



Inflation and west African sectoral stock price indices: An asymmetric kernel method analysis

Libaud Rudy Aurelien Doho^{a,*}, Sobom Matthieu Somé^{b,c}, Jean Michel Banto^d

^a LASTIC, École Supérieure Africaine des Technologies de L'Information et de la Communication, Abidjan, Côte D'Ivoire

^b LaST, Université Thomas SANKARA, Ouagadougou, Burkina Faso

^c LANIBIO, Université Joseph KI-ZERBO, Ouagadougou, Burkina Faso

^d EMS, Université Paris 1 Panthéon-Sorbonne, Paris, France

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ABSTRACT

Our work puts into perspective the relationship between inflation and West African sectoral indices between November 2001 and January 2020 using the asymmetric kernel method. The sectoral indices considered for the analysis include retail, finance, industry, utilities, agriculture, transportation, and other sectors. Our work reveals that while all sectors are sensitive to inflation, the utilities and agriculture sectors are more sensitive to changes in inflation. Moreover, we discover that the relationship between inflation and sectoral stock market indices is rather non-linear to support the hypothesis that the relationship between inflation and stock market indices varies across different inflationary economies. These results imply that investors modify the structure of their investment portfolio according to the variation in the levels of inflation to the extent that this variation ultimately affects future dividends.

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1. Introduction

In theory, the Fisher hypothesis states that movements in nominal interest rates in the financial market closely follow price movements in the goods and services market. Therefore, investors behaviours are influenced by inflation when hedging against changes in the real value of nominal interest rate payments.

According to this Fisherian hypothesis, the resulting relationship between stock prices and nominal interest rates reflects on the ability of an investor to change the structure of his portfolio from stocks to bonds and vice versa; a rise in interest rates induces the investor to change the structure of his portfolio in favour of bonds whereas a fall in interest rates leads the investor to switch to stocks.

At the same time, various arguments are put forward to explain this behaviour. [Cragg and Malkiel \(1982\)](#) as well as, [Modigliani and](#)

* Corresponding author.

E-mail address: libaud.doho@esatic.edu.ci (L.R.A. Doho).

Cohn (1979) argue that interest rates appear to be one of the most important determinants of stock prices. According to Clark (1993), inflation reduces investment and therefore economic growth and future profits. Huizinga (1993) and Zion et al. (1993), argue that inflation leads to less relative price stability, which results in greater uncertainty in investment and output. In other words, there is a negative effect between inflation uncertainty and real economic activity - the Friedman effect (Friedman, 1977). This implies a negative association between inflation and stock prices. Inflation uncertainty leads to higher risks associated with investment and production in the corporate sector. This uncertainty implies a non-optimal allocation of investment resulting in lower stock prices (Schwert, 1981). Simultaneously, higher inflation tends to lead to higher taxes on corporate profits as well as taxes paid by shareholders (Feldstein and Summers, 1979).

However, from an empirical point of view, the link between inflation and stock prices does not seem to be definitively clear. Some empirical attempts by Choudhry (2001), Diaz and Jareno (2009), and Alagidede and Panagiotidis (2012) have provided evidence in favour of a positive rather than negative relationship between interest rates and stock prices. Asprem (1989), for example, argues that such a positive relationship is present in small and illiquid financial markets.

Markets that are allocated sub-categories, are a complexity for researchers to determine whether inflation affects nominal interest rates in any or all components of the market. In general, empirical research is not quite interested in the relationship between stock prices and inflation at the sub-category level of the different economic sectors.

However, since the super-bubble crisis and the phenomenon of crisis contagion, it is easy to see that the relationship between inflation and stock market returns may be more pronounced in some sectors than in others. Similarly, in times of crisis, the most affected sectors may cause a ripple effect on others. With this in mind, the analysis of the relationship between inflation and stock prices by sector become relevant. This analysis in the context of a market such as the Regional Securities Exchange (*Bourse Regionale des Valeurs Mobilières* - BRVM) easily confirms this behaviour.

In addition to being subdivided into six components, this market occupies a lower position in terms of capitalisation, trading volume, the number of listed companies and market liquidity compared to other stock exchanges in developed and emerging countries. Subsequently, the BRVM is exposed to the economic situations within and without the West African Monetary Union (WAMU). Regional and international price variations in these sectors could affect economic growth, private investment and by extension, interest rates in the WAMU regional financial market. However, to our knowledge, no study has specifically addressed this topic in the BRVM.

Therefore, in this article, we ask ourselves how sectoral prices in the BRVM would behave following a change in inflation in WAMU. In other words, what are the links between the sectoral prices of securities on the WAMU stock market and inflation in the region?

The main objective of this article is to therefore determine the nature of the links between the sectoral stock prices of the BRVM and inflation in the WAMU area.

In the rest of the paper, we plan to shed light on the relationship between inflation and sectoral stock prices in WAMU using an appropriate (asymmetric) kernel approach to estimate regression model. Thus, we proceed successively to a literature review, methodological analysis, and empirical results. The concluding analysis will focus on the implications thereof for economic policy.

2. Methodology and data

In this section, the research methodology and the data used in this analysis are presented in turn.

2.1. Methodology

To carry out our work, we use the log-normal, gamma and reciprocal inverse Gaussian kernels because our data are continuous and nonnegative. These associated (asymmetric) kernels are already available in the *Ake* package of Wansouwé et al. (2016) for the smoothing of density and regression functions, and will be recalled below.

We here consider the relation between a response variable Y and an explanatory variable x given by:

$$Y = m(x) + \varepsilon \quad (1)$$

where m is the unknown regression function from $T \subseteq R$ to R and ε is a disturbance.

term with null mean and finite variance. As in Scaillet (2004), Calabrese and Zenga (2010), let $(X_1, Y_1), \dots, (X_n, Y_n)$ be a sequence random variables on $T \times R (\subseteq R^2)$ with $m(x) = E(X = x)$ of (1). The regression estimator \hat{m}_n of m from Nadaraya (1964) and Watson (1964) using associated kernels is:

$$\tilde{m}_n(x; h) = \frac{\sum_{i=1}^n Y_i K_{x,h}(X_i)}{\sum_{i=1}^n K_{x,h}(X_i)} = \tilde{m}_n(x), \forall x \in T_1 \subseteq R \quad (2)$$

where $h \equiv h_n$ is a bandwidth parameter such that $h_n \rightarrow 0$ as $n \rightarrow \infty$. Notice that the nonparametric topic of associated kernels is adaptable to any support T_1 (e.g. $\{0, 1, \dots, N\}$, $[a, b]$ or $[0, \infty)$ for given integer N and reals $a < b$) of continuous or discrete regression functions), and has been widely studied in very recent years; see, for example, Somé (2022), Huang et al. (2022), Hirukawa and Sakudo (2014, 2015), Somé and Kokonendji (2016, 2022), Erçelik and Nadar (2021), Kokonendji and Somé (2018, 2021) and Kakizawa (2022) and the references therein. More precisely, we recall the definition which includes both continuous and discrete cases.

