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A new way of measuring effects of financial crisis on contagion in currency markets

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ABSTRACT

Contagion is an extremely important topic in finance. Contagion is at the core of most major financial crises, in particular the global financial crisis that started in 2007. Although various approaches to quantifying contagion have been proposed, many of them lack a causal interpretation. We will present a new measure for contagion among individual currencies within the Foreign exchange market and show how the paths of contagion work within the Forex market using causal inference. This approach will allow us to pinpoint sources of contagion and to find which currencies offer good options for diversification and which are more susceptible to systemic risk, ultimately resulting in feedback on the level of global systemic risk. In particular, we will focus on the effects of the Covid-19 global pandemic.

1. Introduction

In order to see how resilient financial networks are to contagion, financial regulators need to understand how contagion propagates and where the sources of contagion reside (Stiglitz, 2010). There are various ways to define financial contagion.

The first descriptions of contagion are predominantly in terms of what today we would call behavioural finance — in terms of sentiments, emotions, behavioural biases and crowd effects (Hansen, 2021). Modern research into contagion within the academic literature began to appear in the wake of the 1987 market crash and exploded during the 1995 Mexican crisis, the 1997 Asian financial crisis and the related 1998 Russian financial crisis that followed. The main goal was to explain how a series of potentially local issues could spread from country to country, creating a financial crisis with global repercussions (Claessens & Forbes, 2013; Edwards, 2000). These events caught many economists off guard and so most papers during this period concentrate on explaining (Calvo & Reinhart, 1996; Edwards, 2000), or explaining away (Collins & Biekpe, 2003; Forbes & Rigobon, 2002; Karolyi, 2004), this new market behaviour. Most of the definitions of contagion during the period define it as shocks or correlations that are unexplained or unexpected or significantly higher than usual, in contrast to expected and explainable changes and correlations, called spillovers and interdependence (Rigobon, 2019).

The 2007–2010 global financial crisis rekindled interest into analysing contagion. This time around there has been less research into whether contagion exists and more into how to estimate and model it properly to be ready for future crises. During this period we see the appearance of network theory applications that set the tone for future research (Battiston & Martinez-Jaramillo, 2018; Elliott, Golub, & Jackson, 2014; Gai, Haldane, & Kapadia, 2011; Glasserman & Young, 2015; Nier, Yang, Yorulmazer, & Alentorn, 2007; Soramäki & Cook, 2016).

There have been various approaches to contagion estimation: the copula approach (Rodriguez, 2007; Wen, Wei, & Huang, 2012); the vector moving average and variance decomposition, related to the Impulse Response modelling (Barigozzi & Hallin, 2017; Barigozzi, Hallin, Soccorsi, & von Sachs, 2020; Diebold & Yılmaz, 2014); and new approaches of Vector Autoregression (VAR) estimation in structural models (Agosto, Ahelegbey, & Giudici, 2020; Ahelegbey, Billio, & Casarin, 2016; Avdjiev, Giudici, & Spelta, 2019; Dahlhaus & Eichler, 2003; Eichler, 2007; Giudici & Abu-Hashish, 2019; Giudici & Parisi, 2018; Giudici, Sarlin, & Spelta, 2020). Each of these methods has its own advantages but they lack an intervention-based causality interpretation. Traditionally when it comes to causality economists have relied on the Granger Causality concept (Stavroglou, Pantelous, Soramaki, & Zuev, 2017), but this concept merely relies on temporal correlations rather then structural causation (Sugihara et al., 2012).

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We will analyse contagion through changes in price due to factors spreading from currency to currency that cannot be explained by individual trends. This type of contagion can be interpreted as "pure contagion" defined by Van Rijckeghem and Weder (2001). Combining causal networks with a structural VAR model, we are able to extract from the log returns of the exchange rates which part of a change in the value of a currency is caused by the idiosyncratic characteristics of the currency and which part is caused by contemporaneous contagion effects from other currencies. The structural VAR part of our approach is an extension of Giudici and Parisi (2018). Similar VAR approaches have been used to analyse systemic risk within the foreign exchange market; none, however, look at the causal direction of such effects.

In order to analyse the contagion paths in the foreign exchange market, we will recreate directed partial correlation based networks using the causality concepts from Pearl (2009) extended into practical methods by Spirtes and Glymour (1991) and Colombo and Maathuis (2014).

The rest of this paper is organised as follows. In Section 2, we first explain basic concepts of network theory and causal inference and then describe how we estimate contagion using Causal Graphical models within a structural VAR model. In Section 4 we analyse contagion within a subset of currencies on the Forex market during the years 2000–2021; and we conclude in Section 5 by summarising the main advantages of this approach to measuring contagion in finance, while noting the remaining challenges.

2. A structural equation model for contagion

Our measure of contagion within a network relies on causal graphical model theory. In this section we will introduce the main underlying concepts and notation. A network is a collection or system of interconnected objects such as things, people or groups of people (like institutions or countries, for example). In mathematics these interconnections are represented as graphs, defined as a set of nodes or vertices that are connected by links or edges.

In this work we will analyse directed networks by estimating causal links that are not directly observed between financial instruments or assets. Such networks are called causal networks, a specific type of a graphical model (also often called Bayesian or belief networks). These networks incorporate probabilistic relationships between the nodes in the form of a Directed Acyclic Graph or DAG (Howard & Matheson, 2005; Pearl, 1988).

Bayesian networks can be analysed using several different types of algorithms. There are the so-called constraint-based algorithms that look for conditional independence (Colombo & Maathuis, 2014) and the main algorithm of this group, the PC-algorithm (Spirtes & Glymour, 1991), is the one we will use in Section 2.3. The other type of algorithms are the so-called score-based algorithms, which maximise a causal objective function. A comparison between these methods in terms of speed and accuracy can be found in Scutari, Graafland, and Gutiérrez (2018). Importantly, they find that "constraint-based algorithms are more accurate than score-based algorithms for small sample sizes".

2.1. Causal graphical models

Here we present the mathematics underlying causal graphical models. We consider N assets that we want to analyse and their log returns are represented as the multivariate random variable $X = (X_1, \dots, X_N)$. Each of these N assets will represent a node in our network. We can analyse X as a directed graphical model (GM) represented by a causal DAG. The arrows in the network G_X are to be interpreted in terms of conditional independence (CI) with the additional causal interpretation.

A DAG G_X is causal for a probability distribution $f(x)$ if $f(x)$ recursively factorises with respect to G_X and the following intervention formula holds for all subsets A in V, the set of all nodes:

$$\forall A \subseteq V \quad f(x \parallel x_A^*) = \prod_{\alpha \in V \setminus A} f(x_\alpha | X_{pa(\alpha)} = x_{pa(\alpha)})\Big|_{X_A = x_A^*} \tag{1}$$

where $f(x \parallel x_A^*) = f(x | x_A \leftarrow x_A^*)$ is the distribution of X under the knowledge that a subset A of the nodes V in the network have been imposed a value x_A^*. An example of this could be when a central bank decides to fix its exchange rate with respect to another currency and we want to see the impact on the other currencies in the market. The conditional distributions $f(x_\alpha | X_{pa(\alpha)})$ are assumed stable under interventions that do not involve x_α — hence the condition that α represent nodes in V but not in the intervention subset A. This conditioning by intervention allows for much more specific causal interpretation than the conditional distribution. The random variable of interest X is a causal GM if it is a directed GM, as described above, such that the intervention factorisation in Eq. (1) holds. This definition is often referred to as the Lauritzen's causal graph with interventions by replacement (Lauritzen, 2001) or as Pearl's do-intervention (Pearl, 2009).

2.2. Defining contagion

In this section we will present a network-based measure for contagion. It is based on the causal graphical models presented in the previous section, combined with an autoregressive approach to contagion as described in Giudici and Parisi (2018). Giudici and Parisi (2018) introduce a structural vector autoregression (VAR) to analyse the contagion impact on the cost of insuring public debt during the European sovereign debt crisis.

We propose a structural equation model for the evolution of the log returns X_{it} on a financial asset i at time t through a structural VAR consisting of an autoregressive part $AR(i,t)$ and a network contagion part that we will call NECO(i,t):

$$\underbrace{X_{i,t}}_{\text{LogReturn on Asset i}} \leftarrow \alpha_{0,i} + \overbrace{\sum_{\ell=1}^{L} \alpha_i^\ell X_{i,t-l}}^{\text{AR(i,t)}} + \overbrace{\sum_{j \in pa(i)} \beta_{ji} \underbrace{X_{j,t}}_{\text{Assets that affect asset i}}}^{\text{Contagion=NECO}(i,t)} + \underbrace{\varepsilon_{i,t}}_{\text{Noise}} \tag{2}$$

where ℓ are the number of considered lags for the autoregressive part, α_i^ℓ are the autoregressive coefficients at lag ℓ for asset i and β_{ji} the causal effects of asset j on asset i or X_j on X_i. In the causal literature, the causal effects are defined as the partial derivative of the expected log return $\frac{d}{dx_j} E(X_{i,t} | X_{-i,t}, X_{i,t-\ell})$ which in our case is equal to β_{ji}. Just like we do for the autoregressive part, lags can be added to the NECO part. We leave this extension for future research. The arrow in Eq. (2) is to be interpreted in a generative manner, such as in a structural equation model (Bollen & Pearl, 2013). The right-hand side is the driving force behind the value of X_{it}.

Eq. (2) can be summarised as:

$$X_{it} = \alpha_{0,i} + \text{AR}_{it} + \text{NECO}_{it} + \varepsilon_{it} \tag{3}$$

where the NECO$_{it}$ measures the totality of the contagion effect on the market. As a measure of the impact of contagion on the price of an individual asset, we propose the Network Contagion Factor (NECOF), which is computed as follows:

$$\text{NECOF}(i) = \frac{\sigma_{i,NC}^2}{\sigma_{i,AR}^2 + \sigma_{i,NC}^2 + \sigma_i^2} = 1 - \frac{\sigma_{i,AR}^2 + \sigma_i^2}{\sigma_{i,AR}^2 + \sigma_{i,NC}^2 + \sigma_i^2} \tag{4}$$

where $\sigma_{i,AR}^2 = V(AR_{it})$, $\sigma_{i,NC}^2 = V(\text{NECO}_{it})$ and $\sigma_i^2 = V(\varepsilon_{it})$, under the assumption that AR$_{it}$, NECO$_{it}$ and ε_{it} are independent. This independence assumption is realistic, given that the considered contagion is assumed to be instantaneous and therefore by definition isolated from the idiosyncratic effects AR_{it}.

