The Effect of Global Crises on Stock Market Correlations: Evidence from Scalar Regressions via Functional Data Analysis

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Abstract

This paper presents a novel, mixed-frequency based regression approach, derived from Functional Data Analysis (FDA), to analyze the effect of global crises on stock market correlations, using a long span of data, dating as far back as early 1800s, thus covering a wide range of global crises that have not yet been examined in the literature in this context. Focusing on the advanced nations in the G7 group, we observe heterogeneous effects of global crises on the time-varying correlations between the US stock market and its counterparts in the G7. While the post World War II period experienced a general rise in the level of correlations among developed stock market returns, we find that global crises in general have resulted in a stronger association of US stock market performance with that in the UK and Canada, whereas the opposite holds when it comes to how European and Japanese stock markets co-move with the US. Further analysis of sub-periods, however, reveals that the crises-effect over stock market correlations is largely driven by the context and nature of the crises that possibly drive the perception of risk in financial markets. Overall, our results tend to suggest that in the wake of crises that are global in nature, diversification benefits will be limited by moving funds across the US and UK stock markets whereas possible diversification benefits would have been possible during the crises-ridden period of the early twentieth century by holding positions in equities in the remaining G7 nations to supplement positions in the US. However, these diversification benefits seem to have frittered away in the post World War II period, highlighting the role of emerging markets and alternative assets to improve diversification benefits in the modern era.

Keywords: Functional data analysis; global crises; stock markets; comovements; G7.

JEL Codes: C22, G01, G15.

1. Introduction

Correlation estimates are critical inputs for not only asset allocation decisions, but also for risk management and hedging applications. Consequently, there is a large literature on equity market correlations, documenting the presence of a conditional pattern in return correlations with respect market conditions. The so-called correlation asymmetry phenomena reported in a number of studies including Longin and Solnik (1995, 2001); Ang and Bekaert (2002); Campbell et al. (2002); Goetzmann et al. (2005); Bekaert et al. (2009), among others, refers to the asymmetric pattern in which equity returns tend to be more correlated during bear market regimes as well as during periods of extreme price fluctuations. Building on this evidence, Krishnan et al. (2009) further documents the presence of a correlation risk premium in returns in that correlation (after controlling for asset volatility and other risk factors) carries a significant negative price of risk. Hence, understanding the drivers of asset correlations is not only a topic of interest for effective diversification strategies, but also has implications for pricing and hedging.

From an asset pricing perspective, it can be argued that the time variation in correlations among stock prices reflects comovement in fundamental values (Barberis et al., 2005; Baele et al., 2010; Baele and Soriano, 2010), which follows as a direct corollary of the efficient market hypothesis (EMH). Under EMH, the market price of an asset reflects its fundamental value that can be computed as the sum of rationally forecasted cash flows discounted at a rate appropriate for the associated risk. Hence, any comovement in prices across assets must be due to the common movement in fundamentals. Considering that changes in an asset's fundamental value can be driven by cash-flow and/or discount rate related news, one can argue that correlations among stock returns would also be driven by the correlation in news associated with cash flows and/or discount rates. Recent research highlights the importance of discount rate factors in the time variation of global equity market correlations, partially driven by changes in the level of risk aversion in financial markets (Miranda-Agrippino and Rey, 2015; Rey, 2015; Bekaert et al., 2019; Pastor and Veronesi, 2018; Xu, 2017; Demirer et al., 2018). Considering that macroeconomic and financial crises, particularly those that are global in nature, can lead to significant shifts in the state of the economy, earnings projections as well as the level of risk aversion among investors, a large number of studies have analyzed stock market correlations in the context of financial crises using post World War II data (see Horvath and Poldauf (2012); Hwang et al. (2013); Yarovaya and Lau (2016); Jiang et al. (2017) and Ji et al. (2018) for detailed reviews).

This paper contributes to this literature by (i) examining the role of global crises on stock market correlations using a long span of data, dating as far back as late 1800s, thus covering a wide range of global crises that have not been examined in the literature in this context and allowing to track the entire evolution of these markets from their inception; and (ii) adopting the novel statistical approach of Functional Data Analysis (FDA) in order to fully utilize mixed frequency data without loss of information due to averaging/aggregation. More specifically, we analyze the effect of global crises on the time-varying (rolling) correlations between the stock markets of the United States (US) and the remaining G7 countries, i.e., Canada, France, Germany, Italy, Japan, and the United Kingdom (UK) using historical data spanning over a century (at times) of monthly data. Global crises are proxied by an index of global macroeconomic and financial crises (henceforth referred to as Global

Crises Index (GCI)) developed by Reinhart and Rogoff (2009), computed as a composite index of banking, currency, sovereign default and inflation crises, and stock market crashes (weighted by the share of world income of sixty-six countries). Given that the crises index data is only available at annual frequency while stock market correlations are monthly, we handle mixed frequency data via FDA-based regressions, thus overcoming the limitations of the traditional time series approach without having to first extract statistical indexes from the data. Compared to the alternative DCC-GARCH-MIDAS model (dynamic conditional correlation generalized autoregressive conditional heteroskedastic model with mixed data sampling) of Colacito et al. (2011), or RU-MIDAS model (reverse unrestricted mixed data sampling model) of Foroni et al. (2018), the FDA approach offers several advantages besides tackling mixed-frequency data with ease. For instance, the FDA approach does not suffer from the issues of algebraic non-existence, mathematical irregularity, and non-asymptotic properties (McAleer, 2019), as well as problems of convergence often observed with DCC-type models at frequencies lower than daily data due to overparametrization (Balcilar et al., 2017; Fang et al., 2018). In addition, FDA also does not require the use of stationary data as in both the DCC-GARCH-MIDAS and RU-MIDAS approaches, and hence allows us to retain the variables in original form without any transformations. This is a particularly important concern in the case of return correlations, which (as shown later in the paper) are not necessarily mean-reverting. Furthermore, the FDA method (based on functional curves) allows us to obtain the relationship between equity market correlations and the metric of crises at each observation point (i.e. months) within a given annual window, which in turn is important, given that the annual measure of crises is likely to have an impact over an entire year. To that end, this paper provides a novel approach to correlation modeling as asset allocation decisions generally rely on short-run data while the parameters of interest may be influenced by factors that are observable at low frequencies only. To the best of our knowledge, this is the first paper to analyse the role of global crises on stock market comovements in a mixed frequency setup covering, in some instances, over a century of data.

Our findings indicate heterogeneous effects of global crises on the time-varying correlations between the US stock market and its counterparts in the G7 group. While global crises in general have resulted in a stronger association of US stock market performance with that in the UK and Canada, we observe the opposite effect of crises on correlations when it comes to how European and Japanese stock markets co-move with the US. The analysis of sub-samples, however, reveals that the crises effect over stock market correlations is largely driven by the context and nature of the crises that drive the perception of risk in financial markets. Barring the case of US-UK correlations, we observe that the full-sample results were primarily driven by the sub-sample that encompassed the early part of the twentieth century. Interestingly, during the post World War II period of 1950 to 2010 (when the correlation for the stock markets of all economies relative to the US had actually increased), global crises were found to have a significant positive effect on the correlations particularly for the (US-UK) and (US-Japan) stock markets. Although a similar positive crisis effect on correlations is also observed for France, Germany and Italy over this period, this effect is found to be statistically insignificant. On the other hand, the opposite is observed in the case of US-Canada correlations, with global crises negatively affecting the correlations between these two markets over the period from 1950 to 2010.

Overall, our results tend to suggest that in the wake of crises that are global in nature, diversification benefits will be limited by moving funds across the US and UK stock markets whereas possible diversification benefits would have been possible during the crises-ridden period of the early twentieth century by holding positions in equities in the remaining G7 nations (France, Germany, Italy or Japan) to supplement positions in the US. However, these diversification benefits seem to have frittered away in the post second World War period, highlighting the role of emerging markets and alternative assets to supplement diversification strategies. The only exception is the Canadian stock market, which appears to have provided diversification gain over the second half of the twentieth century, although it was not the case during the inter-war period.

The rest of the paper is organized as follows. Section 2 presents the background on the FDA-based regression methodology, including smoothing of the data while Section 3 provides the description of the data used in our empirical analysis. Section 4 presents the empirical findings for the full and sub-samples. Finally, Section 5 concludes with some discussion regarding the implications of the findings and possible extensions to future work.

2. Methodology

In our investigation, the two variables under study are not in the same frequency, specifically one is at monthly frequency, while the other is a single value for each year: the G7 stock returns and their associated correlations with the US are observed monthly while the GCI is annual. In classic time series and regression methods, variables in the model must be sampled at the same frequency, and if they are not in the same frequency, then data available at higher-frequency is converted into the lowest-frequency by, say, averaging/aggregating the higher frequency data, which in turn, leads to some of the information being lost (Clements and Galvao, 2008; Foroni and Marcellino, 2013). In addition, Foroni and Marcellino (2013) argue that direct modelling of mixed frequency data can be useful, and does improve the predictive ability of the dependent variable.

In recent times, a family of regression models referred to as the Mixed-Data Sampling (MIDAS) models have been used to model mixed frequency data (Ghysels et al., 2004, 2005, 2006, 2007). But in these models, the dependent variable is at lower frequency compared to its predictor(s). In our case, it is the reverse, and would in turn require the RU-MIDAS approach discussed above. But, these mixed-frequency time series models are primarily based on the assumption of stationarity, with most time series data violating this assumption, and hence requires transformations to ensure mean-reversion. In FDA, stationarity of the underlying process is not needed. As such, FDA is in some way, a set of techniques that overcomes the limitations of traditional time series approach and extends classical statistical methods to the functional framework, without having to first extract statistical indexes out of the data, a process which can lead to information loss, and thus these techniques allow for more attractive flexible modelling (Muller, 2011). The functional regression model allows us to model the relationship between the impact of the low-frequency (annual) GCI and the high-frequency (monthly) comovements of the stock returns in a relatively effortless way. In section 2.1 we discuss how to convert discrete data into functional form, and in Section 2.2 we discuss the theoretical foundations of Functional Linear Regression.