Definition 1. (Wansouwé et al., 2016) Let $T \subseteq R$ be the support of the regression function, to be estimated, $x \in T$ a target and h a

bandwidth. A parametrized probability or mass function (pdf) $K_{x, h}(\cdot)$ of support $S_{x, h}(\subseteq \mathbb{R})$ is called ‘‘associated kernel’’ if the following conditions are satisfied:

$$x \in S_{x,h}, E(z_{x,h}) = x + a(x, h), \text{ and } Var(z_{x,h}) = b(x, h),$$

where $z_{x, h}$ denotes the random variable with pdf $K_{x, h}$ and both $a(x, h)$ and $b(x, h)$ tend to 0 as h goes to 0. We only recall the main continuous univariate kernels in the Ake package of Wansouwé et al. (2016); see Kokonendji and Somé (2021) for a review of these continuous univariate kernels in the literature. These three asymmetric kernels are suitable for the smoothing of density or regression functions on nonnegative support. All these associated kernels satisfy Definition 1.

- The gamma kernel is given on $S_{x, h} = [0, \infty) = T$ with $x \in T$ and $h > 0$:

$$G_{x,h}(u) = \frac{u^{x/h}}{\Gamma(1+x/h)h^{1+x/h}} \exp\left(-\frac{u}{h}\right) I_{(0,\infty)}(u),$$

where I_A denotes the indicator function of any given event A and $\Gamma(v) = \int_0^\infty s^{v-1} \exp(-s) ds$ is the classical gamma function with $v > 0$; see Chen (2000). It comes from the pdf of the gamma distribution $G(1+x/h, h)$ with shape parameter $1+x/h$ and scale parameter h .

- The lognormal kernel is defined on $S_{x, h} = [0, \infty) = T$ with $x \in T$ and $h > 0$ such that:

$$LN_{x,h}(u) = \frac{1}{uh\sqrt{2\pi}} \exp\left\{-\frac{1}{2}\left(\frac{1}{h} \log\left(\frac{u}{x}\right) - h\right)^2\right\} I_{S_{x,h}}(u);$$

see Libengué Dobélé-Kpoka and Kokonendji (2017) and also Kokonendji and Somé (2021). It is the pdf of the classical lognormal distribution with mean $\log(x) + h^2$ and standard deviation h .

The reciprocal inverse Gaussian kernel is given on $S_{x, h} = [0, \infty) = T$ with $x \in T$ and $h > 0$ by

$$RIG_{x,h}(u) = \frac{1}{\sqrt{2\pi hu}} \exp\left\{\frac{(x^2+xh)^{1/2}}{2h} \left(\frac{u}{(x^2+xh)^{1/2}} - 2 + \frac{(x^2+xh)^{1/2}}{u}\right)\right\} I_{S_{x,h}}(u),$$

see Libengué Dobélé-Kpoka and Kokonendji (2017) and also Kokonendji and Somé (2021). It is the pdf of the classical reciprocal inverse Gaussian distribution with mean $1/\sqrt{x^2+xh}$ and standard deviation $1/h$.

In the context of univariate kernel regression, the bandwidth parameter selection is obtained by the well-known unbiased cross-validation (UCV) implemented in the Ake package; see, for instance, Ziane et al. (2018) for a Bayesian approach. In fact, for a given associated kernel, the optimal bandwidth (smoothing) parameter $\hat{h}_{ucv} = \arg \min_{h>0} UCV(h)$ with

$$UCV(h) = \frac{1}{n} \sum_{i=1}^n \left\{ Y_i - \tilde{m}_{-i}(X_i) \right\}^2 \tag{3}$$

where $\tilde{m}_{-i}(X_i)$ is computed as \tilde{m}_n of (2) excluding X_i .

Besides the kernel choice, we retain the practical coefficient of determination R^2 which quantifies the proportion of variation of the response variable Y_i explained by the non-intercept regressor x_i :

$$R^2 = \frac{\sum_{i=1}^n \left\{ \tilde{m}_n(x_i) - \underline{y} \right\}^2}{\sum_{i=1}^n (y_i - \underline{y})^2},$$

with $\underline{y} = n^{-1}(y_1 + \dots + y_n)$. Unless specified otherwise, all computations and graphics in Section 4.2 have been done using the Ake package in the R software; see R Development Core Team (2021).

2.2. Data

Our work uses monthly data from the BRVM and inflation levels in WAMU within the period from September 1998 to January 2020. The price data of the BRVM sector indices are taken from the Reuters Eikon Datastream database. The data relating to inflation in the WAMU zone comes from the database of the Central Bank of West African States (BCEAO). We preferred monthly data instead of intraday, daily, or weekly data (Tiwari et al., 2015; Aktürk, 2016; Boons et al., 2020; Jawadi et al., 2015; Jawadi et al., 2016; Diaz and Jareno, 2009; Gourène et al., 2019). Intraday and daily data relating to inflation are non-existent in the BCEAO database and only

monthly and annual inflation data are available from the same database.

In addition, we underline twofold. Firstly, there is no daily or weekly data in the database of the Central Bank of West African States and on Reuters Eikon Datastream (to which we have access). The original idea was to use daily data but there is no such data. That is why we focused on monthly data that is available on the database of the Central Bank of West African States. Secondly, before writing the article, we wanted to see the relationship between sectoral inflation and the seven sectoral indices in the WAMU area. After several searches on different databases (Bloomberg, Ministry of Economy, Central Bank of West African States, IMF, World Bank...) we found that there is no data on sectoral inflation in the WAMU area (being a group of developing countries) whereas there is for several developed countries. This is why we used this measure of inflation.

Finally, the WAMU market includes several indices and particularly the BRVM 10 index, the BRVM Composite index (BRVMC), as well as sector indices. The BRVM 10 index integrates the activity of the top ten companies with the largest market capitalization in the BRVM. Among these companies, we have Total Côte d'Ivoire, Sonatel SN, and Ecobank Transnational Incorporated TG. Subsequently, BRVMC includes all other companies listed on this stock exchange. Alongside The sector indices which is the subject of our work includes companies in the stock exchange that are divided according to different market sectors. There are seven sectors including industry, utilities, finance, transport, agriculture, retail, and others.

Table 1 summarizes the acronym, the meaning and the sources of the variables retained in our work.

3. Empirical results

In this section, we present the various empirical results obtained from our work. This includes a descriptive analysis and associated (asymmetric) kernel method results.

3.1. Descriptive analysis

Figs. F1 and F2 above chronicle the evolutions of inflation in the WAMU zone and that of the sector indices respectively. These charts retrace the progression of inflation, symbolized by the Consumer Price Index (CPI) and sector indices between September 1998 and July 2019. Before show the results of the associated kernel method, we will first discuss the results of the descriptive statistics represented in Table 2 below.

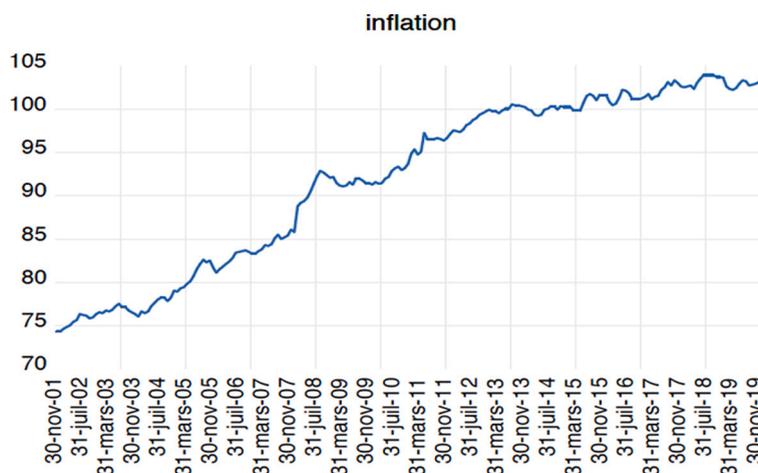


Fig. F1. Evolution of inflation

Table 1
Choice of variables.