The NECOF is expressed in percentages and shows the impact of contagion on the return of the asset i. A NECOF of 0% would mean that contagion has no impact on the considered asset. On the opposite end of the spectrum, a NECOF of 100% would indicate that the impact of contagion for the given asset is absolute. The NECOF measure alone is very useful to identify which assets are at higher risk of outside influence - information that can be useful for investment and diversification strategies alike. We call the NECO a network-based measure because it depends on the underlying causal graph.

2.3. Identifying contagion paths

This section shows how the causal networks and causal NECO coefficients β_{ji} in Eq. (2) are estimated. Once we estimate the NECO coefficients and the NECOF we can recover the contagion factor for each financial instrument. In order to estimate the causal coefficients correctly, we first need to establish the causal structure, which means finding all the causal parents for every considered asset i in our graph.

We estimate the causal structure using a more robust version of the standard PC-algorithm from Spirtes and Glymour (1991) called the PC-stable algorithm (Colombo & Maathuis, 2014).[1] The PC-Algorithm uses two steps in order to find the sources of contagion, which are summarised in Appendix A. We add a third step to estimate the size of the contagion effects, β_{ji}, by performing a series of linear regressions on Eq. (4). Given the set of parents for each asset, the non-zero β_{ji} are to be estimated from the obtained DAG. If at the end of Step 2 we achieve a Completed Partially Directed Acyclic Graph (CPDAG), a subset of Markov equivalent DAGs that can explain our data, we will also find a multiset of possible NECO estimates $\hat{\beta}_{ij}$. We can combine these into a range estimator as in Maathuis, Kalisch, Bühlmann, et al. (2009). Once we have estimated the NECO we can estimate the NECOF of interest for each financial instrument in our model using the following equation:

$$\widehat{\mathrm{NECOF}}_i = 1 - \frac{RSS_{NECO}(i)}{SS(i)} \tag{5}$$

that we obtain by applying the Type II[2] Sums of Squares to Eq. (3) such that:

$$RSS_{NECO}(i) = \sum_t \left[X_{i,t} - \widehat{\mathrm{NECO}}(i,t)\right]^2 \text{ and } SS(i) = \sum_t \left[X_{i,t} - \mu_{i,t}\right]^2 \tag{6}$$

2.4. Community detection

Using the contagion paths established in the previous section we can identify communities of financial instruments. These communities are groups of nodes that are more connected among themselves within the group then with the other groups. These groups are called communities, clusters or modules. Communities can be seen as sub-graphs that have specific properties not shared by the whole network and this allows for a next-level analysis of the network, moving from a single node to a more meaningful structure. These communities can be also seen as meta-nodes when representing and analysing very large networks, where considering and plotting each singular node would not be practically feasible.

There are many different algorithms to identify communities within a network; for a comparative study see Lancichinetti and Fortunato (2009). We will be using the Louvain algorithm from Blondel, Guillaume, Lambiotte, and Lefebvre (2008) to establish communities among the nodes, because it a benchmark among the clustering algorithm thanks to its robust and efficient results, making the results easier to compare with other studies.

2.5. Creating dynamic contagion maps

In the previous sections we defined a measurement of the contagion and the sources of this contagion, assuming that the NECO and its coefficients would remain constant for the entire time period in consideration. In this section we will add a dynamic component, and in doing so not only allow for the $\mathrm{AR}(i,t)$ and $\mathrm{NECO}(i,t)$ in Eq. (2) to change with time but also for the whole causal structure of our contagion graph to change with time. A dynamic version of (2) is written as,

$$X_{it} \leftarrow \alpha_{0,i} + \sum_{l=1}^{L} \alpha_{l,i}^t X_{i,t-l} + \sum_{\forall j \in pa(i,t)} \beta_{ji}^t X_{j,t} + \varepsilon_{i,t} \tag{7}$$

describing a dynamic causal graphical model. From an inferential point of view, we will estimate the coefficients in a piecewise-constant way. At each timepoint t we evaluate a new DAG and the associated $\widehat{\mathrm{NECOF}}$ estimates, creating a sequence of contagion maps. The contagion effect is considered to be contemporaneous within the considered window of time $[t-1,t]$. The length of the window will vary with the use case and depends on the data being analysed, what kind of short or long term trends are associated and the purpose of the study.

3. Description of empirical exchange rates 2000–2021

The Forex market is an important financial market, trading \$6.6 trillion per day (Wooldridge, 2019). Given that the most traded exchange rates are those over the USD we consider the interaction of 23 exchange rates over the USD for the years 2000–2021 as published daily by the Federal Reserve of New York. This allows us to evaluate the networks among highly traded currencies by expressing their value in terms of the US Dollar, the most liquid of all currencies, based on reliable historic data. Alternative approaches include using exchange rates based on a the special drawing right (SDR) as in Wang, Xie, Han, and Sun (2012) or a benchmark based on the average, or geometric average, of different exchange rates as in Hovanov, Kolari, and Sokolov (2004) and Giudici, Leach, and Pagnottoni (2022). SDR reflects the price of a basket of five major currencies and is periodically rebalanced and published on a daily basis by the International Monetary Fund (IMF). Another option for the base currency is to choose a currency that is of lesser importance, but still not completely illiquid. An example of this approach can be found in Keskin, Deviren, and Kocakaplan (2011) who use the Turkish Lira as a base. A comparison of different currencies being used as the base currency can be found in Kwapień, Gworek, Drożdż, and Górski (2009). One final approach taken by Fenn et al. (2012) is that of ignoring the base currency issue altogether and using each exchange rate as a separate financial asset.

We consider the log returns on the spot exchange rates. Table 1 shows summary statistics for the 23 currencies considered here. The distribution of log returns on the exchange rates is often assumed normal, but as with most financial assets there is the presence of fat tails as can be seen in the last column of Table 1. Johnston and Scott (1999) analyse this problem, without finding any better alternative that would hold for every currency and time frame. Some studies even find that trading strategies based on the assumption of log-normality do in fact maximise profit (Sarpong, 2019). The presence of fat tails will cause the significance level for the individual conditional independence tests within the PC-Algorithm to be empirical slightly higher than the nominal value.

Fig. 1 shows the series of 23 log returns for our time frame, from January 2000 until April 2021. As we can see the CNY, HKD, LKR, MYR and VEB present periods of very low variance. These currencies

[1] We perform the PC-Algorithm using the pcalg package in R as described in Hauser and Bühlmann (2012) and Kalisch, Mächler, Colombo, Maathuis, and Bühlmann (2012).

[2] Similar to Type I but not dependent on the order of entry of terms into the model (Yandell, 1997).

Table 1
Overview of the summary statistics for the dataset of log returns on individual 23 exchange rates over the USD, for the period January 2000 to April 2021. The higher the Jarque Bera Test the less normally distributed the data is (all of the statistics have a p-value < 0.0001). There are 5325 observations for each currency, with no missing values.

Code	Currency name	Minimum	Median	Mean	Maximum	StDev	Skewness	Kurtosis	Jarque Bera
AUD	Australian Dollar	−0.0771	−0.0003	−0.0000	0.0822	0.0080	0.6261	11.8178	31335
BRL	Brazilian Real	−0.0967	0.0000	0.0002	0.0867	0.0104	−0.0052	8.3711	15548
CAD	Canadian Dollar	−0.0507	0.0000	−0.0000	0.0381	0.0056	−0.0714	5.6143	6998
CHF	Swiss Franc	−0.1302	0.0000	−0.0001	0.0889	0.0067	−1.1203	35.1797	275708
CNY	Chinese Yuan Renminbi	−0.0202	0.0000	−0.0000	0.0182	0.0015	0.1610	22.2054	109425
DKK	Danish Krone	−0.0580	−0.0000	−0.0000	0.0494	0.0061	−0.1555	4.5734	4662
EUR	Euro	−0.0463	0.0000	−0.0000	0.0300	0.0060	−0.0775	2.4789	1369
GBP	British Pound	−0.0443	0.0000	0.0000	0.0817	0.0060	0.6707	10.6119	25385
HKD	Hong Kong Dollar	−0.0045	0.0000	0.0000	0.0033	0.0003	−1.2511	26.3958	155978
INR	Indian Rupee	−0.0376	0.0000	0.0001	0.0394	0.0044	0.1993	10.2796	23481
JPY	Japanese Yen	−0.0522	0.0001	0.0000	0.0334	0.0062	−0.3187	4.3307	4251
KRW	South Korean Won	−0.1322	−0.0001	−0.0000	0.1014	0.0067	−0.5492	50.7331	571339
LKR	Sri Lankan Rupee	−0.0339	0.0000	0.0002	0.0641	0.0029	2.7858	75.1652	1260440
MYR	Malaysian Ringgit	−0.0366	0.0000	0.0000	0.0277	0.0035	−0.2993	8.5426	16271
NOK	Norwegian Krone	−0.0644	−0.0001	0.0000	0.0612	0.0077	0.2195	4.7907	5135
NZD	New Zealand Dollar	−0.0593	−0.0002	−0.0001	0.0618	0.0082	0.3886	4.7691	5180
SEK	Swedish Krona	−0.0530	−0.0000	0.0000	0.0547	0.0074	−0.0544	3.8772	3338
SGD	Singapore Dollar	−0.0238	−0.0001	−0.0000	0.0269	0.0033	0.0239	4.9815	5507
THB	Thai Baht	−0.0353	0.0000	−0.0000	0.0447	0.0037	0.1773	11.5344	29547
TWD	New Taiwan Dollar	−0.0342	0.0000	−0.0000	0.0320	0.0031	−0.3537	16.1074	57676
VEB	Venezuelan Bolivar	−11.5129	0.0000	0.0028	5.8126	0.1857	−37.8364	2974.1949	1963940216
ZAR	South African Rand	−0.0916	−0.0001	0.0002	0.0843	0.0108	0.2563	4.3936	4341

