Financial fragility and unemployment in the Italian regions

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Abstract

This paper studies the dynamic effects of financial fragility shocks on unemployment at the regional level for Italy, and analyses the correlation between some regional characteristics and the regional responses to such shocks. I construct a new quarterly dataset for the 20 Italian regions, ranging from 1997-Q1 to 2023-Q3, including the bad loans rates, unemployment rates and bank interest rates. The results show that sudden increases in financial fragility have important negative dynamic effects on regional employment, and the least developed regions are the hardest hit. Moreover, the regional heterogeneous effects on unemployment are positively associated with regional credit risk, unemployment rate levels and the regional share of temporary workers, and negatively correlated with regional economic and financial development levels, regional competitiveness, labour market efficiency and education levels.

Keywords: *Regional unemployment; Financial fragility; Italian regions; Regional quarterly data.*
JEL Classification: *A10; C32; E00; R10.*

1 Introduction and related literature

The recent financial crises have increased the need to understand the relationship between financial markets and the real economy, generating a new wave of research that has sought to quantify the real costs of financial instability. Empirical research has focused on these extraordinary events as important drivers of economic fluctuations. For example, Caldara et al. (2016) show that financial shocks negatively affect the real economy, estimating a contraction of real US industrial production between 0.6 and 1 per cent. Mallick and Sousa (2013) find a drop in output after a shock to financial stress conditions in the Euro Area. Consequently, financial shocks and increased financial fragility have also been found to lead to job losses (Boeri et al., 2013; Chletsos and Sintos, 2021). In this paper, I study the effects of financial fragility shocks, in terms of an increase in the bad loans rates, on unemployment at the regional level for Italy. Financial fragility may, in the first place, influence unemployment indirectly, through its negative effects on economic growth (Chletsos and Sintos, 2021). As already mentioned, the negative real effects of financial shocks are well documented. Moreover, financial fragility and financial shocks can directly affect employment in different ways. For example, liquidity shortages during financial crises lead companies to have difficulty hiring labour, and workers with fixed-term contracts may lose their jobs, thus giving rise to unemployment. The difficulty for companies to access finance goes in the same direction. Furthermore, the increase in risk aversion on the part of firms, the financing of investment costs for hiring and training the workforce and the strong dependence of firms on bank loans in a context of sticky relations between banks and borrowers mean that shocks in the financial sector are quickly transmitted to the business sector, affecting hiring and thus employment (Boeri et al., 2013). I study this aspect at the regional level for Italy. The contributions of this study can be listed as follows. First, I construct a new quarterly data set for the 20 Italian administrative regions, covering the period from 1997Q1 to 2023Q3, exploiting detailed data sources for the regional credit markets from the Bank of Italy and for the labour market from the National Institute of Statistics (ISTAT). I am not aware of any studies on Italian regions that have such a long time coverage with quarterly data[1]. This makes it possible to have enough temporal observations for each region . Secondly, due to the long period covered with quarterly frequency, I can avoid pooling the dataset and estimate the model region by region, introducing full heterogeneity in the panel data model, very much in the spirit of Pesaran and Smith (1995), and then studying the effects on average and by subgroups of regions depending on economic and structural conditions. Furthermore, this allows for region-specific effects that can be linked to certain regional structural characteristics, thus going deeper into regional heterogeneity, which is relevant in the Italian regional context, as I will show below and throughout the paper. Third, the relationship between financial shocks and the real economy has been deeply studied, both theoretically and empirically (see for example, Jerman and Quadrini, 2012; Silvestrini and Zaghini, 2015; Caldara et al., 2016). However, as highlighted by Liotti (2020), the effects of financial crises have been widely analysed at the international level and there are few papers looking at within country dynamics and subnational entities. To the best of my knowledge, few studies have investigated the effects of financial shocks on regions. Examples are Mian and Sufi (2014) for US counties and Dijkstra et al. (2015) and Compagnucci et al. (2022) for European regions, which however focus on international financial crises episodes, namely, the 2007-2009 global financial crisis and the sovereign debt crisis. As for Italy, Di Caro (2015) and Lagravinese (2015) also analyse the effects of international or nation-wide economic crises (e.g. by constructing dummies for the period of the crises), whereas Liotti (2020) focuses on economic crises defined as the one which occurs when regional real growth is negative. Unlike these studies, this paper investigates the effects of region-specific shocks in the financial sector occurring over a longer time span, without focusing on international or nation-wide economic and financial crises and introducing fully regional heterogeneity. I try to fill this gap by setting up a regional Vector Auto-Regression (VAR) including bank interest rates, the bad loans rate and the unemployment rate to study the dynamic effects of regional financial fragility shocks on regional unemployment. This is possible thanks to the construction of the new dataset, as mentioned above, which span a longer time period with quarterly data relative to current studies on Italian regions. It allows to obtain region-specific estimates that can

[1] In particular, data on bank interest rates are not as easy to collect as those on the unemployment rate and the bad loans rate. Detailed information on the construction of this proxy for regional credit market conditions over the period 1997Q1-2023Q3 can be found in Appendix A. Therefore, this work could provide a very long time series on credit market conditions that can be easily extended and used by other researchers. The data are shared at the following link `https://data.mendeley.com/datasets/d4443mb9jd/1`.

be linked to regional characteristics which may influence how regions react to shocks and therefore, analyse how the economic and structural imbalances among the Italian regions influence the response of the regions to the financial fragility shock. In this regard, Italy is a relevant case study, given its regional heterogeneity in terms of economic and structural conditions and the centuries-old gap between the more developed area in the North and the less developed area in the South, also known as the 'Mezzogiorno'. As shown by Figure 1, the latter area has a lower level of GDP per capita and higher unemployment rates.

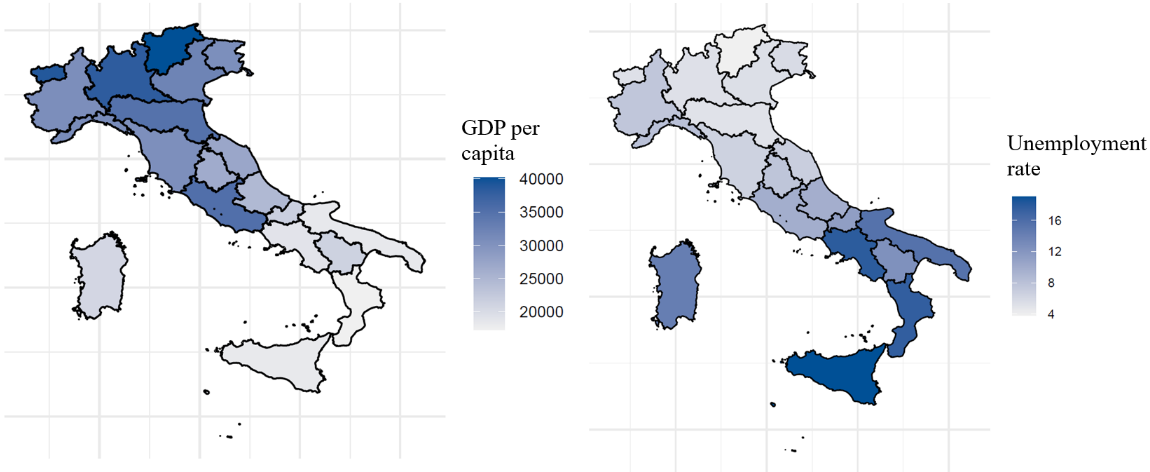

Figure 1: Regional GDP per capita and unemployment rates (averages over the period 1997-2023).

The gap between the North and the South in terms of unemployment has been stable over time and widened during and around recent financial crises, as Figure 2 clearly demonstrates. Notably, the gray bars, which show the difference between the average unemployment rate in the South and the average unemployment rate in the Centre-North, increases after 2008 and 2011. Moreover, as highlighted by Camussi and Aimone Gigio (2023), the South is characterised by lower job quality, which is accompanied by a worse type of jobs created, since, between 2014-2019, only part-time positions and temporary contracts contributed to job creation in the area. In line with this, the share of temporary contracts is higher in the South and the duration of permanent jobs is shorter (Modena et al., 2024). All these stylised facts may indicate that employment in the South may be more vulnerable to the occurrence of financial shocks.

Concerning the credit market, Alessandrini et al. (2009) show that the wave of mergers and acquisitions in the Italian banking system, which led to a geographical concentration of banks' decision-making centres, increased the distance between them and local communities (what they call "functional distance"), exacerbating financial constraints especially for small enterprises located in the less developed southern provinces. This process of banking consolidation accelerated even after the Global Financial Crisis (GFC), and gave centrality to a few banking centres in Northern Italy at the expense of the credit markets in the southern regions (Papi et al., 2017). This has important implications in the Italian

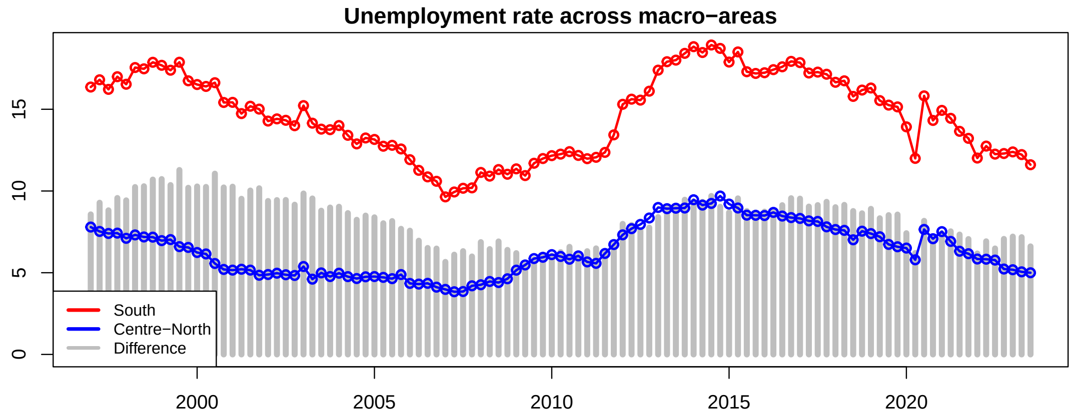

Figure 2: Unemployment across macro-areas. Notes: the plot shows the evolution over time of the average unemployment rate in Southern and Central-Northern Italian regions and their difference.

