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Inflation and systemic risk: A network econometric model

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Inflation and Systemic Risk: A Network Econometric Model

Abstract

This paper builds a network econometric model capable of analysing the impact of inflation on systemic risk. Its main contribution is the identification of a robust inverse relationship which reverses when controlling monetary policy. This reveals that the former effect is due to monetary policy reactions to inflation. It is further analysed whether this effect comes from overindebtness as in a Minsky moment. There is no evidence supporting it, which suggests that mechanisms other than excess credit underlie such a relationship. The results presented in this paper are of particular importance for understanding monetary policy reactions to current inflationary cycles.

Keywords: Inflation; Systemic Risk; Macro-Financial Links; Connectedness; Financial Networks.
JEL Codes: E31, E44, G32

1 Introduction

Analogously to many other macro-financial linkages, the effects of inflation on systemic risk are, to a large extent, still unknown. This is the result of a disconnection between the interplay of the economy and financial markets which has dominated macroeconomic research in recent decades. However, the financial crisis of 2007-2009 made clear that there is a constant interaction between the economic system and financial markets (Abbas et al., 2019; Aliyu, 2012; Balcilar and Bekun, 2020; Cotter et al., 2020; Diebold and Yılmaz, 2015; Festić et al., 2011; Silva et al., 2017), highlighting the need to consider additional contagion channels rather than the traditional interbank market (Silva et al., 2018). Thus, many of the macro-financial variables depend the other dimension, potentially in a non-linear way, as it has been theoretically argued (Bernanke et al., 1999; Brunnermeier and Sannikov, 2014; Gertler and Kiyotaki, 2010; Mendoza, 2010) and empirically estimated (Giglio et al., 2016).

In particular, the effects of inflation on systemic risk are of special importance nowadays. After more than 20 years of relatively low inflation (see red line Figure 1, quantified on the right axis), the study of the inflation-financial stability binomial have not been of upmost importance. Thus, some studies have analysed the impact of inflation on the performance of the financial sector (Boyd et al., 2001), financial development (Festić et al., 2011), and many have analysed the relationship between inflation and public debt (Bhattarai et al., 2014; Cherif and Hasanov, 2018; Krause and Moyen, 2016). However, the recent inflationary shock has caused "seismic waves" for the stability of the financial system, as contractive monetary policy stances have revealed, among other concerns, overexposures to interest rate risks by financial institutions. Therefore, discounting monetary policy, there may exist a relationship between inflation and systemic risk which could make controlling inflation a major concern not only for the correct functioning of the economy, but also for ensuring the stability of the financial system. As shown in Figure 1, this correlation between inflation and systemic risk connectedness may exist *a priori*.