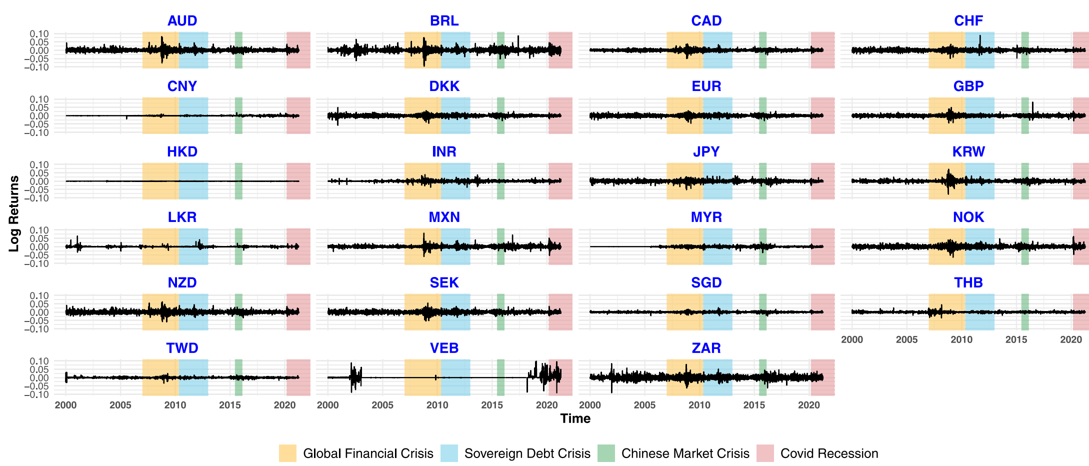


Fig. 1. Log returns for each currency. The financial crises highlighted are: the Global Financial Crisis (August 2007–April 2010) with the following Sovereign Debt Crisis (May 2010–December 2012), the Chinese Market Crisis (June 2015–February 2016) and the Covid recession (starting March 2020).

have been pegged to the USD, whereby the Central Banks keep their exchange rate within a clearly pre-defined band. Within these bands, the market is allowed to operate, and therefore some level of contagion can spread to and from these currencies. China switched from a fixed exchange rate to a less restricted regime in July 2005, with Malaysia following suit. This has resulted in the value of those currencies getting closer to their perceived market value — for the MYR an appreciation and for the CNY a depreciation. The Chinese government is only slowly allowing more flexibility of the exchange rate (Reuters, 2010), but it remains a highly influential rate and is the first emerging market currency to be held as a reserve by the International Monetary Fund (IMF). The Venezuelan Bolívar (VEB) also shows an unusual history of returns. This dynamic reflects periods of hyperinflation and the subsequent government sanctioned devaluation of the currency. We will show that our model is capable of handling even these extreme types of behaviour.

On Fig. 1 the highlighted areas show the financial crisis considered in the subsequent analysis. The financial crises highlighted are: the Global Financial Crisis (August 2007–April 2010) with the following Sovereign Debt Crisis (May 2010–December 2012), the Chinese Market Crisis (June 2015–February 2016) and the Covid recession (starting March 2020). All of the exchange rates have been impacted by the Global Financial Crisis at least in some way; even highly managed currencies like the Venezuelan Bolívar (VEB) or the Chinese Yuan Renminbi (CNY) show some turbulence during this period. In the following sections we will analyse the impact of these crises on contagion on the Forex market.

4. Contagion in the currency market

This section will present results of applying the methods from Section 2 to the Forex returns data described in Section 3. There is vast research into the interdependencies within the Forex market. The scope of this paper is to show how this innovative causal approach is able to find these dependencies within one single model with an immediate and easy interpretability of the results.

What a static approach using the correlation networks can reveal is shown in Fig. 2, which represents the correlation heatmap between the considered currencies. The heatmap can detect the outlines of the main clusters present on the Forex market. The clusters include a European cluster (EUR, NOK, SEK, DKK, GDP, CHF), the Commonwealth cluster (AUD, NZD, CAD, ZAR, SGP), a small cluster of emerging economies

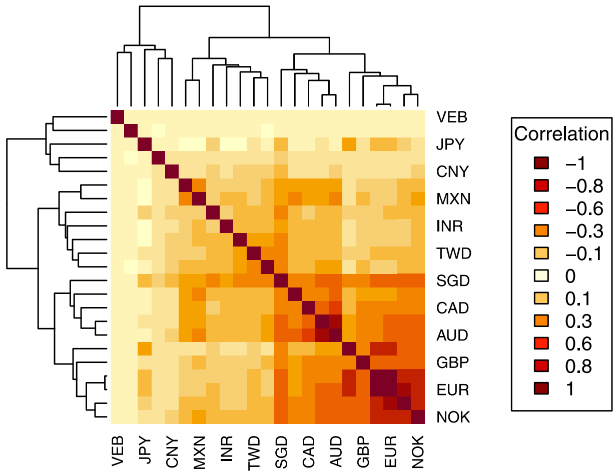


Fig. 2. Correlation heatmap for the time period 2000–2021.

(BRL and MXN) and then a somewhat sparse geographically based cluster of the Asian currencies. Applying the models from Section 2.1 we will be able look more deeply and more detail into the dynamics within the Forex of these currencies.

Fig. 3 shows the causal network created from the complete set of returns data (2000–2021). The nodes are the 23 currencies in our dataset and the links represent the causal effects of contagion from one currency to the other. The colour of the nodes shows the community classification, based on the Louvain clustering algorithm described in Section 2.4. Green arrows indicate a positive contagion coefficient and red arrows a negative coefficient of the corresponding causal effect. The width of the links reflects the strength of the causal effect.

The network shows some obvious connections, like the Euro (EUR) having an impact on the Danish Krone (DKK) exchange rate, and whole contagion paths, like the one starting from the Euro (EUR) to the British Pound (GBP), to the Canadian Dollar (CAD) and ending with an effect on the Mexican Peso (MXN). Most of the contagion coefficients are positive, apart from the effect of the Japanase Yen (JPY) on the Mexican Peso (MXN), which is indicative of the carry trade activity between the pair (Heath, Galati, & McGuire, 2007; Pengelly, 2009; Zhang, Chen, & Li, 2022). With the causal networks we can establish where the currency of interest is positioned and, from a systemic risk point of view, where contagion could come from. Informed readers will be aware of some of these connections. Since causal inference has not been applied to the analysis of contagion within the Forex market before, we use them to validate our model. A key takeaway from this section is how much more informative Fig. 3 is in comparison to Fig. 2. Furthermore, our approach enables us to quantify these causal effects and compare them through time, as seen in the next Section.

4.1. Overall development of contagion on Forex

We estimate the model from Section 2.5 with a time window of one year (250 business days), rolled over every three months. This allows us to analyse the development of contagion on the Forex from a macro-economic point of view. For each contagion map, we estimate the NECOF at each time period. We consider and analyse three contagion indices: Market NECOF, number of clusters and market density. We tested the reaction of these indices to major financial crises and reported the detailed results in Appendix C.

Fig. 4(a) shows the evolution of the market NECOF. The contagion increased significantly at the beginning of the 2000s from a NECOF of 17% to 37%, and then oscillated at a higher level, between 25% and 35%. For a more in-depth analysis of the change in contagion network statistics over time, refer to Appendix C. The rise at the beginning is caused by some of the currencies that were formerly pegged to the USD becoming more free and hence more connected to the other currencies on the Forex. This initial rise is interrupted by a peak around Sovereign Debt Crisis of low and middle-income countries that began in 2002 as defined by Laeven and Valencia (2018). We tested the reaction of all three contagion indices to major financial crises and reported the results in Appendix C. After major events during financial crises, the market NECOF tends to increase (p-value < 0.0001). This is particularly evident in the case of the Global Financial Crisis (p-value $= 0.001$), the Sovereign Debt Crisis (p-value < 0.0001), and the Covid Recession (p-value $= 0.036$). The NECOF values appear to be promising indicators of what is happening in the economy and how systemic risk evolves during periods of high uncertainty.

Fig. 4(b) shows how clustering evolves through time and in response to economic events. The clustering effect is represented by counting the number of clusters present on the network using the Louvain algorithm: the lower the number of clusters, the higher the clustering of the network. The high number of clusters at the beginning of the considered period is driven by the many currencies that were pegged to the USD during the 2000s, whose exchange rates over the USD remained nearly constant. If a currency does not show any variation it will by definition be counted as its own cluster, hence increasing the overall number of clusters detected. As the currencies became more freely traded, in a similar way as the market NECOF rose, so did the number of clusters drop. This negative relationship is confirmed by a correlation between the market NECOF and the number of clusters of −0.6. Clustering is a prominent topic when analysing the Forex topology, especially during periods of financial crisis (Keskin et al., 2011; Kwapień et al., 2009; Wang et al., 2012; Wang, Xie, Zhang, Han, & Chen, 2014). There is no evidence that the numbers of clusters in the causal contagion network change during periods of financial crisis (p-value $= 0.38$), although in the next section we will find that the structure of the clusters does change.

Fig. 4(c) shows that the Forex is predominantly a sparse graph with a relatively low market network density overall. The effect of globalisation and increased interconnectedness is reflected in the positive trend in the density development over first decade of the 2000s. Once the Global Financial Crisis began in 2007, however, the density decreased slightly and then levelled off. What we can observe is that the contagion network tends to become denser during to financial crises (p-value $= 0.009$).