context, given the high share of small businesses operating in the Italian economy, which are highly dependent on loans from local banks to finance their investments and business activity, and thus this may in turn affect employment. A study by Presbitero et al. (2014) showed that Italy was hit by a severe credit contraction during the global financial crisis and that this contraction was exacerbated by the increase in the aforementioned 'functional distance' between banks and local borrowers. The analysis conducted by Cipollini and Parla (2018) finds that the negative shocks to credit supply during the Great Recession had severe detrimental effects on employment in the Italian provinces, with the area most affected being the South. Moreover, credit is riskier in the South (Casolaro et al., 2024) and small enterprises in this area face greater liquidity constraints (Sarno, 2005). These economic and structural differences may be important factors influencing the reaction of regional economies to financial fragility shocks. As far as the empirical strategy is concerned, I identify shocks hitting the regional bad loans rates, which I will also call 'financial fragility shocks' , using the sign restriction approach (Uhlig, 2005). This approach is quite common in the empirical literature that seeks to identify shocks in the credit market (Mumtaz et al., 2018). The identification restrictions are based on the fact that periods of high financial fragility are associated with higher credit risk, which occurs when the value of non-performing loans increases relative to the stock of good loans. In such a situation, the number of defaulting borrowers increases and banks bear a higher risk, thus increasing interest rates on loans. This is reminiscent of a well-known relationship between risk and return, i.e. the risk-return trade-off in the financial theory literature, proposed by Markowitz (1952). Furthermore, the theory concerning the presence of information asymmetries and the occurrence of adverse selections, which introduce credit constraints, can explain the presence of a positive relationship between risk and return (Stiglitz and Weiss, 1981). Higher riskiness leads to lower expected loan yields for banks, which pass them on to future borrowers by raising interest rates. Therefore, in times of rising NPLs ratios, banks may charge higher risk premiums, resulting in higher interest rates charged on loans. In periods of high financial stress, the increase in non-performing loans relative to the amount of outstanding good loans is associated with the deterioration of borrowers' balance sheets and the increase in risk premiums, resulting in tighter financial conditions and thus higher bank interest rates. Based on these insights, I identify the financial fragility shock as the one that raises the bad loans rate and bank interest rates. I find that a one standard deviation shock to the bad loans rate produces high real costs, increasing the regional unemployment rate by 0.20 percentage points, on average, after ten quarters. However, the results are heterogeneous across the Italian regions. Different structural and economic conditions across the country seem to influence how regions react to the shock. In line with Chletsos and Sintos (2021), I find that the real costs of financial fragility are higher in the South of Italy and in the group of regions with a GDP per capita lower than the median, and worsen when considering regions in the bottom quartile of the distribution of GDP per capita. Furthermore, having an estimate of the region-specific effects of the financial fragility shock on unemployment, I calculate cross-regional correlations between these effects and various regional characteristics. I find that regions with a lower level of economic development, financial development, competitiveness, education and labour market efficiency tend to experience higher employment costs after the financial fragility shock. Moreover, regions with a lower level of factor utilisation, a higher credit risk and a higher share of temporary workers suffer the highest effects of the financial fragility shock on unemployment. The rest of the paper is organised as follows. Section 2 provides information on the construction of the dataset, with additional information in Appendix A. Section 3 explains the methodology, with further details in Appendix B and C. Section 4 discusses the baseline results on the average regional effects and provides some robustness checks. Section 5 is devoted to the analysis of heterogeneous effects between groups of regions and the relationship between regional effects and regional characteristics. Finally, Section 6 concludes.

2 Data

I construct a novel quarterly data set for 20 Italian regions over the period 1997Q1-2023Q3, which contains regional unemployment rates, interest rates applied to bank loans in each region and the regional non-performing loan ratios. The unemployment rate is calculated using unemployment and labour force data from the ISTAT database. Interest rates and non-performing loan ratios come from the Bank of Italy's BDS (Base Dati Statistica) database. The bad loans rate is calculated by the Bank of Italy as the ratio of loans entering non-performing status during the quarter to the stock of good loans at the end of the previous quarter. An increase in this ratio is read as an increase in financial fragility and banking instability and has been used as a proxy for these phenomena (Chletsos and Sintos 2021; Phan et al. 2022; Demetriades et al. 2024). The regional interest rate series are also constructed from the Bank of Italy's BDS database. Unlike the other two variables, constructing regional interest rate series is more complicated. This paper can therefore

Table 1: Descriptive statistics

variables	mean	standard deviation	minimum	maximum
real interest rate	6.80	2.26	0.90	13.80
bad loans rate	0.53	0.45	0.02	5.02
unemployment rate	9.70	5.22	2.03	25.70

Table 2: Correlation matrix of the regional median of the variables

	Interest rate	Bad loans rate	Unemployment rate
Interest rate	1		
Bad loans rate	0.38***	1	
Unemployment rate	0.03	0.69***	1

Note *** indicate statistical significance at the 5% level. This test is based on z Fisher Transform, which has a t-distribution with n-2 d.g.f under null hypothesis of two independent normal distributions.

provide a new and longer proxy for the series of regional interest rates at quarterly frequency for Italy, and that are specifically related to interest rates on callable credit lines. These are used as a proxy for regional credit market conditions. After constructing these series, I used the Italian GDP deflator (at quarterly frequency from the FRED database) to calculate the inflation rate and transform interest rates into real terms (more details on the construction of the dataset can be found in Appendix A, where it is also shown that the constructed regional series on bank interest rates are in line with the Italian lending rate from the IMF database).

Table 1 provides some descriptive statistics on the variables, while Figures 3 and 4 show their evolution over time and the regional averages of interest rates and bad loans rate, respectively, whereas the regional averages of the unemployment rate are shown in Figure 1. They show strong heterogeneity, both over time and between regions.

From Figure 3, one can read some common patterns across the Italian regions. There was a downward trend in interest rates after the creation of the Euro Area, temporarily interrupted by the financial and sovereign crises that followed, and again by inflationary pressure after the Covid-19 pandemic and during the war tensions in Ukraine. Higher bad loans rates are evident during major financial recessions and some peaks occurred in the late 1990s and during the financial and sovereign debt crisis. Unemployment also shows a decreasing path in the early part of the sample, temporarily interrupted by the financial crises and the Covid-19 pandemic. Table 2 shows a strong and statistically significant positive correlation between the unemployment rate and the bad loans rate and between interest rates and the bad loans rate. Periods of high financial fragility are associated with higher interest rates and unemployment rates. Despite these common paths, regional heterogeneity is considerable in Italy, with southern regions suffering from higher unemployment rates, as shown by the panel on the right in Figure 1, and higher interest rates and default rates, as shown in Figure 4. This cross-regional heterogeneity is important for the effects of financial shocks on unemployment, as I will show later, which is one of the main contributions of this study.

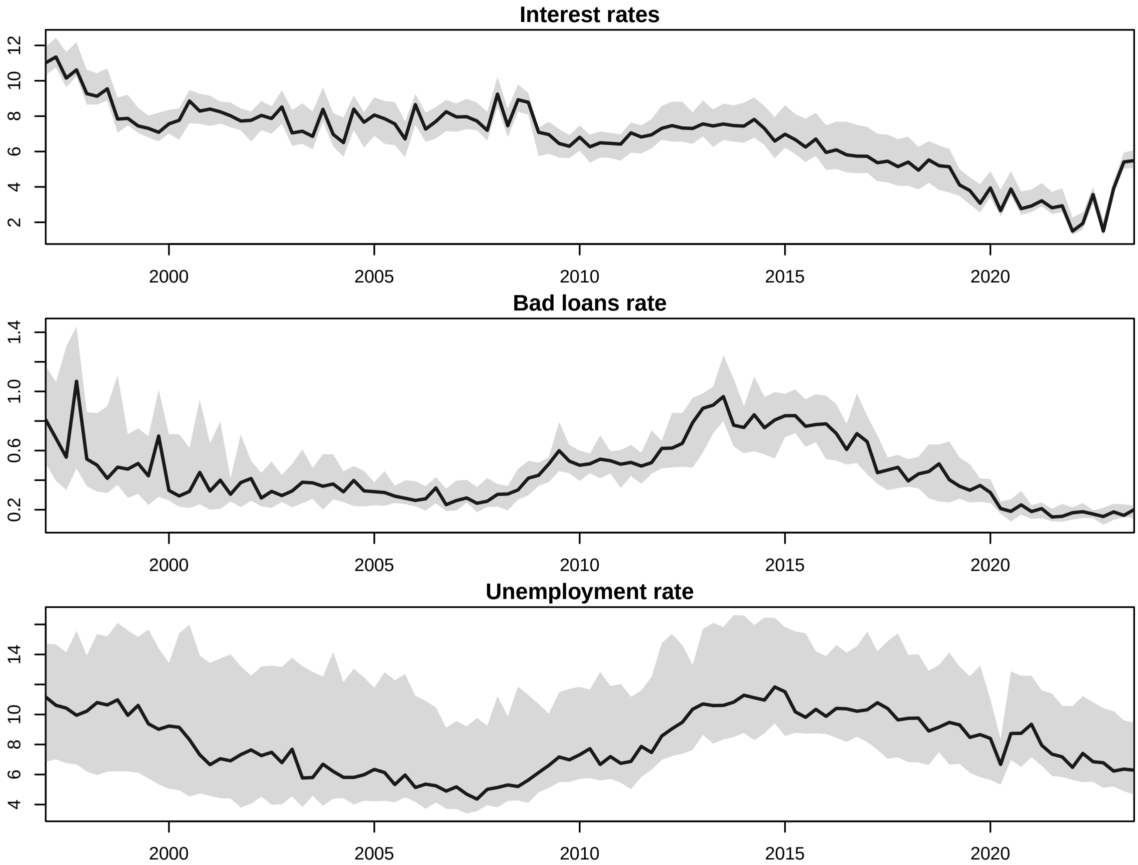

Figure 3: Regional distribution of the variables over time. Notes: the black solid line is the median across regions. The shaded area represents the inter-quartile range of the regional distribution.