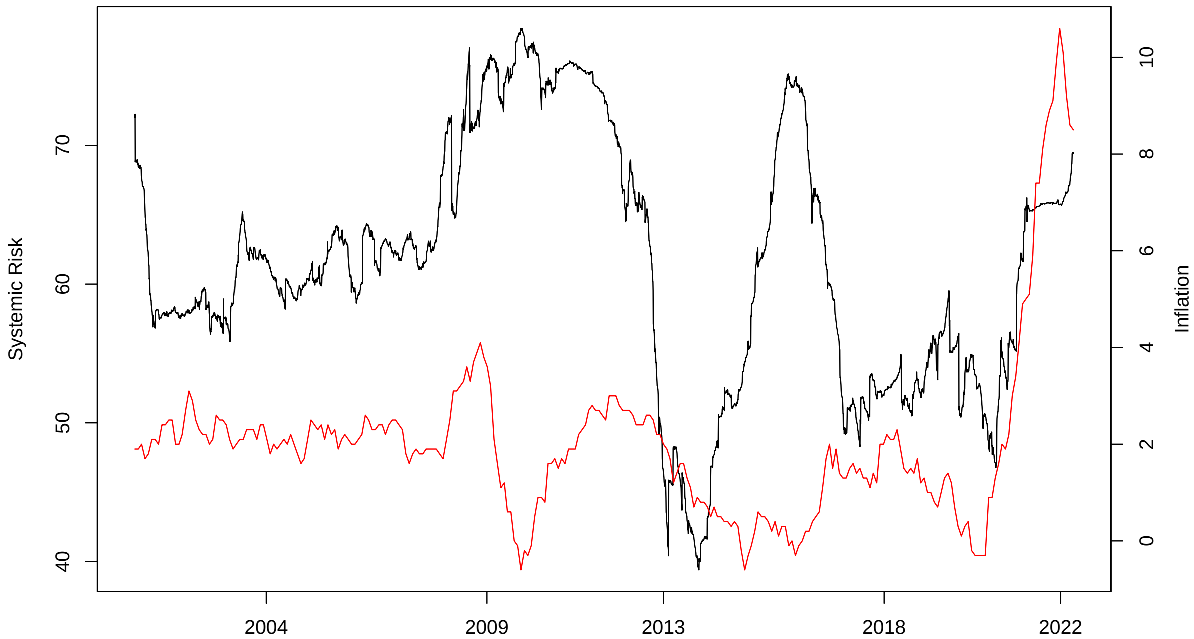

Figure 1: Systemic risk (*black line, left axis*) and inflation in Europe (*red line, right axis*).

But knowledge of the existence of this effect is important not only to quantify its magnitude but also to measure the effects of macroeconomic and macroprudential policies. For example, determining whether increasing inflation has a higher impact on systemic risk than higher interest rates could justify an aggressive monetary policy intervention after an inflationary shock, such as the recently experienced. On the other hand, if the link between inflation and systemic risk comes from an excessive indebtedness when there is a boom in the economy, this could support the adoption of preventive and ex-post countercyclical measures. In effect, credit can be enhanced due to the he procyclicality of banking sector performance (Festić et al., 2011). Therefore, periods of high economic activity tend to result in higher money circulation which then gives rise to inflation (Sasongko and Huruta, 2018) and this can lead to a systemic risk via higher risk appetite and excessive lending.

Many studies have explored the risk of financial contagion by employing bilateral exposures (Furfine, 2003; Georg, 2013; Martínez-Jaramillo et al., 2010) (a historical approach to systemic risk can be found in Brunnermeier and Oehmke (2013)). Other works have documented a substantial impact of the COVID-19 pandemic on financial connectedness and systemic risk (Borri and Di Giorgio, 2022; Huynh et al., 2022). Some other studies have analysed how financial economic risks affect economic activity (Cotter et al., 2020; Giglio et al., 2016). However, it would appear that parameters about the direct effects of inflation on systemic risk are still unknown. Only Sánchez García and Cruz Rambaud (2023) have provided some relevant evidence, which will be extended and contrasted in this paper.

The main objective of this research work is to analyse the existence, robustness and magnitude of the effect of inflation on systemic risk. The presence of this effect is estimated by discounting monetary policy reactions to inflation and the potential credit channel that may exist.

The remainder of the paper is structured as follows. Section 2 describes the econometric framework, models and data employed. Section 3 examines the empirical evidence. Finally, Section 4 summarizes and concludes.

2 The Model

2.1 Econometric Framework

This paper applies the two-step methodology detailed in Sánchez García and Cruz Rambaud (2023). The strength of the approach relies on that it allows to measure how much a random variable affects the probability of adding one link to the network at a certain level of statistical significance. Since the empirical model connects the countries by its financial stress, this is directly translated into inferences about the effect of the factor on systemic risk. The first step, i.e., the connectedness approach, is well established in the macro-financial literature (Demirer et al., 2018; Diebold and Yilmaz, 2012; Diebold and Yılmaz, 2014). This section briefly overviews the second part of the methodology for statistical inferences in financial networks.