4.2. Contagion clustering in Forex

In Fig. 5 we show the evolution of the clustering through the 21 years of data. The structure of these cluster plots is similar to that of an adjacency matrix and shows the rows and columns labelled by the different currencies. Instead of showing links or link weights, however the matrix shows how often pairs of currencies belong to the same cluster. The more often two currencies are assigned to the same community by the Louvain algorithm during the specified time frame, the darker and larger the dot connecting the pair gets. If the dot connecting two currencies is a solid dark blue, it means that the pair of currencies were within the same cluster 100% of the time within the considered period. The only pair that shows such perfect 100% connection is the Euro (EUR) with the Danish Krone (DKK). Empty cells indicate that the corresponding currencies were never placed in the same cluster within the specified time period.

The classically assumed geographically based clusters can be roughly identified within these cluster plots — but the structure is not so obvious and, more importantly, it changes in reaction to economic events. The main clusters can be roughly divided into a European cluster, a Commonwealth cluster, an Emerging Economies cluster and finally an Asian cluster. Within the European clusters we have some clear oddities. The British Pound (GBP) switches between the European

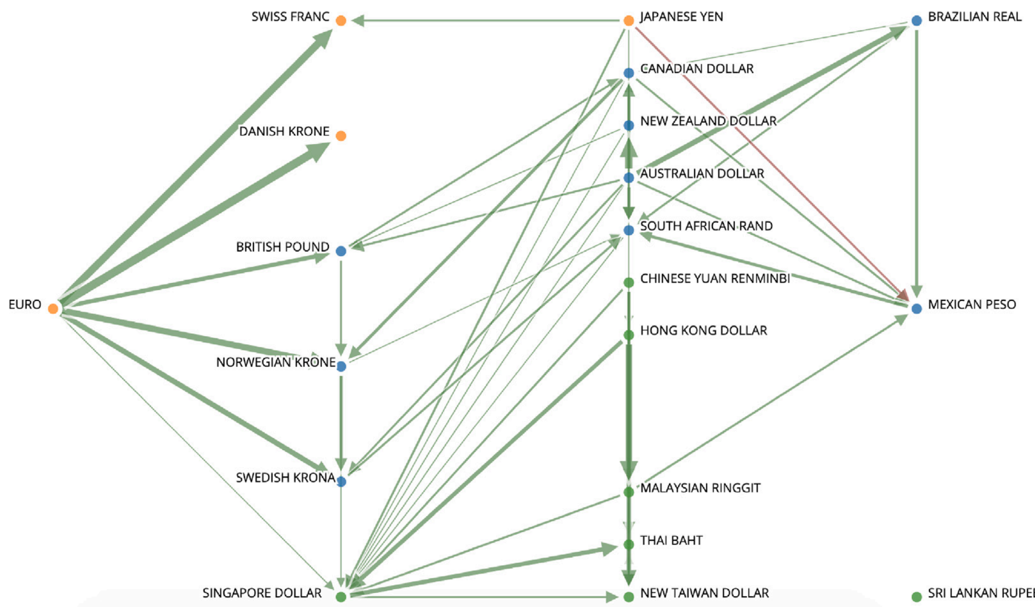


Fig. 3. Causal network showing the interconnections and contagion paths within the 23 foreign exchange rates for years 2000–2021. Note that node colours represent Louvain clusters; green (red) arrows indicate a positive (negative) contagion coefficient of the corresponding causal effect; the width of the arrows reflect the strength of the causal effect.

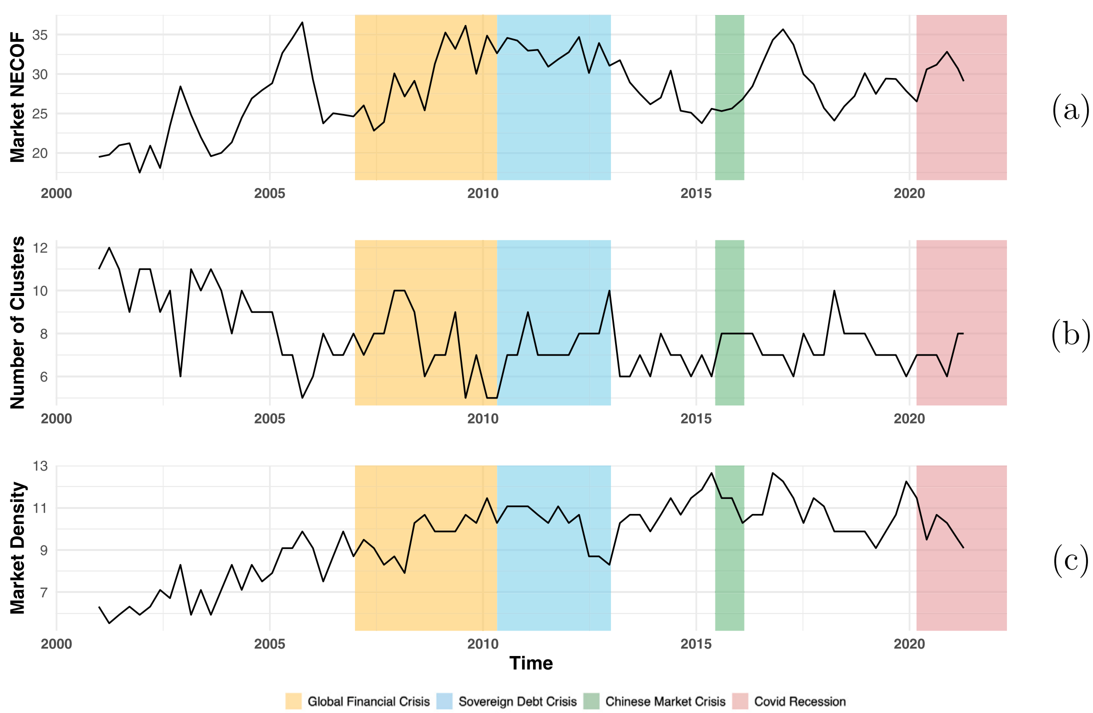
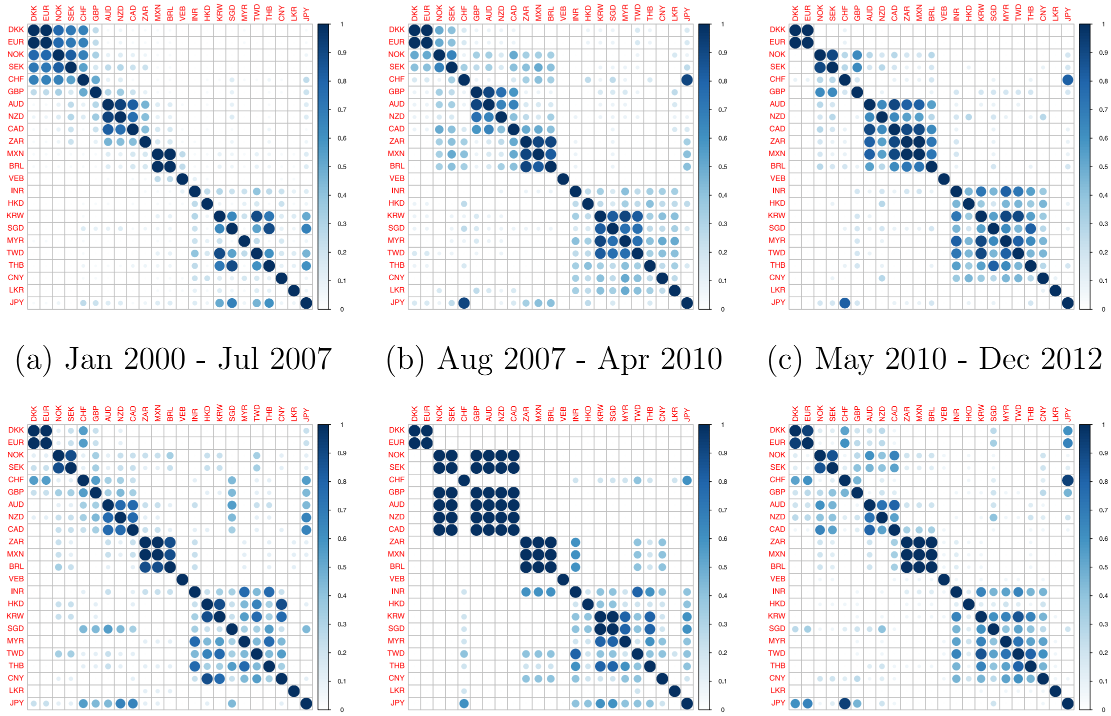


Fig. 4. (a) The market NECOF as average over all currencies; (b) The number of Louvain clusters as a measure of clustering; (c) The market network density of the Causal Network, which is the percentage of links to all possible links. The financial crises highlighted are: the Global Financial Crisis (August 2007–April 2010) with the following Sovereign Debt Crisis (May 2010–December 2012), the Chinese Market Crisis (June 2015–February 2016) and the Covid recession (starting March 2020).

cluster and the Commonwealth cluster. The Japanese Yen (JPY) is often more connected to the European cluster and specifically the Swiss Franc (CHF), especially so during a crisis. The behaviour of CHF and JPY during a financial crisis is very interesting and will be described in more depth in Section 4.3.

As stated in the previous section, we do not find a significant change in the number of clusters before and during a financial crisis. Where we find a difference however is in the stability of memberships within a cluster. The stability refers to whether a currency remains within the same cluster between two periods. In Fig. 5 the increased stability is reflected in the prevalence of large, dark blue dots and fewer, smaller, light dots. By testing the stability of memberships within a cluster, we find that during the Sovereign Debt Crisis the clustering stability was higher than that in the Global Financial Crisis (p.value = 0.0139).