Sigle	Signification	Sources
CPI	Consumer Price index	CBWAS: Central Bank of West African States
RETAIL	Stock market index for the retail sector	Eikon Reuters Datastream
FINANCE	Financial sector stock index	Eikon Reuters Datastream
INDUSTRIES	Stock market index for the industrial sector	Eikon Reuters Datastream
UTILITIES	Stock market index for the utilities sector	Eikon Reuters Datastream
AGRICULTURAL	Stock market index for the agriculture sector	Eikon Reuters Datastream
TRANSPORT	Stock market index for the transport sector	Eikon Reuters Datastream
OTHERS	Stock market index for other sectors	Eikon Reuters Datastream

Table 2
Descriptive statistics.

	Obs.	Mean	Maximum	Minimum	Std-dev.	Skewness	Kurtosis	Jacque-Bera
CPI	219	92.14	104.00	74.30	9.81	-0.46	1.69	23.24***
RETAIL	219	0.36	1.33	0.09	0.27	1.39	4.56	93.03***
FINANCES	219	0.17	0.37	0.09	0.05	0.95	3.94	40.48***
INDUSTRIES	219	0.19	0.38	0.06	0.08	0.44	2.07	15.06***
UTILITIES	219	0.80	1.48	0.09	0.42	-0.29	1.85	15.18***
AGRIC	219	0.35	0.99	0.04	0.24	0.68	2.54	19.08***
TRANSPORT	219	0.81	2.62	0.10	0.70	0.97	2.65	35.44***
OTHERS	219	0.31	1.22	0.08	0.27	1.44	4.03	85.61***

Source: Authors, based on Eviews 11 software.

CPI: inflation, RETAIL: retail sector, FINANCES: financial sector, INDUSTRIES: industrial sector, UTILITIES: utilities sector, AGRIC: agricultural sector, TRANSPORT: transportation sector, OTHERS: others sectors.

*, **, *** significant at 10%, 5% and 1% respectively,

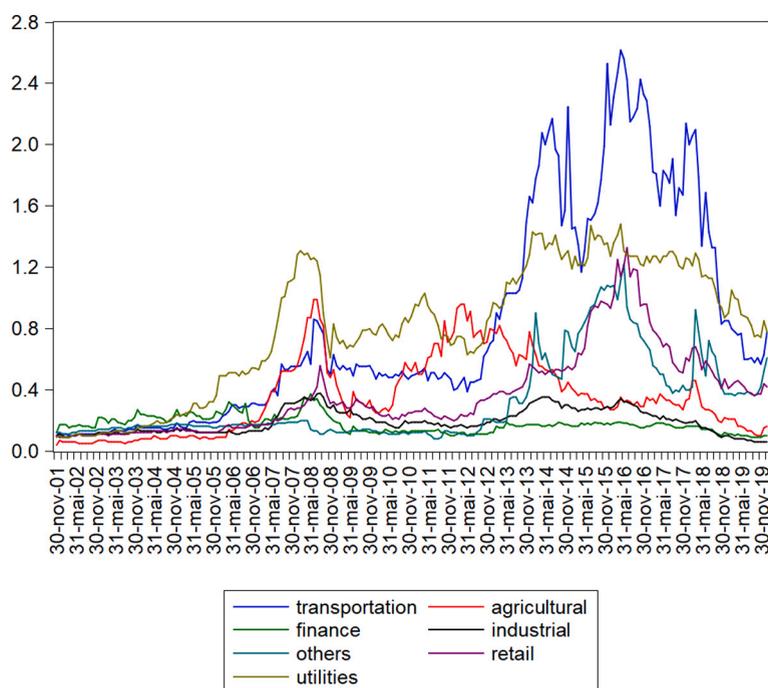


Fig. F2. Evolution of sector indices.

According to [Table 2](#), on the one hand, the average inflation is 92.14 and on the other, the standard deviation associated with inflation is estimated at 9.81. This result is lower than 10 and indicates price stability in the WAMU zone ([Ndjokou et Tsopmo, 2017](#)). Next, we observe that the utilities and transport sectors have the highest averages in the WAMU area, estimated at 0.80 and 0.81 respectively. On the contrary, the financial and industrial sectors have the lowest average chronicles, estimated at 0.17 and 0.18 respectively. On the other hand, the transport sector has the highest level of volatility, estimated at 0.70. This result could be explained by the high volatility of oil prices and by certain occasional social tensions in the localities where transport companies operate, which lead to a strong variation (upwards and downwards) in transport prices, the outcome of which is also volatility in stock prices linked to the transport sector. In contrast to the transport sector, the financial and industrial sectors have low volatilities, estimated at 0.05 and 0.08 respectively.

The skewness coefficients for inflation and utilities are negative, this is estimated at -0.46 and -0.29 respectively, and indicates that the retail is skewed to the left. The skewness coefficients of the retail, finance, industry, agriculture, transport, and other sector indices are positive, indicating that their retails are skewed to the right. Therefore, these sectoral indices react more to positive shock than to a negative one. Secondly, we find that the kurtosis coefficients of inflation and the sectoral indices are all positive. Moreover, the kurtosis coefficients of inflation for the industry, utilities, agriculture, and transport sectors are below 3.

Finally, we note that the normality hypothesis is rejected within the time series studied. Indeed, the Jacque-Bera statistic associated with each variable illustrates a non-normality and more precisely, the p -value (0.000) associated with this statistic leads to the rejection of the null hypothesis of normality. Hence, the acceptance of the non-normality hypothesis in the evolutionary process of our time series. This possible non-linearity may indicate the presence of an ARCH (conditionally heteroscedastic autoregressive) effect, which is frequently encountered in financial series ([Lardic and Mignon, 2002](#); [Ndri, 2007](#)).

3.2. Results of the kernel method

Here we will first look at technical analysis then followed by the empirical analysis of graphs.

3.2.1. Technical analysis of graphs

Figures 1 to 7 present the results corresponding to the nonparametric regressions between inflation (on the x-axis) and the sectoral stock market indices. More specifically, we run nonparametric regressions using several kernels including the gamma kernel (red), the log normal kernel (blue) plus the reciprocal inverse Gaussian one (green). Both reciprocal inverse Gaussian (green) and gamma (red) kernels have similar performances. Therefore, the gamma e two curves of the gamma kernel and the reciprocal inverse Gaussian kernel are merged.

Figure 1 shows the nonparametric estimates between inflation (x-axis) and the retail sector index (y-axis). We notice that the gamma kernel (red) has an hcv = 0.01 and R2 = 79.60%, then the log-normal kernel (blue) has an hcv = 0.01 and R2 = 84.80%, finally the reciprocal inverse Gaussian kernel (green) has an hcv = 0.01 and R2 = 79.60%. The log-normal kernel (blue) has the best R2 of the three. Although the gamma kernel has a lower R2 than the log-normal kernel, we chose the log-normal kernel as it best fits the data in Fig. 1.

