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Financial Market Turbulence and Macro-Financial Developments in Ireland: a Mixed Data Sampling (MIDAS) Approach*†

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Abstract

In this paper, we construct a weekly measure of systemic stress across a range of indicators for Irish financial markets, covering money, sovereign bonds, equity, banking and foreign exchange markets by using a time-varying correlation-based approach. We compare the ability of the resulting index to capture known financial market stress events in Ireland with existing alternative measures. Furthermore, we use the indicator as a proxy of financial distress to assess the high-frequency propagation mechanism of financial markets shocks to the macroeconomy. Given that macroeconomic variables are sampled at a monthly frequency, the temporal transmission of shocks is carried through a structural Bayesian mixed-frequency Vector Autoregressive model. We find evidence of a moderate temporal aggregation bias due to aggregating weekly observations of the financial stress indicator to a monthly frequency. In particular, the results suggest that the response of the macroeconomic variables depends on the timing of the shocks within the month.

JEL classification: C32, E44, G10.

Keywords: Financial stress index, macro-financial linkages, Mixed-Frequency VAR, MIDAS.

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Non-technical summary

Since the 2007-08 Global Financial Crisis, there has been an increasing interest in understanding the transmission of financial market stress to the macroeconomy. The recent COVID-19 outbreak and the rapid changes in the global macroeconomic outlook have given rise to a renewed awareness of how a real-time monitoring of financial markets developments can be crucial in the analysis of macro-financial linkages (see e.g. Duprey, 2020).

This paper analyses the high-frequency propagation of financial market disturbances to a set of macroeconomic and banking aggregates in Ireland, over the last two decades. We propose a new weekly indicator, the Irish Composite Stress Indicator (ICSI), to measure financial market stress in Ireland. The ICSI incorporates information from money, sovereign bonds, equity, banking, and foreign exchange markets by using the time-varying correlation-based methodology proposed by Holló *et al.* (2012). After comparing the ICSI with existing alternative indicators of financial market distress computed by the European Central Bank (ECB) for Ireland, we study the effects of high-frequency financial market shocks on the macroeconomic and banking variables. Given that these variables are available only at a lower-frequency (i.e. monthly), the empirical analysis is carried out by relying on a mixed data sampling (MIDAS) approach.

In terms of results, we find that an exogenous increase in the ICSI leads to a decline in economic activity (as proxied by the level of unemployment) and consumer prices. Furthermore, following a shock to financial market conditions, the empirical findings reveal a reduction in both loans to the non-financial private sector and the related interest rate. Moreover, the responses of the low-frequency macroeconomic and banking variables depend on the timing of the shocks within the month (larger in the first weeks than at the end of the month). Finally, we find that in the case of mixed-frequency analysis, the responses of the macroeconomy and loan activity are smaller (with less uncertainty around the estimates) than those obtained by aggregating the variables (including the ICSI) to the common low-sampling frequency.

1 Introduction

Since the 2007-08 Global Financial Crisis, there has been an increasing interest in understanding the transmission of financial market stress to the macroeconomy. The recent COVID-19 outbreak and the rapid changes in the global macroeconomic outlook have given rise to a renewed awareness of how a real-time monitoring of financial markets developments can be crucial in the analysis of macro-financial linkages (see e.g. Duprey, 2020).

In this paper, we contribute to the literature on macro-financial spillovers in two ways. First, we propose a new weekly measure of financial markets stress for Ireland, namely the Irish Composite Stress Indicator (ICSI), that aggregates information from money, sovereign bonds, equity, banking and foreign exchange markets by using the time-varying correlation-based approach proposed by Holló *et al.* (2012).[1]

This measure differs from the monthly Country-Level Index of Financial Stress (CLIFS) for Ireland proposed by Duprey *et al.* (2017). While the CLIFS includes series capturing stress only on sovereign bonds, equity and foreign exchange markets, we extend the information set to also include money and banking sectors.[2] This choice is in line with the daily Composite Indicator of Systemic Stress (CISS) for Ireland, recently introduced by Chavleishvili & Kremer (2021).[3]

Following Chatterjee *et al.* (2017) and, more recently, Duprey (2020), we compare the ability of the ICSI to capture known financial market stress episodes with the alternative measures available for Ireland, by computing the Area Under the Receiver Operating Characteristic (AUROC) curve. As a result, we find that the ICSI reports the largest AUROC among the alternative Irish financial stress indicators.

Our second contribution is based on the assessment of the transmission mechanism of financial market stress to the real economy. Empirical evidence of the negative response of real economic activity to financial markets shocks has been provided for US (see Hubrich & Tetlow, 2015; Caldara *et al.*, 2016; Alessandri & Mumtaz, 2017; Furlanetto *et al.*, 2019, among others), for euro area (Holló *et al.*, 2012), for UK (Chatterjee *et al.*, 2017), for Canada (Duprey, 2020) or for Italy (Miglietta & Venditti, 2019). While the aforementioned studies assess the propagation mechanism of financial distress using data sampled at the same low-frequency, we rely on a mixed data sampling (MIDAS) approach.

In particular, we study the effects of high-frequency financial market stress (proxied by an unexpected increase in the weekly series of the ICSI) to a set of macroeconomic and banking aggregates in Ireland, over the period 2003-2019. Since these variables are

[1] The index proposed in our paper is built on the work of O'Grady (mimeo) that constructs a daily financial stress indicator for Ireland based on Holló *et al.* (2012). However, our index differs from that proposed by O'Grady (mimeo) in terms of both methodology and data selection. As for the methodology, we closely follow the suggestion of Holló *et al.* (2012) and we compute the calendar weekly average of each raw stress indicator (i.e. we do not rely on moving standard deviation to compute daily volatility). Furthermore, in our paper the selection of the financial markets series entering the index is driven by the possibility to update the indicator without any discontinuity.

[2] The CLIFS is updated by the European Central Bank (ECB) at the end of each month reporting values for the previous month.

[3] This indicator is published by the ECB at a daily frequency. We thank Manfred Kremer and Paul Konietschke for sending us details on the construction of the New Irish CISS.

available only at a monthly frequency, we estimate a stacked mixed-frequency Vector Autoregressive (MF-VAR) model à la Ghysels (2016).

To our knowledge, the only study that estimates the macroeconomic effects of financial market stress using data sampled at different frequencies is Cipollini & Mikaliunaite (2020) for the Lithuanian economy. However, differently from this study, where the authors estimate a stacked MF-VAR via the ordinary least squares (OLS) method, we rely on Bayesian estimation techniques using the approach proposed by Götz *et al.* (2016) and, more recently, by Paccagnini & Parla (2021). This approach is suitable to deal with a potential parameters proliferation that is typical of stacked MF-VARs.[4]

In our empirical application, the use of a MF-VAR allows to analyse the intra-month response of the macroeconomic and banking variables to worsening financial conditions. Furthermore, the model allows to evaluate whether the aggregation of high-frequency series (i.e. the ICSI) to a lower frequency (that of the macro and banking variables) leads to a temporal aggregation bias, affecting the impact of financial market distress on the variables of interest.[5] Empirical evidence of temporal aggregation bias has been provided by a number of studies (see Foroni & Marcellino, 2016; Bacchiocchi *et al.*, 2020; Cipollini & Mikaliunaite, 2020; Paccagnini & Parla, 2021, among others).

The empirical analysis provides interesting findings. First, the responses of the macroeconomic and banking variables resemble those generated by negative demand shocks. Moreover, the results reveal evidence of a moderate temporal aggregation bias. In particular, the response of the low-frequency variables depends on the timing of the shocks within the month (larger in the first weeks than at the end of the month). Furthermore, we find that the responses of the macro and banking aggregates to financial market stress from a MF-VAR are different (in terms of magnitude) from those obtained by estimating a common-frequency VAR (CF-VAR), where the ICSI is aggregated to a monthly frequency.

The ICSI complements the existing analytical tools used by the Central Bank of Ireland for the assessment of financial stability risks. Among other indicators, the ICSI provides a valid real-time measure for monitoring financial market conditions. Furthermore, as discussed in our empirical application, the ICSI can be also used as an input of empirical models that seek to estimate the transmission mechanism of financial market distress to the real economy, such as growth at risk models (i.e. O'Brien & Wosser, 2021).

This paper is structured as follows. Section 2 provides a literature overview on financial stress indicators and on the analysis of the transmission of financial distress to the real economy. Section 3 describes the approach used for the construction of the ICSI. Section 4 assesses recent developments of the ICSI and provides a comparison with alternative financial stress indicators available for Ireland. Section 5 provides an empirical application on the propagation mechanism of high-frequency financial markets shocks to the Irish macroeconomy and Section 6 concludes.

[4] See Götz *et al.* (2016), for a technical discussion.

[5] Most of the studies that use high-frequency financial stress indicators generally aggregate daily (or weekly) observations to match the lower frequency (e.g. monthly/quarterly) of the macroeconomic variables and then estimate a model fitted to series sampled at the same frequency (see Holló *et al.*, 2012; Miglietta & Venditti, 2019, among others).

2 Related literature

In recent years, a large and growing amount of research has proposed measures of financial stress by aggregating information on different market segments.[6] One of the first studies that develops an index of financial stress is the work of Illing & Liu (2006). In this study, the authors propose a daily financial stress index for the Canadian economy by aggregating 9 raw indicators that capture stress in four segments of the financial system (equity, debt, banking and foreign exchange markets). Cardarelli *et al.* (2011) construct a quarterly financial stress index for 17 advanced economies (excluding Ireland) by aggregating 7 indicators representative of banking, securities and foreign exchange markets through a variance-equal weighting scheme.[7]

A number of financial stress indices have been proposed for the US economy. For example, Hakkio & Keeton (2009) aggregate 11 financial market series to construct a monthly measure of financial stress (Kansas City Financial Stress Index) using principal component analysis. The same methodology is used by the study of Kliesen & Smith (2010), which develops a weekly financial stress index (Federal Reserve Bank of St. Louis Index) by extending the information set to 18 financial market series, including interest rates and yield spreads.[8]

While the aforementioned studies for the US take into account only cross-sectional correlations to determine the weights of each financial series entering the index, the studies of Brave & Butters (2011, 2012) construct a measure of financial conditions by also exploring dynamic correlations across the series. In particular, the authors develop a weekly measure of financial conditions (that is the National Financial Conditions Index produced by the Federal Reserve Bank of Chicago) through the estimation of a dynamic factor model fitted to 100 financial market series, representative of money, debt, equity and banking markets.