2.1. Smoothing

We remind the reader that the term "functional data" refers to data where each observation is a curve. The individual datum in FDA is a whole function defined on a common interval, usually time. The first step in FDA is smoothing the data, i.e. converting the discrete data into a continuous functional object. For example, let us consider monthly data observed each year. We can thus express that data as:

$$y_i = y^*(t_i) + \epsilon_i, \tag{1}$$

where y_i is the observed data, $y^*(t_i)$ is the assumed function at time t, and ϵ_i is the observational error, $i = 1, 2, \cdots, 12$.

Spline smoothing is a popular method for converting discrete data into the functional form (Shang, 2014). Spline functions, by definition, approximate the shape of a curvilinear stochastic function without the necessity of pre-specifying the mathematical form of the function, and are further defined as piecewise polynomials of degree s. The pieces join at the endpoints (knots), and must fulfil continuity conditions for the function itself, with a spline function of degree s being a continuous function with $s - 1$ continuous derivatives. For the more interested reader, the properties of the splines are well defined by Wold (1974), Craven and Wahba (1978), Suits et al. (1978) and Ramsay and Siverman (2005) among others. In our case, we smooth the data using a B-spline with a roughness penalty as defined by Ramsay and Siverman (2005). The roughness penalty, denoted by λ, is a value which compromises between the goodness of fit and smoothness. The goodness of fit is given by the sum of squared errors (SSE):

$$SSE = \sum_i |y_i - y^*(t_i)|^2 \tag{2}$$

where y^* is the estimated curve and y_i is the observed data. The roughness of a function is quantified by the integrated squared second derivative or total curvature (denoted by PEN):

$$PEN = \int \left|D^2 y^*(t)\right|^2 dt \tag{3}$$

where D^2 denotes the second derivative. A smaller PEN value indicates a less wiggle/variable function, while a larger PEN value indicates a rougher curve. A penalised residual sum of squares is thus formed by combining the above two equations into:

$$PENSSE = SSE + \lambda \cdot PEN \tag{4}$$

where λ controls the data fit and smoothness. If λ is close to zero, we obtain an estimate close to the data. If λ is too large we obtain a straight line (or to be precise, an approximation of the linear regression line), and consequently, the shape of the data might be lost. Therefore, it is important to select a reasonable smoothing parameter λ. An optimal value of λ may be chosen by trial and error, i.e. subjectively chosen using visual judgement as suggested by Ramsay and Siverman (2005). For details of other methods for choosing λ, the reader is directed to Craven and Wahba (1978).

2.2. The functional linear regression model

The general functional linear model is defined by:

$$y_i\left(t\right) = \beta_0\left(t\right) + \sum_{j=1}^{q-1} \beta_j\left(t\right) x_{ij}\left(t\right) + \epsilon_i\left(t\right) \tag{5}$$

where $x_{ij}\left(t\right)$ are $q-1$ functional observations which are the covariate variables and $y_i(t)$ is the i^{th} response curve, $i = 1, 2, \cdots, N$. Even if x_{ij} is a scalar observation, it is simply treated as a constant function that is continuous over t. It is to be noted that $\beta_0\left(t\right)$ and the $\beta_j\left(t\right)$, the regression constant and coefficients respectively, are smooth functions that can be interpreted the same way as multiple regression, over time t.

To compute the regression coefficients, we use the method of Ramsay and Siverman (2005) and Ramsay et al. (2009). Let the $N \times q$ vector function matrix $\mathbf{Z}$ contain the $x_{ij}(t)$ functions, and let the vector $\boldsymbol{\beta}$ of length q contain each of the regression functions (including the intercept coefficient). The functional linear model, in matrix notation, is thus defined as:

$$\mathbf{y}(t) = \mathbf{Z}(t)\boldsymbol{\beta}(t) + \boldsymbol{\epsilon}(t) \tag{6}$$

where $\mathbf{y}(t)$ is a function vector of length N containing the response functions. A basis function for each of the regression functions $\beta_j(t)$, $j = 0, 1, \cdots, q-1$, must be estimated. The regression functions $\beta_j(t)$ have the expansion:

$$\beta_j(t) = \sum_{k=1}^{K_j} b_{jk}\theta_{jk}(t) = \boldsymbol{\theta}_j(t)'\mathbf{b}_j, \tag{7}$$

in terms of K_j basis functions θ_{jk}, $j = 0, 1, \cdots, q-1$ and where the vector $\mathbf{b}_j$ indicates a vector of length K_j of the coefficients b_{jk}. Let $K_\beta = \sum_{j=0}^{q-1} K_j$, and thus a vector $\mathbf{b}$ of length K_β can be constructed by stacking the $\mathbf{b}_j$ vectors vertically, $\mathbf{b} = (\mathbf{b}_0', \mathbf{b}_1', \cdots, \mathbf{b}_{q-1}')$. The $q \times K_\beta$ matrix function $\boldsymbol{\Theta}(t)$ is given by:

$$\boldsymbol{\Theta}(t) = \begin{bmatrix} \theta_0\left(t\right)' & 0 & \cdots & 0 \\ 0 & \theta_1\left(t\right)' & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & \theta_{q-1}\left(t\right)' \end{bmatrix}.$$

It must be noted that $\boldsymbol{\beta}(t) = \boldsymbol{\Theta}(t)\mathbf{b}$. Thus the model in equation (6), can be expressed as:

$$\mathbf{y}(t) = \mathbf{Z}(t)\boldsymbol{\Theta}(t)\mathbf{b} + \boldsymbol{\epsilon}(t), \tag{8}$$

and the vector of residuals can be expressed as $\mathbf{r}(t) = \mathbf{y}(t) - \mathbf{Z}(t)\boldsymbol{\Theta}(t)\mathbf{b}$. The vector $\mathbf{b}$ can be found as follows:

$$\hat{\mathbf{b}} = \frac{\left[\int \boldsymbol{\Theta}'(t)\mathbf{Z}'(t)\mathbf{y}(t)dt\right]}{\left[\int \boldsymbol{\Theta}'(t)\mathbf{Z}'(t)\mathbf{Z}(t)\boldsymbol{\Theta}(t)dt + \mathbf{R}(\lambda)\right]}, \tag{9}$$

where $\mathbf{R}(\lambda)$ is a symmetric block diagonal matrix included to take care of the roughness (penalties) of the respective coefficients. A solution to the above can be found using numerical integration (Ramsay and Siverman, 2005). Substituting $\hat{\mathbf{b}}$ into equation (7) gives us the estimated coefficients. For a detailed explanation of the full model and estimation, the reader is refered to Ramsay and Siverman (2005) and Ramsay et al. (2009). Readers interested in a more detailed compilation on the implementation and practical use of functional regression models are directed to Greven and Scheipl (2017) who offer a more general framework for these models. Greven and Scheipl (2017) offer cautionary notes and potential solutions to some of the computational difficulties associated with these models, such as non-identifiability of the coefficients of the bases functions used to estimate the regression coefficient functions and potential computational complexity of the implementation of these models.

As aforementioned, in general, neither the independent variable nor the dependent variables are required to be functions. So, for our specific problem, the model is defined by (analogously to equation (5)):

$$y_i\,(t) = \beta_0\,(t) + \beta_1(t)x_i + \epsilon_i(t) \tag{10}$$

where $y_i\,(t)$ is the i^{th} functional observations, x_i is the i^{th} scalar observation and $\epsilon_i(t)$ are the error terms of the regression model. In this case, we have one covariate and thus $q = 2$. We once again make the point that for analytical purposes, the x_i are converted into functional variables with a constant basis.

All analysis was carried out using R Core Team (2018) software, in particular the R package *fda* (Ramsay et al., 2017), and its dependencies, within the R-Studio environment.

3. Data

3.1. Stock Returns and the Global Crises Index (GCI)

The stock market data includes monthly stock index returns (i.e. the first-difference of the natural logarithm of the stock index times 100) for G7 countries since the inception of each respective stock exchange. Specifically, we consider the S&P/TSX 300 Composite (Canada, 1915:02-2010:12), the CAC All-Tradable Index (France, 1898:01-2010:12), the CDAX Composite Index (Germany, 1870:01-2010:12), the Banca Commerciale Italiana Index (Italy, 1905:02-2010:12), the Nikkei 225 (Japan, 1914:08-2010:12), the FTSE All Share Index (UK, 1693:02-2010:12), and the S&P500 (USA, 1791:09-2010:12), obtained in their level-form from the Global Financial Database. The choice of G7 equity markets is primarily motivated by their importance in the global economy, with these countries representing nearly two-third of global net wealth, and nearly half of world output. Moreover, these markets are mature markets, some of which were established as early as 1800s, allowing us to explore correlation dynamics over a long span of data. Using the longest possible data span for these markets in the context of global crises allows us to avoid our results to be dominated by a specific stage of development of these equity markets and thus prevents any bias that may result by looking at certain selective recent crises only. In that regard, our analysis does not suffer from the so-called sample selection bias and hence provides a more comprehensive picture of the role of the Global Financial Index (GCI) on the comovement of stock markets from a historical perspective. However, we also conduct sub-sample analysis to check whether the effect of the GCI on equity market correlations has changed over time.

The annual BCDI index of Reinhart and Rogoff (2009) (which we call the Global Crises Index, GCI), is a function of four types of crises, namely: banking, currency, (domestic and external) sovereign default and inflation. Reinhart and Rogoff (2009) suggests GCI to be a quantitative index that accounts for crises globally. To our knowledge, GCI offers the broadest representation of crises globally as it includes 13 African countries, 12 Asian countries, 19 European countries, 18 Latin American countries, Australia, New Zealand and the two countries in North America, covering a total of 66 countries that account for about 90% of the world's GDP. This index is calculated annually starting from 1800 to 2010. The GCI used in our empirical analysis is formed by first summing the number of crises for each country in a given year and then calculating a weighted average across countries with the weight determined by the country's share of world income. The crisis data is available for download from: `http://www.carmenreinhart.com/data/browse-by-topic/topics/8/`. The GCI plot presented in Figure 1 exhibits several notable upticks in the index value, and using a threshold value of 50, captures significant crises periods that include World War I, World War II, the Great Depression, the oil shock of 1973, the dotcom bubble, and the 2017/2018 global financial crisis. This pattern is also supported by non-normal behavior in the index series (with positive skewness and excess kurtosis) as shown in Table 1.