This effect is visible when we compare Fig. 5(b) and Fig. 5(c) - the clusters in Fig. 5(c) (the sovereign debt crisis) are much more defined than the ones in Fig. 5(b) (the Global Financial Crisis). The European cluster fully de-constructs during this period and does not really ever recover its original structure, unlike the other clusters. The European sovereign debt crisis seems to have caused structural changes to the



(a) Jan 2000 - Jul 2007 (b) Aug 2007 - Apr 2010 (c) May 2010 - Dec 2012

(d) Jan 2013 - May 2015 (e) Jun 2015 - Feb 2016 (f) Mar 2016 - Feb 2020

Fig. 5. These figures show the evolution of the clustering over time and the impact of financial crises. The results are normalised to account for the different length of each period. We subdivide our dataset into the following periods: (a) Beginning Period: January 2000–July 2007; (b) Global Financial Crisis: August 2007–April 2010; (c) Sovereign Debt Crisis: May 2010–December 2012; (d) Intermediate Period January 2013–May 2015; (e) Chinese Stock Market Crash: June 2015–February 2016; (f) Post-Crisis Period: March 2016–February 2020.

contagion structure between the Euro and the rest of the European currencies, with effects still lasting to date. These changes cannot really be attributed to the growth and change within the Euro zone as such, because most of these changes took place well before the sovereign debt crisis hit.

The Commonwealth cluster of New Zealand, Australia, Canada, South Africa and sometimes Britain merges during the Global Financial Crisis with the New Economies cluster of Mexico and Brazil. The clustering effect of the Global Financial Crisis period can be seen much more clearly when considering changes in clustering during specific time periods than when considering clusters using the full 21-year time series.

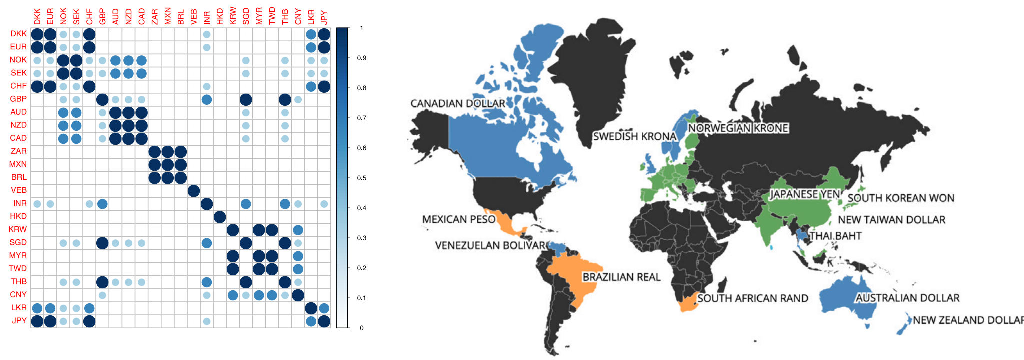
During the Chinese Market Crash, the market NECOF only minimally goes up and the global number of clusters does not change much during this crisis, but Fig. 5(e) shows some signs of clustering nonetheless. The European, the Commonwealth and the Emerging Economies clusters are notably more defined. There are some changes within these communities: the Norwegian Krone (NEK) and Swedish Krona (SEK) join the Commonwealth cluster and the Indian Rupee (INR) and the South African Rand (ZAR) move from their respective clusters to the Emerging Economies cluster. It is notable that India, although a member of the Commonwealth, finds itself rarely if at all within the Commonwealth cluster.

Unsurprisingly, the Chinese Market Crash seems to have had the largest impact on the structure of the Asian cluster. Even though Fig. 5(e) covers a relatively short period, the Asian currencies are spread all over the map and almost do not look like a clear cluster at all. During the crisis several of the Asian currencies find more connection with currencies outside of the Asian cluster. The Chinese Yuan Renminbi (CNY), for example, interacts much more with other currencies than in the previous periods. Also, interesting is the behaviour of the Swiss Franc (CHF) during this crisis — it completely leaves the Euro-centred community and has only connections with Asian currencies, probably due to its traditional role of a safe-haven currency (De Bock & de Carvalho Filho, 2015; Henderson, 2006; Jäggi, Schlegel, & Zanetti, 2019).

The period from March 2016 until February 2020 is a period of relative calm, and the clustering resembles the first plot of similar calm, apart of course from the European cluster. One other interesting mention is the Japanese Yen (JPY) that finally moves away from the Asian cluster almost completely.

In March 2020 the Covid Pandemic became a global crisis, and the Covid Recession officially started. We see from Fig. 4 that the market contagion expressed in the market NECOF increased immediately at the beginning of the pandemic, but the number of clusters did not change very much. What changed, as in the previous crisis, is the redistribution of the currencies within the clusters themselves — but in a different and more dramatic fashion. Fig. 6 shows this redistribution. The network is much more compact and in fact the density does sharply go down, i.e. the network has fewer links. This means we have new clustering with a lower number of links, but more significant links that lead to a much higher contagion on the markets. The CNY and the INR join the European cluster, whereas the GBP, SEK and NOK move together to join the Commonwealth cluster. That the impact of the Covid Pandemic on the contagion map and clustering within the Forex market would be somewhat different from the previous financial crisis was to be expected — even the markets reacted very differently. The stock markets fell faster than ever before[3] and the impact of

[3] For example the S&P 500 index fell by 34% between Feb. 19 and March 23, which constitutes the fastest fall in market in history, for further details see Roubini (2020).



Mar 2020 - Apr 2021

(a) (b)

Fig. 6. (a) Impact of the Covid Recession on the contagion-based clustering, for the period starting in March 2020. (b) Louvain clustering of the contagion network during the Covid Recession. Green Cluster: CHF, CNY, DKK, EUR, HKD, INR, JPY, KRW, MYR, SGD, TWD; Orange cluster: BRL, MXN, ZAR; Blue cluster: AUD, CAD, GBP, NOK, NZD, SEK, THB, VEB; Turquoise Cluster: LKR. The countries in black are not part of the analysis.

the Covid-19 recession seems to be having an impact on the global structure of the world economy (Carlsson-Szlezak, Reeves, & Swartz, 2020; Sułkowski et al., 2020). The cross-border financial interventions and foreign aid spending reached unprecedented levels during the Covid Pandemic (OECD, 2021). All of these could also explain changes within the clustering.

4.3. Individual network contagion dynamics

In this section we will examine some interesting behaviours of individual currencies to illustrate the different types of scenarios that can be encountered on the Forex market. Fig. 7 shows how the individual network contagion factors, NECOFs, evolve for the chosen currencies: Swiss Franc (CHF), Danish Krone (DKK), Euro (EUR), British Pounds (GBP), Japanese Yen (JPY) and Malaysian Ringgit (MYR). EUR and DKK represent currencies with consistent high and low levels of contagion, respectively. As the membership of the cluster changes frequently in the GBP, it demonstrates the importance of dynamic analysis. In times of crisis, CHF and JPY are considered safe haven currencies. MYR was pegged to the USD until 2005, when it was abandoned and became a floating currency. We look at MYR in more detail to demonstrate how our model can deal with artificially controlled market movements.

We previously discussed the pair EUR and DKK and their very high correlation. As described in Thomsen (2003), this is a well-known special relationship and serves as a good example for how to read the causality network and NECOFs. Considering the causality links we are able to see immediately that it is the EUR that influences the DKK and not vice versa, as shown in Figs. 8 and 2(b). The NECOF measure is much more meaningful than a correlation analysis in describing the risk of contagion of a financial asset. Two currencies can have a very high correlation and yet completely opposite NECOFs. In this example, the DKK shows a NECOF of almost 100% most of the time, with a median of 99.6%, while the NECOF of the EUR is usually at 0% — increasing significantly only once at the beginning of the Global Financial Crisis in 2007. It is evident that this causal relationship between the EUR and the DKK has been maintained throughout the 21-year period considered, demonstrating that the model can identify such a relationship simply by reviewing observational data on the prices, without requiring further analysis.

The next interesting example of a NECOF path is that of the GBP. In the previous section we saw that the GBP has a tendency to switch clusters between Europe and the Commonwealth cluster. It usually is a currency that influences others and generally has a low NECOF around 0% — this is in line with what Giudici and Parisi (2018) find for the United Kingdom based on Corporate Default Swap spreads (CDS). In our study however, we find that GBP's NECOF does not stay at zero throughout. This is especially true for the Global Financial Crisis (p-value = 0.0292). From a qualitative point of view we see a NECOF for the GBP rise from 26% before the start of the Global Financial Crisis to 57% in the first months. Curiously, the GBP was hardly ever under the influence, from a contagion point of view, of the EUR — unless, again, there was a crisis. The GBP experienced contagion from the EUR in 2007, during the Global Financial Crisis, and then during Brexit, around the time when the first draft withdrawal agreement was negotiated and endorsed by the EU members at the end of 2019, as seen in Fig. 8.

The CHF is traditionally considered a safe-haven currency (De Bock & de Carvalho Filho, 2015; Henderson, 2006; Jäggi et al., 2019). The CHF presents a relatively volatile and often high NECOF which is in contrast to the assumed safety of the CHF. CHF has mean NECOF 62% and the highest volatility in terms of NECOF among all of the currencies considered, with a standard deviation of 28.5. What speaks for the safe haven status is CHF behaviour during periods of financial crisis: CHF NECOF reacts to financial crisis (p-value < 0.0001) and it goes down during the Global Financial Crisis (p-value 0.0016), the Sovereign Debt Crisis (p-value < 0.0001) and Chinese Market Crisis (p-value < 0.0001). The details of all the tests performed are in Appendix C. The low NECOFs in Fig. 7 during the European Sovereign Debt Crisis are an example of this behaviour. The sharp fall of the NECOF at the end of 2014 is due to the intervention of the Swiss central bank, which tried to peg the currency to the EUR to prevent the increase in value of CHF. This attempt was however scrapped in January of 2015. And after the Chinese market crash passed, the NECOF shot up again.