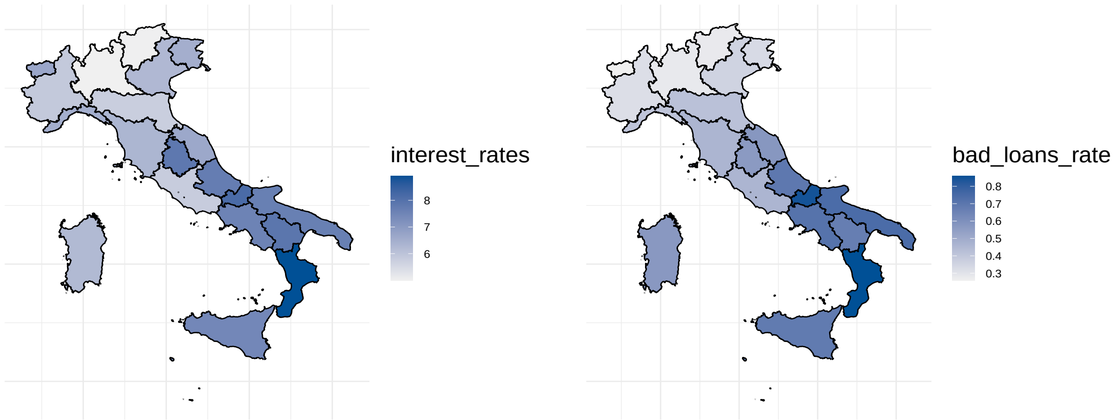

Figure 4: Regional averages of interest rates and bad loans rate over the period 1997Q1-2023Q3.

3 Econometric strategy

To estimate the dynamic effects of a shock to financial fragility on unemployment in the Italian regions, I use a vector autoregression (VAR) approach. Since I have a panel dataset with $N = 20$ regions and a much longer time dimension, $T = 107$, I do not pool the data and estimate the model for each Italian region and then average the results across regions, in the spirit of the mean group estimator proposed by Pesaran and Smith (1995) in the frequentist framework. The model reads as follows:

$$\mathbf{Y}_{i,t} = \alpha_i + \mathbf{A}_i(L)\mathbf{Y}_{i,t-1} + \mathbf{u}_{i,t} \tag{1}$$

where $\mathbf{Y}_{i,t} = [r_{i,t}, blr_{i,t}, unemp_{i,t}]$ is the vector of endogenous variables which contains the real interest rate ($r_{i,t}$), the bad loans rate ($blr_{i,t}$) and the unemployment rate ($unemp_{i,t}$) in region i at quarter t. The matrix of VAR coefficients for each region is $\mathbf{A}_i$ whereas α_i represents the vector of regional constants. The lag operator (L) introduces lags in the VAR, which in the baseline model are set equal to 4 according to the frequency of the dataset. The vector of VAR innovations is represented by $\mathbf{u}_{i,t} \sim \mathcal{N}(\mathbf{0}, \Omega_i)$. I estimate this model using a standard and widely used Bayesian technique, which imposes a Normal-Inverse Whishart prior implemented through dummy observations (Bańbura et al. 2010). Following most empirical studies, I impose a Minnesota prior on the VAR matrix, considering the persistent behavior of macroeconomic variables in levels, thus setting the coefficient of the first lag of each endogenous variable equal to one (Litterman 1986)[2]. This framework allows me to obtain posterior distributions of the object of interest, i.e. the impulse response functions (IRFs) to a financial fragility shock, which I will use to make inference (details on the Bayesian approach used are provided in Appendix A).

Identification of financial fragility shocks through sign restrictions. To identify the shock hitting the bad loans rate, I rely on the sign restriction approach (Uhlig 2005). This approach requires the imposition of reasonable restrictions on the sign of the response of certain variables to the shock of interest, based on economic theory and evidence, and has been widely used to identify shocks in the credit market (Mumtaz et al. 2018). The vector of endogenous variables consists of two financial variables, namely bank interest rates and the bad loans rate, and one real variable, namely the unemployment rate. The main interest is to identify the effects of a financial fragility shock on the unemployment rate. The presence of bank interest rates in the VAR helps to identify the shock of interest. In particular, I follow the financial literature on the risk-return trade-off, according to which higher risk leads to higher returns (Markowitz 1952). Indeed, in periods of high credit risk, banks may demand higher risk premiums. Hence, periods of high financial fragility,

[2] I follow empirical works using Bayesian VAR with the endogenous variables in levels. The information that macroeconomic variables in levels behave as random walks with unit root is incorporated into the model through the prior, as already mentioned. In addition, working with the variables in levels preserves the cointegrating relationships among the endogenous variables. I also apply the panel cointegration tests of Pedroni (1999) and reassuringly find the presence of cointegration in the regional time series (the results of these tests are available upon request).

characterised by an increase in the number of defaulting borrowers and thus an increase in the flow of NPLs relative to the stock of good loans, push banks to increase the interest rates charged on loans. Moreover, in those periods credit constraints become more binding and information asymmetries arise (Stiglitz and Weiss, 1981), leading to a deterioration of credit market conditions and an increase in the cost of borrowing. Therefore, I identify this type of shock affecting the bad loans rate, which I will also call a 'financial fragility shock', as one that increases both bank interest rates on loans and the bad loans rate. Being the outcome variable of interest, the unemployment response is left unrestricted. The sign restrictions are summarised in Table 3.

Endogenous variables	Financial fragility shock
Interest rates	+
Bad loans rate	+
Unemployment rate	O

Table 3: Sign restrictions. *Note* O means that the response of the variable to the shock is left unrestricted.

Compared to other identification strategies, this approach has the advantage of being feasible and also suitable, the literature on the risk-return trade-off being well established. The use of zero restrictions in the short run, which has been widely used in applied research using VARs, implies that the response of some variables to the shock of interest is constrained to zero within a quarter. In the analysis of this paper, it is difficult to say which of the variables is the most exogenous within a quarter. Perhaps the financial variables are more quickly responsive to shocks, while the unemployment rate is a slower moving variable than the other two. However, it is difficult to say that the unemployment rate responds with a one-quarter lag to the financial shock, because labour contracts expiring at the time of the financial shock may not be renewed in the same quarter as the financial shock occurs, leading to an increase in unemployment. The application of the sign restriction framework represents a great advantage in this respect, because it does not impose zero exclusion restrictions on the contemporaneous effects of a shock on a variable. Another feasible approach would be the proxy-SVAR that requires finding an instrumental variable for the shock of interest. However, as mentioned above, it is already extremely difficult to find quarterly regional data over a long period of time and thus much more complicated to find a variable that satisfies the conditions of exogeneity and relevance typical of IVs. Compared to this approach, the sign restriction approach exploits the information provided by the endogenous variables alone, without the need to introduce external instruments, and makes it possible to easily identify the shock based on the theoretical literature already mentioned on the risk-return trade-off, which allows the imposition of unambiguous restrictions on the sign of the response of interest rates and the bad loans rate to the financial fragility shock. This approach was also used by Cipollini and Parla (2018) to identify credit supply and demand shocks in a panel of 103 Italian provinces during the Great Recession.

As far as the implementation of this approach is concerned, after estimating the reduced-form VAR in equation (1), I adopt the approach described in Rubio-Ramirez et al. (2010), Arias et al. (2014) and Dieppe et al. (2016). In general, the covariance matrix Ω of the reduced-form VAR can be decomposed as $\Omega = A_0^{'}A_0$, where A_0 is the matrix containing the on impact response of the endogenous variables to the structural shocks, and therefore it links the reduced-form shocks (VAR residuals) to the structural shocks, $\mathbf{u}_{i,t} = A_{0,i}\epsilon_{i,t}$. The method consists of drawing a $n \times n$ matrix M from a multivariate normal distribution, taking the QR decomposition of M and computing the candidate for the structural impact matrix as $A_0 = PQ$, where P is the Cholesky decomposition of Ω, $P = chol(\Omega)$. This candidate matrix is retained if it satisfies the sign restrictions on the shock to the bad loans rate, summarized in Table 3 (the details of this algorithm are provided in Appendix C).

4 Results

I begin by showing the average regional effects and conducting robustness checks on these results. Next, I will focus on macro-regional differences and the analysis of the association between the regional effects of the financial fragility shock on unemployment and some regional characteristics.

