 0 & \sqrt{q_{22}} & \cdots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sqrt{q_{mm}} \end{bmatrix}$.

where $Q_t = (1 - a - b)\overline{Q_t} + a\varepsilon_{t-1}\varepsilon'_{t-1} + bQ_{t-1}$

where Q_t^* is the diagonal matrix of its diagonal elements, and Q_t is a symetric postive definite conditional correlation matrix, and $\overline{Q_t} = E\left(\varepsilon_t \varepsilon'_t\right)$ is unconditional covariance of the standadized residual of univariate GARCH model.

The likelihood of the DCC estimator (see Engle and Sheppard 2001) is:

$$L = -0.5 \sum_{t=1}^{T} (Klog(2\pi) + 2\log(|D_t|)) + \log(|R_t|) + \varepsilon'_t R_t \varepsilon_t)$$

The volatility (D_t) and the correlation (R_t) components may vary, thus the estimation process achieved in two steps. Firstly the volatility (L_v). is maximized:

$$L_v = -0.5 \sum_{t=1}^{T} (Klog(2\pi) + 2\log(|D_t|)) + r'_t D_t^{-2} r_t)$$

Then the correlation (L_c) is maximized

$$L_c = -0.5 \sum_{t=1}^{T} \left(Klog(R_t)\right) + \varepsilon'_t R_t^{-1} \varepsilon_t - \varepsilon'_t \varepsilon_t)$$

Wavelet theory and analyse method

Wavelet analysis originated in the mid-1980s as an alternative to the well-known Fourier analysis. Fourier analysis is only suitable for stationary time series. In contrast, wavelet analysis has significant superiority over the Fourier analysis when the time series under study are non-stationary or locally stationary (Roueff & Sachs, 2011). Moreover, wavelet analysis allows us to estimate the spectral characteristics of a time series as a function of time and then extracts localized information in both time and frequency domains (Aguiar-Conraria et al., 2008).

The time series can be expanded into a time frequency space where its time- and (or) frequency-varying oscillations are observed in a highly intuitive way. Often, two classes of wavelet transforms exist: discrete wavelet transforms (DWT) and continuous wavelet transforms (CWT). But, the CWT is more helpful for feature extraction and data self-similarity detection (Loh, 2013). As such, the CWT is widely used in economics and finance (Caraiani, 2012; Rua, 2012).

Given a time series $x(t) \in L^2(R)$ and given the mother wavelet $\psi(t)$ the CWT is defined as an inner product of $x(t)$ with the family $\psi_{\tau,s}(t)$ of wavelet daughter.

$$W_{x;\psi}(\tau,s) = x(t), \psi_{\tau,s}(t) = \int_{-\infty}^{+\infty} x(t)\psi^*_{\tau,s}(t)dt \tag{1}$$

The asterisk (*) denotes complex conjugation (see Jiang et al., 2015), $\psi^*_{\tau,s}(t)$ are complex conjugate functions of the daughter wavelet functions $\psi_{\tau,s}(t)$. With constructing the picture, it shows both the amplitude of any features present in $x(t)$ versus the scale and how this amplitude evolves over time. In addition, τ *and* s are real values that vary continuously for this, $W_{x;\psi}(\tau,s)$ is then named as continuous wavelet transform (more information sees: Daubechies, 1992; Goupillaud et al., 1984; Torrence & Compo, 1998).

To analyze the dynamic relationship between Fear migration indices, we should pay greater attention to the wavelet coherency and phase difference. We start with the wavelet coherency, which can be calculated using the cross-wavelet spectrum and the auto-wavelet spectrums as follows:

$$R^2_{xy}(\tau,s) = \frac{\left|S(s^{-1}W_{xy;\psi}(\tau,s)\right|^2}{S\left(s^{-1}\left|W_{x;\psi}(\tau,s)\right|^2\right)S\left(s^{-1}\left|W_{y;\psi}(\tau,s)\right|^2\right)} \tag{2}$$

In this case, it is noted that the wavelet coherency under study is represented as a squared type similar to previous studies (Aguiar-Conraria et al. 2008; Rua, 2012).

After smoothed by a smoothing operator S, the squared wavelet coherency gives a quantity between 0 and 1 in a time–frequency space. It is represented by colors in wavelet coherency plots, with red corresponding to a strong correlation and blue corresponding to a weak correlation. In this way, wavelet coherency allows for a three-dimensional analysis that can simultaneously consider the time and frequency components as well as the strength of correlation. Therefore, it helps us to distinguish the local correlation between our time series and to identify structural changes over time and the short-run and long-run relations across frequencies (Loh, 2013).

Because the wavelet coherency is squared, we cannot distinguish between positive and negative correlations. Therefore, we need the phase difference tool to present positive or negative suggestions for correlations and lead-lag relationships between series.