In the past, the JPY was seen more "as a low interest rate or funding currency" (Henderson, 2006), but most recent studies classify it a safe-haven currency (Botman, de Carvalho Filho, & Lam, 2013; Jäggi et al., 2019). As with the CHF, the JPY seems to appreciate in value during a crisis and during high volatility periods (Ranaldo & Söderlind, 2010). As Fig. 7 shows, the JPY presents a very low NECOF for most of the time. A median NECOF of 0% and a mean NECOF of 7% seem to validate the consideration of the JPY as a safe-haven currency. We further find a dependency of the CHF on the JPY, illustrated in Fig. 8. The arrow goes from the JPY to the CHF in 75% of the networks (never in the opposite direction), which indicates that there is contagion that goes from the JPY to the CHF. The causal effect from the JPY to the CHF and the lower NECOF of the JPY in general would suggest that the JPY could be even considered a better safe haven than the CHF. This is exactly what Fatum and Yamamoto (2016) and De Bock and de Carvalho Filho (2015) find when comparing these two currencies in terms of safe-haven characteristics.

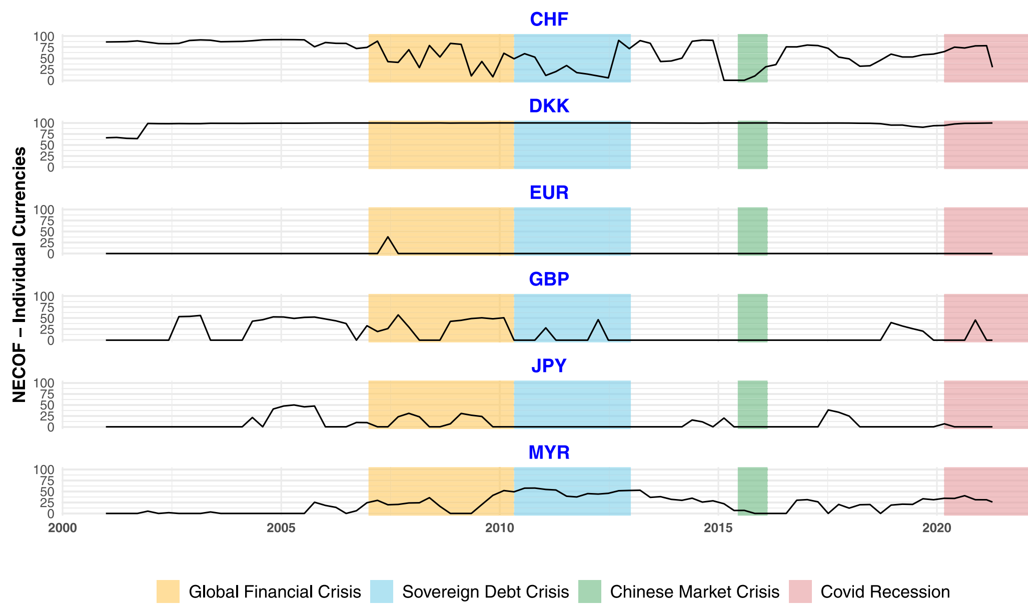


Fig. 7. NECOF through time for the currencies CHF, DKK, EUR, GBP, JPY and MYR. The financial crises highlighted are: the Global Financial Crisis (August 2007–April 2010) with the following Sovereign Debt Crisis (May 2010–December 2012), the Chinese Market Crisis (June 2015–February 2016) and the Covid recession (starting March 2020).

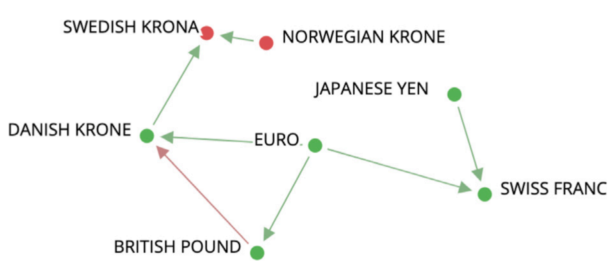


Fig. 8. Subgraph of the causal network for the GBP in 2019.

The last currency we will consider in detail is the MYR. The MYR shows the NECOF evolution of an Asian currency that was pegged to the USD until the 2005. The NECOF falls in 2008 and after the 2015 Chines stock market crash, mainly because of the intervention by the Bank Negara (the Central Bank of Malaysia) to prevent the exchange rate over the USD from plummeting. At times of important intervention by a central bank the contagion from other currencies clearly decreases. The Malaysian economy and financial sector have grown during the 20 years considered here, and it is interesting how resilient to contagion it seems to be, unlike the other south Asian currencies maintaining an average NECOF of 20.5% with a maximum of 57% during the Sovereign Debt Crisis. Details for all NECOFs of all currencies can be found in the Appendix B.

5. Conclusion

Financial contagion measures have always had causal aspirations. In this work we have unified this concept of causality with a defined measure that allows for a quantifiable causal interpretation of contagion relationships on the Forex market. We corroborate and extend results from different studies within one unifying framework and are able to answer very practical questions like how contagion spreads on the Forex market and which currencies are at the highest risk of contagion at any given time.

We have recreated a series of causal networks based on 23 exchange rates over the USD, spanning over 21 years, and present both the overall development of contagion on the Forex market as well as individual network contagion dynamics. We have shown how to read these causal networks as contagion maps to pinpoint sources of contagion and how the contagion paths on the Forex market evolve through time. We were able to identify a new promising group of financial indicators that take contagion and systemic risk directly into account. The newly identified measure of network contagion (NECO) seems to be of value for both a market level evaluation and the analysis of single currency alike. We discussed the network contagion factors' (NECOF) evolution for a subset of currencies, to demonstrate how this metric can be used to identify and evaluate a currency from an investment and hedging point of view.

In contrast to correlation networks, we obtain causal directions. Because they are inherently sparse, causal networks do not have to be filtered, e.g. via Minimum Spanning Tree (MST) methods (Mantegna, 1999), and can be easily analysed and evaluated. Kazemilari and Djauhari (2013) compare the use of different centrality measures in constructing MSTs for the Forex market, (including degree, betweenness, closeness and eigenvector). Filtering is found to be important, but results are sensitive to the exact measure of correlation used as well as the distance measure. There are other filtering methods and so the choice of the method itself will also affect results (Marcaccioli & Livan, 2019; Serrano, Boguná, & Vespignani, 2009; Soramäki & Cook, 2016; Tumminello, Aste, Di Matteo, & Mantegna, 2005).

The application of causal graphical models to financial data is in its infancy and there are still interesting challenges. In our case we assumed normality for log returns and found our sample to be stationary, but a model that could deal automatically with non-normality, fat-tails, heteroskedasticity and non-stationarity of the data would be advantageous for further applications in finance. The trading on the Forex market is active 24 h a day (Goodhart & Hesse, 1993) and so we were able to use prices for all currencies at the same time instant. This is not the case for most other markets and assets being traded, and hence the impact of asynchronously observed returns on the analysis would have to be taken into account (Burns, Engle, & Mezrich, 1998). Whereas the contemporaneous contagion is the most significant in a fast moving and liquid market, it could also be of interest to consider economic cycles and longer time delays. Lastly, any measurable confounder can be added into our model, should we want to see how other variables, e.g. interest rates or inflation, impact the contagion. For unmeasured confounders and latent variables The Fast Causal Inference algorithm (FCI) (Spirtes, Glymour, Scheines, & Heckerman, 2000; Spirtes, Meek,

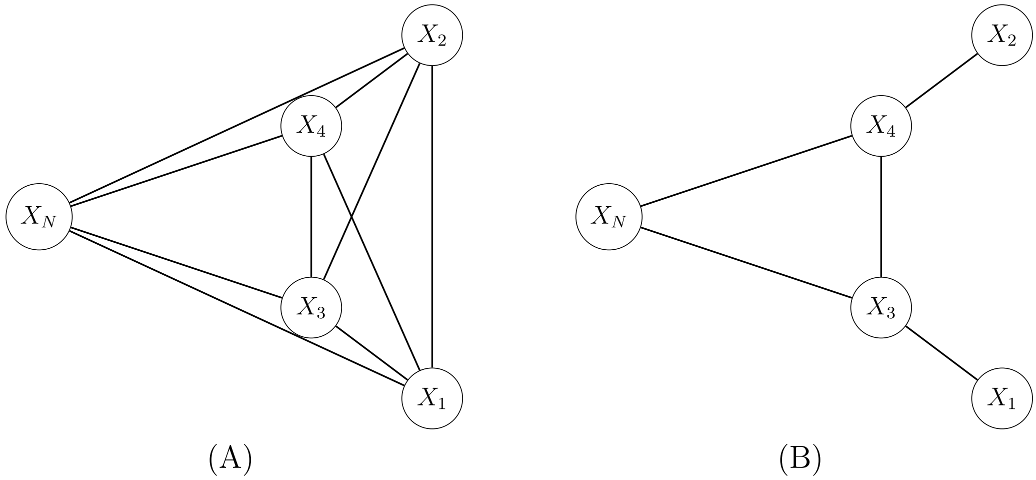


Fig. A.9. (A) Complete causal graph for five financial instruments of interest. (B) The skeleton obtained from the complete graph using STEP 1.

& Richardson, 1995) can be used. Although our approach has been validated on the Forex market, it can be extended to markets of many other financial instruments. Looking at applications beyond financial contagion, our approach fits well the recent demand for explainability of machine learning and artificial intelligence methods (Kuang et al., 2020).

Acknowledgements

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Appendix A. PC stable algorithm

STEP 1 - Finding the skeleton. We begin the procedure by defining all nodes of interest X and link all of them to create a complete graph, as in Fig. A.9 (A).

Once we have the complete graph, we eliminate links between nodes X_i and X_j that are independent or conditionally independent, conditioning iteratively on a growing subset of the other nodes X_C in the graph. The algorithm considers all possible separating subsets X_C for each pair of nodes to test the hypothesis H_0 that nodes X_i and X_j are independent. If there is any subset X_C for which H_0 is not rejected at the specified significance level (often set at $\alpha = 0.05$), the link between the two nodes is removed from the network. Whatever is left at the end of the process is the so-called skeleton, an undirected graph G such that nodes (X_i, X_j) are connected with a link if and only if no set X_C can be found to make them conditionally independent. See an example of a skeleton in Fig. A.9 (B).