As the GCI data is only available until the end of 2010, the sample period ends in 2010 for all stock markets. Figure 1 presents a plot of the monthly returns, with the global crisis index plotted on the secondary axis. As the sample periods vary based on the inception date of each stock exchange, the descriptive statistics presented in Table 1 do not allow for a meaningful comparison of these markets; however, not surprisingly, we observe that the Jarque-Bera test strongly rejects the null of normality due to excess kurtosis and negative skewness (barring Italy and Japan) at 1% level of significance.

Table 1: Summary statistics of the stock returns.

Country	Start date	Min	Q_1	Median	Q_3	Max	Mean	SD	Kurtosis	Skewness	Jarque-Bera Test Statistic
UK	1693:02	-73.54	-1.16	0.13	1.57	54	0.13	3.98	57.29	-0.51	479074.17*
USA	1791:09	-30.75	-1.30	0.25	2.27	41	0.25	3.83	14.82	-0.59	15281.18*
Germany	1870:01	-146.00	-1.75	0.24	2.57	69	0.24	7.1	116.71	-4.75	963445.31*
France	1898:01	-27.61	-2.33	0.55	3.37	24	0.55	5.11	4.89	-0.10	216.48*
Italy	1905:02	-30.76	-2.85	0.43	3.57	47	0.43	6.76	9.44	1.00	2565.96*
Japan	1914:08	-30.79	-2.41	0.56	3.65	51	0.56	6.13	10.09	0.35	2626.43*
Canada	1915:02	-33.46	-1.59	0.40	3.00	21	0.40	4.50	9.02	-1.06	2095.79*
GFI	1800	0	15.87	35.9	49.11	138	35.9	27.63	4.46	1.18	67.40*

Note: * indicates rejection of the null of normality at 1 percent level of significance.

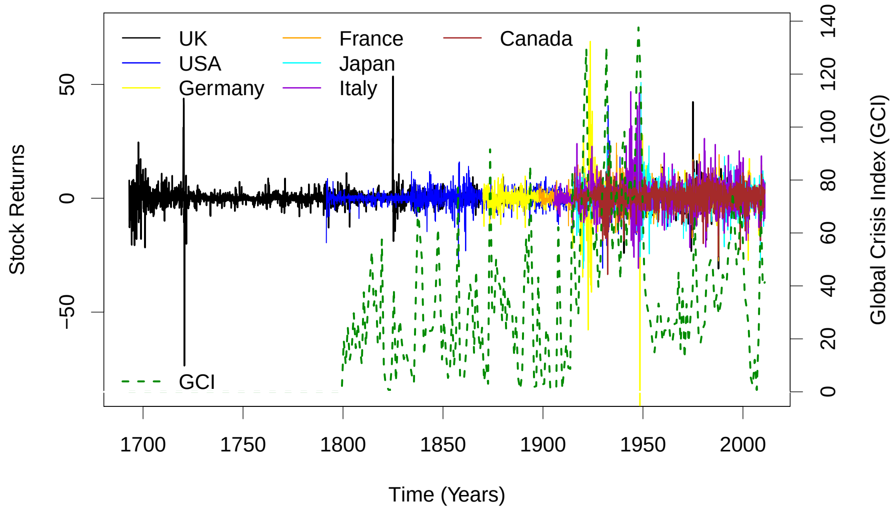

Figure 1: Stock returns of the G7 countries with the Global Crises Index (GCI) superimposed.

3.2. Stock Market Correlations

In our empirical analysis, we specifically focus on the correlations between the US stock market and the remaining G7 markets due to the evidence that the US stock market possesses strong predictive power over advanced stock markets (Rapach et al., 2013; Aye et al., 2017). Furthermore, given the dominance of the US dollar as the global currency and the US economy as the major global economic powerhouse, it can be argued that the US stock market, relative to other equity markets, offers a relatively better quality investment choice, particularly during periods of market stress, thus making it a standard benchmark among stock markets (Mwamba et al., 2017; Nasr et al., 2018; Bouri et al., 2018). Given the importance of correlations in financial management applications, the focus in our empirical analysis is the role of GCI in the time-variation of stock market comovements, specifically how the rest of G7 stock markets co-move with the U.S. market, which is considered a major driver of global financial flows. For this purpose, motivated by the suggestion in Adams et al. (2017) that a rolling-window sample correlation is often a better choice for empirical applications in finance, allowing to avoid spurious correlations due to structural breaks in the time series, we use rolling-window correlations and estimate monthly correlations of U.S. stock market returns with the rest of the G7 nations. Balcilar et al. (2010) point out that there is no strict criterion for selecting the window-size and in our application, we choose a rolling window of 101 months, i.e., approximately eight and a half years. Although arbitrary, the choice of this window size is motivated by our goal to start the analysis of the impact of GCI on UK-US correlations (covering 1791:09 to 1800:01) from 1800, which is the starting date of the crises index, without losing any observations from the GCI time series.

Figures 2 and 3 present the rolling-window correlation estimates and the corresponding t-statistics values, respectively. The t-statistic estimate for the rolling correlation ($\hat{\rho}$) for window size of n is computed as follows:

$$t_{stat} = \frac{\hat{\rho}_t \sqrt{n-2}}{\sqrt{1-\hat{\rho}_t}} \tag{11}$$

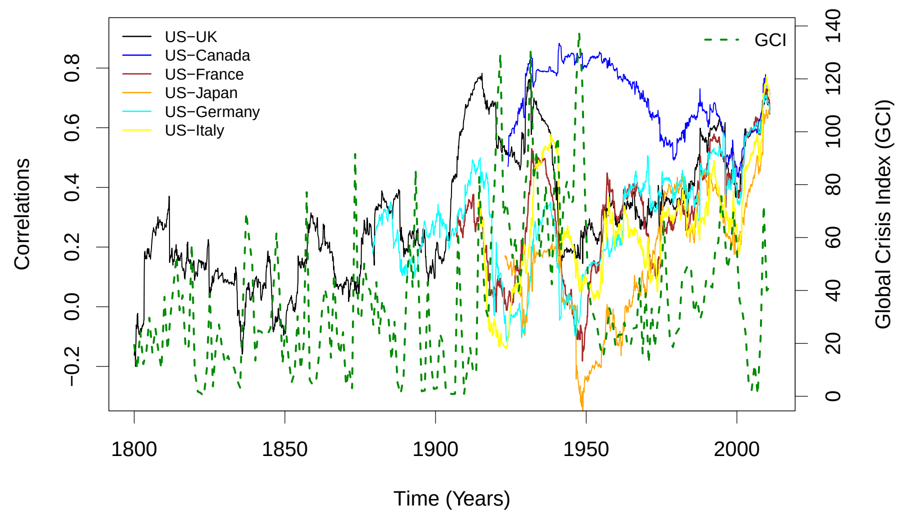

Figure 2: Comovement of stock returns between the US and other G7 nations.

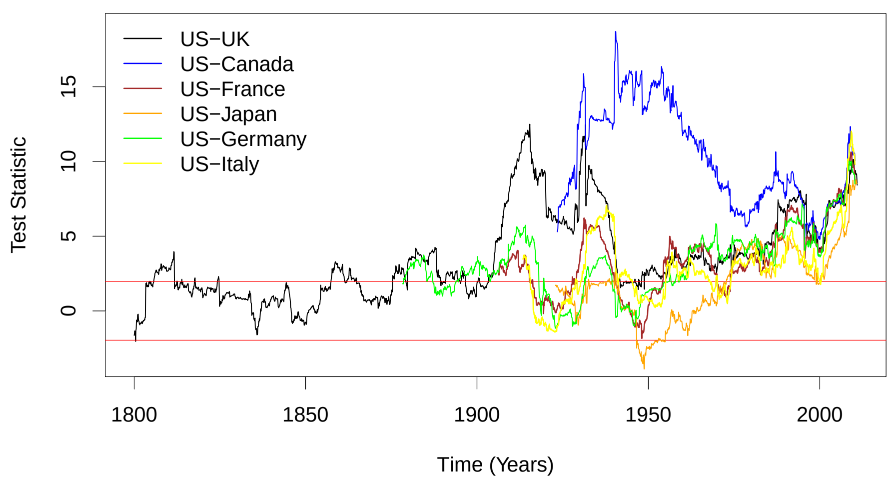

Figure 3: t-statistics of the correlations. The area between the red lines signifies an insignificant correlation (at a 95% confidence level).

Note that in Figure 3, the test statistics that fall in the areas between the red-lines indicate failure to reject the null of insignificant correlations at a 95% confidence level. Examining the estimates presented in Figures 2 and 3, we observe that, barring several initial years around early 1900 and late 1940s, the comovements for US-UK stock returns are generally significant and positive starting with 1900. On the other hand, 1800s display generally insignificant correlation values, likely due to lack of integration in the early stages of development in these two economies. In the case of US and Canada, we observe consistently positive and significant correlation values whereas the U.S. market correlations with the European nations of France, Germany and Italy turn positive and significant mainly after 1950s, highlighting strong integration during the post-World War II era. Interestingly, the Japanese stock market seems to be the only exception, displaying negative correlations with the U.S., specifically around the World War II period, however, turning positive and significant starting with the mid 1970s. Overall, the preliminary visual analysis suggests a general rise in stock market correlations over time, specifically during the post-1950 period, highlighting increasing integration of financial markets over time. From a statistical perspective, considering the FDA based framework adopted in our study, these preliminary findings rule out the possibility of a spurious relationship with the GCI in subsequent tests, which could be driven by non-stationary in the underlying correlations.