Let G be a graph. Starting from an Exponential Random Graph Model (ERGM), it is possible to estimate the probability of that the network generated by the model (Y) is identical to an observed network (y). The general or canonical form of an ERGM model is:

$$P(Y = y) = \frac{1}{\psi(\beta)} \exp\{\beta \cdot v(G)\},$$

where β is a vector of parameters, $v(G)$ represents the vector of variables in the network, and $\psi(\beta) := \sum_{x \in X} \exp\{\beta \cdot v(G)\}$ (i.e., the normalization constant which is needed to obtain a valid probability distribution).

To obtain the parameters of the model, let G_{ij} be the variable which represents the presence or absence of a link between the nodes i and j in such a way that, if i is linked to j, then $G_{ij} = 1$; otherwise, $G_{ij} = 0$. Assume that the log-probability of the link between i and j can be determined by a set of n explanatory variables and parameters in the following way:

$$P(G_{ij} = 1) = \exp\left\{\sum_{k=1}^{n} \beta_k X_k\right\} = \exp\{\beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n\},$$

where $\beta := (\beta_1, \beta_2, \ldots, \beta_n)$ is the vector of relevant parameters, $X := (X_1, X_2, \ldots, X_n)$ the vector of explanatory variables.

As some characteristics of the model can be subgraphs and enter the model by their number, the counts of those features are not similar when the link ij is present or absent (Van der Pol, 2019). Therefore, being $v(G_{ij}^{+})$ the vector of features when the link ij is present and $v(G_{ij}^{-})$ when it is not, it can be shown that:

$$\text{logit}[G_{ij} = 1 | G_{ij}^{0}] = \beta_1' v_1(\Delta_1 N_{ij}) + \cdots + \beta_n' v_n(\Delta_n N_{ij}),$$

where β' is the transposed matrix of β, β_k' the transposed of β_k $(k = 1, 2, \ldots, n)$, G_{ij}^{0} denotes the graph without the link ij, and $v_k(\Delta_k G_{ij}) := v_k(N_{ij}^{+}) - v_k(G_{ij}^{-})$ the change statistic of a ij tie of the feature k, which leads to the logit expression of the ERGM.

2.2 Specifications

For a financial network N with systemic risk ties between agents i and j, where $i = 1, \ldots, n;\ j = 1, \ldots, n;$ $i \neq j$, being N_{ij}^{0} the network without the link ij, and n the total number of nodes of the network, the following econometric specifications can be considered:

Specification 1: Simple ERGM

$$\text{logit}[N_{ij} = 1 | N_{ij}^{0}] = \beta_1 e + \beta_2 m + \beta_k v_k(\Delta_k N_{ij}), \quad (1)$$

where $k = 1, \ldots, s$ is the number of variables, e is the control variable "edges" which acts similarly to the intercept in linear regression models, and m is the variable "mutual" which controls how many ties are reciprocated in the observed network in comparison with the random network. With this specification, each inflation variable k in the estimation is rotated up to the total number of inflation variables s.

Specification 2: Hierarchical ERGM

$$\text{logit}[N_{ij} = 1|N_{ij}^0] = \beta_1 e + \beta_2 m + \beta_1 v_1(\Delta_1 N_{ij}) + \beta_{t+1} v_{t+1}(\Delta_{t+1} N_{ij}), \tag{2}$$

where, in each iteration of the model $t = 0, \ldots, T-1$, another inflation variable is included in the model.

Specification 3: Multiple ERGM

$$\text{logit}[N_{ij} = 1|N_{ij}^0] = \beta_1 e + \beta_2 m + \beta_1 v_1(\Delta_1 N_{ij}) + \beta_2 v_2(\Delta_2 N_{ij}) + \cdots + \beta_s v_s(\Delta_s N_{ij}), \tag{3}$$

In Specification 3, several variables have been included in the model at the same time to analyse their multivariate behaviour.