Therefore, following Bloomfield et al (2004), the phase difference between x(t) and y(t) is defined as follows:

$$\phi_{xy} = tan^{-1}\left|\left(\frac{I\{S(s^{-1}W_{xy;\psi}(\tau,s))\}}{R\{S(s^{-1}W_{xy;\psi}(\tau,s))\}}\right)\right|, \quad with\ \varphi_{xy} \in [-\pi,\pi] \tag{3}$$

where I and R are the imaginary and real parts of the smoothed cross-wavelet transform, respectively. According to Voiculescu and Usoskin (2012) and Aguiar-Conraria and Soares (2013), we can easily convert the phase difference into the instantaneous time lag between x(t) and y(t) as the following:

$$(\Delta t)_{xy} = \frac{\phi_{xy}}{2\pi f}$$

where $2\pi f$ is the angular frequency with respect to the time scale.

In our following work, the phase differences are represented as arrows in the wavelet coherency plots. Arrows pointing to the right mean that x(t) and y(t) are in phase (or positively related), while arrows pointing to left mean that x(t) and y(t) are out of phase (or negatively related if up or down). Arrows pointing to other directions mean lags or leads between them. It is noteworthy that phase differences can also be suggestive of causality between x(t) and y(t) (Grinsted et al., 2004; Tiwari et al., 2013).

In our present study, we use the Wavelet transform analyze thanks to its ability to decompose the micro and macroeconomic time series, whereas data can also be presented in their time scale components. Most time series techniques interpret data in short run and long run time frames, while in reality, it could not be explained precisely how long is the long and how short is the short.

Thus, wavelet coherence analysis gives an idea of the direction of the effects by indicating the leading variable and the lagging one. So, this method offers a useful analysis in the economic, financial, political and sociological field which presents the source of the effect and the destination of repercussion.

Data and descriptive statistics

Considering the availability of data and seeing that France, Germany, United Kingdom, and the United States are the countries attracting job seekers and seekers of liberty and luxury living, they are the most affected by the waves of migration. For this our study sample is composed by these four countries.

We use quarterly data on Fear migration index for France, Germany, United Kingdom, and united states which will be noted respectively FR-Fear, GER_Fear, UK_Fear and, USA_Fear.

The data series are downloaded from the following website: www.policyuncertainty.com.

To construct the Migration Fear Indices, Baker et al (2015) define the following term sets:

- Migration (M): "border control", Schengen, "open borders", migrant, migration, asylum, refugee, immigrant, immigration, assimilation, "human trafficking"
- Fear (F): anxiety, panic, bomb, fear, crime, terror, worry, concern, violent

These term sets are translated into German and French with the assistance of native speakers. Finally, Baker et al (2015) count the number of newspaper articles with at least one term from each of the M and F term sets, and then divide by the total count of newspaper articles (in the same calendar quarter and country). Figure 1 present periodic properties for these four series. To explore more details about the periodic properties, we subsequently divide the full samples of these four series into two subsamples as shown in Fig. 1 (low mean and variance, high mean, and high variance) by estimating one date break based on Bai–Perron and Zivot–Andrews approaches. Furthermore, descriptive statistics are simply used here to identify their main features within each subsample.

When computing the descriptive statistics and matrix of correlation as indicated respectively in Tables 1 and 2, we notice that the mean in the skewness coefficients are positive for all Fear series of the countries, which indicate right-skewed distributions. For the kurtosis coefficients, all are greater than 3, indicating that the Fear series index in a leptokurtic distribution. Moreover, Jarque–Bera tests show that all series are non-normally distributed.

Table 2 presents results of correlation matrix of Fear series index of the selected countries (French, Germany, United Kingdom, and USA). All values are positive which shows that Fear series move in the same direction. So, the correlation between variables, mean, and variance analysis indicate the possible existence of contagion effect. Results showed in Tables 1 and 2 justified the uses of DCC- GARCH empirical analysis.

Empirical findings

Our modeling strategy is to first investigate the presence structural date beak in "Date beak estimation" section. "DCC-GARCH analysis" section presents the DCC-GARCH estimation results. With the estimated conditional correlations, we can test the existence