4.1 The average regional effects of financial fragility shocks

Figure 5 shows the average regional dynamic effects of a financial fragility shock on the three endogenous variables included in the VAR, i.e. the Impulse Response Functions (IRFs), obtained by averaging the posterior distribution of these IRFs across regions. The x-axis represents the quarters after the shock and the dynamic effects are represented up to 5 years (20 quarters) after the shock. The solid black lines represent the median of the IRF posterior distributions, while the darker and lighter grey shaded areas represent the 68% and 90% posterior credibility intervals, respectively. Although the response of interest rates and the bad loans rate is constrained to be positive on impact, their IRFs remain positive for the majority of the quarters following the shock and the credibility intervals are very narrow. A one standard deviation shock to the bad loans rate produces an increase of 0.35 percentage points on itself and thereafter the response begins to fall, reaching values close to zero after 17 quarters. Interest rates increase by about 0.12 percentage points at the time of the shock and then their response also starts to decline. The financial fragility shock produces high real costs, increasing the regional unemployment rate. The response is about 0.06 percentage points at the time of the shock, which, however, becomes stronger afterwards, reaching a value close to 0.20 percentage points after ten quarters. These results show that a financial fragility shock has high and significant negative regional effects. Increases in financial fragility, characterised by higher default rates, which signal deteriorating private sector economic conditions and worsening bank balance sheets, cause high and significant job losses. These results are in line with findings in the literature showing high and negative economic effects of financial shocks and financial fragility (Mallick and Sousa, 2013; Caldara et al., 2016) and those showing that financial shocks and financial fragility have negative effects on employment (Boeri et al., 2013; Chletsos and Sintos, 2021). Moreover, these findings are in line with studies such as those of Mian and Sufi (2014), Dijkstra et al. (2015), Di Caro (2015) and Compagnucci et al. (2022) which show that financial shocks and financial crises are also detrimental to regional economies.

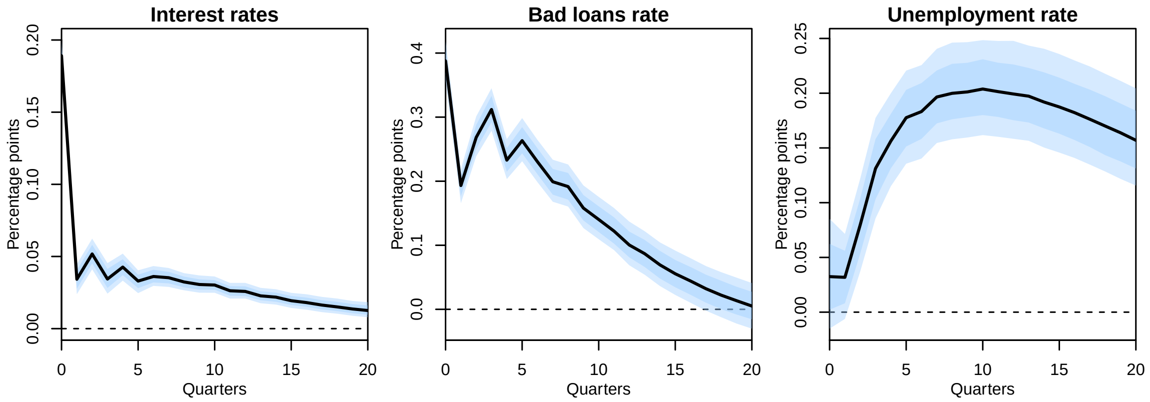

Figure 5: Impulse response functions to a financial fragility shock. Notes: The black solid lines represent the posterior median. Darker and lighter shaded areas are, respectively, 68% and 90% credibility intervals.

4.2 Robustness checks

Before moving on to the extension of the analysis, I conduct some robustness checks for the baseline results of the previous section. Figure 6 shows the results of these tests, where the empirical exercises are represented by row and the variables by column.

VAR lag order. The first robustness test concerns the choice of the number of lags in the VAR model. In the baseline model, I use the standard rule of setting the number of lags equal to the frequency of the dataset, thus including four lags. I test whether the results are driven by this choice by estimating the VAR with different lag lengths, from 2 to 6. The first row of Figure 5 shows that, reassuringly, the choice of the lag length has no effect on the results, the dashed lines being very close to the baseline results and within the 68% and 90% credibility intervals of the baseline model.

Exclusion of the Covid-19 period and the subsequent sample. The period after the first quarter of 2020 was characterised by the occurrence of the Covid-19 pandemic, which saw large movements in the macroeconomic time series, creating some problems for the estimation of time series models such as the VAR (see Lenza and Primiceri, 2022). Although the regional time series that I use in this analysis did not show these large movements, as shown in Figure 3, for reasons such as the substantial measures put in place by the Italian government to minimise job losses and limit bank defaults, I test whether the exclusion of this sample, as suggested by Lenza and Primiceri (2022), introduces large changes in the baseline results. Therefore, I estimate the model using data up to the last quarter of 2019.

The results in the second row of Figure 4 show that the IRFs are very close to the ones obtained from the baseline model and mostly within its 68% and 90% credibility intervals.

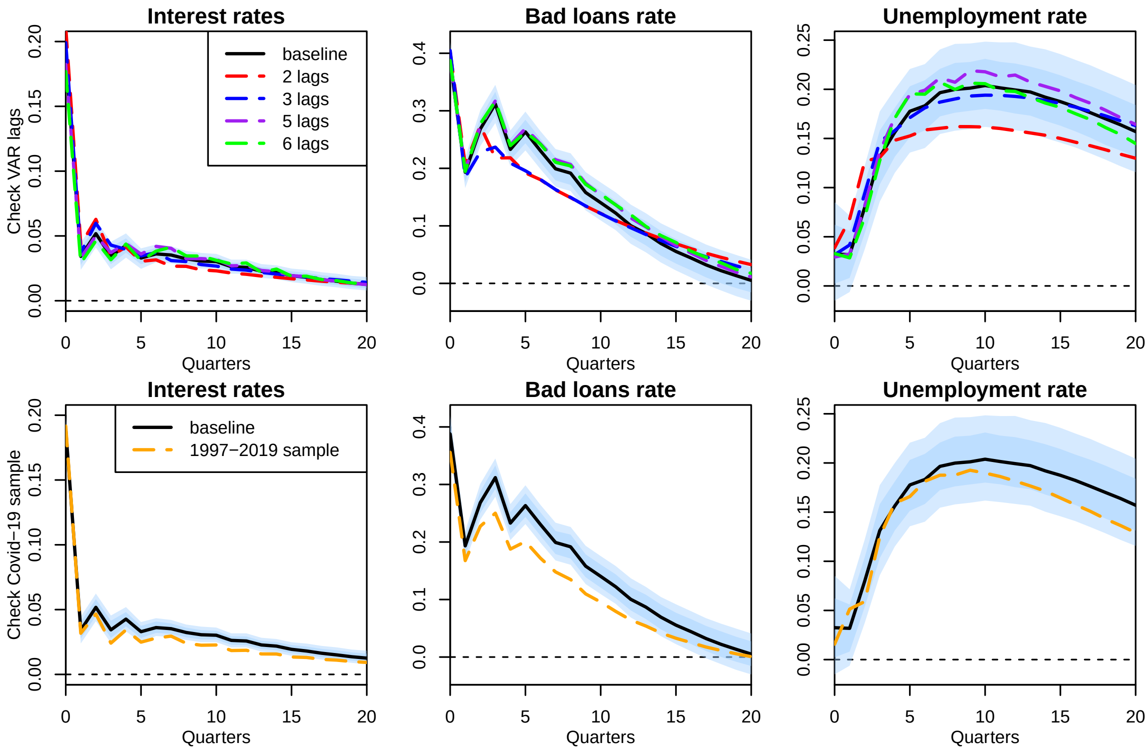

Figure 6: Robustness checks. Notes: Darker and lighter shaded areas are, respectively, 68% and 90% credibility intervals of the baseline VAR.

5 Delving into regional heterogeneity

In Section 1 and 2, I already mentioned that the Italian regions are particularly heterogeneous and that there is a clear division into two parts, the North, which historically has a higher level of economic and financial development, and the South, also known as 'Mezzogiorno', characterised by lower levels of development and worse structural conditions. These different economic and structural characteristics of the two areas can influence how regions react to shocks like the one I study in this article. Regions with a higher level of economic development are better positioned to absorb a financial shock, and a higher level of financial development makes regional economies more resilient to this shock and better equipped to cushion the consequences of financial fragility. Indeed, country-level evidence from Chletsos and Sintos (2021) finds larger negative effects of financial fragility on employment in countries with a lower level of financial and economic development. Another feature of the Italian economy is the marked difference in unemployment levels between the two macro-areas. Figure 1 clearly shows higher average levels of unemployment rate, during the sample period, in the South of the country. Furthermore, in Figure 2 it can be noted that unemployment rates are persistently higher in the South. In fact, the time series of the unemployment rate in the South is always higher than that of the Centre-North. Furthermore, as indicated by the gray bars, this gap widened around 2007-08 and increased even more in 2011, meaning that the South suffered greater job losses during the financial crisis. All this suggests that regions in the South have worse economic and structural conditions and may be more vulnerable and less resilient to shocks. Therefore, I analyse whether the effects of the financial fragility shock on unemployment differ between North and "Mezzogiorno" of Italy and depending on the level of development. First, I consider the geographical division, calculating the average IRF across regions belonging to the Centre-North and the South. Second, I compare the results of regions with values below and above the median regional GDP per capita. Third, I move towards the tails of the per capita GDP distribution to see how the effects change when comparing regions in the bottom quartile of the per capita GDP distribution and those in the top quartile. Fourth, I try to link the regional effects of the financial fragility shock on unemployment to certain regional characteristics related to the economy, the credit market, competitiveness and the labour market.

5.1 The heterogeneous effects in the Centre-North and 'Mezzogiorno'

Given the marked difference between Northern and Southern Italy, highlighted above, I first compare the effects in these two macro-areas. I average the IRFs for the North-Central and Southern regions[3].