2.3 Data regularities

The datasets used in this paper are publicly available at the ECB, World Bank, OCDE, FRED and BIS webpages. For measuring the financial stress, the Composite Indicator of Systemic Stress (CISS) provided by the ECB has been employed (for details, see Hollo et al. (2012)). Instead of considering individual countries, this paper concentrates on the systemic risk of the whole financial network, i.e., on the connectedness of the financial stress. Indeed this is an effective approximation to systemic risk as an increasing connectedness of the financial stress of individual countries translates into an increasing stress in the whole network. Here, the main objective is then to analyse how different forms of inflation affect such connectedness, as graphically shown in Figure 2.

The countries of the network are eleven European countries that are expected to share important commercial and financial links due to the free circulation of goods, capital and workers stated by Treaty on the Functioning of the European Union. Additionally, the United States was added due to its worldwide economic and financial importance, as well as its important economic and financial relations with Europe, and as a result of both, to its potential to transmit inflation and financial stress.

For measuring inflation, this paper employs the Headline Consumer Price Index (CPI), Food CPI, Energy CPI, the core CPI, the Producer Price Index (PPI), the Deflator of the GDP and the professional forecasts of inflation as inflation expectations, all provided by the World Bank. As credit flows, the credit to the non-financial sector has been used; and, for interest rates, the nominal interest rate of government debt of the country. For all the variables, the intertemporal mean has been considered. The dataset corresponds to the twelve countries shown in Figure 2. In order to consider only important systemic linkages and to make the ERGM informative, only the edges beyond a threshold value of 0.3 have been taken into account.

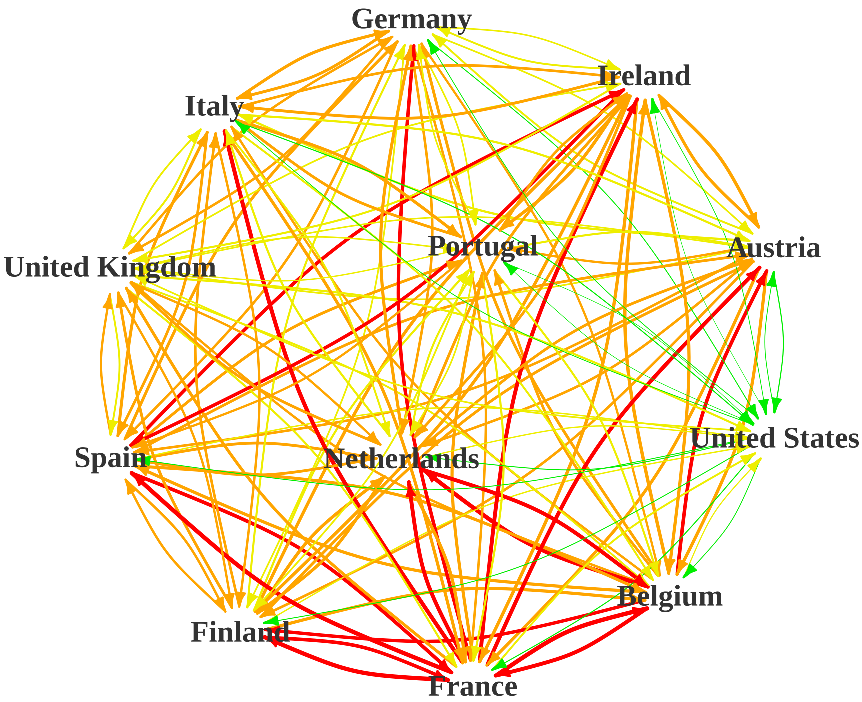

Figure 2: Network of systemic risk.
The nodes represent the countries considered whilst the edges consist of the normalized directed connectedness of the financial stress indicator between each pair of countries.