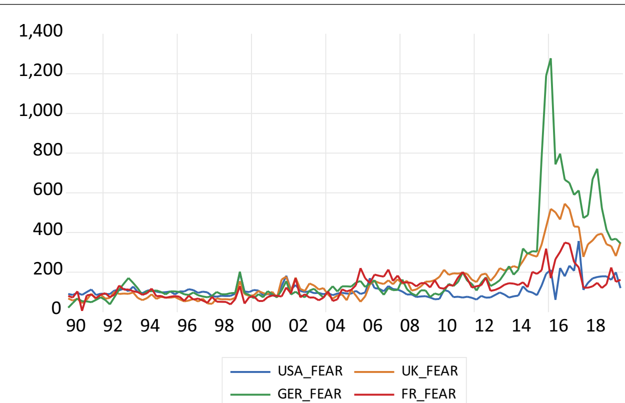

Fig. 1 Time series plots of FR-Fear, GER_Fear, UK_Fear and USA_Fear

Table 1 Descriptive statistics of the full sample

	GER	UK	USA	FR
Mean	196.8175	162.1711	109.4085	123.4420
Median	109.0361	117.5482	98.62323	117.1796
Maximum	1277.677	545.2397	356.8282	349.5620
Minimum	21.22936	40.11375	61.08892	4.982467
Std. Dev	219.5385	119.3211	42.56996	62.27233
Skewness	2.713872	1.487527	2.538657	1.313936
Kurtosis	10.87248	4.518476	12.13650	5.302724
Jarque–Bera	457.1821	55.78360	546.2739	61.04127
Probability	0.000000	0.000000	0.000000	0.000000
Sum	23,618.10	19,460.53	13,129.02	14,813.04
Sum Sq. Dev	5,735,461	1,694,265	215,652.0	461,463.4
Observations	120	120	120	120

Table 2 Correlation matrix in the full sample

	USA	UK	FR	GER
USA	1.000000	0.630606	0.487337	0.654667
UK		1.000000	0.776050	0.883848
FR			1.000000	0.664798
GER				1.000000

of the contagion effect. Finally, the CWT shows firstly the contagion leading country and the lagging one. It, also, analyze the dynamic relationship between Fear migration indices, coherency, and phase difference.

Date beak estimation

To examine the evolution of different dynamic correlations, analyze their ability to track important events, and the co-movements between the series we will start by considering the Zivot–Andrews and Bai and Perron (L + 1 versus L) tests for testing structural changes. These approaches focus on the instability problem in time series.

We use our different Fear series index: FR_Fear, Ger_Fear, UK_Fear and USA_Fear, from Q1-1990 to Q2-2019. In the presence of multiple breaks, the Bai–Perron estimate of the break fraction will converge to one of the true break fractions, the one that is dominant in the sense that taking it into account allows the greatest reduction in the sum of squared residuals. The break date founded is Q3-2013. This break point clearly appears in Fig. 1 and it corresponds to European refugees' crisis (Table 3).

Based on the Zivot–Andrews t-Statistics in case of one structural break of unit root test, our empirical results are illustrated in Table 3. In this univariate case, the results (Table 3) show one structural break in such variables. According to the two tests (Bai–Perron and Zivot–Andrews) results our significant structural break is Q3-2013 which explains the European refuges crisis.

Table 3 Unit root tests and time break estimation

Variable	Bai–Perron LR test ($l+1$ versus l) breaks)			Zivot–Andrews t-statistics (1 break)			Accepted hypothesis
	l versus $l+1$	Estimated break date	Statistics	Estimated break date		Statistics (*p* value)	
FR-Fear	0 versus 1	2013 Q3	12.026**	1 Break	2013 Q2	− 4.1408 (0.1124)	I(1)
	1 versus 2		3.594				
GER-Fear	0 versus 1	2013 Q3	9.358**	1 Break	2013 Q3	− 4.4490 (0.05201)	I(1)
	1 versus 2		1.112				
UK-Fear	0 versus 1	2013 Q4	6.715**	1 Break	2013 Q3	− 3.6936 (0.2858)	I(1)
	1 versus 2		5.937				
USA_Fear	0 versus 1	2015Q4	33.513**	1 Break	2015 Q3	− 4.4023 (0.0542)	I(1)
	1 versus 2		1.883				

**Indicates the 5% significance level, and I(1) indicates that series is non-stationary and one order integrated

Table 4 Descriptive statistics of pre and at European refugee's crisis period

	European refugee's pre-crisis period				European refugee's crisis period			
	FR_FEAR	GER_FEAR	UK_FEAR	USA_FEAR	FR_FEAR	GER_FEAR	UK_FEAR	USA_FEAR
Mean	104.98	106.33	109.87	97.38	193.57	540.65	360.91	155.09
Median	94.268	103.05	91.82	95.68	161.64	486.98	340.26	160.71
Maximum	220.38	202.18	220.36	196.88	349.56	1277.67	545.23	356.82
Minimum	4.982	21.22	40.11	61.96	120.09	187.36	218.00	61.08
Std. Dev	43.50	35.24	48.00	21.819	73.10	280.27	97.95	66.142
Skewness	1.930	1.469	1.564	1.899	2.909	1.046	1.345	0.936
Kurtosis	5.76	6.23	5.08	9.039	8.559	3.77	12.053	4.474
Jarque–Bera	6.683	7.701	8.365	201.50	7.649	5.188	7.430	5.916
Probability	0.0061	0.0157	0.0152	0.000	0.0061	0.074	0.0049	0.051
Observations	95	95	95	95	25	25	25	25

In the following work we divide our sample into two periods. The first period contains the observations before the crisis and the second one, during the European refugee's crisis.