Figure 7 shows the results. The top panels contain the IRFs averaged across the two macro-areas. The red lines with dots represent the effects in the South and the darker and lighter pink shaded areas are the associated 68% and 90% credibility intervals, respectively. The blue solid lines show the results for the Centre-North, while the blue dashed lines are the associated 68% and 90% credibility intervals. I also calculate medians and intervals for the difference in the IRFs between the two groups of regions. Having the posterior distribution available, I can compute the difference between the posterior distribution of the IRFs in the two macro-areas and calculate the quantiles of this distribution, to make inference on the differential effects between the two macro-areas, which makes it easy to check whether this difference is statistically significant. The bottom panels show the median of the posterior distribution of the difference in the IRFs with green lines, and the 68% and 90% credibility intervals are represented by green shaded areas. The effects of the shock on the bad loans rate are similar in the two areas and the difference is not significant, as is clear from the bottom panels. Although interest rates increase more in the South at the time of the shock, the difference with the North decreases thereafter and is mostly not significant. Focusing on the target variable, one can see much higher real costs of the financial shock in the South. The unemployment rate increases by about 0.12 percentage points at the time of the shock in this macro-area, compared to a smaller response in the North, which is about

[3]The regions in the Centre-North are those in the NUTS-1 (Nomenclature of Territorial Units for Statistics level 1) area classified as North-West, North-East and Centre, i.e. Piemonte, Valle d'Aosta, Liguria, Lombardia, Trentino-Alto Adige, Veneto, Friuli-Venezia Giulia, Emilia-Romagna, Toscana, Umbria, Marche, Lazio. In the Southern area, I consider the regions of the South and the Islands according to the NUTS-1 classification. They are the following: Abruzzo, Molise, Campania, Puglia, Basilicata, Calabria, Sicilia e Sardegna.

0.10 percentage points lower. This difference is significant at the 68% level. The peak of the unemployment response in the South is about 0.25 percentage points, compared to less than 0.15 percentage points in the North. The peak of the differential response in the two macro-areas occurs 8 quarters after the shock and is about 0.10 percentage points. Therefore, I find that the financial fragility shock has worse consequences in the South. This area is more affected and suffers more job losses after the bad loan rate shock. In contrast, the Centre-North is more resilient and suffers lower costs from the financial shock.

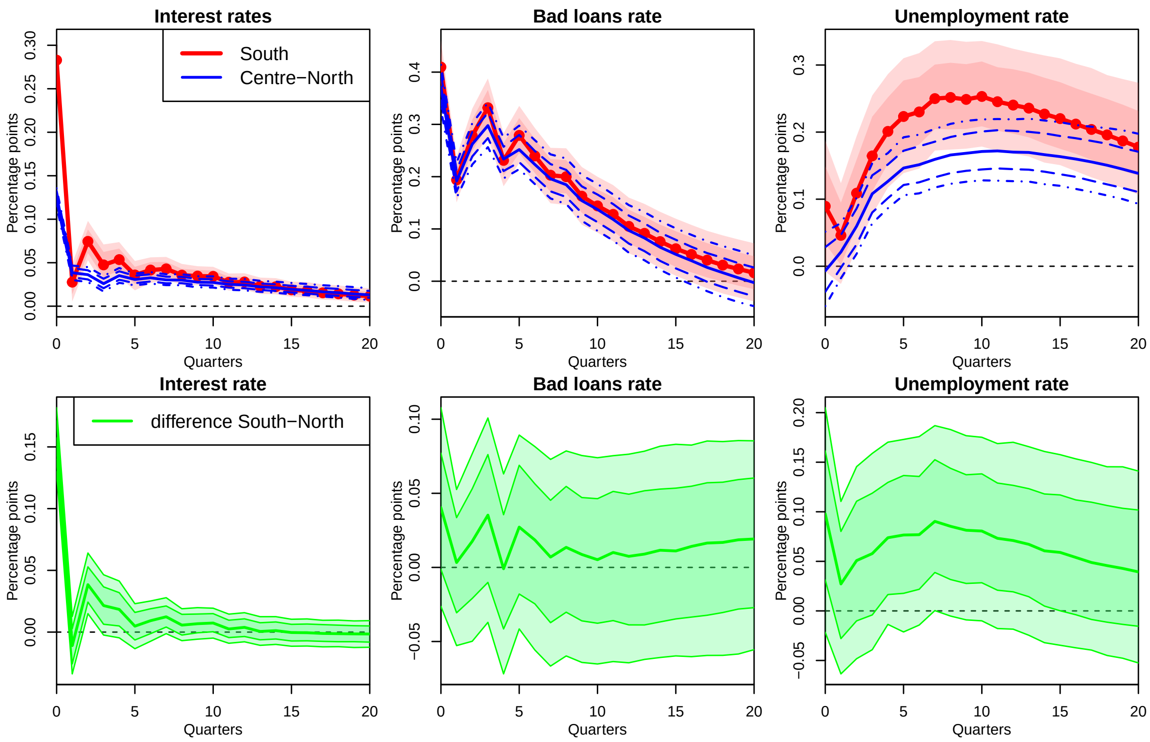

Figure 7: Effects in the South and Centre-North. Notes: The top panels show the IRFs in the South and Centre-North. The red lines with dots are for the South, with the pink shaded areas representing the associated 68% and 90% credibility intervals. The blue lines are for the Centre-North, with the blue dashed lines representing the associated 68% and 90% credibility intervals. The bottom panels show the difference in IRFs between the two macro-areas. The solid green lines represent the posterior median of this difference, and the green shaded areas the 68% and 90% credibility intervals.

5.2 The role of economic development

As already mentioned, the Italian regions are very heterogeneous in terms of levels of economic development. Figure 1 shows that there are large differences in regional GDP per capita levels. In this section, I analyse the difference in the responses to the financial fragility shock in different groups of regions depending on the distribution of regional GDP per capita. First, I divide the sample into regions with a GDP per capita level above the median and take the average IRF in these regions. I compare them with the average IRF obtained from the subsample of regions with a GDP per capita level below the median. Figure 8 shows the results of this exercise, where the top panels contain the IRFs for the two subgroups of regions, in red for less developed regions and in blue for more developed ones. Furthermore, as in the previous section, I plot the median and quantiles of the posterior distribution of the differences in the IRFs in the two groups of regions. As can be seen from Figure 8, the effects of the financial fragility shock vary according to the level of economic development. The response of the bad loans rate to the financial fragility shock is slightly higher in less developed areas and the difference is only significant at the 68% level. This means that the increase in credit risk is somewhat higher in less developed areas. In addition, less developed regions experience a greater deterioration in credit market conditions, as interest rates rise more in these regions, and the difference with respect to the effects in more developed regions is significant up to twelve quarters after the shock. The economic costs of the financial fragility shock are higher in the less developed area, as shown by the response of the unemployment rate in Figure 8. Looking at the last plot in the bottom panels of Figure 8, this difference is significant at the 90% level between four and sixteen quarters after the shock and is almost always significant at the 68% level. The maximum difference is about 0.12 percentage points and occurs about one year after the shock.

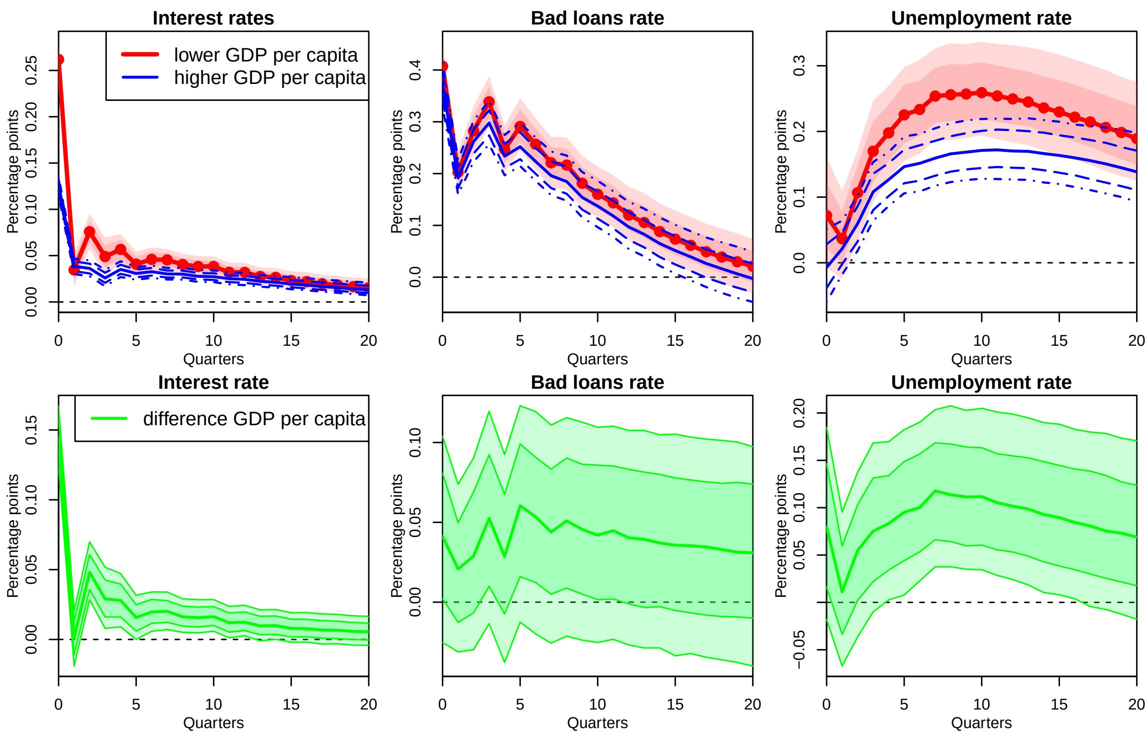

Figure 8: Effects in more versus less developed regions. Notes: The top panels show the IRFs in the sub-group of regions with a GDP per capita lower than the median (red lines with dots, with the pink shaded areas representing the associated 68% and 90% credibility intervals) and in the sub-group of regions with a GDP per capita higher than the median (blue lines, with the blue dashed lines representing the associated 68% and 90% credibility intervals. The bottom panels show the difference in IRFs between these two sub-groups of regions. The solid green lines represent the posterior median of this difference, and the green shaded areas are the associated 68% and 90% credibility intervals.