The study of Holló *et al.* (2012) proposes a Composite Indicator of Systemic Stress (CISS) for the euro area as a whole. The index, which is published by the European Central Bank (ECB) on a weekly basis, combines information on 15 indicators capturing stress in money, equity, sovereign bonds, banking and foreign exchange markets through the application of a standard portfolio theory. In particular, in a first step, the 15 indicators are grouped into five sub-indices (one for each market) through arithmetic average. Finally, these sub-indices are aggregated into the financial stress index for the euro area by taking into account their time-varying cross-correlations structure.

Recently, the ECB has published a daily version of the CISS (namely New CISS), developed by Chavleishvili & Kremer (2021), for a set of euro area countries (including Ireland), euro area as a whole, China, UK and US. Compared to the earlier version, the new CISS aggregates daily series by using an alternative and equal weighting scheme.

Other studies have used the methodology proposed by Holló *et al.* (2012). For example, Louzis & Vouldis (2012) construct a monthly index of financial stress for the Greek economy by aggregating information on 14 indicators that capture stress in

[6] For an extensive survey on financial stress and financial conditions indicators, see also Kliesen *et al.* (2012).

[7] Ireland is not included in the sample due to lack of observations in the long-term corporate bond yield series.

[8] Also the study of Oet *et al.* (2011) proposes a daily financial stress index for US (Cleveland Financial Stress Indicator) by aggregating information on 11 series representative of credit, foreign exchange, equity and interbank markets.

the economic fundamentals, equity market, banking sector and money market.[9] More recently, Duprey *et al.* (2017) have proposed a Country-Level Index of Financial Stress (CLIFS) for each of the 27 EU countries (including Ireland) and for UK, whose series are published by the ECB on a monthly basis. The index combines information on 6 indicators capturing stress in three financial market segments: sovereign bonds, equity and foreign exchange markets. Chatterjee *et al.* (2017) aggregate information on 13 indicators representative of six financial market segments, including equity, government bonds, foreign exchange, corporate bonds, money and housing markets, to construct a financial stress index for UK, available at a monthly frequency. Miglietta & Venditti (2019) construct a weekly measure of financial distress for the Italian economy by combining information on 13 financial measures that capture stress in five sub-markets, i.e. money, sovereign bonds, equity, foreign exchange and financial intermediaries markets. Finally, Duprey (2020) proposes a financial stress index for Canada (available at a monthly frequency), constructed by aggregating series representative of seven sub-market segments, including equity, sovereign bonds, foreign exchange, money, banking, corporate bonds and housing markets.

Extensive research has shown that an increase in financial market distress is associated with a contraction in real economic activity. Dynamic stochastic general equilibrium (DSGE)-based studies have highlighted the important role played by financial frictions as a source of business cycle and as amplification of the transmission mechanism of uncertainty shocks to the real economy (see Jermann & Quadrini, 2012; Gilchrist *et al.*, 2014, among others).[10]

A large number of empirical studies have shown that a worsening in financial conditions has detrimental effects on real economic activity. Caldara *et al.* (2016) assess the macroeconomic impact of financial and uncertainty shocks, finding that, while both shocks have negative effects on the real economic activity, uncertainty shocks have a larger effect in presence of concomitant tightening of financial conditions. Similar results for US have been provided by the study of Furlanetto *et al.* (2019), which shows that financial shocks (e.g. those originating in credit markets) have a stronger impact on macroeconomic aggregates than uncertainty shocks.

Another strand of literature has investigated the non-linear interactions between financial stress and real economic activity. In particular, these studies highlight a state-dependent response of the macroeconomic outlook to financial distress, with real economic activity contracting more during high-stress periods than during low-stress periods (see Holló *et al.*, 2012; Hubrich & Tetlow, 2015; Alessandri & Mumtaz, 2017; Miglietta & Venditti, 2019, among others).

All the aforementioned studies analyse the transmission mechanism of financial distress to the real economy by relying on a common-frequency approach. However, the

[9] Differently from Holló *et al.* (2012), in the study of Louzis & Vouldis (2012) the aggregation of the 14 indicators into the four market sub-indices (i.e. economic fundamentals, banking sector, equity market and money market) is carried out by extracting common factors from each group of indicators.

[10] In a second stage, Gilchrist *et al.* (2014) use micro-level data on daily stock returns for domestic non-financial corporations to investigate the interactions between uncertainty and financial conditions. Both at a micro and aggregate level, the authors provide evidence on the important role played by financial conditions in influencing the response of investment to fluctuations in idiosyncratic uncertainty.

aggregation of high-frequency data to a lower-frequency could lead to a temporal aggregation bias, which might affect the impact of financial shocks to the macroeconomy (see Ghysels, 2016).[11] To our knowledge, the only study that investigates the transmission of financial markets shocks to the real economy using a mixed-frequency data model is Cipollini & Mikaliunaite (2020), for Lithuania. The empirical evidence provided by the authors suggests the presence of a mild temporal aggregation bias due to estimating the model with data sampled at a common (lower) frequency.

3 The Irish Composite Stress Indicator

In line with Holló *et al.* (2012) and, more recently, with Miglietta & Venditti (2019), the ICSI is constructed by combining information on 5 representative financial market segments, that is money (MON), equity (EQU), sovereign bonds (GOV), banking (BANK) and foreign exchange (FX) markets.
The raw series capturing stress in the Irish financial markets are selected based on the aforementioned studies (see Table 1). As can be seen from Table 1, financial market stress is captured mainly by asset return volatilities, risk spreads, valuation losses and time-varying correlations. These price-based financial indicators are available at a higher frequency and for a longer time period than quantity-based series. In particular, we use daily observations on 12 financial market series to compute 13 weekly raw stress indicators, over the period January 1973 – October 2020 (see Figure 1).[12]
As suggested by Holló *et al.* (2012), the aggregation of the weekly raw indicators into the financial stress index requires two steps.
The first step consists of standardizing each financial market series by computing its empirical cumulative distribution function (ECDF). In particular, given a raw stress indicator $x_t = \{x_1, x_2, \ldots, x_n\}$, for $t = 1, \ldots, n$, where n is the sample size, and ordering the observations in a non-decreasing sequence, such that $x_{[1]} \leq x_{[2]} \leq \ldots x_{[n]}$, the ECDF is computed as follows:

$$\hat{x}_t = F_n(x_t) = \begin{cases} \frac{r}{n} & \text{for } x_{[r]} \leq x_t < x_{[r+1]} \ , \ r = 1, 2, \ldots, n-1 \\ 1 & \text{for } x_t \geq x_{[n]} \end{cases} \tag{1}$$

where r is the ranking associated with a particular realization of x_t. This standardization allows to obtain unit-free indicators, $\hat{x}_t$, whose values range in the interval $(0, 1]$. Following Holló *et al.* (2012), the ECDF is first computed over an initial fixed sample (i.e. pre-recursive sample), ending on 4 January 2002.[13] After this period, the observations are standardized by applying the ECDF recursively over expanding samples (that is by adding a new observation at time) (see Figure 2).
In the second step, the standardized indicators, $\hat{x}_t$, are combined into the composite stress index for Ireland. In particular, the transformed series are aggregated into 5 sub-indices, $S_{i,t}$, for $i = 1, \ldots, 5$, one for each of the five selected financial markets (MON,

[11] Evidence of temporal aggregation bias has been reported by a number of empirical studies based on a MIDAS approach (see e.g. Foroni & Marcellino, 2016; Bacchiocchi *et al.*, 2020; Cipollini & Mikaliunaite, 2020; Paccagnini & Parla, 2021, among others).

[12] Data are from Thomson Reuters Datastream. The last observation is 23 October 2020.

[13] In line with Holló *et al.* (2012), the number of observations included in the pre-recursive sample varies across the different raw stress indicators, that is depending on the data availability (see Table 1).

GOV, EQU, BANK and FX) through arithmetic average (see Figure 3).
Once obtaining the 5 financial markets sub-indices, the ICSI is computed using the time-varying correlation-based approach proposed by Holló *et al.* (2012) as follows:

$$ICSI_t = (w \times S_t)\, C_t\, (w \times S_t)' \;, \quad \text{for } t = 1, \ldots, T \tag{2}$$

where $S_t = (S_{MON,t}, S_{GOV,t}, S_{EQU,t}, S_{BANK,t}, S_{FX,t})'$ is a 5-dimensional vector of sub-indices and w is a 5-dimensional vector of equal time-invariant weights.[14] Furthermore, C_t is the 5×5 matrix containing the time-varying correlations computed across the financial market sub-indices, $\rho_{ij,t}$:

$$C_t = \begin{bmatrix} 1 & \rho_{12,t} & \rho_{13,t} & \rho_{14,t} & \rho_{15,t} \\ \rho_{21,t} & 1 & \rho_{23,t} & \rho_{24,t} & \rho_{25,t} \\ \rho_{31,t} & \rho_{32,t} & 1 & \rho_{34,t} & \rho_{35,t} \\ \rho_{41,t} & \rho_{42,t} & \rho_{43,t} & 1 & \rho_{45,t} \\ \rho_{51,t} & \rho_{52,t} & \rho_{53,t} & \rho_{54,t} & 1 \end{bmatrix} \quad , \quad \text{for } i,j = 1, \ldots, 5 \text{ and for } t = 1, \ldots, T \tag{3}$$

where each entry element of the time-varying cross-correlations matrix (C_t), that is $\rho_{ij,t} = \sigma_{ij,t}/\sigma_{i,t}\sigma_{j,t}$, for $i, j = 1, \ldots, 5$ and for $i \neq j$, is estimated recursively using an exponentially weighted moving average (EWMA) specification. In particular, the EWMA for the covariances ($\sigma_{ij,t}$) and the volatilities ($\sigma^2_{i,t}$) is computed as follows:

$$\begin{cases} \sigma_{ij,t} = \lambda\sigma_{ij,t-1} + (1-\lambda)\bar{S}_{i,t}\bar{S}_{j,t} \quad , & \text{for } i,j = 1, \ldots, 5 \text{ and } i \neq j \\ \sigma^2_{i,t} = \lambda\sigma^2_{i,t-1} + (1-\lambda)\bar{S}^2_{i,t} \quad , & \text{for } i = 1, \ldots, 5 \end{cases} \tag{4}$$

where λ is a constant smoothing parameter and $\bar{S}_{i,t} = S_{i,t} - 0.5$ is the i-th demenaed financial market sub-index (with 0.5 being its "theoretical" median value).[15] As in Holló *et al.* (2012), the covariances ($\sigma_{ij,t}$) and the volatilities ($\sigma^2_{i,t}$) are initialized using their average values over the pre-recursive sample.