STEP 2 - Applying causal orientation rules. First, for each pair of nodes X_i and X_j that are not connected by a link, but both connecting to a common neighbour X_k, we check whether X_k belongs to the subset of links X_C from the previous step. Since we do not have a link between X_i and X_j, we know that a subset X_C exists such that these two are conditionally independent. If X_k does not belong to the subset X_C and yet we still have a link between these three nodes, we know that X_i and X_j influence X_k and not vice versa. This means we add directions $X_i \rightarrow X_k$ and $X_j \rightarrow X_k$ as seen in Fig. A.10. This primary orientation is often referred to as a collider or inverted fork or V orientation. We can think of colliders as nodes that stop a path unless the analysis is conditioned on them — colliders are random variables that appear on the left-hand side in a structural equation model with multiple variables on the right-hand side.

Once we have established all colliders within the graph, the PC algorithm tries to orient as many of the remaining links as possible by a set of consistency rules, as in Meek (1995). The rules ensure that no newly directed link disrupts the previously established structure and no cycle is created. An example of such a rule is shown in Fig. A.11.

Not all links can always be successfully oriented at the end of this step. If the graph we obtain after implementing the orientation rules is not fully directed, it is referred to as a Completed Partially Directed Acyclic Graph (CPDAG). In that case a CPDAG is the best possible outcome we can obtain. It describes an equivalence class of DAGs that cannot be distinguished even with an infinite amount of data. An example of a CPDAG can be seen in Fig. A.12. Unlike in Fig. A.10, we cannot find a collider, and so all three DAGs (B),(C) and (D) can equally explain the skeleton in (A).

The more nodes or variables we have in a network, and therefore the more connectivity we have, the easier it is for the PC Algorithm to detect directions. This is in contrast to the curse of dimensionality that most models have. A trivial example would be a network with just two nodes: In such a situation no amount of observational data on these two nodes would allow the PC Algorithm to orient the graph and decide on the direction of the arrow between the two nodes.

Appendix B. Individual NECOFs

In this section we present the individual NECOFs for all 23 currencies, according to formula (5). The values in Table B.2 are in percentages (0–100) and express the amount of contagion from other currencies in the overall period 2000–2021. Fig. B.13 shows the development of the NECOF scores through time for each of the currencies.

Appendix C. Supplemental materials to Section 4

In these supplementary materials we provide the details of the various analyses performed in the manuscript.

C.1. Change in contagion network statistics over time

In the paper it was claimed that the various statistics describing the contagion in the Forex market change through time. Figs. C.14–C.16 show the development of the Market NECOF, number of clusters in the causal network and the market density, respectively. Table C.3 shows the significance level of the test for the need of a temporal spline for each of the three contagion indices. They show a highly significant result, meaning that the indices are not constant over time. From Fig. C.14 it is clear that the market NECOF increases over time. Fig. C.15 shows that the number of clusters in the contagion network

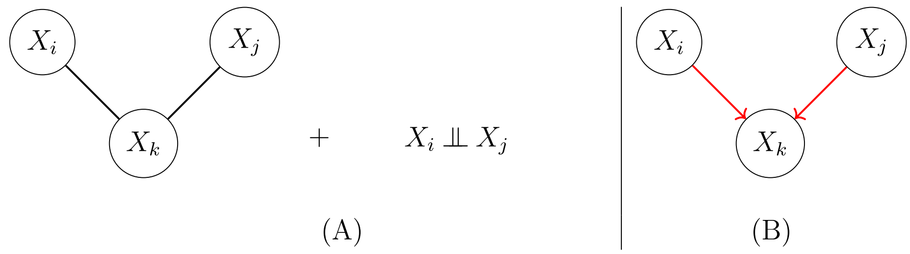

Fig. A.10. Example of a collider.
Knowing that X_k is not a parent node for X_i and/or X_j as shown in (A), only one direction for the links between the three variables is logically possible – the red arrows shown in (B).

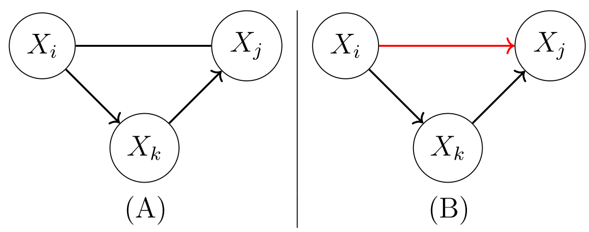

Fig. A.11. Example of a consistency rule. The graph in (A) necessarily implies the graph in (B), because if the link went in the other direction the three nodes would form a cycle.

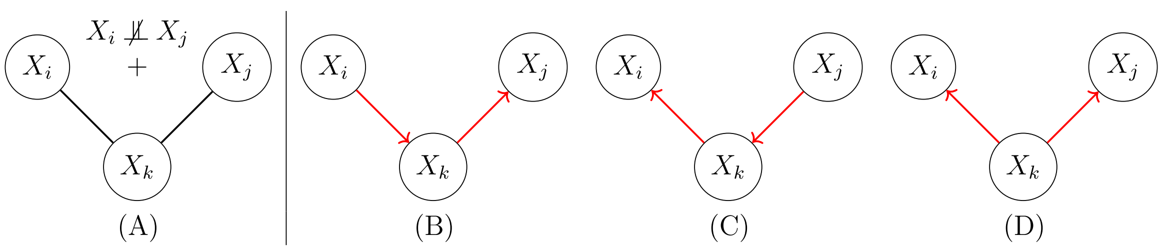

Fig. A.12. Example of a CPDAG based on the Skeleton shown in (A). (B), (C) and (D) are Markov equivalent DAGs, or CPDAGs, under the assumption that X_k belongs to the subset of X_C that made X_i and X_j independent and so a collider solution as in Figure Fig. A.10 was not possible.

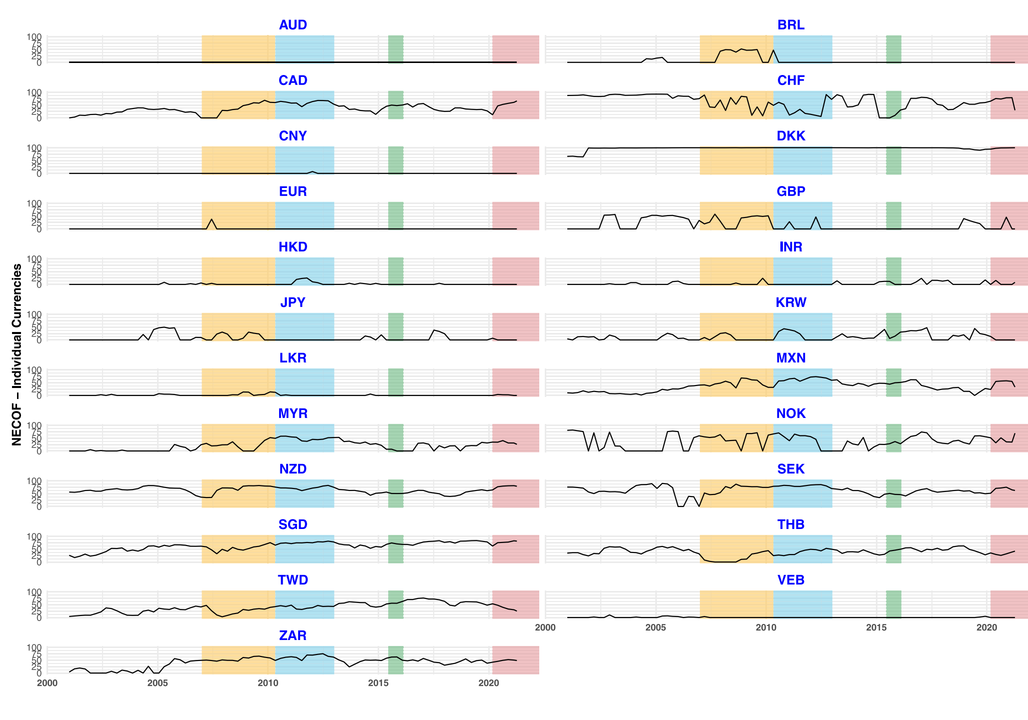

Fig. B.13. NECOF through time for each currency. The financial crises highlighted are: the Global Financial Crisis (August 2007–April 2010) with the following Sovereign Debt Crisis (May 2010–December 2012), the Chinese Market Crisis (June 2015–February 2016) and the Covid recession (starting March 2020).

Table B.2
Overview of the summary statistics for the Network Contagion Factors (NECOFs) on individual 23 exchange rates over the USD, for the period January 2000 to April 2021. The values are in percentages between 0 and 100.

Code	Currency name	Minimum	Median	Mean	Maximum	StDev
AUD	AUSTRALIAN DOLLAR	0	0	0	0	0
BRL	BRAZILIAN REAL	0	0	5.68	52.1	14.73
CAD	CANADIAN DOLLAR	0	33.95	36.53	68.3	18.43
CHF	SWISS FRANC	0	72.9	61.73	92.3	28.48
CNY	CHINESE YUAN RENMINBI	0	0	0.08	7.2	0.78
DKK	DANISH KRONE	64.3	99.6	97.42	99.9	7.29
EUR	EURO	0	0	0.44	38	4.1
GBP	BRITISH POUND	0	0	15.51	57.4	21.76
HKD	HONG KONG DOLLAR	0	0	1.48	25	4.5
INR	INDIAN RUPEE	0	0	2.99	24.1	5.97
JPY	JAPANESE YEN	0	0	6.77	49.6	13.48
KRW	SOUTH KOREAN WON	0	6.4	11.42	47.5	13.68
LKR	SRI LANKAN RUPEE	0	0	1.28	13.9	3.07
MXN	MEXICAN PESO	0	37.1	36.48	73	20.13
MYR	MALAYSIAN RINGGIT	0	20.5	20.5	57.6	18.33
NOK	NORWEGIAN KRONE	0	40.2	38.5	81.4	26.76
NZD	NEW ZEALAND DOLLAR	34.7	64.55	63.89	81.9	12.3
SEK	SWEDISH KRONA	0	63.95	62.99	89.7	18.19
SGD	SINGAPORE DOLLAR	17.2	65.75	62.57	83.2	16.22
THB	THAI BAHT	0	39.9	38.27	62.6	15.58
TWD	NEW TAIWAN DOLLAR	2.9	39.6	39.1	75.8	18.74
VEB	VENEZUELAN BOLIVAR	0	0	0.57	10	1.68
ZAR	SOUTH AFRICAN RAND	0	48.45	41.43	75.1	20.64

Table C.3
Significance test for the temporal change in, respectively, market NECOF, number of clusters, and market density.