3 Empirical evidence

Table 1 provides the estimates for Specification 1. By including the control variable "mutual", the explanatory power of the model increases by approximately 30% and 26% respectively according to the AIC and

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Edges	1.36^{***}	-1.53^{***}	9.04^{***}	0.34	-2.39^{+}	-1.72^{**}	-1.03	4.16^{+}	10.07^{**}
	(0.22)	(0.53)	(3.05)	(1.19)	(1.40)	(0.58)	(0.72)	(2.45)	(3.64)
Mutual	–	4.53^{***}	3.96^{***}	4.36^{***}	4.48^{***}	4.49^{***}	4.46	4.37^{***}	4.10^{***}
		(0.93)	(0.98)	(0.92)	(0.95)	(0.96)	(0.97)	(0.99)	(1.02)
CPI	–	–	-2.76^{***}	–	–	–	–	–	–
			(0.77)						
Food	–	–	–	-0.47^{*}	–	–	–	–	–
				(0.26)					
Energy	–	–	–	–	0.15	–	–	–	–
					(0.21)				
Core	–	–	–	–	–	0.06	–	–	–
						(0.07)			
Producer	–	–	–	–	–	–	-0.11	–	–
							(0.11)		
Deflator	–	–	–	–	–	–	–	-1.55	–
								(0.62)	
I. Expectations	–	–	–	–	–	–	–	–	-3.36^{***}
									(1.01)
AIC	135.8	104.6	86.5	102	105.2	105.1	105	98.6	90.94
BIC	138.6	110.4	95.2	110.7	113.9	113.7	113.7	107.3	99.58

Table 1: Estimates for the Specification 1.
α significance levels are: *** for the 0.00, ** for the 0.01, * for the 0.05 and + for the 0.10.

BIC criteria. By including "inflation" as the only explanatory variable of the model, the fit of the model improves by 21% and 16%, respectively. With respect to the rest of models in Specification 1, only the "deflator of the GDP" and "inflation expectations" significantly improve the fit in comparison with a model which only employs controls (6% AIC and 4% BIC, and 15% AIC and 10% BIC). Only the parameter "inflation expectations" is statistically significant.

Model (3) is the best in Table 1 with "inflation" as the only explanatory variable. The parameter -2.76 indicates that an increase in inflation reduces the log-odds of financial stress. When considering "inflation expectations", the magnitude of this effect is -3.36. Finally, the coefficient of "food inflation" is -0.47. These are the only three forms of inflation which are statistically significant.

Quantitatively speaking, inflation reduces the odds of generating a new link by a factor of 0.94, inflation expectations by 0.97, and food inflation by 0.37.[1] With respect to the marginal effects[2], they are of -0.000033 for inflation, -0.0053 for food inflation, and -0.000019 for inflation expectations. The sign of the coefficient of inflation is robust to food inflation, producer inflation, the deflator of the GDP and inflation expectations,

[1] As the parameters are in logit or log-odds scale, the decreasing effect on the odds are calculated by $1 - \exp(\beta)$. However, odds-ratios can be misleading and will not be considered here (Davies et al. (1998)).

[2] The marginal effects are calculated by $ME = \frac{1}{1+\exp(-X'\beta)} - \frac{1}{1+\exp(-X'\beta_0)}$, where β is the vector of parameters incorporating the variable of interest, and β_0 is the same vector but without the variable (Stock, Watson, et al., 2003).