4 Financial market stress in Ireland

In this section, we document how the ICSI and the different composite indicators available for Ireland capture financial market stress episodes. In particular, Section 4.1 describes the ICSI's dynamics around a set of financial stress events and how the sub-market sectors contribute to these dynamics. Section 4.2 compares the ICSI with the financial stress indicators for Ireland published by the ECB.

[14] The equal weighting scheme differs from the strategy proposed by Holló *et al.* (2012), which compute the weights based on the impact of each sub-index on the euro area industrial production growth rate, through the estimation of VARs (i.e. by computing impulse responses). Given that the results might change depending on the lag structures and on the forecast horizons, we prefer to assign the same weight to each sub-index. This strategy is also in line with the work of Duprey *et al.* (2017) and of Chavleishvili & Kremer (2021). However, it is important to note that Holló *et al.* (2012) find small differences between the CISS constructed using weights based on impulse responses and that computed using equal weights.

[15] Following Holló *et al.* (2012), we set the smoothing parameter λ equal to 0.93.

4.1 ICSI and financial market stress

In Figure 4, we report the weekly ICSI computed from equation 2, over the period 1999M1 – 2020M10.[16] The figure also displays a list of financial distress episodes, including the recent COVID-19 outbreak.[17] As can be seen from the chart, the ICSI captures the financial market stress episodes over the last 20 years. In particular, the index shows its highest values around the Global Financial Crisis (GFC), reaching its peak in January 2009. Large values of the ICSI are registered during the sovereign debt crisis (started around late 2009), with notably high level of stress captured during the downgrade of the Irish government bonds ratings (July 2011). More recently, on 3 April 2020, the financial stress index jumps at 0.34 (from a value of 0.07 reported one month before, i.e. 6 March 2020).

Figure 5 shows the time-varying average pairwise correlations computed across the 5 financial market sub-indices (panel a) and the ICSI (panel b).[18] Following Holló *et al.* (2012) and Miglietta & Venditti (2019), we also report the ICSI computed under a perfect correlation scenario (ICSI$_{p.c.}$), that is the scenario where the financial sub-markets are perfectly correlated (see Figure 5, panel b). The average pairwise correlations can be interpreted as a measure of synchronization of the stress reported in a specific sub-market (e.g. GOV) with that arising from the rest of the financial system. Given that the ICSI (as described in Section 3) puts relatively more weight on situations in which stress prevails in several financial markets at the same time, the higher the correlation across the sub-markets the larger the value reported by the financial stress indicator. For example, as can be seen from Figure 5 (panel a), during the GFC all the financial market sectors are highly positive correlated. This high degree of synchronization is associated with an increase in the ICSI that reaches values above 0.8 (almost overlapping those reported by the ICSI$_{p.c.}$) (see Figure 5, panel b).

The contributions from the financial market sub-sectors to the ICSI's dynamics are shown in Figure 6.[19] As can be seen from the chart, all the financial markets contribute to the increase observed in the ICSI during the GFC, while the large values registered around the sovereign debt crisis are mainly driven by stress in the sovereign bonds market. In Figure 6, we also report the contribution from all the cross-correlations, jointly, to developments in the financial stress indicator, which is computed as the difference between the ICSI and the ICSI$_{p.c.}$ (i.e. the sum of the financial sub-markets contributions). As shown in Figure 6, the contribution from the cross-correlations, jointly, tends to be small during periods of high synchronization across financial markets risks (e.g. during GFC). This suggests that when the degrees of stress in multiple financial

[16] As a further exercise, we also extend the ICSI to a daily frequency (see Appendix A).

[17] Financial market stress episodes include: the Dot-com bubble (around March 2000), the September 11 attacks, the collapse of Lehman Brothers (15 September 2008), the Greek financial support programme (May 2010), the downgrade of the Irish government bonds ratings (July 2011), the Brexit referendum (23 June 2016) and the COVID-19 outbreak (with the first cases of Coronavirus registered in the Republic of Ireland in early March 2020).

[18] The time-varying average pairwise correlations are computed as follows: $\bar{\rho}_{it} = \big(\sum_{j=0}^{5} \rho_{ijt} - 1\big)/(5-1)$, for $i, j \in (S_{MON,t}, S_{GOV,t}, S_{EQU,t}, S_{BANK,t}, S_{FX,t})$, $i \neq j$ and $t = 1, \dots, T$.

[19] Each contribution (V_{it}) is computed as follows: 1) $s_{it} = (S_{it} \times w_i)^2 / \sum_{i=1}^{5} (S_{it} \times w_i)^2$, where S_{it} is the i-th financial market sub-index, with $S_{it} \in (S_{MON,t}, S_{GOV,t}, S_{EQU,t}, S_{BANK,t}, S_{FX,t})$; 2) $V_{it} = s_{it} \times$ ICSI$_{p.c.}$. To avoid clutter, in Figures 5 and 6, we report information from January 2004. The same charts containing data from January 1999 are available upon request.

markets are highly correlated, portfolio diversification (and cross-correlations) play a limited role in lowering systemic risk.

4.2 Alternative measures of financial market stress in Ireland

In this section, we compare the ICSI with two alternative measures of financial market stress available for Ireland: the CLIFS (Country-Level Index of Financial Stress) and the New CISS (Composite Indicator of Systemic Stress) (see Figure 7).

The CLIFS, which has been introduced by the study of Duprey *et al.* (2017), incorporates information on three financial market segments (equity, sovereign bonds and foreign exchange markets) and it is updated by the ECB at a monthly frequency (see Figure 7, panel a).[20] A second alternative measure is the New CISS that has been recently developed by Chavleishvili & Kremer (2021) for a set of euro area countries (including Ireland), UK, US and China (see Figure 7, panel b). This daily indicator (updated by the ECB) is constructed by aggregating both euro area and country-specific financial market series. The raw indicators capture stress in equity market (for both non-financial and financial corporations), money market, sovereign and corporate bond markets and foreign exchange markets.[21] Finally, we also report the weekly series of the ICSI (see Figure 7, panel c).

In each of the three charts, we include the set of financial market stress events described in Section 4.1. As can be seen from Figure 7 (panel a), the CLIFS captures the GFC and the stress associated with the Greek's government debt crisis. However, the index does not capture well the other financial market stress episodes. Oppositely, both the New CISS for Ireland and the ICSI capture most of the selected financial market stress episodes (see Figure 7, panel b and c). What is striking in these two charts is the difference between the level of stress reported by the two indicators around the European sovereign debt crisis. In particular, while the ICSI reaches higher level of stress during the downgrade of the Irish government bonds ratings than the Greek's debt crisis, the New CISS exhibits the opposite dynamic.

Following Chatterjee *et al.* (2017), and more recently, Duprey (2020), we compare the ability of the three aforementioned measures to capture episodes of financial distress by computing the area under the receiver operating characteristic (AUROC) curve. This statistic captures the ability of an indicator to signal the onset of a crisis.[22] As in Chatterjee *et al.* (2017), we select the financial market stress episodes for Ireland by using the database provided by Lo Duca *et al.* (2017) for a set of European countries.[23]

The AUROC curve computed for each of the three measures of financial market stress is reported in Figure 8. In particular, for each value of the threshold, the AUROC curve reports the percentage of false alarm (horizontal axis), i.e. the index is above a threshold value and no crisis occurs (Type II error), and the percentage of well predicted crisis

[20]The series of CLIFS for Ireland starts from February 1983 and it is available at https://sdw.ecb.europa.eu/browse.do?node=9693347.

[21]The series of New CISS for Ireland is available (from 5 January 1999) at https://sdw.ecb.europa.eu/browse.do?node=9689686.

[22]The AUROC curve has been extensively used in studies on early warning signals and providing an overview of the literature is beyond the scope of this paper. See Chatterjee *et al.* (2017), for technical details on the use of the AUROC curve in financial stress indicators.

[23]For Ireland, only one financial stress episode is labelled as systemic financial crisis (i.e. the 2008M9–2013M12 period).

(vertical axis), i.e. the index is above a threshold value and a crisis occurs (1 - Type I error, where Type I error denotes the missed crisis). The larger the area under the curve the better the ability of an indicator to predict a crisis. The 45-degree diagonal line corresponds to an uninformative indicator. As can be seen from Figure 8, the AUROC computed for the ICSI (87.5%) is higher than that computed for the New CISS (82.8%) and for the CLIFS (73.4%).

5 Transmission of financial market stress on macro-financial outcomes

In this section, we study the transmission mechanism of financial market distress on the Irish macro-financial environment, over the period 2003-2019.[24] The weekly series of the ICSI is used as a proxy of financial market stress. Given that the selected macroeconomic and banking variables are observed only at a monthly frequency, we rely on a MIDAS approach. In particular, Section 5.1 introduces the model and describes the structural identification strategy. Section 5.2 describes data. Section 5.3 provides empirical findings and Section 5.4 describes some robustness checks.

5.1 Structural mixed-frequency VAR

We estimate a stacked MF-VAR à la Ghysels (2016) fitted to a $Kh = 1$ high-frequency variable (i.e. weekly ICSI) and to proxies of real economic activity and banking aggregates, which are sampled at a monthly frequency:

$$Z_t = \sum_{\ell=1}^{p} A_\ell Z_{t-\ell} + c + u_t \tag{5}$$

where $Z_t = \left[X_t', ICSI_{t-3/4}', ICSI_{t-2/4}', ICSI_{t-1/4}', ICSI_t'\right]'$, is the K-dimensional stacked vector of mixed-frequency variables, with $K = Kl + (m \times Kh)$, and $u_t \sim \mathcal{N}(0, \Sigma)$ are the reduced-form residuals, with a covariance matrix Σ which is not assumed to be diagonal. The Kl-dimensional vector of monthly variables (X_t), observed every $m = 4$ weeks, includes proxies of the real and the banking sectors of the economy: the level of consumer price index (CPI), the level of unemployment (UNEMP), the outstanding amounts of loans to non-financial private sector (LOANS) and the interest rate on loans (LENDING RATE) (see Section 5.2 for more details on the data).[25] All the variables enter the MF-VAR in log levels, with the only exception of the ICSI and the LENDING

[24] In our empirical application, we exclude data after December 2019 from the sample period. The choice is made to avoid the inclusion of extreme observations reported by several aggregates during the COVID-19 period (e.g. the level of unemployment in Ireland increases by 18 percent in July 2020 compared to the previous month, source Eurostat database). For example, for US, Lenza & Primiceri (2020) suggest to treat the presence of such outliers by introducing breaks in the shock volatilities. However, the authors find that the results (i.e. impulse responses) are similar to those obtained by estimating the model without data related to the COVID-19 period. We leave the treatment of COVID-19 data using MIDAS techniques for future research.