DCC-GARCH analysis

According to Table 4, means and variances values are higher in the European refugee's crisis period. We notice that the means and standards deviations of the fear migration indices increase during the crisis period compared to the pre-crisis period under study. Table 4 shows that all series are right-skewed and leptokurtic distribution.

Table 5 presents the correlation matrix of the two subsamples. all values of the two correlations matrices are positive. Except the correlation between FR-Fear and GER-Fear, all values of the correlation coefficients increase during the crisis period. Results showed by Tables 4 and 5 indicate the existence of contagion effect of Fear migration for the Four countries under study.

Table 5 Correlation matrix pre and European refugee's crisis period

	Pre-European refugee's crisis period				European refugee's crisis period			
	FR_FEAR	GER_FEAR	UK_FEAR	USA_FEAR	FR_FEAR	GER_FEAR	UK_FEAR	USA_FEAR
FR_FEAR	1	0.5757	0.6293	0.109	1	0.4820	0.7126	0.369
GER_FEAR		1	0.574	0.223		1	0.7676	0.485
UK_FEAR			1	0.054			1	0.572
USA_FEAR				1				1

Table 6 DCC-GARCH estimation results

	Pre-European refugee's crisis period				European refugee's crisis period			
	FR_Fear	GER_Fear	UK_Fear	USA_Fear	FR_Fear	GER_Fear	UK_Fear	USA_Fear
c_0	144.643	132.876***	121.07***	101.79***	154.52***	523.612***	326.94***	129.941***
φ	0.566**	0.647**	0.88***	0.794***	0.612***	0.513***	0.478***	0.422**
ω_0	377.88***	378.97***	379.33***	296.542**	677.00**	1552.55***	993.58**	306.38**
a	0.42***	0.368***	0.496**	0.602***	0.141**	0.626**	0.38***	0.534**
b	0.49**	0.395***	0.420**	0.342**	0.714***	0.231**	0.595***	0.457**
$DCC(\alpha)$	0.430**				0.428**			
$DCC(\beta)$	0.590**				0.515**			
Df	7.580**				8.234**			
Log likelihood	442.989				3291.77			
AIC	36.557				265.58			
SC	37.41				266.94			

***, ** and * indicate respectively the signficance at 1%, 5% and 10% level

To study the contagion effect of migration fear in the France, Germany, United Kingdom, and United states, we estimate a multivariate Student's t distribution DCC-GARCH. Based on Maximum Likelihood values and Akaike (AIC) and Schwarz (SC) criterion our selected model is ARIMA(1,1,0) -GARCH(1,1).

The coefficients of GARCH (1,1) in Table 6, are observed to be significant and positive which clearly exhibit that the volatility is captured by the GARCH model. All the estimated parameters are statistically significant at least 5% significance level. The GARCH error parameter, a, measures the reaction of conditional volatility to world migration events. So, a higher value of parameter a, indicates that volatility then volatility is very sensitive to migration events. Our results show that all parameters a are higher than 0.1. The GARCH lag parameter, b, measures the persistence in conditional volatility irrespective of anything happening in the world migration conditions. When ß is higher than 0.9 then volatility takes a long time to die out following a crisis (Alexender, 2008). In our case b for all the countries is less than 0.9 which indicates that Fear migration volatility is sensitive to world crisis and not persistent to new significant events in the world.

The appropriate model is:

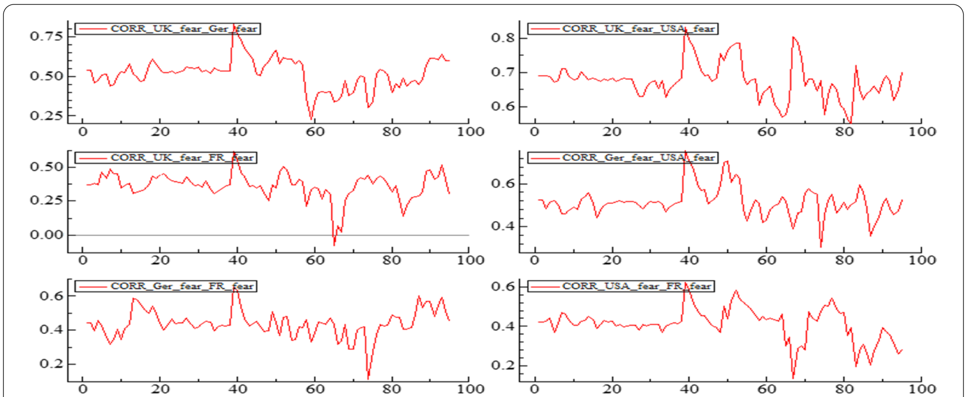

Fig. 2 Dynamic Conditional Correlations in European refugee's pre-crisis period

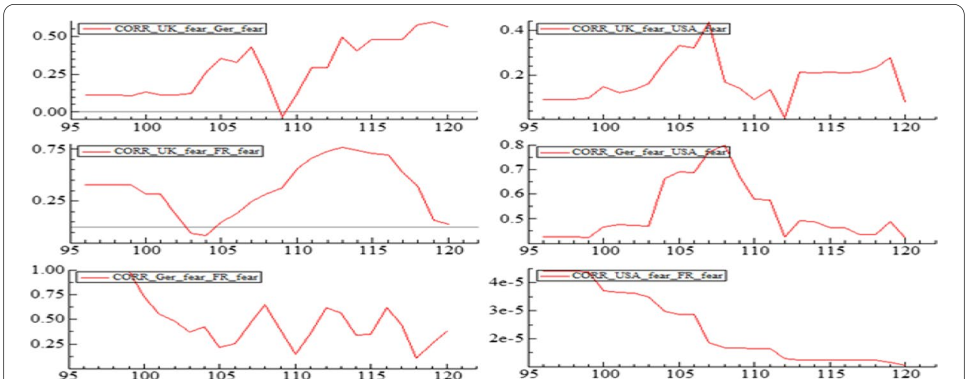

Fig. 3 Dynamic Conditional Correlations in European refugee's crisis period

$$\begin{cases} F\_MI_t = c_0 + \varphi F\_MI_{t-1} + \varepsilon_t \\ h_t^2 = \omega_0 + a\varepsilon_{t-1}^2 + b\sigma_{t-1}^2 \end{cases}$$

$$and\ t = \begin{cases} 1, \ldots, 95\ if\ t \in Pre - crisis\ period\ sample \\ 96, \ldots, 120\ if\ t \in crisis\ period\ sample \end{cases}$$

where F_MI_t is Fear migration index.

According to Figs. 2, 3, graphs clearly show variation in the dynamic conditional correlations across our two subsamples (pre-crisis and crisis periods). The most conditional correlations between fear migration indices are positive and increase in the crisis period compared to the those in the pre-crisis period as expected. But conditional correlation UK-FR and UK-GER are negative in some times in pre-crisis period. These conditional correlation coefficients coincide with the Brexit crisis period. For instance, the UK-FR conditional correlations take the negative sign in end of year 2016 date of the agreement of twenty-Seven member countries of the European Council to start negotiations with the United Kingdom over its withdrawal from the EU. Also, we found a negative conditional correlation between Germany and United Kingdom in crisis period in date in middle of year 2017: date of First round of negotiations between the EU and the UK in Brussels.

The conditional correlations are positive in the two sub-samples, but the relationship between the UK and the European countries (Germany and France) loses consistency during the Brexit period. the British have the idea of withdrawal from EU and think that they will build their own system of protection against migration. These findings appear clear at the level of the conditional correlation which has become weak in most of the time of the second sub-sample.

The unconditional and conditional positive correlations in the pre and crisis periods of European refugees indicate the existence of a contagion effect of the fear of migration thanks to a great security, political and economic interdependence between the selected countries.

Tables 7 and 8 presented in "Appendix" show the results of the residuals diagnostic. We use Box–Pierce Hosking's Multivariate Portmanteau Statistics on standardized and squared standardized residuals tests.

Results show that the null hypothesis of no serial correlation is always accepted in different lags of the Q-statistics. This residuals diagnostic indicates that residuals are not correlated and lead us to confirm the robustness of our estimation results.

Wavelet empirical analysis in European refugees pre and crisis periods

In this section, we plot wavelet coherencies and phase differences between Fear migration indices for France, Germany, United Kingdom, and United States.

See that our variables are non-stationary and to better show the dynamic relationships and the transient dynamics between them, we apply the Continuous Wavelet Transform (CWT) approach. According to Grinsted et al (2004), Aguiar-Conraria et al. (2008) and Aguiar-Conraria and Soares (2013) we analyses the relationships between variables to study the synchronization, delays and leads between each to time series across different frequencies or timescales.

As mentioned in the following, the results inside the cone of influence and the regions above the 5% significance level are not reliable indications of correlations and lead-lag suggestion. The X-axis present the time periods which represent quarterly data spanning from 1990 to 2019. We classify the frequency on the y-axis into three bands: 2–8 quarter time scale, 8- to 16-quarter time scales, and 16- to 32-quarter time scales, corresponding respectively to short-run, medium-run, and long-run relationships between Fear migration indices.