In addition, I also move towards the tails of the GDP per capita distribution to see whether the difference in the reaction of the regions to the shock increases when comparing regions with very low levels of GDP per capita and those with very high levels of GDP per capita. For this purpose, I average the IRFs across the regions that are below the first quartile of the GDP per capita distribution and those with GDP per capita levels above the third quartile. The results of this exercise are shown in Figure 9, where, in the top panels, the red lines represent the results for the lower quartile regions, while the blue lines are for the upper quartile regions. The bottom panels show the median, 68% and 90% credibility intervals of the difference in the posterior distribution of IRFs between the two groups of regions considered in this exercise.

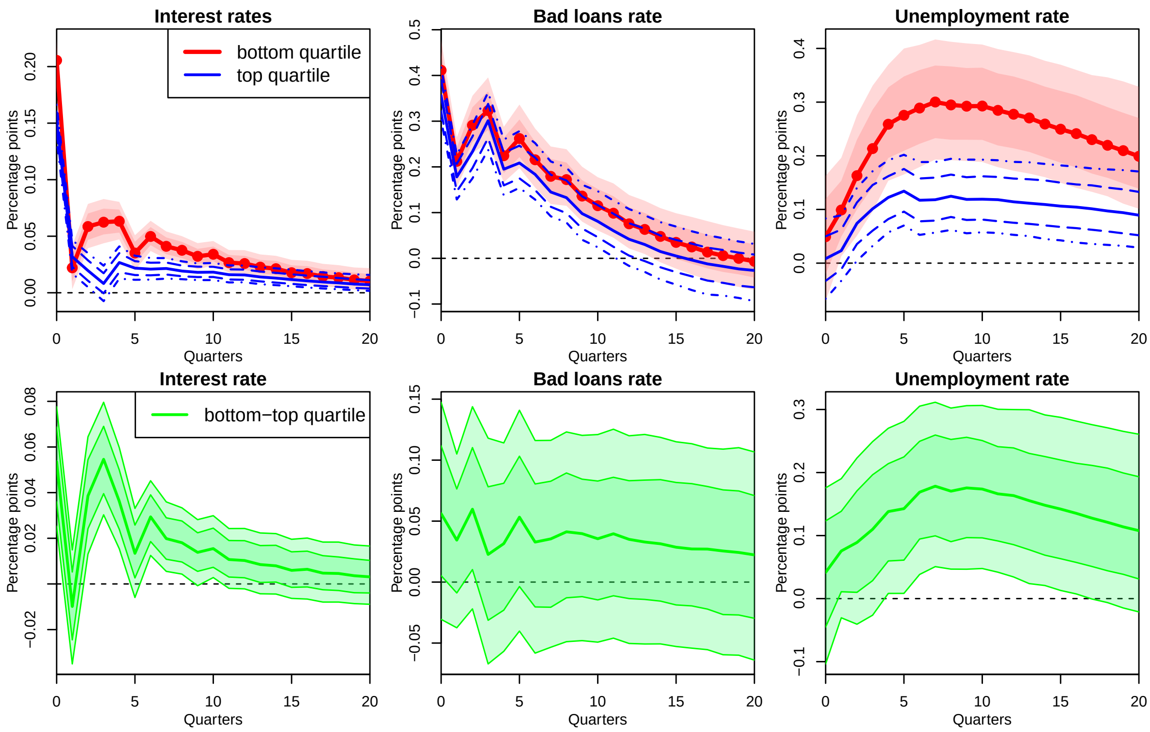

Figure 9: Effects in regions located in the bottom and top quartile of the regional GDP per capita distribution. Notes: The top panels show the IRFs in the sub-group of regions with a GDP per capita lower than the first quartile (red lines with dots, with the pink shaded areas representing the associated 68% and 90% credibility intervals) and in the sub-group of regions with a GDP per capita higher than the third quartile (blue lines, with the blue dashed lines representing the associated 68% and 90% credibility intervals. The bottom panels show the difference in IRFs between these two sub-groups of regions. The solid green lines represent the posterior median of this difference, and the green shaded areas are the associated 68% and 90% credibility intervals.

The response of the bad loans rate is somewhat higher in the very least developed regions. Interest rates are significantly higher at some horizons after the shock in regions in the bottom quartile of the distribution of GDP per capita. Remarkably, the difference in the unemployment response increases when comparing regions in the first and third quartiles of the GDP per capita distribution compared to the previous case where the median is used as the cut-off to divide regions. The reaction of the unemployment rate is much stronger in regions in the bottom quartile of the distribution of GDP per capita. The peak effect is about 0.3 percentage points in these less developed regions, compared to a peak response of about 0.1 percentage points in regions in the upper quartile. The difference is significant at both the 68% and 90% level for most quarters after the shock, as shown in the last plot of the bottom panels in Figure 8. In summary, increasing levels of local financial fragility, when default rates rise and borrowers find it difficult to repay loans to banks, thus also causing problems for the latter and leading to a deterioration of the balance sheets of both the non-financial private sector and banks, has negative effects on regional unemployment in Italy. These effects are accentuated when focusing on Southern Italy and when considering the less developed regions in terms of GDP per capita, with even higher employment costs when considering Italian regions in the bottom quartile of the GDP per capita distribution. The difference in the response of unemployment to the financial shock compared to that observed for the more developed regions is important both economically and statistically, with a peak of almost 0.20 percentage points, which means that the financial shock leads to an increase in unemployment in the less developed regions of 0.20 percentage points higher than that in the more developed area. Given the heterogeneity of the regional effects of the financial fragility shock, in the next subsection I will try to investigate some potential determinants of this difference, linking the regional effects to some regional economic and structural characteristics.

5.3 What could be the potential regional characteristics related to the heterogeneous impact of the financial fragility shock in the Italian regions?

This subsection is devoted to the analysis of the potential regional characteristics that may be associated with the heterogeneous effects of the financial fragility shock across the Italian regions. I follow Destefanis et al. (2022) and Coppola et al. (2024) by collecting data on some regional factors and analysing the association of these factors with the regional effects of the financial fragility shock on unemployment. In particular, I calculate the correlations between these effects and some potential regional determinants related to the economy, the credit market and the labour market[4]. Table 4 contains estimates of these correlations for the effects at impact and at one, two, three, four and five years after the financial fragility shock.

First, along the lines of the previous section, I test whether the regional effects are correlated with the level of regional economic development by estimating the correlation between these effects and regional GDP per capita. I find a negative correlation, suggesting that the regions with a lower level of economic development tend to experience worse effects of financial fragility shocks. This is in line with the results presented in Section 5.2, where I compare the IRFs across groups of regions characterised by different levels

[4]These data are only available at annual frequency and some refer to multi-year periods (in particular the RCI, labour market efficiency and level of education proxies). In addition, some of them are available for shorter periods. I use regional averages of these variables, calculated using data from the period of the main dataset constructed in section 2 (1997-2023), when available, or in sub-periods when data are not available for the entire period of the main dataset. Details on these variables and their sources are given in Appendix A.

of GDP per capita, and is also consistent with the empirical results of the cross-country evidence provided by Chletsos and Sintos (2021), which shows more negative effects of financial fragility on employment in less developed countries. Secondly, regional effects are positively correlated with unemployment rate levels, which means that financial fragility shocks have more negative effects in regions with more available unused resources (a lower degree of utilisation of factors such as employment). Third, I consider some factors related to the regional credit markets. In particular, I take the loans-to-GDP ratio and the number of bank branches per inhabitants as proxies for banking sector development and financial deepening[5], the bad loans rate as a proxy for credit risk and bank interest rates as a proxy for regional financial constraints[6].

Time after the shock	impact	one year	two years	three years	four years	five years
GDP per capita	-0.40*	-0.53**	-0.60***	-0.58***	-0.54**	-0.49**
Unemployment	0.34	0.64***	0.59***	0.52**	0.47**	0.43*
Loans/GDP	-0.52**	-0.13	-0.22	-0.24	-0.23	-0.21
N° bank branches per capita	-0.37	-0.65***	-0.57***	-0.50**	-0.44*	-0.40*
Credit risk	0.47**	0.52**	0.60***	0.53**	0.47**	0.41*
Interest rate levels	0.50**	0.47**	0.59***	0.56***	0.50**	0.44*
RCI	-0.50**	-0.44*	-0.46**	-0.43*	-0.38*	-0.33
Labour market efficiency	-0.36	-0.64***	-0.62***	-0.54**	-0.48**	-0.42*
Higher education	-0.41*	-0.50**	-0.46**	-0.42*	-0.38*	-0.33
Temporary workers share	0.47**	0.60***	0.61***	0.56**	0.47**	0.39*

Table 4: Cross-sectional correlations between regional effects of financial fragility shocks on unemployment (over some selected horizons) and some regional variables. *Note* ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. This test is based on z Fisher Transform, which has a t-distribution with n-2 d.g.f under the null hypothesis of two independent normal distributions.

The response of regional unemployment to financial fragility shocks is negatively correlated with the ratio of loans to GDP and the number of bank branches per inhabitant. The higher the level of financial development/deepening of regions, the lower the effects of financial fragility shocks on unemployment. This negative correlation is particularly strong when considering the number of bank branches per inhabitant. These results are in line with the aforementioned findings of Chletsos and Sintos (2021), which show that employment in countries with a higher level of financial development is less affected by financial fragility shocks. Moreover, the correlation between the regional effects and the level of the bad loans rate is positive, which means that higher credit risk is associated with worse effects of financial fragility shocks on unemployment. Regions with a higher non-performing loans rate tend to be more affected by financial fragility shocks, indicating that the credit risk prevailing in the regional banking market is important when the region is hit by a financial fragility shock. Interest rate levels are also positively correlated with the regional effects. Higher interest rates, i.e. higher financing costs, can be read as meaning that, in regional credit markets, borrowers have more difficulties in accessing

[5]Destefanis et al. (2022) and Rossi and Scalise (2022) use the number of bank branches per inhabitants as proxy for regional financial development.