Figure 2 shows the nonparametric estimates between inflation (x-axis) and the finance sector index (y-axis). We see that the gamma kernel (red) has an hcv = 0.01 and R2 = 59.20%, then the log-normal kernel (blue) has an hcv = 0.016 and R2 = 34.70%, finally the reciprocal inverse Gaussian kernel (green) has an hcv = 0.01 and R2 = 59.20%. In this case, the gamma kernel was chosen because it has a better R2 that perfectly highlights the shape of the data represented.

Figure 3 shows the nonparametric estimates between inflation (x-axis) and the industry sector index (y-axis). We see that the gamma kernel (red) has an hcv = 0.01 and R2 = 59.20%, then the log-normal kernel (blue) has an hcv = 0.016 and R2 = 34.70%, finally the reciprocal inverse Gaussian kernel (green) has an hcv = 0.01 and R2 = 59.20%. Here, we chose the gamma kernel because it has a better R2 and perfectly highlights the shape of the data in Fig. 3.

Figure 4 shows the nonparametric estimates between inflation (x-axis) and the utility sector index (y-axis). We observe that the gamma kernel (red) has an hcv = 0.01 and R2 = 89.70%, then the log-normal kernel (blue) has an hcv = 0.01 and R2 = 92.30%, finally the reciprocal inverse Gaussian kernel (green) has an hcv = 0.01 and R2 = 89.70%. The log-normal kernel (blue) has the best R2 of the three kernels used. However, the gamma kernel was chosen because it has a lower R2 than the log-normal kernel and it best fits the data in Fig. 4.

Figure 5 shows the nonparametric estimates between inflation (x-axis) and the agriculture sector index (y-axis). We observe that the log-normal kernel (blue) has a hcv = 0.01 and R2 = 84.30%, then the gamma kernel (red) has a hcv = 0.01 and R2 = 79.60%, finally the inverse Gaussian kernel (green) has a hcv = 0.01 and R2 = 79.50%. The gamma kernel (red) has the best R2 of the three kernels used. However, we chose the gamma kernel because it has a lower R2 than the log-normal kernel and it best highlights the shape of the data in Fig. 5.

Figure 6 shows the nonparametric estimates between inflation (x-axis) and the transport sector index (y-axis). The analysis of Fig. 6 shows that the gamma kernel (red) has a hcv = 0.01 and R2 = 76.20%, then the log-normal kernel (blue) has a hcv = 0.01 and R2 =

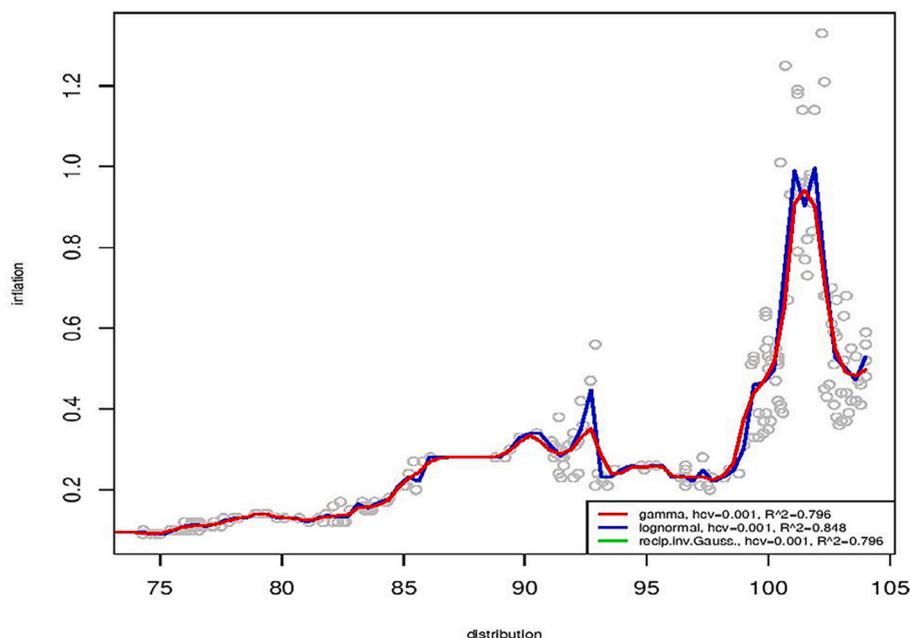


Fig. 1. Relationship between inflation and retail index.

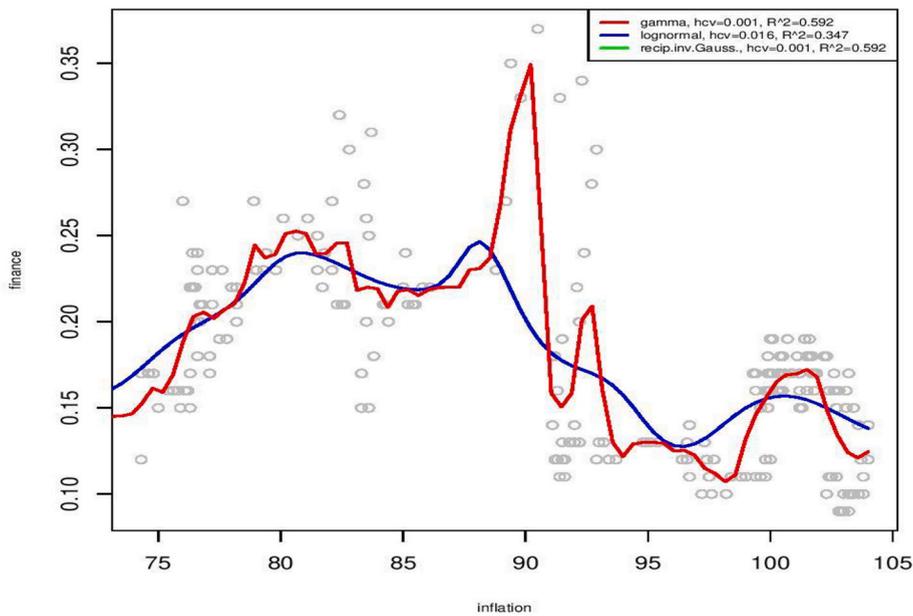


Fig. 2. Relationship between Inflation and Finance Index.