[25] As a robustness check, we estimate the model by replacing the level of unemployment with the unemployment rate. The results, which are qualitatively similar to those obtained in the baseline specification (see Section 5.3), are available upon request.

RATE, which enter the model in levels.[26] The MF-VAR is estimated over the 2003M1 - 2019M12 time span. The lag length is set equal to 13, which is a standard choice with monthly data.[27]
The model in equation (5) is estimated using Bayesian methods.[28] In particular, following the approach recently proposed by Paccagnini & Parla (2021), which in turn builds on the work of Götz *et al.* (2016), we impose a Natural conjugate prior on the MF-VAR coefficients by augmenting the system in equation (5) with a set of dummy observations.[29] While the artificial data for the lagged endogenous variables (X_d) are constructed as in Bańbura *et al.* (2010), to match the Minnesota prior moments for MF-VAR, Y_d is specified *ad-hoc*:

$$\underset{[(Kp+1)+K]\times K}{Y_d} = \begin{pmatrix} \text{diag}\left(\frac{\rho_L^m \sigma_L}{\lambda}\right)_{Kl\times Kl} & \mathbf{0}_{Kl\times 1} & \dots & \mathbf{0}_{Kl\times 1} & \mathbf{0}_{Kl\times 1} \\ \multicolumn{5}{c}{\mathbf{0}_{[(m-1)\times Kh]\times K}} \\ \mathbf{0}_{1\times Kl} & \frac{\rho_H \sigma_H}{\lambda} & \dots & \frac{\rho_H^{m-1}\sigma_H}{\lambda} & \frac{\rho_H^m \sigma_H}{\lambda} \\ \hdashline \multicolumn{5}{c}{\mathbf{0}_{K(p-1)\times K}} \\ \hdashline \multicolumn{5}{c}{\text{diag}(\sigma_{1,L},\dots,\sigma_{Kl,L},\sigma_{1,H},\dots,\sigma_{m,H})_{K\times K}} \\ \hdashline \multicolumn{5}{c}{\mathbf{0}_{1\times K}} \end{pmatrix} \tag{6}$$

where the prior mean of the ICSI (ρ_H) is set equal to zero (as suggested by Ghysels, 2016), while the prior means of the monthly variables, $\rho_L = (\rho_{1,L},\dots,\rho_{Kl,L})$ are centered around the OLS estimates obtained from an AR(1) regression fitted to each variable over a training sample. The scaling factors σ_H and $\sigma_L = (\sigma_{1,L},\dots,\sigma_{Kl,L})$ are set equal to the standard deviations of the residuals from AR(m) and AR(1) regressions fitted to the high- and low-frequency variables, respectively. The hyperparameter that controls for the overall tightness around the prior (λ) is selected by maximizing the marginal likelihood of the MF-VAR (see Carriero *et al.*, 2012). Finally, we impose a diffuse prior on the constant term.
As in CF-VAR, we use the Gibbs sampling algorithm to simulate the posterior distribution of the MF-VAR coefficients (see Appendix B, for more technical details on the estimation procedure). The weekly financial market shocks (proxied by an exogenous increase in the ICSI) are identified by computing the Cholesky decomposition of the reduced-form

[26]Since the model is estimated using Bayesian techniques (i.e. by imposing a Natural conjugate prior on the model coefficients), inference can be conducted also in presence of non-stationary time series (see Sims *et al.*, 1990, for technical details).

[27]As a robustness check, we estimate the model using different lag lengths (3 and 6 lags) (see Section 5.4).

[28]The stacked MF-VAR can be estimated also via OLS (see Ferrara & Guérin, 2018; Bacchiocchi *et al.*, 2020; Cipollini & Mikaliunaite, 2020, among others). However, to cope with a potential parameters proliferation, we rely on Bayesian estimation techniques.

[29]As stated by Bańbura *et al.* (2010), in CF-VAR, augmenting the system with a set of dummy observations is equivalent to imposing a Normal-inverse Wishart prior that satisfies the Minnesota prior moments described in Litterman (1986) (see Sims & Zha, 1998; Bańbura *et al.*, 2010, for technical details).

residuals covariance matrix (Σ), such that $u_t = A_0\varepsilon_t$ and $\Sigma = A_0A_0'$, where A_0 contains the contemporaneous effects of the structural disturbances (ε_t) and $\varepsilon_t \sim \mathcal{N}(0, I_K)$.
The ordering of the variables in the system follows that used in Hubrich & Tetlow (2015) and, more recently, in Cipollini & Mikaliunaite (2020).[30] In particular, as mentioned before, the ICSI is placed after the block of monthly macroeconomic and banking variables (X_t), where $X_t = \left[CPI_t', UNEMP_t', LOANS_t', LENDING\ RATE_t'\right]'$. Unlike Hubrich & Tetlow (2015) and Cipollini & Mikaliunaite (2020), we use the level of unemployment to proxy the real economic activity instead of direct measures of demand, such as industrial production index or consumer spending.[31] Furthermore, since the aim of our research is to assess how financial market distress affects the macroeconomy and lending activity (i.e. banking aggregates), we extend the set of endogenous variables to also include proxies of quantity (i.e. outstanding amount of loans to non-financial private sector) and price (i.e. corresponding lending rate) of credit.
This ordering of the variables has two implications.[32] First, we assume that stress arising from financial markets affects real economic activity and banking aggregates only with a one-month delay.[33] Second, this ordering implies that financial market shocks occurring for example in week 2 have a contemporaneous impact only on that week and on the following ones (i.e. week 3 and week 4).[34]

5.2 Data

In the baseline specification, we use the weekly series of the ICSI and proxies of real economic activity, prices and banking aggregates available at a monthly frequency, over

[30] Hubrich & Tetlow (2015) study the effects of financial stress on real economic activity, inflation and monetary policy in US using a (common-frequency) Markov-switching VAR. In this study, the financial stress index for US is ordered after personal consumption expenditures, inflation, short-term federal funds rate and the nominal M2 monetary aggregate. The work of Cipollini & Mikaliunaite (2020) uses a similar scheme to identify financial distress in Lithuania through the estimation of a MF-VAR.

[31] The choice of excluding the Irish industrial production index reflects issues around the National accounting framework, for example contract manufacturing (see Conefrey & Walsh, 2018). Moreover, since in our empirical application we focus on the mismatch between weekly (ICSI) and monthly (macroeconomic and banking aggregates) frequencies, we do not rely on consumption whose observations are available only at a quarterly frequency.

[32] Since our focus is on financial market shocks (proxied by an exogenous increase in the ICSI), the ordering of the variables in the macroeconomic block (i.e. level of unemployment and level of consumer prices) does not affect the identification of the shock of interest. However, as a robustness check, we estimate the baseline model specification, i.e. the MF-VAR(13), by placing the level of consumer prices after the level of unemployment. The results are qualitatively and quantitatively similar to those discussed in Section 5.3 and they are available upon request.

[33] A similar ordering of the variables is also used by Mumtaz *et al.* (2018) that estimate the effects of credit supply shocks in US using different identification schemes, including a recursive VAR model. In particular, the authors order the financial variables (i.e. Financial Condition Index) after the GDP growth rate, the credit growth rate and the spread of lending rate over the 3-month treasury bill rate.

[34] The same intra-month ordering of the high-frequency variables is used in Ferrara & Guérin (2018) and in Paccagnini & Parla (2021), whose focus is on the estimation of the macroeconomic effects of high-frequency uncertainty shocks.

the period 2003M1–2019M12. In particular, we rely on the level of unemployment as a proxy of real economic activity, while price levels are measured by the harmonised index of consumer prices. Both the two series are from the Eurostat database. Furthermore, the outstanding amounts of loans granted by credit institutions to the Irish non-financial private sector is used as a proxy of bank credit.[35] Finally, we use a composite lending rate computed as the weighted average of the interest rate on loans granted to non-financial corporations and that on loans to households, using the corresponding outstanding amounts of loans as weights. The proxies of quantity and price of credit are taken from the statistical database of the Central Bank of Ireland.

The weekly series of the ICSI is used as a proxy of financial markets distress. Since the number of calendar weeks is likely to vary across months (i.e. four or five weeks per month), to obtain a fixed number of observations, the ICSI is constructed such that each month contains four weekly observations.[36] All the macroeconomic and banking variables are seasonally adjusted using TRAMO-SEATS from the Demetra software.

5.3 Results

In this section, we report the results obtained from the estimation of the baseline MF-VAR (see Section 5.1).[37] In particular, Figures 9-10 show the orthogonalized impulse responses of the macroeconomic and banking variables to a one standard deviation high-frequency financial markets shocks, proxied by an increase in the ICSI. All the charts show the median response (red line) and the 68% and 90% credibility intervals (shading areas). The impulse responses are computed over a 36-month (i.e. 3-year) forecast horizon.

Figure 9 shows the weekly responses of consumer prices, level of unemployment, loans to non-financial private sector and lending rate. As can be seen from the charts, we find that an unexpected increase in the ICSI leads to a decline in economic activity - proxied by the level of unemployment (see Holló *et al.*, 2012; Hubrich & Tetlow, 2015; Duprey, 2020, among others). Moreover, in line with the study of Mallick & Sousa (2013), which focuses on the transmission of financial market stress to the real economy in the euro area, we find that a shock to financial stress conditions is associated with a reduction in consumer prices.[38] As for the banking aggregates, we find that an increase in financial stress negatively affects both the loans to non-financial private sector and the corresponding lending rates. Overall, the impulse response profiles resemble those generated by negative demand shocks. Our findings are consistent with the view that a negative demand shock would trigger a decline in loan demand (i.e. as a consequence of a decrease in the aggregate income). As a result, a reduction in loan demand is associated

[35] The series of loans to non-financial private sector is constructed by taking the sum of loans granted to households and to non-financial corporations.

[36] In particular, we discard the first observation in months that contain more than four weeks. See Götz *et al.* (2016), for a similar approach with daily data.

[37] See Appendix C, for more details on the convergence diagnostics for the Gibbs sampler algorithm.