Figure 3 illustrates the cross-wavelet coherency results from our sample period. The wavelet coherency is used to identify both frequency bands and time intervals within which pairs of series are co-varying. In respect of co-movement between our four countries fear migration indices. We start our analysis by presenting the coherence between indices in the pre-crisis period of European refugees. For the relationships between USA fear migration index and those of France and Germany, the major arrows pointing right in the short, medium, and long run indicate that each two series are in phase. The results show that, in the biggening of our sample period, the arrows are pointing right and down indicating that US-Fear is leading, and the European migration fear indices are lagging with positive correlation.

For the relationship between US-Fear and UK-Fear the results are different. There are a significant and positive link between American Fear index and the one of United

Kingdom. The major arrows are pointing to the right indicating that the two indexes are in phase. So, direction of arrows is divided into several periods. The first periods containing the 11 September attack (2001–2005 = 40th–60th observation) presents a significant dark red area containing arrows pointing right and down indicating that US-Fear is leading in the short and medium run. In the long run the UK index is leading. The second period corresponds with dates 2005–2009 (period of war in Iraq) the arrows become pointing right and up indicating that UK fear is leading. this result is expected because European countries are the most influenced by migration in the event of war in the Middle East countries and Gulf. With these results we understand that the contagion effect of migration fear, in the most cases, take the direction from USA to European countries in pre-crisis period of refugees from 2013 (Fig. 4).

We notice that the nexus between UK-Fear, GER_Fear and FR_Fear, are different. Indeed, the major arrows in the significant areas are pointing right in short, medium, and long run. and sometimes positive and down and positive and up in other times. The positive coherence between European migration fear index depends on events occurred in one of them. So, if occurs a significant political or security event in one the selected countries, this country becomes a leading, and the others are lagging. For instance, in the period of terror attacks in Paris on November 2015, Nice on July 2016, France is leading. Also, period of attack in Berlin on December 2016, Germany is leading. These findings indicate that the contagion effect direction is influenced by significant political, security events. These results take the same direction of results founded by Trines (2017) and Nabeel and Bhatti (2016).

But, from European refugee's crisis period, United Kingdom and Germany are short run positively linked to USA. Indeed, relationship between USA and Germany presents a right and up direction of the arrows indicating that GER-Fear is positively leading in the short run in 2014–2019 period. Also, we focus that at the shorter time scale (4–8), the relationship UK and USA shows arrows with right and up direction in in the period 2014–2016.

In the same subsample, we notice that the nexus between UK-Fear, GER_Fear and FR_Fear, are different. Indeed, the major arrows in the significant areas are pointing right in short, medium, and long run. and sometimes positive and down and positive and up in other times. The positive coherence between European migration fear index depends on events occurred in one of them. So, if occurs a significant political or security event in one the selected countries, this country becomes a leading, and the others are lagging. For instance, in the period of terror attacks in Paris on November 2015, Nice on July 2016, France is leading. Also, period of attack in Berlin on December 2016, Germany is leading. These findings take the same direction of results founded by Trines (2017) and Nabeel and Bhatti (2016).

Our results show the weak relationship between UK and the remaining European union members (France and Germany). Period 2015–2019, in short run scale, presents significant red spaces which contain arrows pointing right and down (if UK takes first position in Fig. 3) or up (If UK take second position) indicating that UK-Fear is positively leading. So, as European country, UK experienced a massive influx of refugees and workers migrants. In this period occurs several terrorist attacks such as London in March/June 2017, and Manchester in May 2017. Public anxiety over immigration was one of the main causes of withdrawal of the UK from the EU known as BREXIT (Arnorsson & Zoega, 2018; Clarke et al., 2017; Meleady et al., 2017).