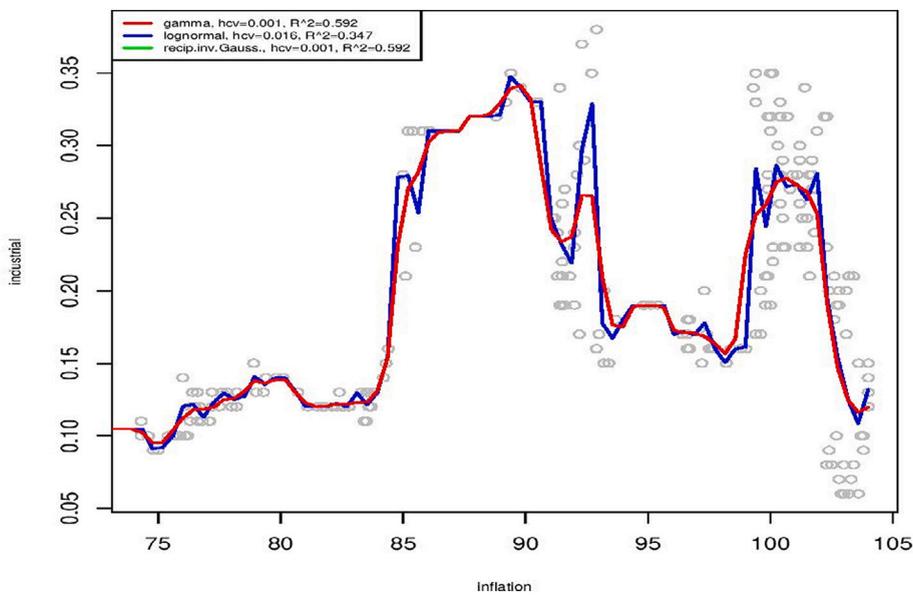


Fig. 3. Relationship between Inflation and Industry Index.

80.40%, finally the reciprocal inverse Gaussian kernel (green) has a $hcv = 0.01$ and $R^2 = 76.20\%$. The log-normal kernel (blue) has the best R^2 . However, the gamma kernel was chosen because it has a lower R^2 than the log-normal kernel and it best fits the data in Fig. 6.

Figure 7 shows the nonparametric estimates between inflation (x-axis) and the index of other sectors (y-axis). The analysis of Fig. 7 shows that the gamma kernel (red) has an $hcv = 0.01$ and $R^2 = 70.50\%$, then the log-normal kernel (blue) has an $hcv = 0.01$ and $R^2 = 78\%$, finally the reciprocal inverse Gaussian kernel (green) has an $hcv = 0.01$ and $R^2 = 70.50\%$. The log-normal kernel (blue) has the best R^2 . However, we chose the gamma kernel because it has a lower R^2 than the log-normal kernel and it best fits the data for Fig. 6.

3.2.2. Analysis of the link between inflation and stock market index prices

From these different figures, we can distinguish three main trends. First, we observe that inflation explains the evolution of the indices linked to the financial sector and the industry sector to the tune of 59.20% - as the level of $R^2 = 59.20\%$. Secondly, we find that inflation explains 76.20%, 79.60%, and 70.50% of the stock market indexes related to transport, retail, and other sectors respectively.

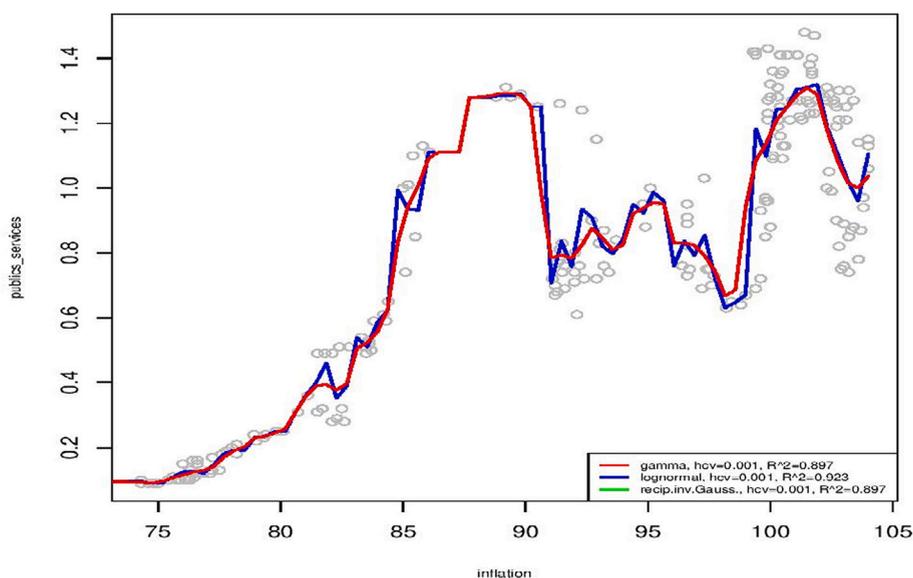


Fig. 4. Relationship between Inflation and Utilities Index.

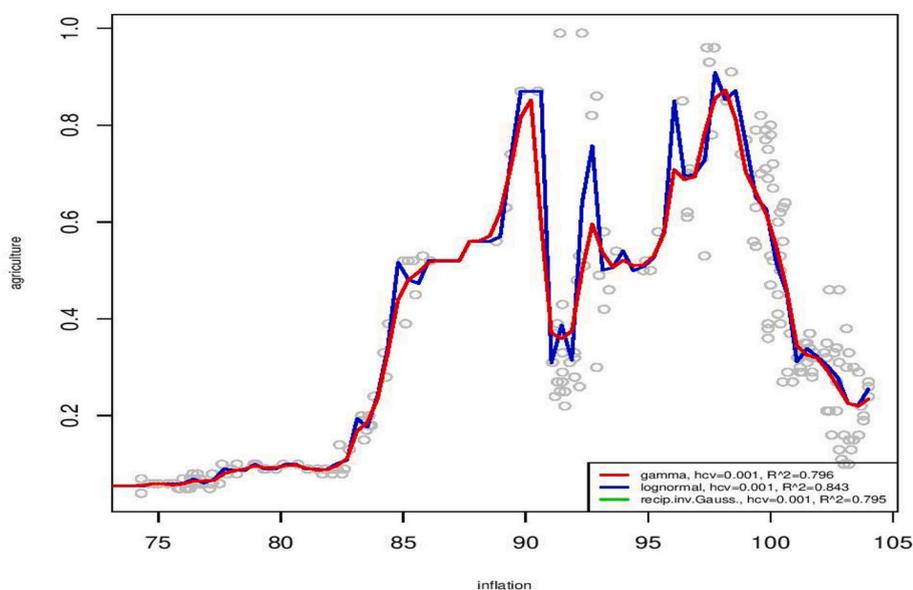


Fig. 5. Relationship between inflation and the agricultural index.

Finally, we find that inflation strongly explains the stock market indices of utilities and agriculture sectors with an estimated R^2 of 89.70% and 84.30% respectively.

Therefore, we can state that the evolutions of the sectoral indices are strongly explained by the level of inflation with an $R^2 > 50\%$. Moreover, we notice that the stock market indices of the financial and industrial sectors are not as vulnerable to variations in inflation rates as the utilities and agriculture sectors which are highly sensitive to variations in inflation. Our results partially corroborate [Moya-Martinez et al. \(2015\)](#) findings that Spanish industries generally have a significant sensitivity to Spanish ten-year government bond yields, although the degree of exposure to interest rates varies considerably across industries and is subject to the time horizon considered. Also, in their findings, the banking sector, regulated sectors such as utilities and highly leveraged sectors such as telecommunications and technology, real estate, and utilities appear to be the most vulnerable to changes in interest rates.

Moreover, all figures show that the relationship between inflation and stock market indices is rather non-linear and support the hypothesis that the relationship between inflation and stock market indices varies across different inflationary economies ([Ahmed and Cardinale, 2005](#); [Lee, 2010](#); [Hong et al., 2013](#)).