	Estimate	Std. Error	t value	Pr(>| t |)
Market NECOF	28.0709	0.3212	87.38	<2e−16 ***
Number of Clusters	7.8023	0.1329	58.7	<2e−16 ***
Market density	9.53663	0.08548	111.6	<2e−16 ***

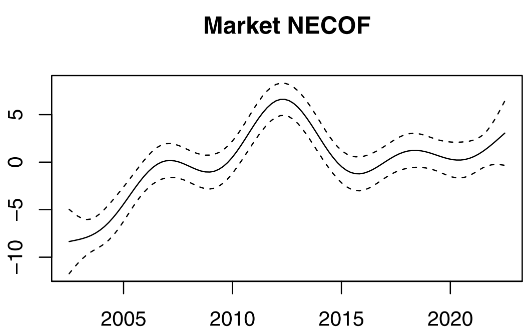

Fig. C.14. Thin plate spline of the temporal change in market NECOF between 2000 and 2021. The upper and lower dotted lines are at 2 standard errors above and below the estimate.

decreases over time, whereas Fig. C.16 illustrates the increase of the market density.

C.2. Significance test of the reaction of contagion indices to major financial crises

This section describes the formal tests for the various contagion indices to the various financial crises. We performed an Analysis of Variance and the results are shown in Table C.4. Both market NECOF and network density are significantly affected by the financial crises, whereas the number of clusters is not. Tables C.5 and C.6 show the results of the linear regression for the market NECOF and the market density each. The market NECOF increased significantly during the Global Financial Crisis, the Sovereign Debt Crisis and the Covid Recession, but stayed relatively flat during the Chinese Market Crisis. The market network density reacted mainly to the Sovereign Debt Crisis, the Chinese Market Crisis, and the Covid Recession.

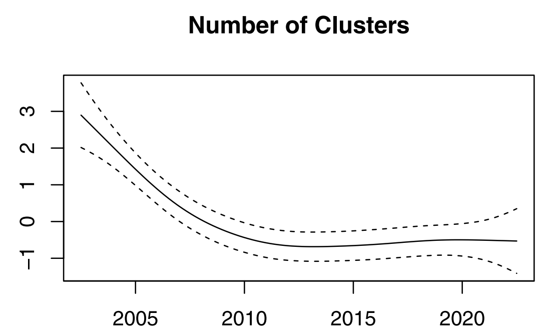

Fig. C.15. Thin plate spline of the temporal development of the number of clusters between 2000 and 2021. The upper and lower dotted lines are at 2 standard errors above and below the estimate.

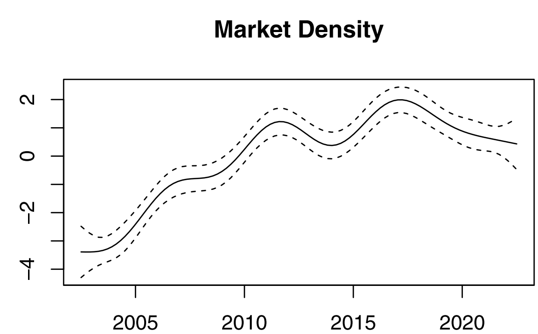

Fig. C.16. Thin plate spline of the market density between 2000 and 2021. The upper and lower dotted lines are at 2 standard errors above and below the estimate.

Table C.4
Analysis of Variance of the reaction of market NECOF to financial crises.

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Market NECOF	4	511.5	127.88	7.916	1.95e−05 ***
Number of Clusters	4	10.77	2.692	1.064	0.38
Contagion Network Density	4	39.1	9.775	3.601	0.00941 **

Table C.5
Result of the linear regression showing the reaction of the market NECOF during the Global Financial Crisis, the Sovereign Debt Crisis, the Chinese Market Crisis and the Covid Recession.

Parametric coefficients	Estimate	Std. Error	t-value	Pr(>| t |)
(Intercept)	26.36189	0.56280	46.840	$< 2e-16$ ***
Global Financial Crisis	4.38811	1.28955	3.403	0.00104 **
Sovereign Debt Crisis	6.38356	1.33616	4.778	7.79e−06 ***
Chinese Market Crisis	−0.01233	1.88350	−0.007	0.99479
Covid Recession	3.45177	1.62003	2.131	0.03615 *

Table C.6
Result of the linear regression showing the reaction of the market density during the Global Financial Crisis, the Sovereign Debt Crisis, the Chinese Market Crisis and the Covid Recession.

Parametric coefficients	Estimate	Std. Error	t-value	Pr(>| t |)
(Intercept)	9.0359	0.2307	39.163	$< 2e-16$ ***
Global Financial Crisis	0.8133	0.5287	1.538	0.12785
Sovereign Debt Crisis	1.1350	0.5478	2.072	0.04144 *
Chinese Market Crisis	2.2681	0.7722	2.937	0.00431 **
Covid Recession	1.3541	0.6641	2.039	0.04472 *

Table C.7
Welch Two Sample t-test result comparing the clustering stability between the Global Financial Crisis (GFC) and Sovereign Debt Crisis (SDC).

Difference	GFC	SDC	df	t-value	p-value
Clustering stability	208.9	222.4	13.787	−2.818	0.01385

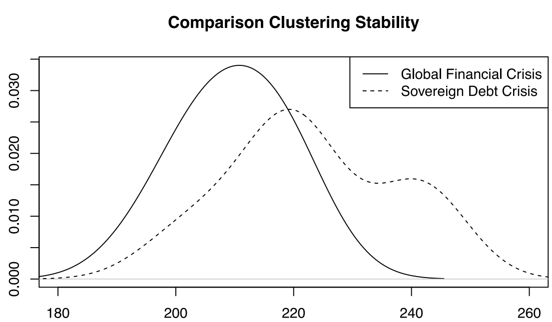

Fig. C.17. Comparison of the estimated probability density function for the stability of memberships within a cluster during the Global Financial Crisis and the Sovereign Debt Crisis, where the right shift during the Sovereign Debt Crisis indicates higher stability in the clustering.

C.3. Stability of clustering effects during the global financial crisis and the sovereign debt crisis

We test the stability of memberships within a cluster and compare it under the Global Financial Crisis and the Sovereign Debt Crisis. The results of the Welch Two Sample t-test comparing the mean values under the Global Financial Crisis and the Sovereign Debt Crisis are presented in Table C.7. The test suggest that the mean value of the clustering stability under Global Financial Crisis group is lower than the mean value of clustering stability under the Sovereign Debt Group. Fig. C.17 shows this higher stability of clustering under the Sovereign Debt Crisis.

C.4. CHF NECOF behaviour during a financial crisis

We claimed in Section 4.3 that NECOF of the Swiss Franc (CHF) has a tendency to go down in times of financial crises. Table C.8 presents the results of the Analysis of Variance on the NECOF of the CHF. The results show that financial crises have a notable and highly significant effect on the NECOF of the CHF during the four crisis periods considered.

Table C.8
Analysis of Variance of the reaction of NECOF for the CHF to financial crises.

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Crises	4	28085	7021	13.91	1.1e−08 ***
Residuals	81	40871	505		

Table C.9
Result of the linear regression showing the reaction of the CHF NECOF during the Global Financial Crisis, the Sovereign Debt Crisis, the Chinese Market Crisis and the Covid Recession.

Parametric coefficients	Estimate	Std. Error	t-value	Pr(>| t |)
(Intercept)	74.137	3.145	23.570	< 2e−16 ***
Global Financial Crisis	−23.596	7.207	−3.274	0.00156 **
Sovereign Debt Crisis	−39.037	7.468	−5.228	1.31e−06 ***
Chinese Market Crisis	−58.937	10.527	−5.599	2.86e−07 ***
Covid Recession	−8.523	9.054	−0.941	0.34933

Table C.10
Analysis of Variance of the reaction of NECOF for the GBP to financial crises.

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Crises	4	5603	1400.6	3.274	0.0154 *
Residuals	81	34655	427.8		

Table C.11
Result of the linear regression showing the reaction of the GBP NECOF during the Global Financial Crisis, the Sovereign Debt Crisis, the Chinese Market Crisis and the Covid Recession.

Parametric coefficients	Estimate	Std. Error	t-value	Pr(>| t |)
(Intercept)	16.461	2.896	5.683	2.01e−07 ***
Global Financial Crisis	14.731	6.636	2.220	0.0292 *
European Debt Crisis	−9.679	6.876	−1.408	0.1631
Chinese Market Crisis	−16.461	9.693	−1.698	0.0933
Covid Recession	−9.932	8.337	−1.191	0.2370

Table C.9 shows the estimates, standard errors, t-values, and p-values for the individual contagion effects during the crises. The results indicate that the CHF NECOF is significantly affected by the Global Financial Crisis, Sovereign Debt Crisis, and Chinese Market Crisis with p-values less than 0.0001.

C.5. GBP NECOF behaviour during a financial crisis

We claimed in Section 4.3 that the NECOF of the British Pound (GBP) reacts to periods of financial crises. The Analysis of Variance results presented in Table C.10 indicate that the being in a period of financial crisis has a statistically significant effect on the NECOF of the GBP. These results suggest that financial crises are an important factor in explaining the variation in the NECOF of the GBP, and should be carefully considered when analysing the factors that affect this variable.

The Table C.11 shows the individual contagion factors for the four financial crises. These estimates indicate the effect of each crisis on the NECOF of the GBP. The most significant effect observed is the increase in the GBP NECOF during the Global Financial Crisis.

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