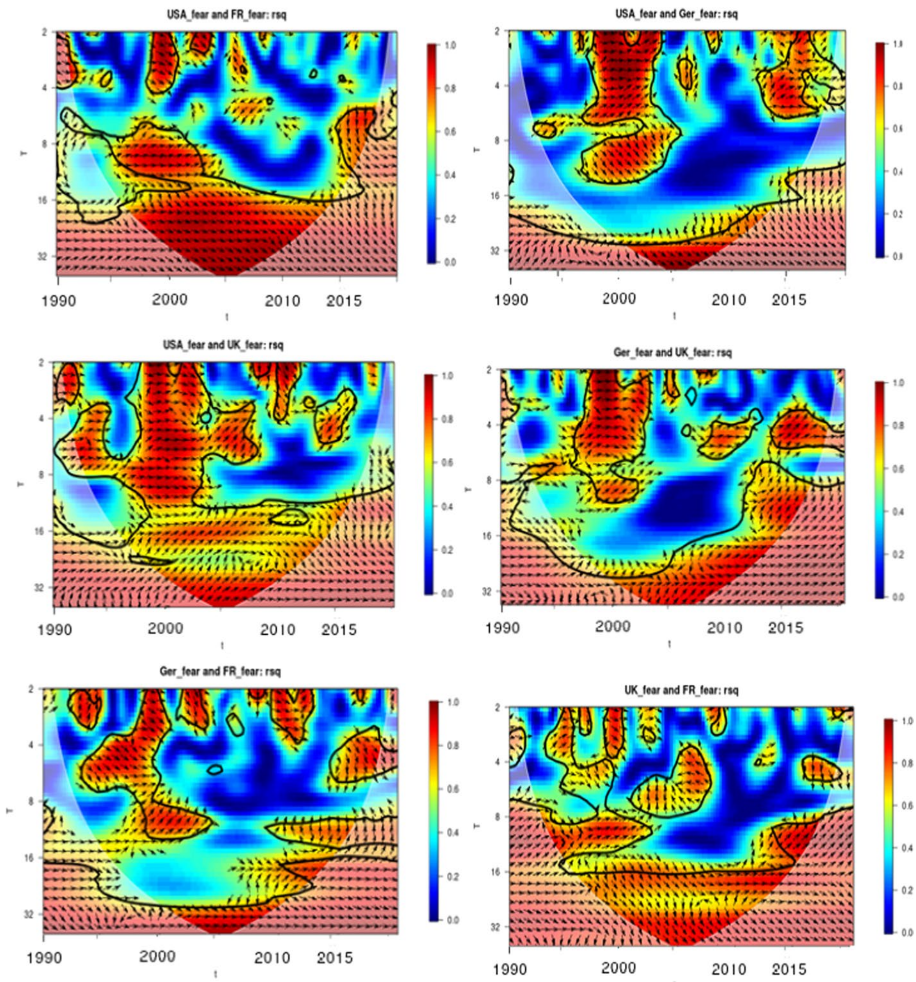

Fig. 4 The squared wavelet coherency and phase difference between different migration Fear indices in European refugees pre and crisis periods. Figure display the squared wavelet coherence of two series. The thick blue contour represents the 5 per cent significance level. The cone of influence, which indicates the region affected by edge effects, is shown with a lighter shade black line. The color code for power ranges from blue (low power) to red (high power). The phase difference between the two series is indicated by arrows. Arrows pointing to the right mean that the variables are in phase. To the right and down, the first series is leading the second series with positive correlation. To the right and up, the second series is leading the first series with positive correlation. Arrows pointing to the left mean that the variables are out of phase. To the left and up, first series is leading the second series with negative correlation. To the left and down, the second series is leading the first series with negative correlation. In-phase indicates that the variables have cyclical effect on each other and out of phase or anti-phase shows that the variables have anticyclical effect on each other. The cone of influence where edge effects should be considered is shown as a lighter shade. The darker red (areas with arrows) regions are the higher degree of co-movement. These areas represent the spaces with high dependence, where R-squared is close to 1. The blue areas are signaling a low dependence meaning a low co-movement. The color scale represents the magnitude of R-squared

This contagion of migration fear between these four countries is transmitted though several channels. For the financial channel, global stock markets and especially those of Europe and the USA are integrated, the massive and sudden waves of migration increase the economic policy uncertainty which in turn negatively influences economic growth and stock markets returns. This lead to negatively influence the investor sentiment (increase of investor fear). In this case, if a stock market responses by decreasing investment, due to decline in returns, the others react in the same direction.

For the economic and societal channel, the deterioration of the employment situation in the country of destination can affect the migrant's income and this leads to thefts and crimes which are the major sources of fear in European and American societies. This is the transmission channel that is probably the most effective.

Finally, Our findings take the same direction of Donadelli et al. (2018) and Fraser and Ungor (2019), despite of the migration-related fears have negative influence on unemployment rates in countries under study, it influences positively the crimes and increases the global uncertainty. So, innovations in the migration related uncertainty indices foreshadow significant declines in investment output which represent the main sources of fear for the economical, financial and policy maker.

Conclusion

This paper is motivated firstly by the lack of studies examining the contagion effect of migration fear and especially by the power of wavelet analysis to provides new evidence of the time–frequency relations between fear migration indices time series. To the best of our knowledge, our paper is one of the first attempts to study the contagion effect of migration fear and examining the dynamic coherence relationships of fear migration indices series based on continuous wavelet transform.

This paper contributes to the literature by providing a study testing the existence of the contagion effect of migration fear for France, Germany, United Kingdom, and United States sample and based on fear migration index database spanning 1990–2019 period. Moreover, in the empirical framework our study is based on DCC-GARCH model and CWT analysis.