In another approach, our work highlights the existence of two distinct relationships - positive and negative - between stock returns

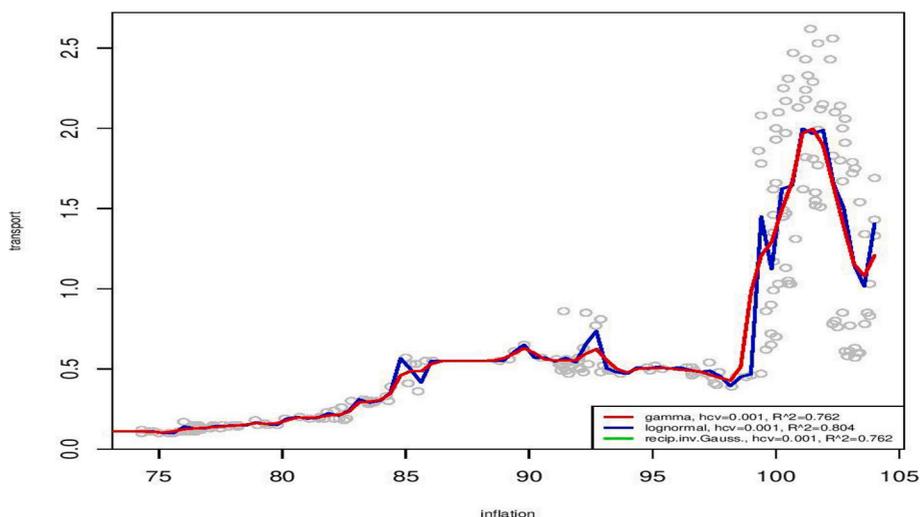


Fig. 6. Relationship between inflation and transportation index.

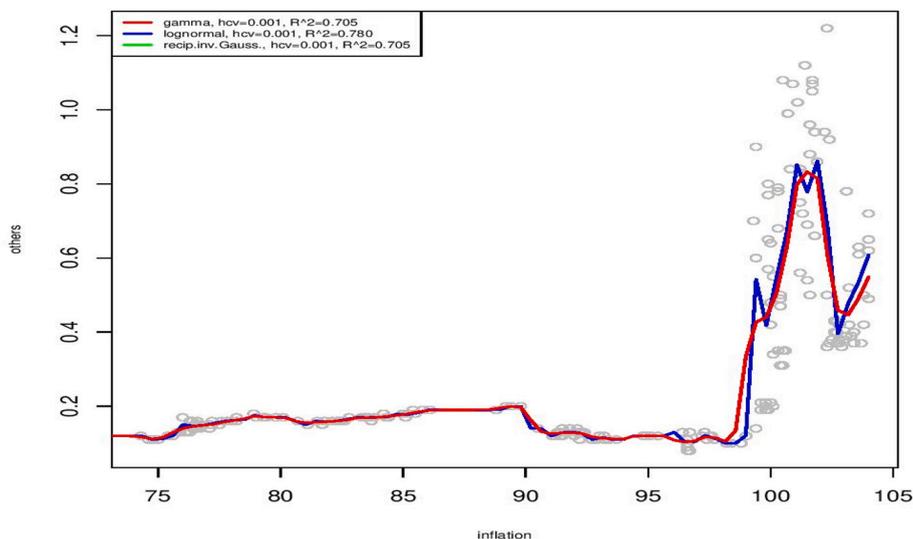


Fig. 7. Relationship between inflation and other sectors' index.

and inflation. This binary is proven through vector autoregression analyses (Engsted and Tangaard, 2002; Du, 2006; Lee, 2010; Oxman, 2012).

4. Robustness test

To judge the robustness of our results, we replaced the inflation rate variable with the monthly average money market rate variable. Indeed, the monthly average money market rate variable can be used as a proxy for monetary policy and by extension as a proxy for inflation. For example, Coupaud (2014) applies the nominal interest rate of the money market as a proxy for monetary policy in analysing the reactions of the Asean+3 member countries to large-scale disturbances utilizing a Structural VAR then highlights the phenomena of pure contagion along with a tendency towards homogeneity in responses, especially in the face of financial disturbances. We will first comment on the results of the kernel method and then present the economic implications of our work.

4.1. Results of the kernel method

The results from the associated kernel method generally confirm our main estimates. Thus, Figs. D1 to D7 present the results corresponding to the nonparametric regressions between the interbank interest rate (x-axis) and the sectoral stock market indices. More precisely, we run nonparametric regressions as in main estimates using several kernels including gamma kernel (red), the log-

normal kernel (blue) and the reciprocal inverse Gaussian kernel (green). On the other hand, the reciprocal inverse Gaussian kernel (green) shows a similar performance to the gamma kernel. Consequently, the two curves of the gamma kernel and the reciprocal inverse Gaussian kernel are merged.

Figure D1 shows the nonparametric estimates between the interbank interest rate (x-axis) and the sector index of the retail (y-axis). We notice that the gamma kernel (red) has an $hcv = 0.02$ and $R2 = 46.90\%$, then the log-normal kernel (blue) has an $hcv = 0.01$ and $R2 = 46.30\%$, finally the reciprocal inverse Gaussian kernel (green) has an $hcv = 0.01$ and $R2 = 46.90\%$. The log-normal kernel (blue) has the best R2. However, the gamma kernel was chosen because it better highlights the shape of the data in Fig. D1.

Figure D2 shows the nonparametric estimates between the interbank interest rate (x-axis) and the finance sector index (y-axis). We note that the gamma kernel (red) has an $hcv = 0.01$ and $R2 = 43.80\%$, then the log-normal kernel (blue) has an $hcv = 0.023$ and $R2 = 41.50\%$, finally the reciprocal inverse Gaussian kernel (green) has an $hcv = 0.01$ and $R2 = 43.80\%$. We chose the gamma kernel because it has a better R2 and perfectly highlights the shape of this data.

Figure D3 shows the nonparametric estimates between the interbank interest rate (abscissa) and the industry sector index (ordinate). We see that the gamma kernel (red) has an $hcv = 0.01$ and $R2 = 46.60\%$, then the log-normal kernel (blue) has an $hcv = 0.019$ and $R2 = 45.60\%$, finally the reciprocal inverse Gaussian kernel (green) has an $hcv = 0.01$ and $R2 = 46.60\%$. The gamma kernel was chosen because it has a better R2 and perfectly highlights the shape of the data in Fig. D3.

Figure D4 shows the nonparametric estimates between the interbank interest rate (x-axis) and the utility sector index (y-axis). We observe that the gamma kernel (red) has an $hcv = 0.01$ and $R2 = 81.40\%$, then the log-normal kernel (blue) has an $hcv = 0.014$ and $R2 = 81.90\%$, finally the reciprocal inverse Gaussian kernel (green) has an $hcv = 0.01$ and $R2 = 81.40\%$. The log-normal kernel (blue) has the best R2 of the three kernels used. However, the gamma kernel was chosen because it has a lower R2 than the log-normal kernel and it best fits the shape of the data in Fig. D4.