[38] The response of inflation to a worsening in financial conditions is ambiguous in literature. For example, a negative response of consumer prices is also found in Alessandri & Mumtaz (2017), which study the effects of financial market shocks (proxied by an increase in the FCI) on the macroeconomy in US. Oppositely, Hubrich & Tetlow (2015) find a positive relationship between financial stress and consumer prices in the US economy by using counterfactual simulations involving alternative paths for the proxy of financial stress. See also Prieto *et al.* (2016).

with a decrease in both the amount of loans and lending rates. Furthermore, the drop in lending rates could be driven by the implicit monetary policy reaction, which is likely to lower money market rate in response to deteriorating financial market conditions. The decrease in the monetary policy instrument might subsequently be transmitted to the bank lending rate (see Hristov *et al.*, 2012).[39]

The estimation of a stacked MF-VAR allows to evaluate whether the responses of the macroeconomic variables depend on the timing of the shock in the month (see Figure 9). In line with a recent strand of literature that studies the high-frequency transmission of uncertainty shocks to business cycle aggregates (i.e. Ferrara & Guérin, 2018; Paccagnini & Parla, 2021), we find that the responses of the macroeconomic and banking variables at the end of the month are different from those obtained in the first weeks.[40]

To investigate the presence of temporal aggregation bias in the responses of the low-frequency variables, we compare the results obtained from the MF-VAR with those obtained from a CF-VAR (i.e. using variables sampled at a monthly frequency).[41] In particular, we aggregate the high-frequency impulse responses by computing the mean over the four weeks.

Figure 10 shows the aggregated median impulse responses of the macroeconomic and banking variables obtained from the estimation of the MF-VAR (red line) and the 68% and 90% credibility intervals (red shading). Each chart displays also the median response obtained from the CF-VAR (black solid line) and the corresponding 90% credibility intervals (black dashed lines).[42] As shown in Figure 10, the responses of the variables exhibit a similar shape in both the MF-VAR and the CF-VAR. However, what is striking in the charts is that the magnitude of the responses obtained from the MF-VAR is smaller than that obtained from the common-frequency model (although the credibility intervals overlap after a 6-month forecast horizon). Furthermore, we find that the uncertainty around the median estimates from the MF-VAR is smaller than that obtained from the CF-VAR. These results, together with the different responses of the low-frequency variables within the month, suggest evidence of a moderate temporal aggregation bias.

5.4 Robustness checks

In this section, we describe a number of robustness checks, including (i) the use of alternative lag structures, (ii) a different ordering of the ICSI in the vector of endogenous variables and (iii) a comparison of the results discussed in Section 5.3 with different

[39] See also Gambetti & Musso (2017), for a discussion on the role played by aggregate and credit demand shocks in shaping both loans and lending rates. However, it is important to note that, since in our paper we do not identify other exogenous disturbances (such as demand, monetary policy, and credit market shocks) beyond those to financial markets, the results should be interpreted with caution. We leave the identification of different structural shocks using mixed-frequency data for future research.

[40] As stated by Ferrara & Guérin (2018), the decreasing magnitude in the response of the low-frequency variables from week 1 to week 4 can be explained by different frequencies in the economic agents' decisions. For example, if economic agents make their decisions at a high-frequency, it is plausible that the responses of the macroeconomic variables (which generally show a strong degree of persistence) are larger in the first weeks than those reported at the end of the month.

[41] The monthly ICSI is computed by averaging out the weekly observations.

[42] For comparison, the CF-VAR is estimated using the same specification (i.e. lag structure, variables) and estimation techniques (i.e. Bayesian methods) as the MF-VAR.

measures of financial market stress for Ireland.
First, we consider alternative lag structures. Figure 11 shows the aggregated impulse response profiles obtained from the estimation of mixed- and common-frequency VAR using different lag structures. In particular, the models are estimated using 3 and 6 lags. As can be seen from the charts, the evidence of temporal aggregation bias (due to aggregating the weekly series of ICSI to a monthly frequency) is also confirmed in the case of different lag lengths.
Second, we check whether the results described in Section 5.3 remain valid also when the variables are ordered differently. In particular, we repeat the empirical exercise by placing the ICSI before the block of macroeconomic and banking variables (hence assumuming exogeneity of the financial stress indicator to macroeconomic fluctuations).[43] Following Holló *et al.* (2012) and, more recently, Miglietta & Venditti (2019), we impose that innovations to the real economy and to the banking aggregates do not affect the financial stress indicator contemporaneously.[44] As shown in Figure 12, the responses of the macroeconomic and banking variables are similar to those obtained by ordering the ICSI last in the vector of observables. Moreover, the evidence of a moderate temporal aggregation bias described in Section 5.3 remains valid.
Third, we compare the responses of the macroeconomic and banking variables to ICSI shocks with those obtained from models where financial stress is proxied by alternative measures available for Ireland (see Figure 13). In particular, we estimate MF-VARs fitted to the weekly series of financial distress (together with the monthly macroeconomic variables) in case of ICSI and New CISS, while the impulse responses to CLIFS shocks are obtained by estimating a monthly VAR (CF-VAR).[45] As can be seen from the charts, the responses obtained by estimating the MF-VAR with the ICSI (Figure 13, panel a) show a similar shape of those obtained by using, respectively, the New CISS (Figure 13, panel b) and, to a lesser extent, the CLIFS (Figure 13, panel c). In particular, while the responses obtained by estimating the MF-VARs with ICSI and New CISS are all statistically significant, we find a relatively larger uncertainty around the estimates in the case of financial stress proxied by the CLIFS.
Overall, the results document a negative effect of high-frequency financial market shocks (proxied by an increase in the ICSI) on the macroeconomic and banking variables. Moreover, the responses of the low-frequency variables depend on the timing of the shocks (i.e. whether they occur in the first weeks or late in the month). Finally, we find evidence of a moderate temporal aggregation bias by comparing the high-frequency responses of the macroeconomic variables with those obtained from a CF-VAR. In particular, we find that the magnitude of the aggregated weekly responses is smaller

[43]See Caggiano *et al.* (2020), for a discussion on the exogeneity of financial conditions to movements in the business cycle.

[44]For example, Holló *et al.* (2012) assess the transmission of financial distress to the real economy in the euro area by estimating a Threshold VAR, where the financial shock is identified through Cholesky decomposition with the CISS ordered before the growth rate of the industrial production index. The authors motivate this choice by arguing that due to publication lags, financial market participants cannot directly observe the current level of the macroeconomic variables, hence these cannot be properly reflected in contemporaneous asset prices (see also Miglietta & Venditti, 2019).

[45]The weekly series of the New CISS for Ireland (available daily) is constructed by following Ferrara & Guérin (2018) (see also Appendix A).

(and with associated tighter confidence bands) than those obtained using a common-frequency approach.

6 Conclusions

In this paper, we have extended the literature on macro-financial linkages by, first, constructing a measure of financial market stress for Ireland (namely ICSI) that is available at a weekly frequency. The ICSI includes financial markets series capturing distress in money, sovereign bonds, equity, banking and foreign exchange markets. Second, we have assessed the propagation mechanism of high-frequency financial market shocks (proxied by an exogenous increase in the ICSI) to a set of Irish macroeconomic and banking aggregates, over the period 2003 – 2019.

Given that the macroeconomic variables are available only at a monthly frequency, the empirical analysis is carried out by using a mixed-frequency data sampling approach. This allows to circumvent the issue of temporal aggregation bias that might arise when aggregating high-frequency information to a lower-frequency. In particular, the transmission of financial stress to the macroeconomy has been studied by estimating a structural mixed-frequency VAR à la Ghysels (2016).

Overall, we find that financial market distress is associated with negative effects on the real economic activity (i.e. Hubrich & Tetlow, 2015; Alessandri & Mumtaz, 2017, among others) and banking aggregates. The impulse response analysis reveals evidence of a moderate temporal aggregation bias. In line with a large body of literature (see i.e Ferrara & Guérin, 2018, among others), we find that the timing of the shocks matters in the response of the low-frequency variables. In particular, the results show that the responses of the macroeconomic variables to financial market shocks diminish moving from week 1 to week 4. Finally, by comparing the impulse responses obtained from a MF-VAR with those from a CF-VAR, we find that the magnitude of the response in the case of mixed-frequency data is smaller (and with tighter confidence bands) than that obtained when aggregating data at the same frequency.

These findings suggest that the use of high-frequency information can assist policy makers to reach a timely interpretation of financial market shocks. Moreover, it might also avoid an overestimation (or underestimation) of the impact of financial market stress on the macro-financial environment. Possible future extensions to this paper include for example the use of COVID-19 data in the estimation sample. In particular, the empirical methodology described in this work could be adapted to take into account potential non-linearities in the relationship between (low-frequency) macroeconomic and (high-frequency) financial market series, due to the current economic crisis.

Appendix A: Extension of the ICSI to a daily frequency

In this appendix, we extend the weekly series of the ICSI to a daily frequency (see Figure A.1). The scope of this exercise is to construct a measure of financial stress for Ireland that can complement (for monitoring purpose), at a higher-frequency, the one described in this paper.
The methodology used for the construction of the daily series of ICSI is the same of that described in Section 3, that is the time-varying correlation-based approach of Holló *et al.* (2012). Also, the raw stress indicators entering the index are the same of those used for the construction of the weekly series (see Table 1). The only difference between the daily and weekly versions of the financial stress index is that in the former the raw series are not aggregated by computing the mean over five consecutive traded days. Hence, we apply the ECDF (for standardization) directly to the daily raw stress indicators.
We repeat the empirical exercise described in Section 5 using the daily series of the ICSI as a measure of financial market stress. However, to compare the results with those described in the manuscript, we aggregate the daily ICSI to a weekly frequency, by following the appraoch of Ferrara & Guérin (2018). In particular, given a number of traded days (D_t) in a specific month, we take the observations $D_t - 15$, $D_t - 10$, $D_t - 5$ and D_t as values for week 1, week 2, week 3 and week 4, respectively.
Figure A.2 shows the structural impulse responses obtained from the estimation of a MF-VAR(13) to a one standard deviations ICSI shock. In particular, we report the posterior median of the aggregated weekly responses (red line) and the corresponding 68% and 90% credibility intervals (red shading). As in the empirical exercise described in Section 5, we also report the median response from a CF-VAR (black line) and the associated 90% credibility intervals (black dashed lines), where the weekly series of the ICSI is aggregated to a monthly frequency. As can be seen from Figure A.2, the responses of the macroeconomic and banking variables are similar to those reported in Section 5.3. There is also evidence of a moderate temporal aggregation bias corroborated by the different magnitude in (and by the different uncertainty around) the responses of the low-frequency variables between mixed- and common-frequency models.
Finally, we compare these responses with those obtained using alternative measures of financial market stress: (1) the weekly ICSI introduced in this paper and described in Section 3, (2) the daily CISS for Ireland and (3) the monthly Irish CLIFS. Figure A.3 collects the impulse responses obtained from the different measures of financial market stress. In particular, we estimate a MF-VAR for the two versions of the ICSI (daily and weekly) and for the Irish CISS, while a CF-VAR is estimated when the CLIFS is used as a measure of financial market stress.[46] Figure A.3 shows identical responses of the low-frequency variables when estimating MF-VARs with either the daily or weekly series of ICSI. As for the other two alternative measures of financial market stress, we find similar median responses (of those obtained from MF-VARs including the ICSI) when estimating the models using the Irish CISS and the CLIFS, with some exceptions for the response of the consumer prices (i.e. CISS) and of the lending rate (i.e. CLIFS).