The main findings are that fear migration indices series are subject of one structural break which coincides with beginning of the European refugee's crisis date (third quarter of 2013). the DCC-GARCH model estimations in a crisis and pre crisis period give, in the most time, a significant and positive conditional correlation with indicate the existence contagion effect of migration fear. We found in pre-crisis period a few times negative conditional correlation which coincide with dates of political or terror events (Brexit negotiations, terror attacks in Paris on November 2015 and Nice on July 2016, attack in Berlin on December 2016). These sign changes show a different behavior in the selected countries especially in refugees' crisis and Brexit negotiations periods.

the cross-wavelet coherency results show, in pre-crisis period, a positive relationship between USA fear migration index and those of France and Germany and the causality direction demonstrate that USA is leading. In the same pre-crisis period, the relationships between European union member countries the contagion effect are lot influenced by the political and terror events. At the European refugee's crisis period, we find changes in the arrow's direction in the significant red space surrounded by lighter shade black line of CWT plots in the sort, medium and long run. Indeed, the contagion effects change their causality direction, as example in the relationship between Germany and USA, Germany becomes a leading and the USA is lagging. Also, we focus that at the shorter time scale (4–8), the relationship UK and USA shows arrows with right and up direction in in the period 2014–2016. In the same subsample, we notice that the nexus between UK-Fear, GER_Fear and FR_Fear, present the major arrows in the significant areas are pointing right in short, medium, and long run and sometimes positive and down and positive and up in other times.

Finally, we can conclude that before the refuge's crisis, Europe is greatly influenced by the politics of migration and the American wars in the world. But in the second period, the contagion effect becomes weak or changes its direction. The contagion relation between European countries France, Germany, and UK are lot influenced by the political events and security problems. So, these findings indicate that European Refugees crisis changes the relationship between European Union countries and USA, and the Brexit changes the European policies towards migrants and refugees and specially to ensure their security which the main factor of the UK withdrawal.

The findings of this research lead us to ask about the future political relations between the source and destination countries of the world, between the developed and the poor countries, between the seeking war countries and those seeking peace.

Appendix

See Tables 7 and 8.

Table 7 Univariate tests of residuals correlation

Variable	Q-statistics on standardized residuals	Q-Statistics on squared standardized residuals
FR_Fear	Q (5) = 9.73815 [0.1830037] Q (10) = 15.5819 [0.1122440] Q (20) = 19.2521 [0.5054989] Q (50) = 48.1240 [0.5489708]	Q (5) = 2.10357 [0.8346369] Q (10) = 9.46889 [0.4882557] Q (20) = 16.5350 [0.6829316] Q (50) = 37.9797 [0.8937025]
GER_Fear	Q (5) = 17.4268 [0.1375716] Q (10) = 36.0702 [0.1208139] Q (20) = 57.9728 [0.2341462] Q (50) = 75.7690 [0.4188069]	Q (5) = 1.70384 [0.8884160] Q (10) = 2.41900 [0.9920042] Q (20) = 3.13821 [0.9999940] Q (50) = 13.7575 [0.9999999]
UK_Fear	Q (5) = 7.82039 [0.1664158] Q (10) = 11.9488 [0.2884998] Q (20) = 26.4900 [0.1502311] Q (50) = 64.9876 [0.0755088]	Q (5) = 1.01779 [0.9611178] Q (10) = 11.4352 [0.3246311] Q (20) = 13.8300 [0.8390111] Q (50) = 33.6690 [0.9629763]
USA-Fear	Q (5) = 6.98172 [0.2220032] Q (10) = 10.4420 [0.4026106] Q (20) = 23.7487 [0.2535436] Q (50) = 61.7412 [0.1233143]	Q (5) = 5.79727 [0.3264481] Q (10) = 8.12911 [0.6162271] Q (20) = 11.2684 [0.9389630] Q (50) = 30.5897 [0.9861625]

[…] indicate the probability (prob)

H0: No serial correlation → Accept H0 when prob. is High [Q < Chisq(lag)]

Table 8 Multivariate tests of residuals correlation

Variable	Hosking's multivariate Portmanteau statistics on standardized residuals	Hosking's multivariate Portmanteau statistics on squared standardized residuals
FR_Fear	Hosking (5) = 109.924 [0.1226950] Hosking (10) = 199.437 [0.1632712] Hosking (20) = 378.861 [0.1184682] Hosking (50) = 876.011 [0.2975651]	Hosking (5) = 132.612 [0.1451138] Hosking (10) = 288.507 [0.1258590] Hosking (20) = 389.349 [0.3820381] Hosking (50) = 704.605 [0.9922171]

[…] indicate the probability (prob)

H0: No serial correlation → Accept H0 when prob > 5%

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Author contributions
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Declarations

Competing interests
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