4. Empirical Results

The variability of a functional variable can be evaluated in terms of the movements of covariates, which may or may not be functions themselves (Ramsay et al., 2009), and hence allows for the investigation of a function-on-scalar regression scenario. As stated earlier, in our empirical application, the independent variable, i.e. GCI, is a constant over a given year whereas the dependent variable (stock market correlations) is computed at monthly frequency. Since our goal is to explore how much of the variability in the monthly return comovements can be explained by the variability in the GCI series, we first convert the computed correlations into a function using the smoothing by spline method. In this process, we aim to balance two opposing objectives, i.e. to fit the data well and to filter out the noise. For this purpose, we use 12 knots to join our piecewise polynomials and using subjective visual judgment, select $\lambda = 0.01$ as the optimal value of the smoothing parameter. Figure A.4 presents the correlations in raw and functional form with the graph on the left displaying raw correlations joined by straight lines, while the graph on the right displays the smoothed data. As can be seen from these graphs, the smoothing does not change the structure of the data significantly.

4.1. Full-sample Regression Results

Considering the evidence in the literature that financial market correlations are generally higher during market downturns as well as periods of large price fluctuations (e.g. Longin and Solnik (2001); Campbell et al. (2002) among others), one can argue that the effect of global crises on stock market correlations would be channeled via contagion and/or "flight-to-safety", "flight-to-quality" effects. In the case of contagion and/or flight-to-safety effects (the role which we do not attempt to differentiate empirically, but rely more on intuition regarding the possible effect of these phenomena), one would expect higher level of GCI to be associated with increased stock market correlations as economic agents would shift funds out of risky equities into safe haven assets like gold or Treasury securities during crisis periods, thus driving similarity in returns across the risky stock markets. On the other hand, the crisis effect on correlations may not be as straightforward to hypothesize when it comes to the flight-to-quality related market activity. Although, U.S. equities are riskier than Treasuries and precious metals, there may be cases when investors choose to increase their exposure to relatively higher quality equities as part of their active risk management strategies in response to a looming crisis. One such scenario could be when investors are not sure about the timing and scale of the impact of a crisis and thus want to still maintain their exposure to equity markets, however, they do this by shifting their funds into higher quality U.S. equities that are denominated in the U.S. dollar, the global currency. Under such a scenario (and especially if the source of the crisis is not in the US), it is entirely possible to see a negative crisis effect on the correlations of U.S. stock returns with the remaining G7 stock markets as global fund flows would mainly be directed towards the U.S. market. Indeed, the recent evidence in Demirer et al. (2018) supports this argument, with notably different effects of the Asian and the 2007/2008 global financial crises on emerging market correlations, suggesting that the context and nature of crises might play a role on possible structural changes in financial market correlations during these periods. To that end, it can be argued that the channels with which crises affect stock market correlations can be expected to display crisis specific patterns.

Panels (a)-(f) of Figure A.5 in the appendix present the findings from regressions for the whole sample period and Table 2 presents a summary of the observations. Recall that, as we lose 101 observations due to the rolling-window size used to estimate the correlations, our full-samples start in 1880, 1924, 1907, 1879, 1914 and 1923 for the US-UK, US-Canada, US-France, US-Germany, US-Italy and US-Japan pairs, respectively. One common observation that can be drawn from Figure A.5 is that the impact of GCI on the correlations are in general quite similar across the twelve months of the year on average over the full-sample period. This is not unexpected given that we are analyzing global-level crises, which are likely to a have persistent effect over the years. Based on these Figures, and as summarized in Table 2, the impact of GCI on the correlations are found to be strongly significant, barring the cases of US-Italy and US-Japan, with the latter showing mild (delayed) significance towards the end of the year. As far as the signs are concerned, the impact of GCI on the correlations is found to be positive for US-UK and US-Canada and negative for all other pairs. This result tends to suggest that contagion and/or flight-to-safety effects may be playing a role in the case of US-UK correlations in the wake of crises, while, given the dominance of the US market, the positive impact of GCI on the US-Canada correlation is more driven by contagion effects. On the other hand, the negative GCI effect on the correlations between the U.S. and the remaining G7 countries (although Italy is found to be statistically insignificant) suggests the presence of possible flight-to-quality effects at play. Nevertheless, as hypothesized earlier, the findings suggest rather heterogeneous patterns in terms of how stock market correlations relate to global crises, with possibly different channels in which the crisis effect is transmitted to these markets.

4.2. Subsample Results

As stated in the data description, our sample covers a long span of data, dating as far back as late 1800s. Considering that the data period includes a number of major events including political regime changes, wars, currency and trade disputes, etc., that could have led to structural changes in financial markets, we next examine sub-samples in order to get a clearer picture of the evolution of the effect of crises on stock market correlations. For this purpose, we examine several sub-periods including the early half of the twentieth century (which of course includes the inter-war era), the post World War II period, and depending on the availability of the data for the US, UK and Germany markets, earlier years covering the nineteenth century. The results for these sub-periods are reported in Figures A.6, A.7, A.8, A.9, A.10 and A.11.

Examining the results for the (US, UK) pair, we observe that the impact of crises on correlations is positive, but statistically insignificant over the early sub-period of 1800-1899 (see A.6a) - a finding not unexpected given that the underlying correlation is generally insignificant over the majority of the nineteenth century as shown in Figure 2. The crises effect on correlations turns negative in the first half of the twentieth century, and becomes statistically significant (barring the early months of the year) as shown in A.6b, possibly driven by the flight-to-quality effects during the World Wars as the US economy generally benefited from these wars, while the same cannot be said for European economies. Furthermore, this sub-period has also seen the "Great Depression" in the US, a period during which the UK equity market might have served as a preferred investment option, hence contributing to a negative crisis effect on the correlations between these two markets. On the other hand, beginning with the second half of the twentieth century until 2010, we see that the impact of crises on correlations turns positive and significant (barring the month of July) as depicted in A.6c, highlighting the greater integration of these two major financial markets and possible flight-to-safety and/or contagion effects, driving similarity in the direction of returns in these markets.

Figures A.7a and A.7b present the findings for US-Canada correlations over the sub-samples covering the first half of the twentieth century and the post World War II period, respectively. We observe a positive and strongly significant crisis effect on US-Canada correlations during the first sub-period, while the effect turns negative and weakly significant during the post World War II period. The positive effect of crises on US-Canada correlations during the early twentieth century is possibly driven by contagion effects due to the Great Depression that occurred during this period. However, the shift in the crisis effect to negative (and weakly significant) during the post World War II period suggests the presence of possible flight-to-quality effects as Canadian equities presented a relatively safe alternative to US equities, considering that the US was plagued by crises more often than Canada.

Finally, in the case of European nations and Japan, we observe strikingly a similar pattern in terms of how crises affect the correlations of these markets with the US. While the crisis effect on correlations is generally found to be negative during the early part of the twentieth century, we see that the effect turns positive during the 1950-2010 sub-period. However, as far as statistical significance is concerned, the effects are found to be weakly significant for France, strongly significant for Germany and Japan, and insignificant for Italy (as shown in Figures A.8a, A.9b, A.10a, and A.11a respectively). The shift in the sign of the crises effect to positive during the second sub-period highlights increasing market integration over time, more significantly in the case of Germany and Japan as major economic powerhouses globally, along with the US. Note for the (US-Germany) pair, the crisis effect was also negative (but insignificant) during the latter part of the nineteenth century, i.e. 1879-1899 (see Figure A.9a). Following World War II however, as observed in Figures A.8b, A.9c, and A.10b, and A.11b, contagion and/or flight-to-safety began to play a more dominant role as markets have become more integrated.

In sum, based on the sub-sample results, it can be concluded that the positive effect of crises on the correlations between the US and UK is primarily driven by the 1950-2010 sub-sample, while the inter-war period dominates the crisis effect over correlations for US and Canada. At the same time, in the case of how European and Japanese stock markets co-move with the US, the negative crisis effect is driven by the tumultuous early twentieth century, which most likely contributed to the segmentation of these nations from its US counterpart. These findings overall highlight the importance of market integration and the nature of crises on how regime shifts in stock market comovements may be driven by market uncertainty.

Table 2: A summary of the results given in Figure A.5, and in subsequent figures.

Country pair	Period	β_1 coefficient	
		Sign	Significant
US-UK	1800-1899	+ve	No
	1900-1949	-ve	No
	1950-2010	+ve	Yes
	Full Period	+ve	Yes
US-Canada	1924-1949	+ve	Yes
	1950-2010	-ve	Mildly
	Full Period	+ve	Yes
US-France	1907-1949	-ve	Weakly
	1950-2010	+ve	No
	Full Period	-ve	Yes
US-Germany	1879-1899	-ve	No
	1900-1949	-ve	Yes
	1950-2010	+ve	No
	Full Period	-ve	Yes
US-Italy	1914-1949	-ve	No
	1950-2010	+ve	No
	Full Period	-ve	No
US- Japan	1923-1949	-ve	Yes
	1950-2010	+ve	Mostly
	Full Period	-ve	Weakly

Reinhart and Rogoff (2009) also develop an extended version of their index, named BCDI+, which included stock market crashes, besides the banking, currency, inflation and sovereign debt crises. Note that, since information on crises related to the international equity markets is available from 1863 only, the BCDI+ index starts from this date. We reconducted our analyses using this version of the index as well. Table A.1 in the Appendix of the paper provides a comparative summary of the results derived under the BCDI and the BCDI+ indices. As can be seen from A.1 our results are qualitatively similar across these two indices, which in turn is not surprising, given that the correlation between BCDI and BCDI+ is 0.95.[1]

5. Conclusion

This paper examines the role of global banking, currency, sovereign default and inflation crises in explaining the time-varying correlations among the G7 stock markets using a long span of data, dating as far back as 1800s. As the data for the global crises index (GCI) is available only at annual frequency while the rolling-window correlations for the stock markets are monthly, we carry out a mixed-frequency analysis that allows us to avoid data averaging/aggregation and thus prevent possible loss of information. For this purpose, we utilize regressions based on the novel statistical approach of Functional Data Analysis (FDA), which allows us to deal with mixed-frequency data in a flexible manner.