	(1)	(2)	(3)	(4)	(5)	(6)
Edges	9.04^{**}	8.88^{**}	6.11^{+}	11.97^{*}	12.12^{*}	12.79
	(3.05)	(3.31)	(3.55)	(5.08)	(5.04)	(0.14)
Mutual	3.96^{***}	3.88^{***}	3.54^{***}	3.20^{**}	3.19^{**}	3.20^{**}
	(0.98)	(0.98)	(1.04)	(1.05)	(1.02)	(0.00)
CPI	-2.76^{***}	-2.82^{**}	-5.12^{**}	-6.03^{***}	-6.06^{***}	-5.27
	(0.77)	(0.96)	(1.57)	(1.77)	(1.79)	(0.14)
Food	–	0.13	0.96^{+}	0.67	0.49	0.69
		(0.31)	(0.52)	(0.52)	(0.59)	(0.57)
Energy	–	$-\ 1.38^{*}$	0.98^{+}	1^{+}	1.09^{+}	
			(0.60)	(0.58)	(0.60)	(0.09)
Core	–	–	–	0.31^{*}	0.35^{*}	0.31^{+}
				(0.16)	(0.15)	(0.06)
Producer	–	–	–	–	0.10	0.13
					(0.23)	(0.57)
Expectations	–	–	–	–	–	-1.46
						(0.83)
AIC	86.6	88.5	81.9	77.7	79.4	81.5
BIC	95.2	100	96.3	94.9	99.6	104.5

Table 2: Estimates for the Specification 2.
α significance levels are: *** for the 0.00, ** for the 0.01, * for the 0.05 and + for the 0.10.

being only the first and the fourth statistically significant.

Table 2 shows the estimations for Specification 2. The $\hat{\beta}$ parameter accompanying inflation is negative and statistically significant in all models, which reveals robustness. In all models, inflation has a negative impact on the log-odds, and the other forms of inflation act as corrective terms. The marginal effects are -0.00004, -0.001, -0.000015 and -0.000014 for models 2, 3, 4 and 5, respectively. The best model according to the information criteria is model (4), which includes all inflation variables except the producer price index. Inflation expectations potentially render other terms individually and statistically insignificant due to collinearity (see Table 1 of the supplementary material).

The negative coefficients of inflation are counterintuitive, and the robustness of the estimations imply that this sign is not due to model misspecifications. However, rising inflation usually provokes monetary policy reactions which may reduce the systemic risk. Further analysis is therefore implemented to see whether interest rates act as a moderating variable in the relationship between inflation and systemic risk. Several models are used which include interest rates, inflation, interaction terms, and systemic risk according to Specification 3. Additionally, credit flows are considered in order to ascertain whether the relationship is altered by overindebtness during inflationary periods.

Table 3 shows positive coefficients for all forms of inflation in all models, whether they include CPI

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Edges	-63.04^{*}	-21.61	-35.19^{+}	-23.71	-15.79	-92.01	6.22	35.13
	(26.00)	(33.14)	(19.52)	(23.7)	(15.71)	(43.66)	(11.73)	(30.17)
Mutual	3.29^{**}	2.88^{*}	3.22^{**}	2.48^{*}	4.18^{***}	1.55	4.24^{***}	2.54^{*}
	(1.16)	(1.14)	(1.11)	(1.24)	(0.94)	(1.35)	(0.98)	(1.25)
CPI	18.6^{*}	0.04	–	–	–	–	–	–
	(7.71)	(1.54)						
Interest rates	12.74^{**}	4.60	3.40^{*}	1.61	3.83	15.60^{*}	-0.88	-5.17
	(4.70)	(5.91)	(1.57)	(2.09)	(3.00)	(2.09)	(1.75)	(4.26)
CPI*Interest rates	-7.41^{**}	-3.04	–	–	–	–	–	–
	(2.72)	(3.36)						
Credit	–	0.30	–	-0.27	–	0.42	-0.12	–
		(0.46)		(0.77)		(1.08)	(0.56)	
CPI*Credit	–	-0.18	–	–	–	–	–	–
		(0.21)						
I. Expectations	–	–	11.24^{+}	9.11	–	–	–	–
			(6.03)	(7.41)				
Expectations*Ir	–	–	-1.25^{*}	-0.81	–	–	–	–
			(0.52)	(0.70)				
Expectations*Credit	–	–	–	0.09	–	–	–	–
				0.40				
Deflator	–	–	–	–	3.42	25.58^{*}	–	–
					(4.04)	(12.12)		
Deflator*Ir	–	–	–	–	-1.90	-9.40^{*}	–	–
					(1.50)	(3.81)		
Deflator*Credit	–	–	–	–	–	-0.29	–	–
						(0.55)		
Food Price	–	–	–	–	–	-8.84	-8.84	
							(8.51)	(8.51)
Food Price*Ir	–	–	–	–	–	-0.24	2.73	
							(1.06)	(2.50)
Food Price*Credit	–	–	–	–	–	–	–	0.00
								(0.24)
AIC	79.7	69.5	79.5	69.9	100.1	60.39	103.2	69.39
BIC	94.1	83.9	93.9	90.08	114.6	80.57	117.7	89.57