Figure D5 shows the nonparametric estimates between the interbank interest rate (x-axis) and the sector index for agriculture (y-axis). We observe that the log-normal kernel (blue) has an $hcv = 0.01$ and $R2 = 52.20\%$, then the gamma kernel (red) has an $hcv = 0.007$ and $R2 = 60.10\%$, finally the reciprocal inverse Gaussian kernel (green) has an $hcv = 0.01$ and $R2 = 52.20\%$. The gamma kernel (red) has the best R2. However, we chose the gamma kernel because it has a lower R2 than the log-normal kernel and best highlights the shape of the data for Fig. D5.

Figure D6 shows the nonparametric estimates between the interbank interest rate (abscissa) and the transport sector index (ordinate). The analysis of Fig. D6 shows the gamma kernel (red) has an $hcv = 0.02$ and $R2 = 52.20\%$, then the log-normal kernel (blue) has an $hcv = 0.026$ and $R2 = 53.70\%$, finally the reciprocal inverse Gaussian kernel (in green) has an $hcv = 0.01$ and $R2 = 52.20\%$. The log-normal kernel (blue) has the best R2. However, the gamma kernel was chosen for its lower R2 compared to the log-normal kernel. It also fits best the shape of the data in Fig. D6.

Figure D7 shows the nonparametric estimates between the interbank interest rate (x-axis) and the index of other sectors (y-axis). The analysis here shows that the gamma kernel (red) has an $hcv = 0.01$ and $R2 = 52.40\%$, then the log-normal kernel (blue) has an $hcv = 0.01$ and $R2 = 56.80\%$, finally the reciprocal inverse Gaussian kernel (green) has an $hcv = 0.01$ and $R2 = 52.40\%$. The log-normal kernel (blue) has the best R2. However, the gamma kernel was chosen for its lower R2 compared to the log-normal kernel plus it's the best fit for the data in Fig. D7.

From the various figures, we distinguish three main trends. First, we observe that the interbank interest rate gives a weak explanation for the evolution of the indices linked to the financial, retail and industrial sectors since the level of R2 is estimated at 43.80%, 46.90% and 46.60% respectively. Secondly, we notice that the interbank interest rate explains on average the price of stock returns related to the agriculture, transport, and other sectors as the level of R2 is estimated at 52.20%, 54.50% and 52.40% respectively. Lastly, we find that the interbank interest rate strongly explains the stock index related to the utilities sector with an R2 that reaches 81.40%. Therefore, we can state that the stock indices of the retail, financial and industrial sectors are not as vulnerable to variations in the inflation rate, as the utilities sector which is extremely sensitive to variations in the interbank interest rate. Furthermore, we note that the relationship between interbank interest rate and returns related to the sectoral indices are non-linear and support the hypothesis that the relationship between interbank interest rate and stock market indices varies across different inflationary economies (Ahmed and Cardinale, 2005; Lee, 2010; Hong et al., 2013).

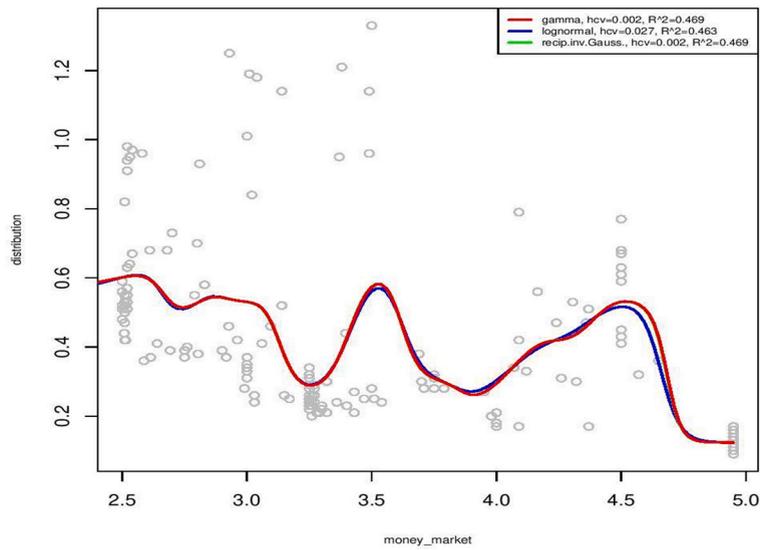


Fig. D1. Relationship between the interbank interest rate and retail index.

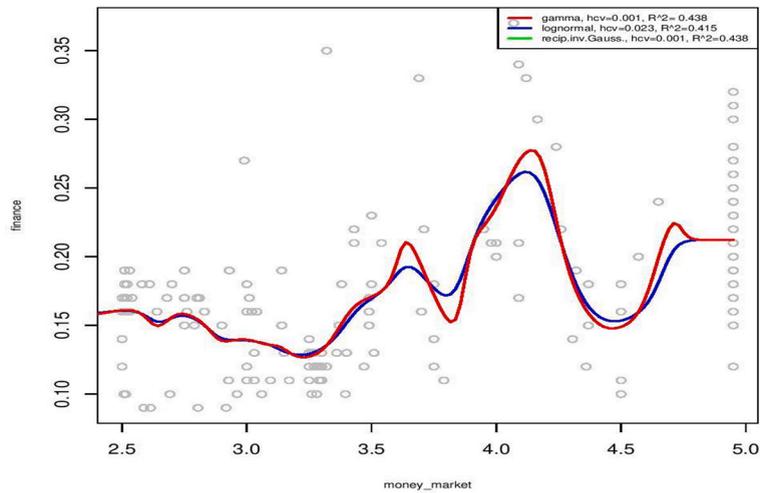


Fig. D2. Relationship between the interbank interest rate and finance index.

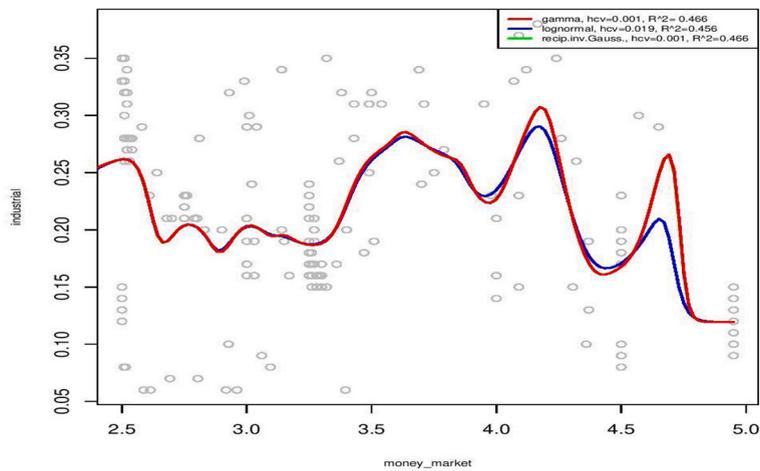


Fig. D3. Relationship between the interbank interest rate and industrial index.

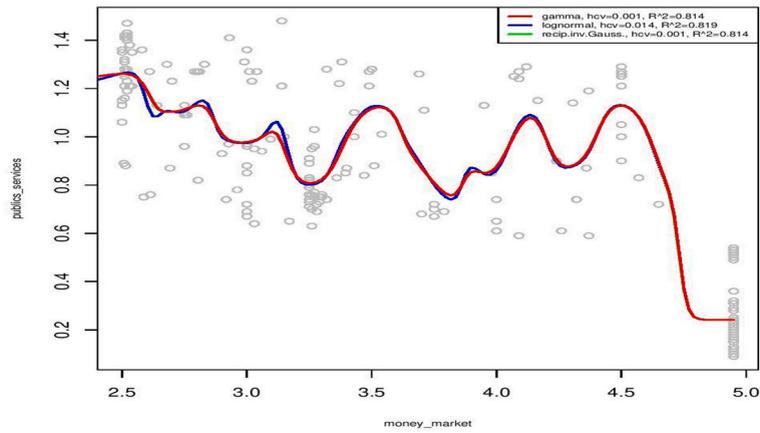


Fig. D4. Relationship between the interbank interest rate and utilities index.