Our findings indicate heterogeneous effects of global crises on the time-varying correlations between the US stock market and its counterparts in the G7 group. While global crises in general have resulted in a stronger association of US stock market performance with that in the UK and Canada, we observe the opposite effect of crises on correlations when it comes to how European and Japanese stock markets co-move with the US. The analysis of sub-samples, however, reveals that the crises effect over stock market correlations is largely driven by the context and nature of the crises that drive the perception of risk in financial markets. Barring the case of US-UK correlations, we observe that the full-sample results were primarily driven by the sub-sample that encompassed the early part of the twentieth century. Interestingly, during the post World War II period of 1950 to 2010 (when the correlation for the stock markets of all economies relative to the US had actually increased), global crises were found to have a significant positive effect on the correlations particularly for the (US-UK) and (US-Japan) stock markets. Although a similar positive crisis effect on correlations is also observed for France, Germany and Italy over this period, this effect is found to be statistically insignificant. On the other hand, the opposite is observed in the case of US-Canada correlations, with global crises negatively affecting the correlations between these two markets over the period from 1950 to 2010.

Overall, our results tend to suggest that in the wake of crises that are global in nature, diversification benefits will be limited by moving funds across the US and UK stock markets whereas possible diversification benefits would have been possible during the crises-ridden period of the early twentieth century by holding positions in equities in the remaining G7 nations (France, Germany, Italy or Japan) to supplement positions in the US. However, these diversification benefits seem to have frittered away in the post second World War period, highlighting the role of emerging markets and alternative assets to supplement diversification strategies. The only exception is the Canadian stock market, which appears to have provided diversification gain over the second half of the twentieth century, although it was not the case during the inter-war period.

As part of future research, it would be interesting to extend the FDA framework to analyze the role of low-frequency global crises in driving high-frequency return dynamics in emerging

[1] Complete details involving the figures for full- and sub-samples for BCDI+ (as in the case of BCDI) are available upon request from the authors.

markets as well as safe haven assets. Given the highly sensitive nature of safe haven assets like precious metals to market uncertainty and crash risks, FDA can provide a useful approach to examine how global crises drive the strength of comovements between safe haves and risky equities.

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Appendix A.

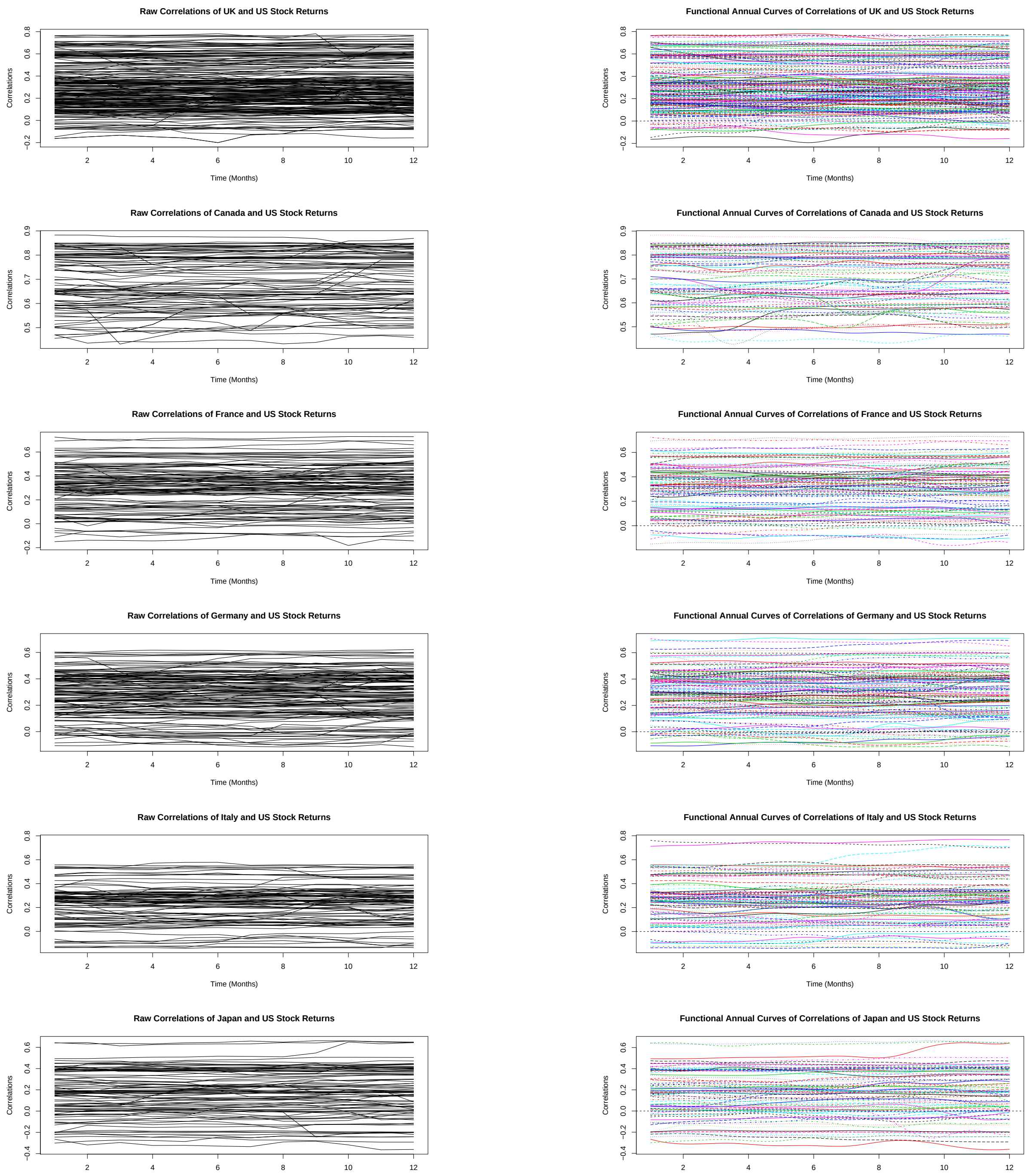
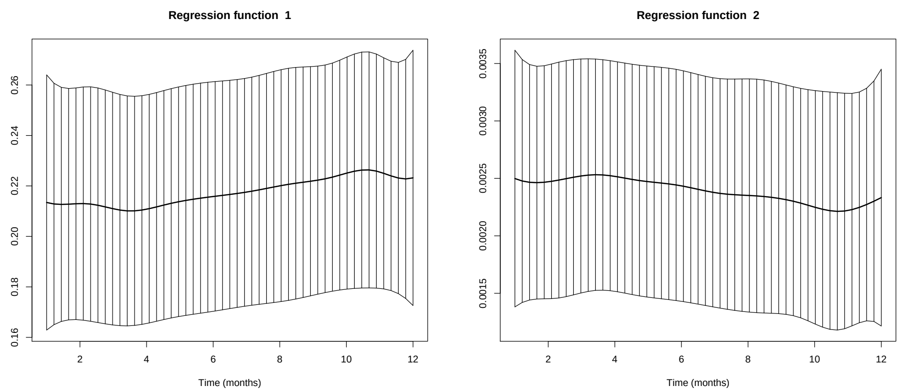
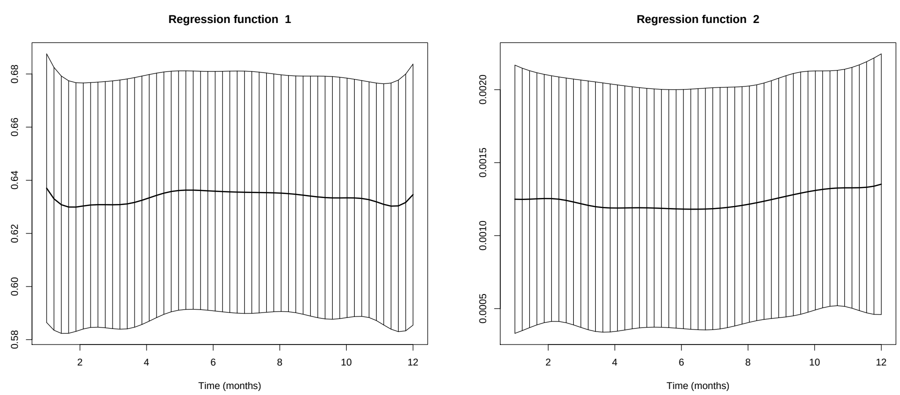


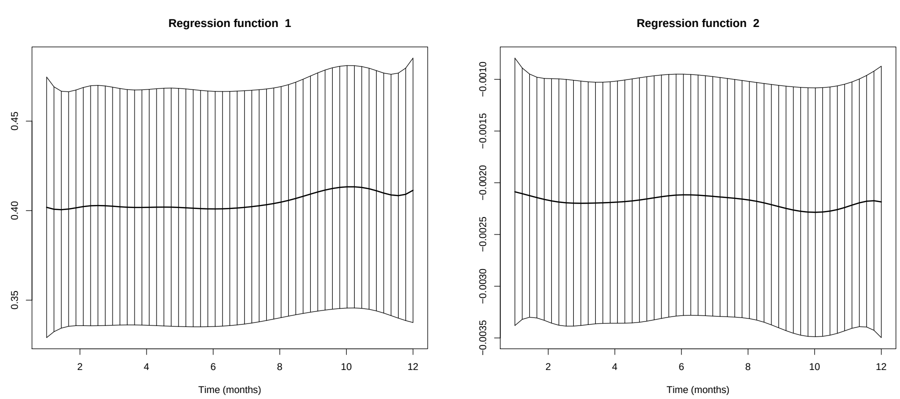
Figure A.4: The left panel is the original annual data joined by straight lines. While the right panel is the smoothed data.