Table 3: Estimates for Specification 3.
α significance levels are: *** for the 0.00, ** for the 0.01, * for the 0.05 and + for the 0.10.

expectations or the GDP deflator. The only exception is food inflation, which is not statistically significant in any model. When including interest rates, as well as the interaction of interest rates and inflation understood as monetary policy reactions to galloping inflation, inflation increases systemic risk. Additionally, when considering the aforementioned interaction, higher interest rates also translate into systemic risk increases, the impact on the log-odds being higher for inflation in all cases.

Regarding statistical significance, headline inflation is significant in model (1), inflation expectations in model (3), and the deflator in model (6). Interestingly enough, the CPI and inflation expectations are significant until credit and its interaction enters the model. In the case of the deflator, the situation reverses, i.e., it is significant in model (6) but not in model (5). Nevertheless, credit and its interaction term are never statistically significant. The marginal effects are $2.78E$-16, $8.53E$-09 and $7.78E$-12 for the headline CPI, inflation expectations and the GDP deflator respectively. The marginal effects present a significant decrease in magnitude in comparison with the models that do not account for monetary policy interventions, disclosing that a substantial part of the inflation-systemic risk binomial acts through these. The biggest effect is seen in inflation expectations, revealing the importance of expected inflation for the stability of financial markets. Nevertheless, due to the novelty of the methodological application, these may be considered as preliminary results and so the magnitudes should be taken with caution as more evidence may be needed to contrast and extend them.

4 Conclusions

This paper has provided some inferences about the effects of inflation on systemic risk in a financial network of twelve countries. It has been found that, after controlling the monetary policy reactions to inflation, inflation increases systemic risk. Furthermore, in the time span considered (2000-2022), inflation increases more systemic risk than interest rates. This provides partial equilibrium evidence in favour of aggressive monetary policy interventions to preserve financial stability and not only to ensure the correct functioning of the economy during inflationary shocks. Indeed, if inflation increases more systemic risk than interest rates, there exists an incentive for the central bank to increase interest rates in presence of rising inflation, since the effect of the latter outweights the negative effect of the bank rate hike for financial stability.

It has been further tested whether the channel through which inflation increases systemic risk is excessive lending during economic booms as in a Minsky moment. However, evidence has not been found which reveals that mechanisms other than excess credit are behind the relationship. All the results presented in this paper are robust to several variable selections and econometric specifications, and extend to inflation expectations as well. Further research can be directed towards increasing the understanding of the relationship between inflation and systemic risk with monetary policy, since a substantial part of it appears to be happening through interest rates.

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Inflation and Systemic Risk: A Network Econometric Model

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Highlights for “Inflation and Systemic Risk: a Network Econometric Model”:

- Novel network econometric model to analyze inflation and systemic risk.

- Inflation increases systemic risk after controlling for monetary policy.

- Inflation has a higher effect on systemic risk than interest rates.

Javier Sanchez Garcia: Conceptualization, Methodology, Writing- Original draft preparation, Visualization, Investigation, Software, Formal Analysis **Salvador Cruz Rambaud:** Supervision, Validation, Writing- Reviewing and Editing, Project administration