[46]Similar to the daily ICSI, also the CISS for Ireland is aggregated to a weekly frequency by following the approach of Ferrara & Guérin (2018).

Appendix B: Estimation procedure

In this appendix, we describe the technical details for the estimation of the Bayesian mixed-frequency Vector Autoregressive (MF-VAR) model described in section 5.1. In particular, the model in equation 5 can be written in compact matrix notation:

$$Z = \underline{Z}B + U \tag{B.1}$$

where $Z = (Z_1, \ldots, Z_T)'$, $\underline{Z} = (\underline{Z}_1, \ldots, \underline{Z}_T)'$, with $\underline{Z}_t = (\underline{Z}'_{t-1}, \ldots, \underline{Z}'_{t-\ell}, 1')$, $B = (A_1, \ldots, A_p, c)'$, $U = (u_1, \ldots, u_t)'$ and $U \sim \mathcal{N}(0, \Sigma)$.
As in Bańbura *et al.* (2010), we use a Natural conjugate prior implemented via a dummy observations approach:

$$\begin{aligned} vec(B)|\Sigma &\sim \mathcal{N}\Big(vec(B_0),\ \Sigma \otimes \Omega_0\Big) \\ \Sigma &\sim \mathcal{IW}\Big(S_0,\ v_0\Big) \end{aligned} \tag{B.2}$$

where B_0, Ω_0, S_0 and v_0 are the prior parameters. Following Götz *et al.* (2016) and, more recently, Paccagnini & Parla (2021), these parameters are selected in order to match the Minnesota moments for the MF-VAR coefficients. In particular, the prior distribution of the slope coefficients (i.e. A_ℓ, for $\ell = 1, \ldots, p$) are centered around a restricted MF-VAR(1):

$$\mathbb{E}(a^\ell_{ij}) = \begin{cases} \rho_H^{m+i-j} & \text{if } i > Kl \ \ \&\ \ j = K \ \ \&\ \ \ell = 1 \\ \rho_L^m & \text{if } i = j \ \ \&\ \ i \le Kl \ \ \&\ \ \ell = 1 \\ 0 & \text{otherwise} \end{cases} \tag{B.3}$$

where a^ℓ_{ij} are the i, j-th entry element in A_ℓ, Kl is the number of low-frequency variables that are observed every m fixed period (i.e. $m = 4$ in our case) and $K = Kl + (m \times Kh)$, with Kh being the number of high-frequency variables (e.g. our proxy of financial market stress). Moreover, $\rho = (\rho_H, \rho_L)$ are the prior means for the high- and low-frequency variables, with $\rho_L = (\rho_{x_1}, \ldots, \rho_{x_{Kl}})$. The prior variance is set as in a CF-VAR:

$$VAR(a^\ell_{ij}) = \begin{cases} \phi\frac{\lambda^2\sigma_H^2}{\ell^2\sigma_L^2} & \text{if } i > Kl \ \ \&\ \ j \le Kl \\ \phi\frac{\lambda^2\sigma_L^2}{\ell^2\sigma_H^2} & \text{if } i \le Kl \ \ \&\ \ j > Kl \\ \frac{\lambda^2}{\ell^2} & \text{otherwise} \end{cases} \tag{B.4}$$

where λ controls the overall tightness of the prior, σ_H and σ_L account for different scales of the variables and ϕ controls the influence of the low-frequency variables on the high-frequency ones and vice versa.[47]
The Normal-inverse Wishart prior is imposed by augmenting the model in equation B.1 with a set of artificial data (Y_d, X_d):

$$Z^* = \underline{Z}^* B + U^* \tag{B.5}$$

[47] We set $\phi = 1$ (see Götz *et al.*, 2016).

where $Z^* = (Z', Y_d')'$ and $\underline{Z}^* = (\underline{Z}', X_d')'$.
To match the prior means and variances of B specified in equations B.3-B.4, we construct *ad hoc* artificial observations for Y_d as follows:

$$\underset{[(Kp+1)+K]\times K}{Y_d} = \begin{pmatrix} \text{diag}\left(\frac{\rho_L^m \sigma_L}{\lambda}\right)_{Kl\times Kl} & \mathbf{0}_{Kl\times 1} & \dots & \mathbf{0}_{Kl\times 1} & \mathbf{0}_{Kl\times 1} \\ & & \mathbf{0}_{[(m-1)\times Kh]\times K} & & \\ \mathbf{0}_{1\times Kl} & \frac{\rho_H \sigma_H}{\lambda} & \dots & \frac{\rho_H^{m-1}\sigma_H}{\lambda} & \frac{\rho_H^m \sigma_H}{\lambda} \\ \hdashline & & \mathbf{0}_{K(p-1)\times K} & & \\ \hdashline & & \text{diag}(\sigma_{1,L},\dots,\sigma_{Kl,L},\sigma_{1,H},\dots,\sigma_{m,H})_{K\times K} & & \\ \hdashline & & \mathbf{0}_{1\times K} & & \end{pmatrix} \tag{B.6}$$

while X_d is constructed as in Bańbura *et al.* (2010):

$$\underset{[(Kp+1)+K]\times(Kp+1)}{X_d} = \begin{pmatrix} J_P \otimes \text{diag}(\sigma_{1,L},\dots,\sigma_{Kl,L},\sigma_{1,H},\dots,\sigma_{m,H})_{Kp\times Kp} & \mathbf{0}_{Kp\times 1} \\ \hdashline \mathbf{0}_{K\times Kp} & \mathbf{0}_{K\times 1} \\ \hdashline \mathbf{0}_{1\times Kp} & \varepsilon \end{pmatrix} \tag{B.7}$$

The prior hyperparameters are set as follows:

- $\rho_H = 0$ as suggested by Ghysels (2016), while $\rho_L = (\rho_{1,L},\dots,\rho_{Kl,L})$ are set equal to the coefficients obtained from the OLS estimation of an AR(1) regression fitted to each endogenous variable;
- σ_H is set equal to the residuals standard deviation obtained from the estimation of an AR(m) regression fitted to the high-frequency variable, while $\sigma_L = (\sigma_{1,L},\dots,\sigma_{Kl,L})$ are equal to the residuals standard deviations obtained from the estimation of AR(1) regressions fitted to each low-frequency variable;
- λ is selected by maximizing the marginal likelihood from a grid of values, that is $\lambda \in \{0.01, 0.05, 0.1, 0.2, 0.5, 1, 1.5, 2, 3\}$ (see also Paccagnini & Parla, 2021);
- $\varepsilon = 1/10000$, denoting a diffuse prior on the intercept.

As in CF-VAR, the conditional posterior distributions for the MF-VAR coefficients, $B = [A_1,\dots,A_p,c]'$, and the covariance matrix (Σ) can be defined as follows:

$$vec(B)|\Sigma, Y \sim \mathcal{N}\Big(vec(B^*),\ \Sigma \otimes (\underline{Z}^{*'}\underline{Z}^*)^{-1}\Big) \tag{B.8}$$
$$\Sigma|Y \sim \mathcal{IW}\Big(S^*,\ v^*\Big)$$

where $B^* = (\underline{Z}^{*'}\underline{Z}^*)^{-1}\underline{Z}^{*'}Z^*$ is the OLS estimate of the augmented regression. Furthermore, $S^* = (Z^* - \underline{Z}^*\tilde{B})'(Z^* - \underline{Z}^*\tilde{B})$ and v^* are, respectively, the scale parameter

and the degrees of freedom of the inverse Wishart distribution in equation (B.8), with $\tilde{B}$ being a draw of the MF-VAR coefficients and v^* equal to the number of observations in the augmented regression.
Finally, the Gibbs sampling algorithm is used to simulate the posterior distribution of the MF-VAR coefficients. In particular, we set the number of replications equal to 15000, using the last 5000 for inference.

Appendix C: Convergence diagnostics

In this appendix, we assess the convergence of the Gibbs sampler algorithm used for the estimation of the baseline MF-VAR described in Section 5.1. As suggested by Primiceri (2005), we compute the autocorrelation functions (ACF) of the retained draws. Figure C.1 shows the 20th order sample autocorrelation computed for the 840 VAR coefficients (i.e. slope coefficients and constant terms) and for the 64 elements entering the residual covariance matrix. As can be seen from Figure C.1, the autocorrelation functions are below 0.1 (in absolute value), suggesting convergence of the algorithm.[48]

[48] The results based on the ACF plots for the alternative specifications of the MF-VAR (i.e. those discussed in Section 5.4) are available upon request.

References

Alessandri, Piergiorgio, & Mumtaz, Haroon. 2017. Financial conditions and density forecasts for US output and inflation. *Review of Economic Dynamics*, **24**, 66–78.

Bacchiocchi, Emanuele, Bastianin, Andrea, Missale, Alessandro, & Rossi, Eduardo. 2020. Structural analysis with mixed-frequency data: A model of US capital flows. *Economic Modelling*, **89**, 427–443.

Bańbura, Marta, Giannone, Domenico, & Reichlin, Lucrezia. 2010. Large Bayesian vector auto regressions. *Journal of Applied Econometrics*, **25**(1), 71–92.

Brave, Scott A., & Butters, Andrew R. 2011. Monitoring Financial Stability: A Financial Conditions Index Approach. *Economic Perspectives, Federal Reserve Bank of Chicago*, **35**(1), 22–43.