(a) Regression estimates for the US and UK correlations.

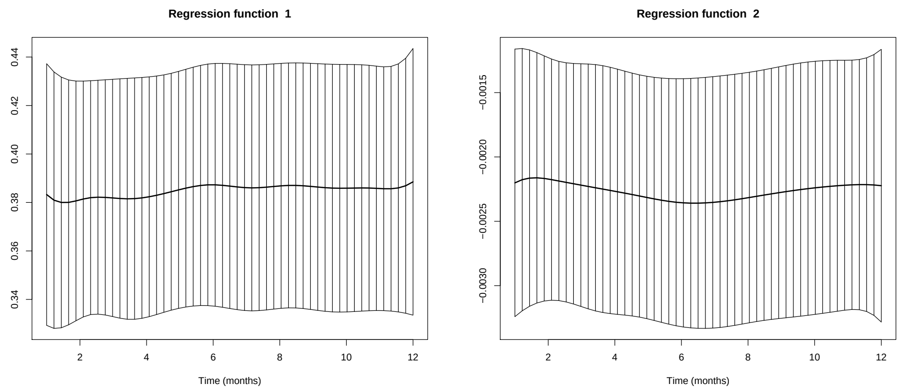


(b) Regression estimates for the US and Canada correlations.

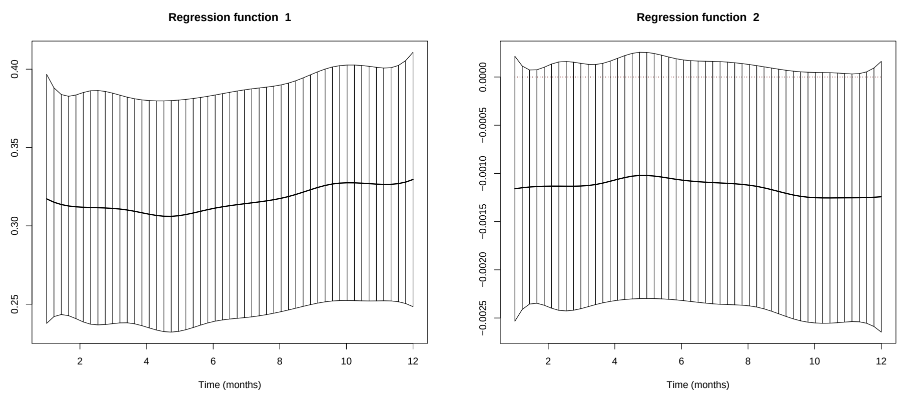


(c) Regression estimates for the US and France correlations.

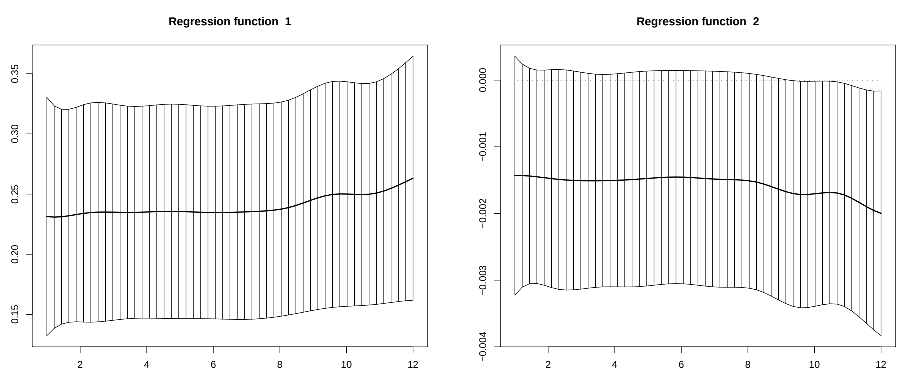
Figure A.5: Full-sample regression results of the G6 relative to the US. Note: The above figures are the estimated regression curves calculated using all the available series in each data set. The left figures (Regression function 1) represents the intercept curve. While the right function (Regression function 2) represents the regression coefficient curve Global Crises Index. The figure continues on the next page.)



(d) Regression estimates for the US and Germany correlations.

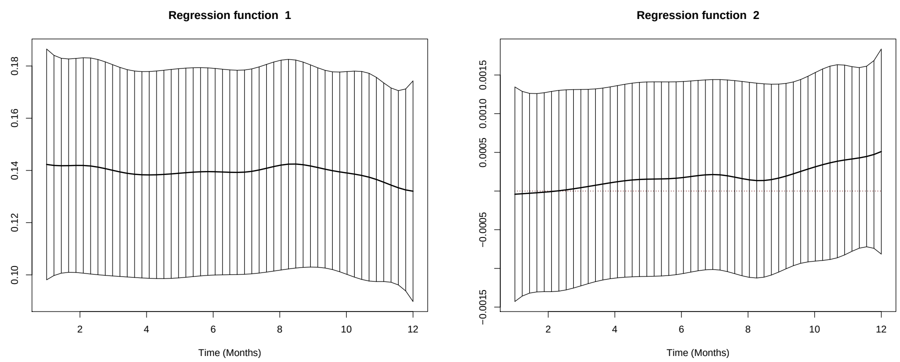


(e) Regression estimates for the US and Italy correlations.

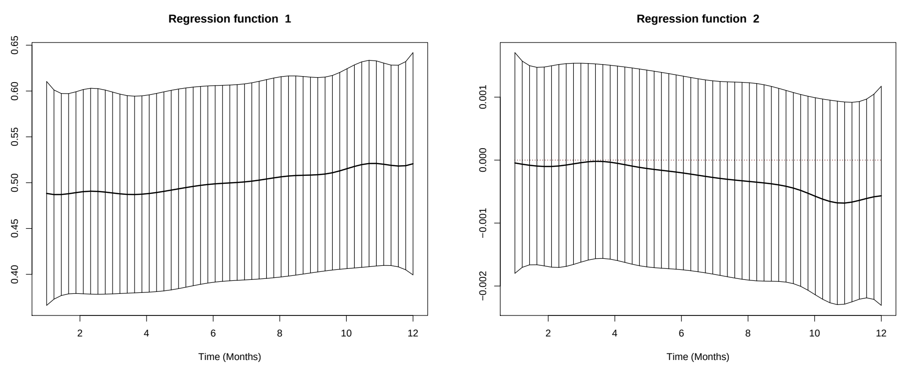


(f) Regression estimates for the US and Japan correlations

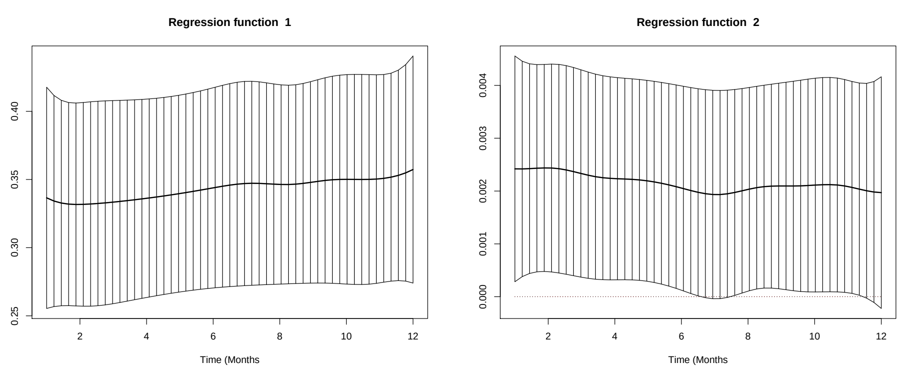
Figure A.5: Full-sample regression results of the G6 relative to the US. Note: See the page immediately above.



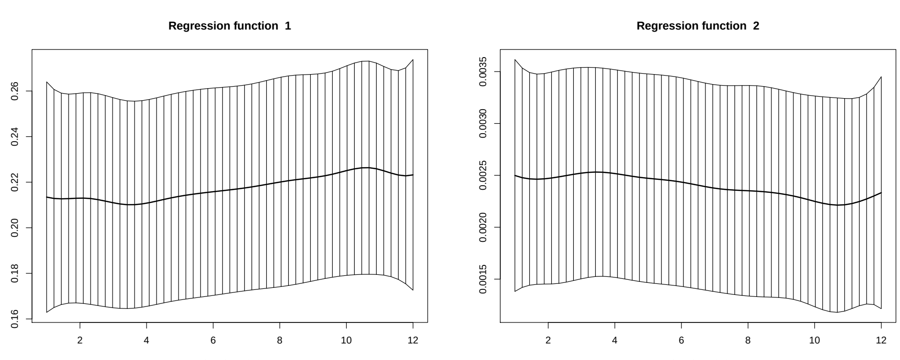
(a) US-UK Subsample 1 – 1800-1899



(b) US-UK Subsample 2 – 1900-1949

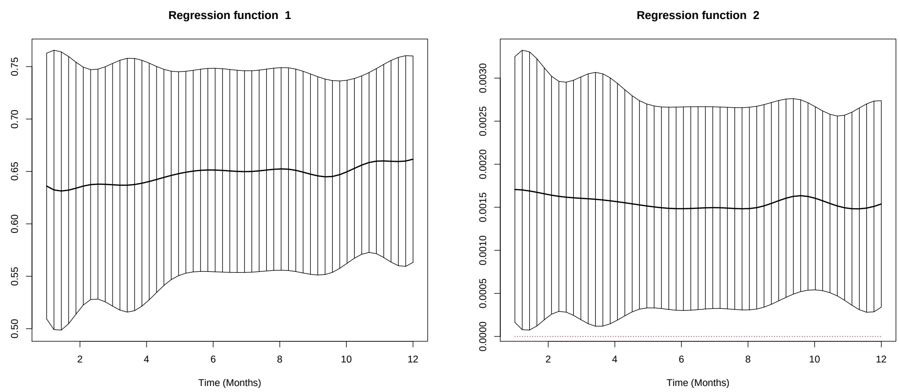


(c) US-UK Subsample 3 – 1950-2010

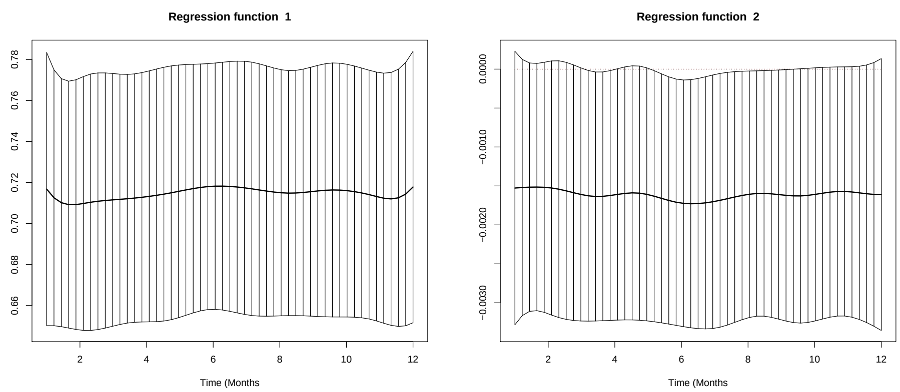


(d) US-UK — All data since inception.