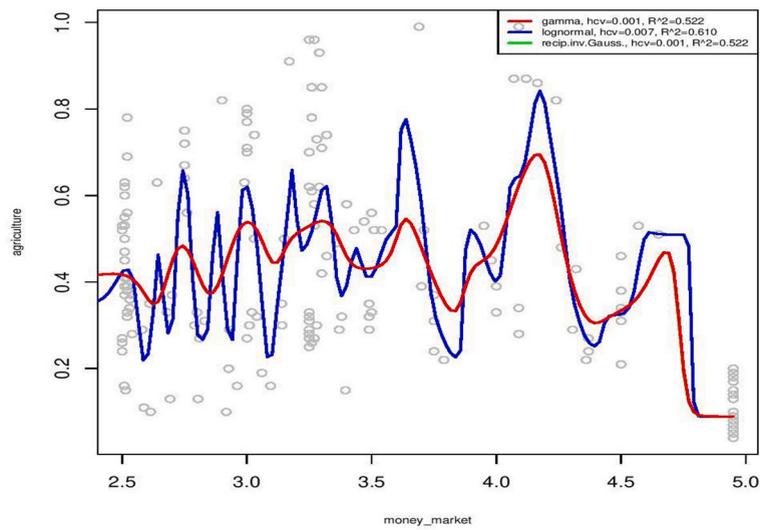


Fig. D5. Relationship between the interbank interest rate and the agricultural index.

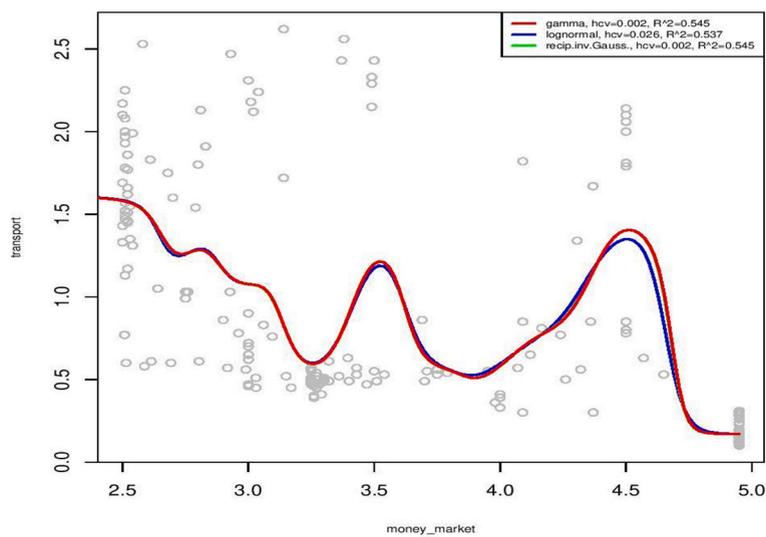


Fig. D6. Relationship between the interbank interest rate and transportation index.

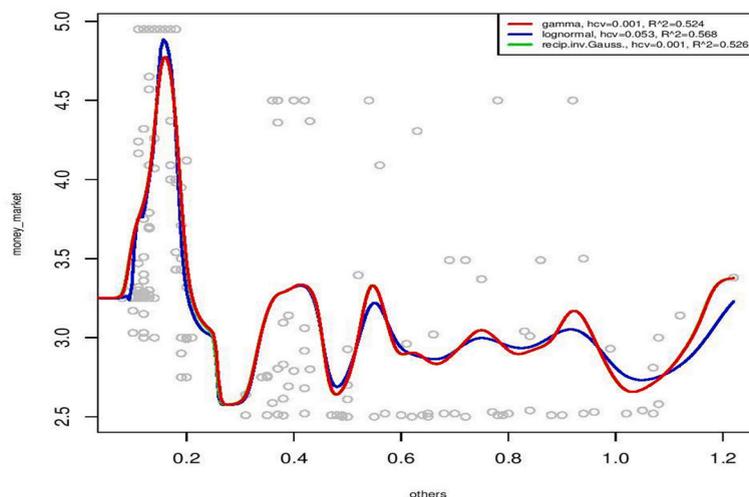


Fig. D7. Relationship between the interbank interest rate and other sectors index.

4.2. Implications of our work

The implications of our work can be twofold, on the one hand, the evolution of future profits of companies listed on the BRVM and the other hand, the action of the BCEAO on West African financial markets.

Firstly, the evolution of the relationship between stock prices and inflation leads to changes in the structure of investors' portfolios in the arbitrage between stocks and other financial assets such as bonds. This relationship results from the relationship between stock prices and nominal interest rates. Specifically, a rise or fall in inflation will induce a similar effect in interest rates causing investors to restructure the weight of bonds in their portfolios. Objectively, investors will expect stock prices to fall or increase; a fall in interest rates increases the value of future dividends (Hashemzadeh and Taylor, 1988).

Second, our empirical results indicate that the influence of inflation on sectoral stock prices listed on the Bourse Régionale des Valeurs Mobilières (BRVM) is high but more pronounced in favour of the utilities and agricultural sectors. Thus, the common monetary policy initiated by the BCEAO seems to be detrimental to the activities of the BRVM. It seems more stimulating for the BRVM. Moreover, although the monetary policy in place in the WAMU zone is essentially based on price stability and is likely to stabilise the stock market, it remains that an inflationary policy could eventually stimulate stock market activity. In the same vein, a monetary policy vision that advocates high inflation may be associated with higher sectoral stock prices.

5. Conclusion

Our work puts into perspective the relationship between inflation and West African sectoral indices between November 2001 and January 2020 using the appropriate (asymmetric) kernel method. The sectoral indices considered for the analysis include retail, finance, industry, utilities, agriculture, transport, and other sectors. Our work reveals that while all sectors are sensitive to inflation, the utilities and agriculture sectors are more sensitive to changes in inflation. Moreover, we discover that the relationship between inflation and sectoral stock market indices is rather non-linear. This argument supports the hypothesis that the relationship between inflation and stock market indices varies across different inflationary economies. These results imply that investors modify the structure of their investment portfolio according to the variation in the levels of inflation to the extent that this variation ultimately affects future dividends.

These results imply that the relationship between sectoral stock price and inflation depends on the cyclical movements of each sector and open several avenues of research, notably in the analysis of the relationship between inflation and the indices of companies listed on the regional stock exchange (BRVM).

Authors statement

We the undersigned declare that this manuscript is original, has not been published before and is not currently being considered for publication elsewhere.

We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us.

We understand that the Corresponding Author is the sole contact for the Editorial process. He/she is responsible for communicating with the other authors about progress, submissions of revisions and final approval of proofs.

Data availability

The authors do not have permission to share data.

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