Brave, Scott A., & Butters, Andrew R. 2012. Diagnosing the Financial System: Financial Conditions and Financial Stress. *International Journal of Central Banking*, **8**(2), 191–239.

Caggiano, Giovanni, Castelnuovo, Efrem, & Kima, Richard. 2020. The global effects of Covid-19-induced uncertainty. *Economics Letters*, **194**, 109392.

Caldara, Dario, Fuentes-Albero, Cristina, Gilchrist, Simon, & Zakrajšek, Egon. 2016. The macroeconomic impact of financial and uncertainty shocks. *European Economic Review*, **88**, 185–207.

Cardarelli, Roberto, Elekdag, Selim, & Lall, Subir. 2011. Financial stress and economic contractions. *Journal of Financial Stability*, **7**(2), 78–97.

Carriero, Andrea, Kapetanios, George, & Marcellino, Massimiliano. 2012. Forecasting government bond yields with large Bayesian vector autoregressions. *Journal of Banking & Finance*, **36**(7), 2026–2047.

Chatterjee,Somnath, Chiu, Ching-Wai Jeremy, Duprey, Thibaut, & Hoke, Sinem Hacioglu. 2017. A financial stress index for the United Kingdom. *Bank of England Staff Working Paper No. 697*.

Chavleishvili, Sulkhan, & Kremer, Manfred. 2021. Measuring Systemic Financial Stress and its Impact on the Macroeconomy. *SSRN*.

Cipollini, Andrea, & Mikaliunaite, Ieva. 2020. Financial distress and real economic activity in Lithuania: a Granger causality test based on mixed-frequency VAR. *Empirical Economics*, 1–27.

Conefrey, Thomas, & Walsh, Graeme. 2018. A Monthly Indicator of Economic Activity for Ireland. *Central Bank of Ireland Economic Letter No. 14*.

Duprey, Thibaut. 2020. Canadian Financial Stress and Macroeconomic Conditions. *Bank of Canada Staff Discussion Paper 2020-4*.

Duprey, Thibaut, Klaus, Benjamin, & Peltonen, Tuomas. 2017. Dating systemic financial stress episodes in the EU countries. *Journal of Financial Stability*, **32**, 30–56.

Ferrara, Laurent, & Guérin, Pierre. 2018. What are the macroeconomic effects of high-frequency uncertainty shocks? *Journal of Applied Econometrics*, **33**(5), 662–679.

Foroni, Claudia, & Marcellino, Massimiliano. 2016. Mixed frequency structural vector auto-regressive models. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, **179**(2), 403–425.

Furlanetto, Francesco, Ravazzolo, Francesco, & Sarferaz, Samad. 2019. Identification of financial factors in economic fluctuations. *The Economic Journal*, **129**(617), 311–337.

Gambetti, Luca, & Musso, Alberto. 2017. Loan Supply Shocks and the Business Cycle. *Journal of Applied Econometrics*, **32**(4), 764–782.

Ghysels, Eric. 2016. Macroeconomics and the reality of mixed frequency data. *Journal of Econometrics*, **193**(2), 294–314.

Gilchrist, Simon, Sim, Jae W, & Zakrajšek, Egon. 2014. Uncertainty, Financial Frictions, and Investment Dynamics. *NBER Working Paper No. 20038*.

Götz, Thomas B, Hecq, Alain, & Smeekes, Stephan. 2016. Testing for Granger causality in large mixed-frequency VARs. *Journal of Econometrics*, **193**(2), 418–432.

Hakkio, Craig S, & Keeton, William R. 2009. Financial stress: what is it, how can it be measured, and why does it matter? *Economic Review, Federal Reserve Bank of Kansas City*, **94**(2), 5–50.

Holló, Dániel, Kremer, Manfred, & Lo Duca, Marco. 2012. CISS - A Composite Indicator of Systemic Stress in the Financial System. *ECB Working Paper No. 1426.*

Hristov, Nikolay, Hülsewig, Oliver, & Wollmershäuser, Timo. 2012. Loan supply shocks during the financial crisis: Evidence for the Euro area. *Journal of International Money and Finance*, **31**(3), 569–592.

Hubrich, Kirstin, & Tetlow, Robert J. 2015. Financial stress and economic dynamics: The transmission of crises. *Journal of Monetary Economics*, **70**, 100–115.

Illing, Mark, & Liu, Ying. 2006. Measuring financial stress in a developed country: An application to Canada. *Journal of Financial Stability*, **2**(3), 243–265.

Jermann, Urban, & Quadrini, Vincenzo. 2012. Macroeconomic Effects of Financial Shocks. *American Economic Review*, **102**(1), 238–271.

Kliesen, Kevin L, & Smith, Douglas C. 2010. Measuring Financial Market Stress. *Federal Reserve Bank of St. Louis Economic Synopses No. 2*.

Kliesen, Kevin L, Owyang, Michael T, & Vermann, E Katarina. 2012. Disentangling Diverse Measures: A Survey of Financial Stress Indexes. *Federal Reserve Bank of St. Louis Review*, **94**(5), 369–397.

Lenza, Michele, & Primiceri, Giorgio E. 2020. How to Estimate a VAR after March 2020. *NBER Working Paper No. 27771*.

Litterman, Robert B. 1986. Forecasting with Bayesian Vector Autoregressions: Five Years of Experience. *Journal of Business & Economic Statistics*, **4**(1), 25–38.

Lo Duca, Marco, Koban, Anne, Basten, Marisa, Bengtsson, Elias, Klaus, Benjamin, Kusmierczyk, Piotr, Lang, Jan Hannes, Detken, Carsten, & Peltonen, Tuomas A. 2017. A new database for financial crises in European countries: ECB/ESRB EU crises database. *ECB Occasional Paper No. 194*.

Louzis, Dimitrios P, & Vouldis, Angelos T. 2012. A methodology for constructing a financial systemic stress index: An application to Greece. *Economic Modelling*, **29**(4), 1228–1241.

Mallick, Sushanta K, & Sousa, Ricardo M. 2013. The real effects of financial stress in the Eurozone. *International Review of Financial Analysis*, **30**, 1–17.

Miglietta, Arianna, & Venditti, Fabrizio. 2019. An indicator of macro-financial stress for Italy. *Bank of Italy Occasional Paper No. 497*.

Mumtaz, Haroon, Pinter, Gabor, & Theodoridis, Konstantinos. 2018. What do VARs tell US about the impact of a credit supply shock? *International Economic Review*, **59**(2), 625–646.

O'Brien, Martin, & Wosser, Michael. 2021. Growth at Risk & Financial Stability. *Central Bank of Ireland Financial Stability Notes No. 2*.

Oet, Mikhail V, Eiben, Ryan, Bianco, Timothy, Gramlich, Dieter, & Ong, Stephen J. 2011. The Financial Stress Index: Identification of Systemic Risk Conditions. *Federal Reserve Bank of Cleveland Working Paper No. 11-30*.

O'Grady, Michael. mimeo. Credit Shocks in Good Times and Bad: Structural Identification using an Irish Composite Stress Index.

Paccagnini, Alessia, & Parla, Fabio. 2021. Identifying High-Frequency Shocks with Bayesian Mixed-Frequency VARs. *CAMA Working Paper No. 26/2021*.

Prieto, Esteban, Eickmeier, Sandra, & Marcellino, Massimiliano. 2016. Time Variation in Macro-Financial Linkages. *Journal of Applied Econometrics*, **31**(7), 1215–1233.

Primiceri, Giorgio E. 2005. Time Varying Structural Vector Autoregressions and Monetary Policy. *The Review of Economic Studies*, **72**(3), 821–852.

Sims, Christopher A, & Zha, Tao. 1998. Bayesian Methods for Dynamic Multivariate Models. *International Economic Review*, **39**(4), 949–968.

Sims, Christopher A, Stock, James H, & Watson, Mark W. 1990. Inference in Linear Time Series Models with Some Unit Roots. *Econometrica*, **58**(1), 113–144.

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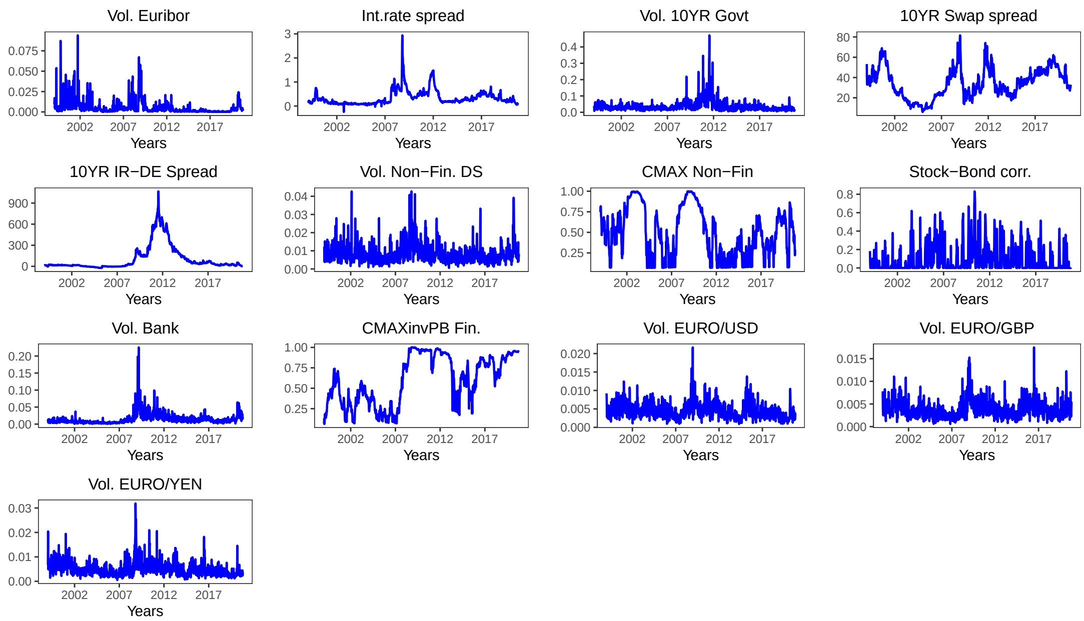
Table 1: Raw stress indicators grouped by financial market segment.