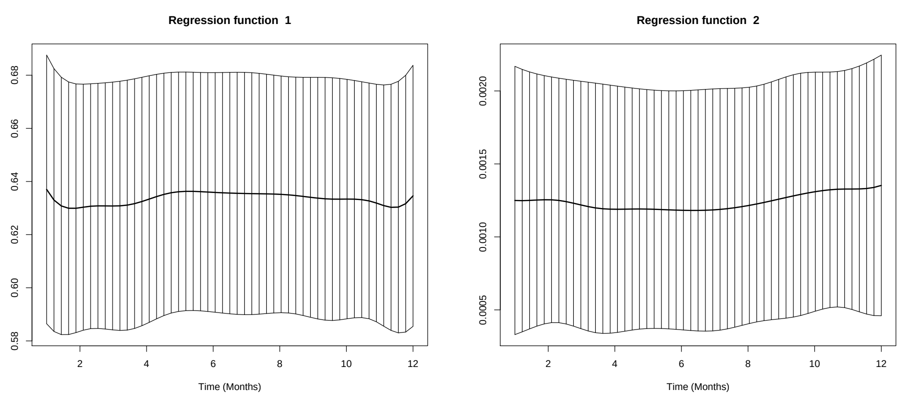
Figure A.6: US-UK regression results for various subsamples. Note: See notes to Figure A.5.



(a) US-Canada Subsample 1 – 1924-1949

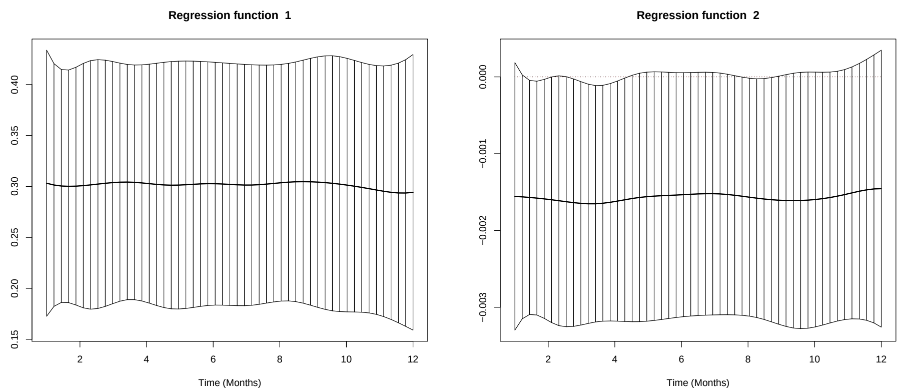


(b) US-Canada Subsample 2 – 1950-2010

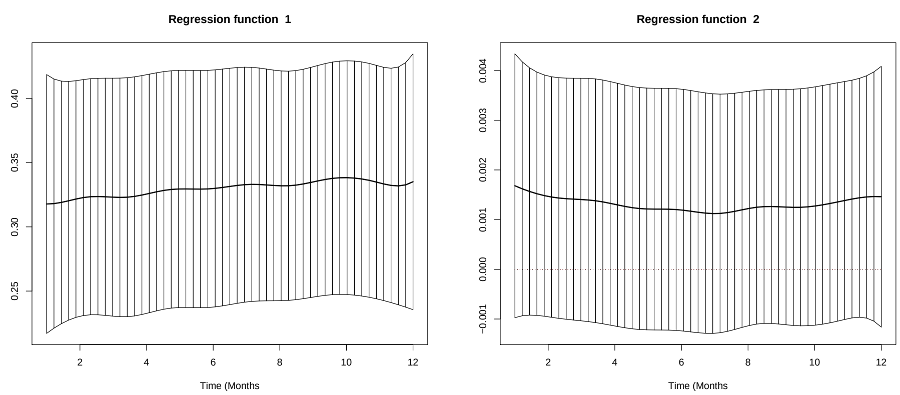


(c) US-Canada — All data since inception.

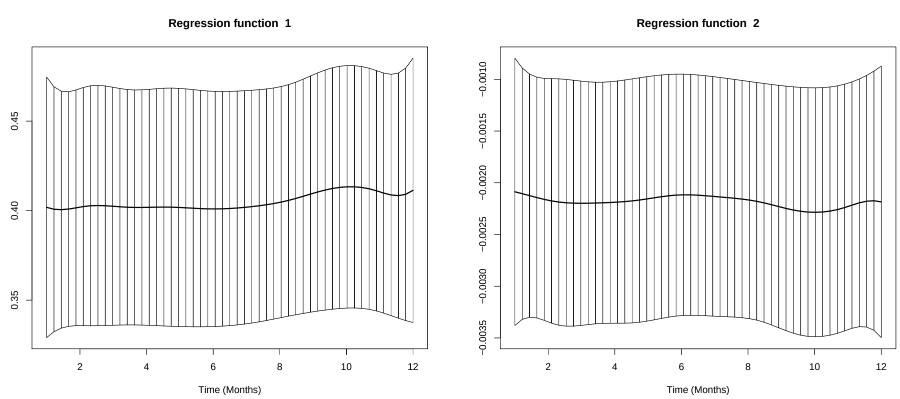
Figure A.7: US-Canada regression results for various subsamples. Note: See notes to Figure A.5.



(a) US-France Subsample 1 – 1907-1949

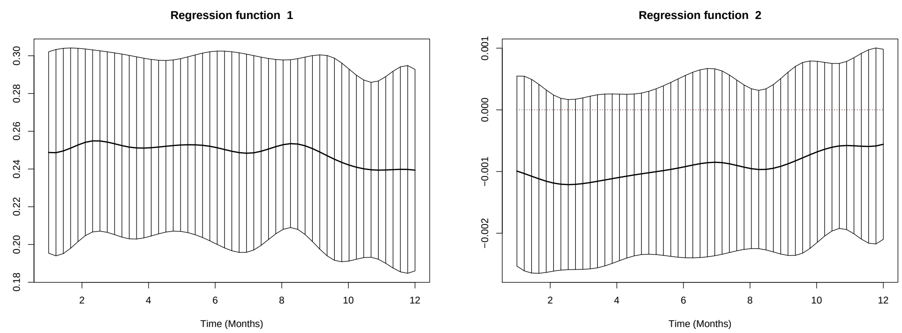


(b) US-France Subsample 2 – 1950-2010

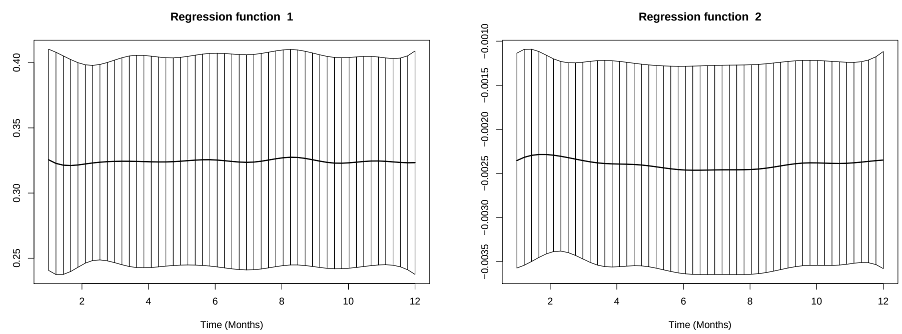


(c) US-France — All data since inception.

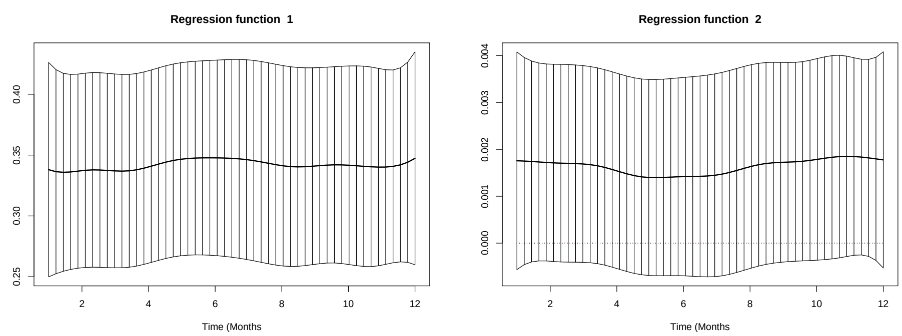
Figure A.8: US-France regression results for various subsamples. Note: See notes to Figure A.5.