[6]I follow Destefanis et al. (2022) and Coppola et al. (2024) in using bank interest rates levels to proxy regional credit market constraints.

the market due to these higher costs, thus indicating more stringent financial constraints. Thus, the positive correlation between interest rate levels and regional effects of the financial fragility shock on unemployment may indicate more damaging effects of this shock in regions with greater financial constraints. In these regions, firms already have more difficulties in obtaining loans, and obviously such difficulties increase when these regions are hit by a financial fragility shock. Firms in regions with more limited access to finance, when hit by a financial fragility shock, may reduce employment and stop hiring, leading to an increase in the unemployment rate after the shock. Fourth, I use the Regional Competitiveness Index (RCI) to test whether the degree of regional competitiveness is somehow correlated with the effects of the bad loans shock on unemployment. There is a negative correlation between the two, which suggests that less competitive regions are more affected by the financial fragility shock. More competitive regions create a better environment for firms, so the less competitive the region, the higher the employment costs it will bear after the shock. Finally, I relate the regional effects of the financial fragility shock on unemployment to some regional labour market characteristics. In particular, I consider labour market efficiency, education level and the share of temporary workers. The results in Table 4 show a high and significant negative correlation with labour market efficiency, whereby the higher the regional labour market efficiency, the lower the increase in regional unemployment after the financial fragility shock. Furthermore, the level of education is negatively associated with the regional effects of financial fragility shocks on unemployment. Regions with a higher level of education experience a smaller increase in unemployment after the shock. The correlation with the share of temporary workers is positive and high. The higher the share of workers with fixed-term contracts, the more vulnerable they are to the occurrence of shocks, as, for example, firms may no longer renew these contracts. Thus, an adverse financial shock leads to greater employment losses in regions with a higher share of temporary workers.

In summary, this section shows that the effects of financial fragility shocks on unemployment are heterogeneous across the Italian regions. The country is characterised by a centuries-old North-South divide with the South being less developed. The different economic and structural conditions of the regions make them more or less vulnerable to negative financial shocks. Indeed, the South suffers from higher unemployment after the financial fragility shock. The level of regional economic development is crucial, with higher effects in less developed regions, which worsen when considering regions in the bottom quartile of the GDP per capita distribution. This regional heterogeneity is associated with certain regional characteristics. In particular, the lower the regions' level of economic and financial development, competitiveness, labour market efficiency and education, the higher the costs, in terms of increased unemployment, that these regions experience after being hit by a financial fragility shock. The same applies to regions with higher levels of unutilised available resources, financial constraints, credit risk and share of temporary workers.

6 Conclusions

This paper analyses the effects of a shock to financial fragility on unemployment in the Italian regions. I construct a novel dataset at quarterly frequency, for the 20 Italian regions over the period 1997Q1-2023Q3, which includes data on bank interest rates and the bad loans rate, collected from the Bank of Italy database, and data on the regional unemployment rate retrieved from the National Institute of Statistics (ISTAT). As a result, this dataset covers a long time span with quarterly frequency for all the Italian regions and allows for an in-depth study not only of average regional effects, but also of regional heterogeneity in the reaction of unemployment rates to deteriorating conditions in regional credit markets, which occurs when the share of non-performing loans increases relative to the stock of good loans. This signals a worsening of the economic conditions of borrowers, i.e. households and businesses, who are unable to repay their loans to banks. Moreover, this creates problems for the banks themselves, which see their balance sheets deteriorate, leading to a drop in lending activity, which aggravates the already vulnerable economic conditions of households and businesses. In such an environment, growth may be low and firms may stop hiring or renewing employment contracts, generating unemployment.

I study this issue by fitting a vector autoregression (VAR) to the above variables, for each Italian region, and identifying the financial fragility shock through sign restrictions. Drawing from the financial literature on the risk-return trade-off (Markowitz 1952), I assume a positive response of bank interest rates and the bad loans rate to the shock, reflecting the fact that higher credit risk leads to lower expected returns for banks, which transfer them to future borrowers by raising interest rates.

The results show negative effects of increased financial fragility on unemployment. A one standard deviation shock to the bad loans rate leads to an increase in regional unemployment rates, which on average peaks at about 0.20 percentage points after 10 quarters. This average effect hides significant regional heterogeneity. In fact, the less developed area of the South is more affected, registering larger increases in unemployment after the shock, where the unemployment rate increases by almost 0.1 percentage points more than in the North. The gap widens when looking at the difference in economic development, proxied by regional GDP per capita. Regions with a GDP per capita below the median experience a larger increase in unemployment after the shock, with the gap widening to about 0.20 percentage points when comparing regions in the bottom quartile with those in the top quartile of the regional GDP per capita distribution. Finally, I relate these regional effects to certain regional characteristics, finding that regions with a lower level of economic and financial development, a lower level of competitiveness and a higher level of unused resources are more affected by the financial fragility shock. Furthermore, regions with a higher credit risk and tighter financial constraints experience higher effects of the financial fragility shock. Finally, larger effects are found in regions with a lower level of education and labour market efficiency and a higher share of temporary workers.

Overall, the paper emphasises the importance of considering the heterogeneous characteristics of regional economies when assessing the consequences of shocks, and that aggregate results may actually conceal significant regional heterogeneity within a country. This is the case in Italy, which historically shows marked regional differences. This calls for an accurate understanding of this heterogeneity when assessing the vulnerability of local entities to economic and financial shocks and suggests tailored local policy interventions. Moreover, it sheds light on the need for a sustained effort to try to improve the economic conditions of regions suffering from worse economic and structural conditions, as in the case of Southern Italy.

Appendices

Appendix A: data details

This appendix details the construction of the dataset and provides information on the other data used in Section 5. The bad loans rate is taken from the Bank of Italy's database, named 'Base Dati Statistica' (BDS). The entire regional time series is available in Table TRI30496 (I used the one which is defined on the amount of loans). However, there are no unified series for interest rates. This data were released in different tables. Therefore, I combined different parts of the database, using the previous and the most recent versions. Furthermore, after 2019, I only found separated data for households and legal entities. Therefore, to represent the general financial conditions applied to any type of borrower, I averaged the interest rates applied to loans to households and the interest rates applied to loans to businesses and other entities. In particular, the regional series on bank interest rates were constructed using the following parts of the BDS database:

- table TDB30610 for the period 1997Q1-2003Q4;
- table TDB30615 for the period 2000Q1-2003Q4;
- table TRI30830 for the period 2004Q1-2019Q4;
- average between data in table TRI31100 and TRI30881, as explained above, for the period 2020Q1-2023Q3.

Since this variable was constructed using different parts of the database, in order to make sure that these regional series well approximate the credit market conditions, I compare the regional distribution of interest rates with the time series of the lending rate in Italy, at annual frequency, from a different data provider, to check whether the size and time evolution of the interest rates series I constructed are plausible and in line. In particular, I take the lending rate for Italy from the IMF/World Bank Database. Figure 10 compares the regional series with the Italian lending rate (all in nominal terms). One can see that the regional interest rates are in line with the size of the Italian lending rate and that the evolution over time is similar.

The unemployment rate is constructed as the ratio between the number of unemployed people and the number of people in the labour force. This information is taken from the Italian National Institute of Statistics (ISTAT).

Here I also provide some details on the data used in section 5. (i) GDP per capita is computed using data on regional GDP and population from ISTAT. (ii) To compute the loans to GDP ratio I use data on regional loans from the Bank of Italy's BDS database. (iii) The number of bank branches per 100000 inhabitants is taken from the Bank of Italy's BDS database. (iv) Credit risk is proxied by the bad loans rate. (v) The Regional Competitiveness Index, along with the indicator of labour market efficiency and higher education, come from the European Commission. The labour market efficiency scores are based on considering labour market characteristics of the regions, such as the employment rate, long-term unemployment, labour productivity, gender balance employment and unemployment, female unemployment, involuntary part-time/temporary employment, the NEET (share of youth people who are neither in employment nor in education or training). The higher educations scores are based on variables such as the following: higher education attainment, lifelong learning, accessibility to universities, early school leavers, lower-secondary completion only, gender balance on tertiary education (more details can be found in the description of the indicators at the link `https://ec.europa.eu/regional_policy/assets/regional-competitiveness/index.html#/`). (vi) Finally, the temporary workers share is computed using data from ISTAT on the number of people with temporary contracts.

(a) Lending rate for Italy from the IMF/World Bank

(b) Distribution of constructed regional series

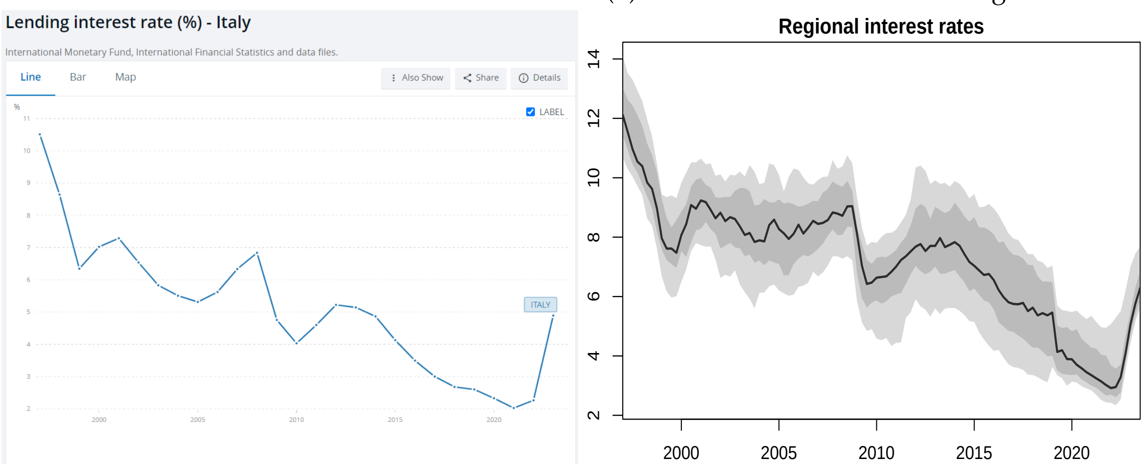

Figure 10: Comparison between Italian lending rate from IMF/World Bank database and the regional series constructed in this paper. *Note* In panel (b), the black solid line is the regional median, the darker gray shaded area is the inter-quartile range of the regional distribution and the lighter gray shaded area is delimited by the 5-th and 95-th quantiles of the regional distribution.

Appendix B: Bayesian estimation of the VAR

To present the Bayesian estimation of equation (1), it is better to represent the model by combining all the regressors $Y_{i,t-1}$ and $W_{i,t}$, in a matrix X_i. I can now re-write the VAR in equation (1) as follows:

$$Y_i = X_i B_i + U_i \tag{2}$$

Let me denote by T the time series length, by n the number of endogenous variables in the VAR, by p the lag length and by m the number of exogenous variables (only the constant, thus $m = 1$). In equation (2), for each region i, Y_i is the $T \times n$ matrix of endogenous variables, X_i is the $T \times (np+m)$ matrix of regressors, with an associated $(np+m) \times n$ matrix of coefficients B_i, and U_i is the $T \times n$ matrix of reduced-form residuals, in stacked form. I introduce a Normal-Inverse Whishart prior, following the approach of Bańbura et al. (2010), by using dummy observations (or artificial data). These dummy observations are added to the observed data, and they are constructed in such a way that allow to introduce the prior assumptions of the econometrician (Blake and Mumtaz, 2012). Let me denote these artificial data by Y_D and X_D, and for ease of exposition, let me remove the subscript i for the regions, knowing that the model is estimate region-by-region. The prior is as follows:

$$\begin{aligned} &p(B|\Sigma) \sim N\left(b_0, \Sigma \otimes (X_D' X_D)^{-1}\right) \\ &p(\Sigma) \sim IW\left(S, T_D - n + m\right) \end{aligned} \tag{3}$$

with prior moments represented by:

$$\begin{aligned} &B_0 = (X_D' X_D)^{-1} X_D' Y_D \\ &b_0 = vec(B_0) \\ &S = (Y_D - X_D B_0)'(Y_D - X_D B_0) \end{aligned} \tag{4}$$

where T_D is the number of artificial observations. The following are the conditional posterior distributions:

$$\begin{aligned} &H(b|\Sigma, Y) \sim N\left(vec(B^*), \Sigma \otimes (X'^* X^*)^{-1}\right) \\ &H(\Sigma|b, Y) \sim IW\left(S^*, T^*\right) \end{aligned} \tag{5}$$

where T^* is the total number of observations with the artificial data appended, and S^* the scale matrix of the Inverse-Wishart distribution:

$$\begin{aligned} &B^* = (X'^* X^*)^{-1} X'^* Y^* \\ &S^* = (Y^* - X^* b)'(Y^* - X^* b) \end{aligned} \tag{6}$$

where $Y^* = \begin{bmatrix} Y \\ Y_D \end{bmatrix}$ and $X^* = \begin{bmatrix} X \\ X_D \end{bmatrix}$ (see Blake and Mumtaz, 2012).

As already anticipated, the artificial observations are constructed as in Bańbura et al. (2010), in order to match the Minnesota moments (Litterman, 1986):

$$Y_D = \begin{pmatrix} \text{diag}(\delta_1\sigma_1, \cdots, \delta_n\sigma_n)/\lambda \\ 0_{n(p-1)\times n} \\ \cdots \\ \text{diag}(\sigma_1, \cdots, \sigma_n) \\ \cdots \\ 0_{m\times n} \end{pmatrix} \quad X_D = \begin{pmatrix} J_p \otimes \text{diag}(\sigma_1, \cdots, \sigma_n)/\lambda & 0_{np\times m} \\ \cdots & \cdots \\ 0_{n\times np} & 0_{n\times m} \\ \cdots & \cdots \\ 0_{m\times np} & \text{diag}(\epsilon)_{m\times m} \end{pmatrix} \quad (7)$$

In setting the parameter in (7) I follow standard empirical macroeconometric literature. In particular, δ_i are the prior means of the first lag of the i-th endogenous variable, which are set equal to 1, as in the Minnesota prior, for their own lag, to reflect the fact that macroeconomic data in levels behave as random walk with unit root; σ_i are estimated by computing the standard deviation of the residual of an AR(1) model fitted to each endogenous variable; $J_p = \text{diag}(1, \cdots, p)$; λ controls the overall tightness of the prior and ϵ controls the tightness of the priors on the constant. In setting these two latter, I follow Mumtaz and Theophilopoulou (2017) and Mumtaz and Theodoridis (2020), among others, by giving a large value to λ (100000) and a small value to ϵ (1/1000), which means imposing a very flat prior and giving more weights to the data, thus letting the results being more data driven. In (7), the first block of the matrices imposes prior information on the coefficients of the lags, the second one on the reduced-form covariance matrix, and the last one on the coefficients of the exogenous variables. This approach requires a Gibbs sampler. I run 2000 repetitions but I use the last 1000 draws for inference, as it is usually done to remove dependence from starting values in the algorithm. The algorithm is described in the two following steps:

- draw the vectorized matrix of VAR parameters from $H(b|\Sigma, Y)$ in (5), keeping stable draws only, i.e. taking the ones whose eigenvalues of the companion matrix are less than or equal to one;
- use the draw of b from the previous step to compute S^*, then draw the covariance matrix of the reduced-form residuals from $H(\Sigma|b, Y)$ in (4).

For each iteration, we save the draws of the VAR coefficients and the covariance matrix. The properties of the retained chains are evaluated by computing, for each region, the inefficiency factors of the VAR parameters and the unique elements of the reduced-form covariance matrix, on the last 1000 draws that we retain. This is done to check whether there is a high degree of autocorrelation in the chains. The inefficiency factor is given by the following: $IF = 1 + 2\sum_{i=1}^{20} \hat{\rho}_i$, where $\hat{\rho}_i$ is the i-th order auto-correlation. The rule of thumb is to consider satisfactory values of the inefficiency factors around or below 20 (see Primiceri 2005). Figure 11 shows very small values, around 3.

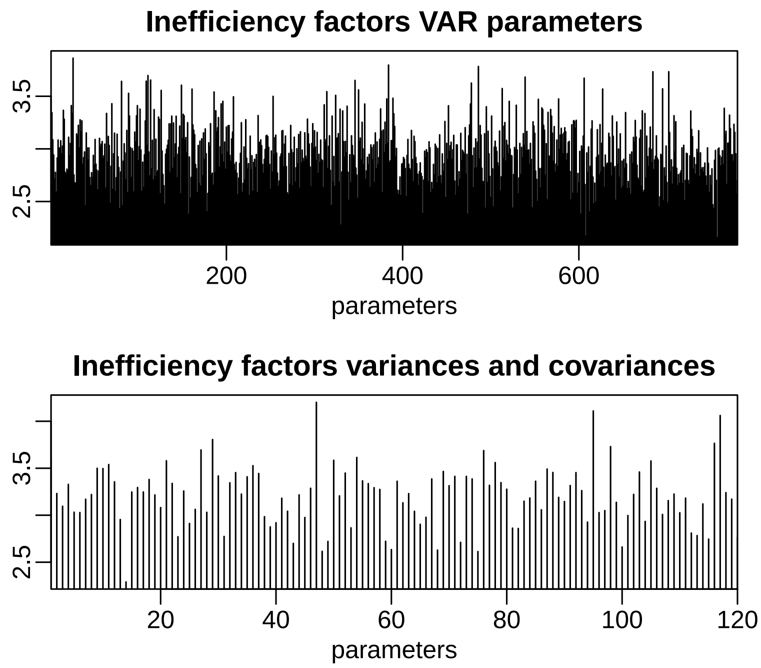

Figure 11: Inefficiency factors of the regional VARs.

Appendix C: Sign restrictions algorithm

In this appendix, I briefly discuss the algorithm used to implement the sign restrictions approach and provide some sensitivity analysis. Let me call the matrices of reduced-form IRFs, obtained from the reduced-form VAR, by Ψ_h. The following steps are performed for each iteration of the Gibbs sampling:

1. Take the lower triangular Cholesky factor, P, of the reduced-form covariance matrix $\Sigma = PP^{'}$, and compute $\bar{\Psi}_h = \Psi_h P$;

2. Define $D = PQ$, where Q is an orthogonal matrix which preserves the Structural VAR property: $D[var(\epsilon)]D^{'} = DID^{'} = PQQ^{'}P^{'} = PIP^{'} = PP^{'} = \Sigma$. I draw a $n \times n$ random matrix M from a multivariate standard normal distribution, $N(0, I)$, and apply the QR decomposition of this matrix, $M = QR$, where Q is an orthogonal matrix and R is an upper triangular matrix. Then, I compute the candidate draws of IRFs as $\tilde{\Psi}_h = \bar{\Psi}_h Q = \Psi_h PQ$.

3. If the candidate IRF draw satisfy the restrictions I save it, otherwise I discard it and repeat step 2.

4. Step 2 to 3 is repeated 100 times, thus obtaining 100 valid draws. In the baseline model I take the median of these 100 draws.

I take the IRFs closest to the median IRF over the 100 draws (the draws for which the distance with the median is minimized as in Mumtaz and Theophilopoulou, 2017). I end up with a posterior distribution of IRFs to the financial fragility shock which I use for inference throughout the paper.

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