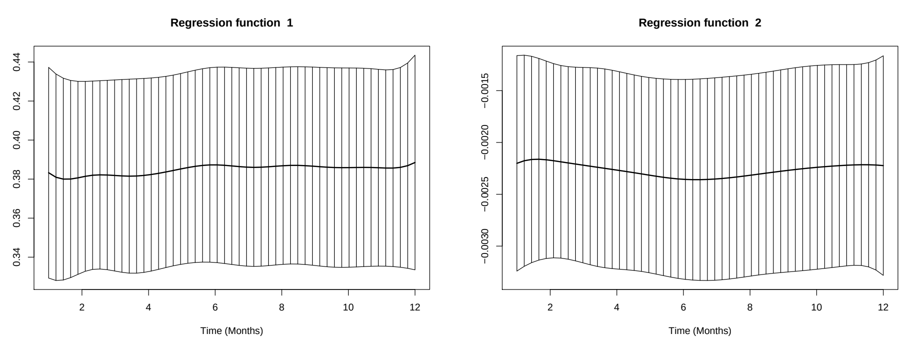
(a) US-Germany Subsample 1 – 1879-1899



(b) US-Germany Subsample 2 – 1900-1949

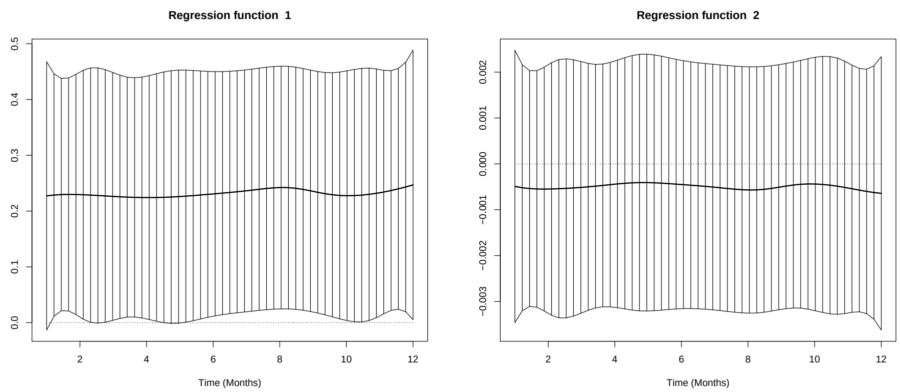


(c) US-Germany Subsample 3 – 1950-2010

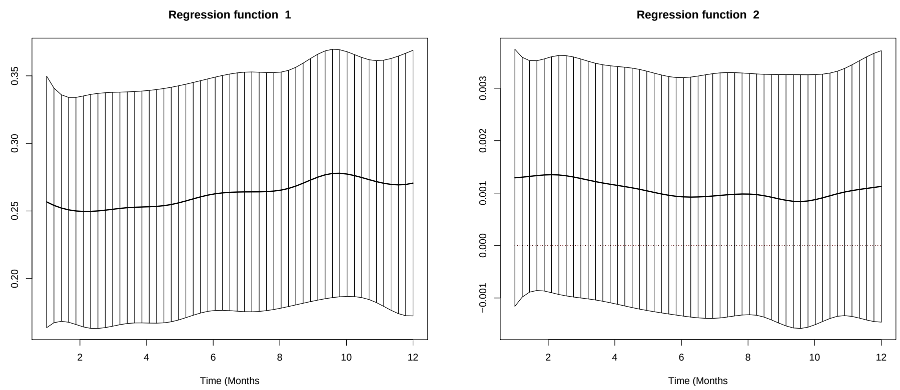


(d) US-Germany — All data since inception.

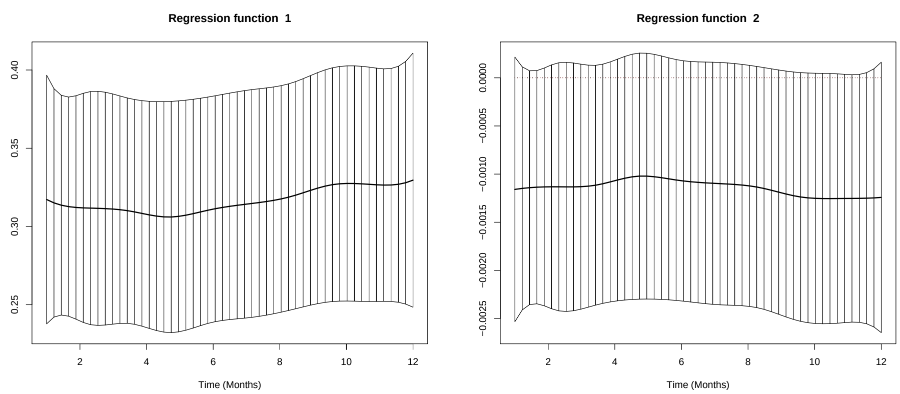
Figure A.9: US-Germany regression results for various subsamples. Note: See notes to Figure A.5.



(a) US-Italy Subsample 2 – 1914-1949

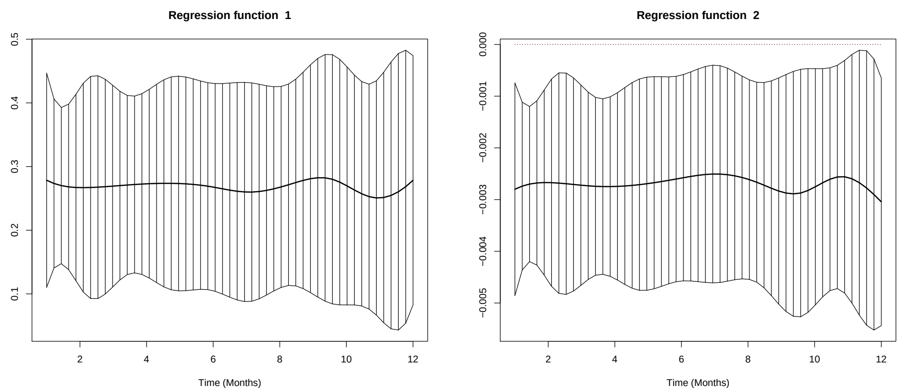


(b) US-Italy Subsample 3 – 1950-2010

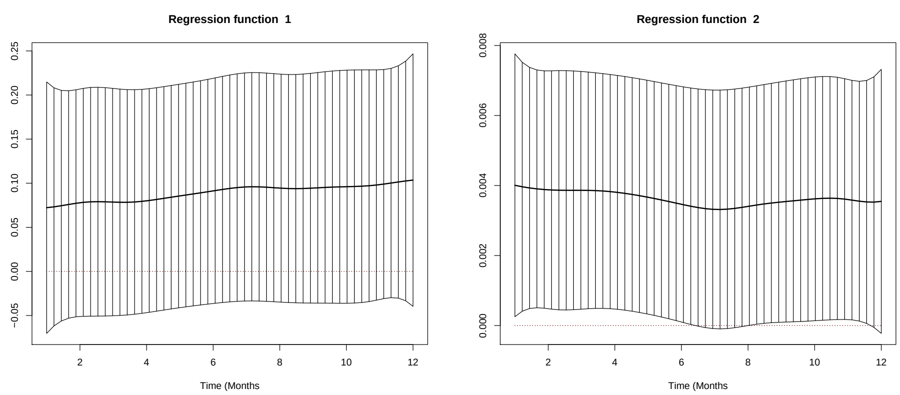


(c) US-Italy — All data since inception.

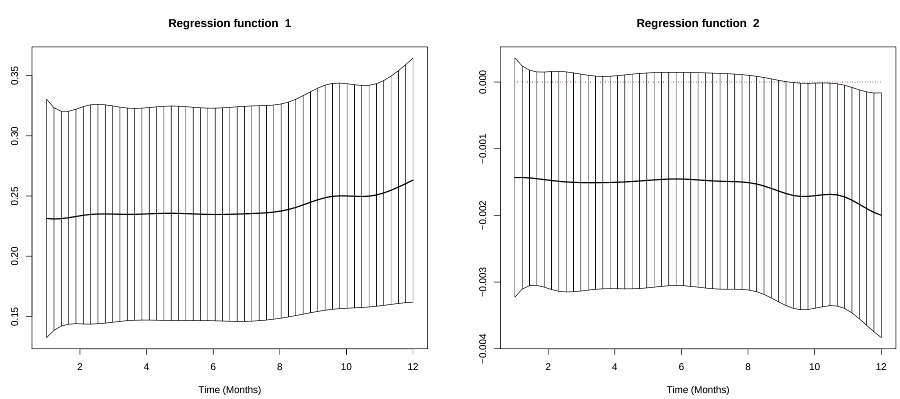
Figure A.10: US-Italy regression results for various subsamples. Note: See notes to Figure A.5.



(a) US-Japan Subsample 2 – 1923-1949



(b) US-Japan Subsample 3 – 1950-2010



(c) US-Japan — All data since inception.

Figure A.11: US-Japan regression results for various subsamples. Note: See notes to Figure A.5.

Table A.1: A summary of the results comparing BCDI and BCDI+.

Country pair	Period	BCDI β_1 coefficient		BCDI+ β_1 coefficient	
		Sign	Significant	Sign	Significant
US-UK	1800(1863)-1899	+ve	No	+ve	No
	1900-1949	-ve	No	+ve	No
	1950-2010	-ve	No	+ve	Yes
	Full Period	+ve	Yes	+ve	Yes
US-Canada	1924-1949	+ve	Yes	+ve	Yes
	1950-2010	-ve	Mildly	-ve	Yes
	Full Period	+ve	Yes	+ve	Yes
US-France	1907-1949	-ve	Weakly	-ve	Weakly
	1950-2010	+ve	No	+ve	No
	Full Period	-ve	Yes	-ve	Yes
US-Germany	1879-1899	-ve	No	-ve	No
	1900-1949	-ve	Yes	-ve	Yes
	1950-2010	+ve	No	+ve	Weakly
	Full Period	-ve	Yes	-ve	Yes
US-Italy	1914-1949	-ve	No	-ve	No
	1950-2010	+ve	No	+ve	No
	Full Period	-ve	No	-ve	Weakly
US- Japan	1923-1949	-ve	Yes	-ve	Mostly
	1950-2010	+ve	Mostly	+ve	Yes
	Full Period	-ve	Weakly	-ve	No

Note: The period under study with BCDI+ is 1863-2010.