Market segment	Stress indicator	Label & first obs.
MONEY		
• Volatility of the 3-month Euribor rate	Volatility calculated as the weekly average of absolute daily rate changes.	**Vol.Euribor** 4 January 1999
• Interest rate spread between the 3-month Euribor and the yield on the government short-term rate	Variable computed as weekly average of daily data.	**Int.rate spread** 4 January 1999
SOVEREIGN BONDS		
• Volatility of the 10-year Govt. benchmark bond index	Volatility calculated as the weekly average of absolute daily yield changes.	**Vol. 10YR Govt** 7 January 1985
• 10-year interest rate swap spread	Variable computed as weekly average of daily data.	**10YR Swap spread** 12 August 1996
• 10-year IR-DE Govt. Bond spread	Variable computed as weekly average of daily data.	**10YR IR-DE Spread** 7 January 1985
EQUITY		
• Volatility of the non-financial sector stock market price index	Volatility calculated as the weekly average of absolute daily log returns.	**Vol. Non-Fin. DS** 8 January 1973
• CMAX for the non-financial sector stock market index	Maximum cumulated losses of the non-financial sector stock market index, over a 2-year rolling window, that is: $CMAX_t = 1 - x_t/max[x \in (x_{t-j}\|j = 0, 1, \ldots, T)]$ where $T = 104$ for weekly data.	**CMAX Non-Fin** 8 January 1973
• Stock-bond correlation	Variable computed as weekly average of the difference between the 4-year (1040 business days) and the 4-week (20 business days) correlation coefficients between daily log returns of total stock market index and the changes in the 10-year Govt. bond yield. The indicator takes value of zero for negative differences.	**Stock-Bond corr.** 2 January 1989
BANKING		
• Volatility of the idiosyncratic equity return of the bank sector stock market index over the total market index	Idiosyncratic return calculated as the residual from an OLS regression of the daily log bank return on the log market return over a 2-year rolling window (i.e. 522 business days). Realised volatility calculated as the weekly average of absolute daily idiosyncratic returns.	**Vol. Bank** 8 January 1973
• CMAX for the financial sector stock market index interacted with the inverse of its price-to-book ratio	Maximum cumulated losses of the financial sector stock market index, over a 2-year rolling window, i.e. $CMAX_t = 1 - x_t/max[x \in (x_{t-j}\|j = 0, 1, \ldots, T)]$ where $T = 104$ for weekly data. The final indicator is constructed as transforming first the CMAX and the inverse price-to-book ratio by their recursive CDF and then take the square root of the interaction between the transformed series.	**CMAXinvPB Fin.** 7 January 1985
FOREIGN EXCHANGE		
• Volatility of the bilateral exchange rate between the Euro and the US dollar	Volatility calculated as the weekly average of absolute daily log foreign exchange returns.	**Vol. EURO/USD** 23 October 1989
• Volatility of the bilateral exchange rate between the Euro and the British Pound	Volatility calculated as the weekly average of absolute daily log foreign exchange returns.	**Vol. EURO/GBP** 2 July 1990
• Volatility of the bilateral exchange rate between the Euro and the Japanese Yen	Volatility calculated as the weekly average of absolute daily log foreign exchange returns.	**Vol. EURO/YEN** 4 June 1990

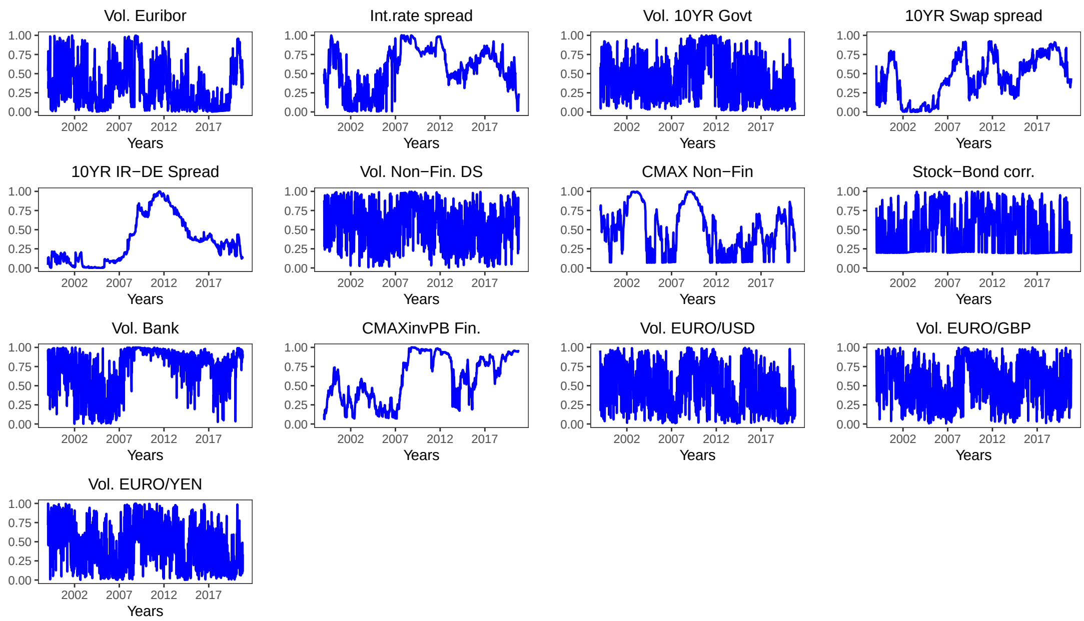
Notes. The table reports the thirteen raw indicators entering the ICSI with a brief description of their calculation (for more details see Holló *et al.*, 2012; Miglietta & Venditti, 2019). The table also reports the labels assigned to each stress indicator and their first observation available. The last observation for all the raw stress indicators is 23 October 2020.

Figure 1: Raw stress indicators (weekly frequency). 1999M1 – 2020M10.



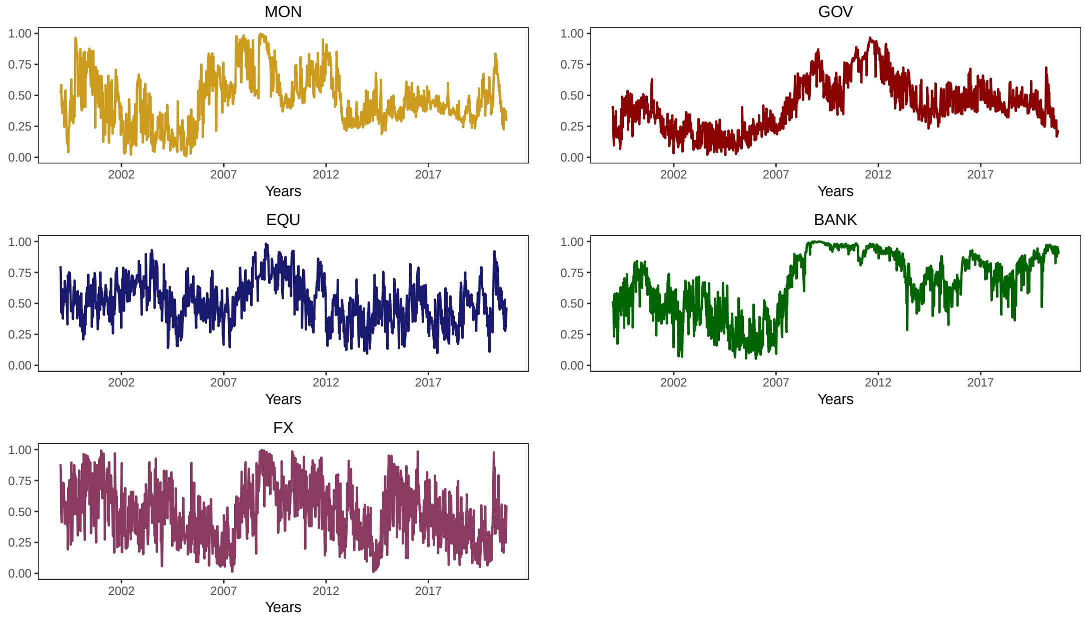
Notes. The charts display the 13 weekly financial stress indicators only from January 1999. A detailed description of the raw stress indicators is reported in Table 1.

Figure 2: Standardized stress indicators (weekly frequency). 1999M1 – 2020M10.



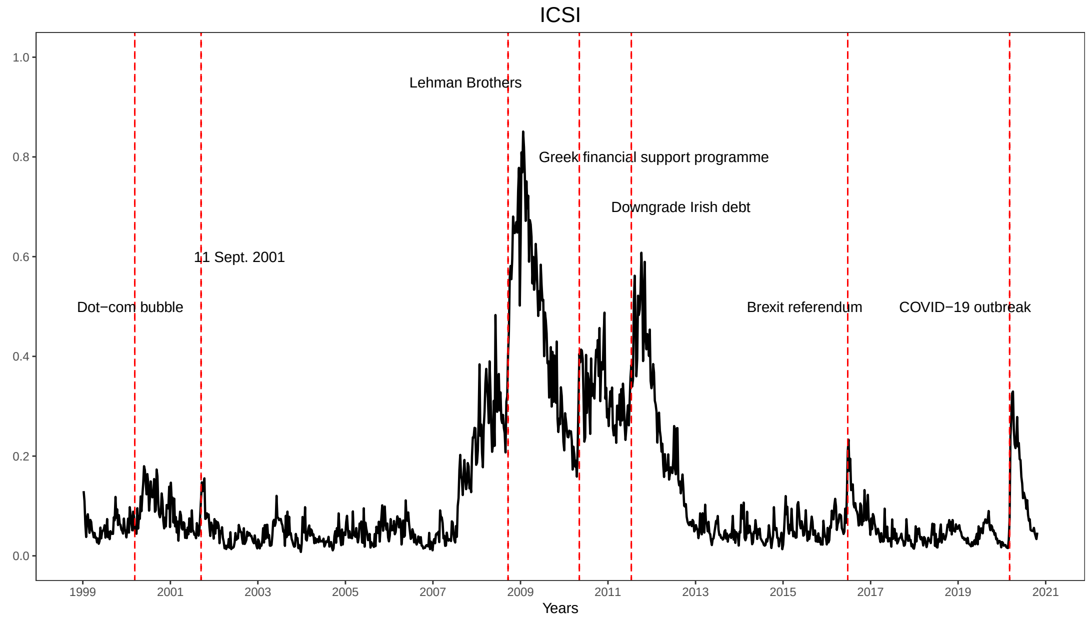
Notes. The figure shows the 13 standardized financial stress indicators computed by applying the empirical cumulative distribution function (ECDF) (see Section 3).

Figure 3: Financial markets sub-indices (weekly frequency). 1999M1 – 2020M10.



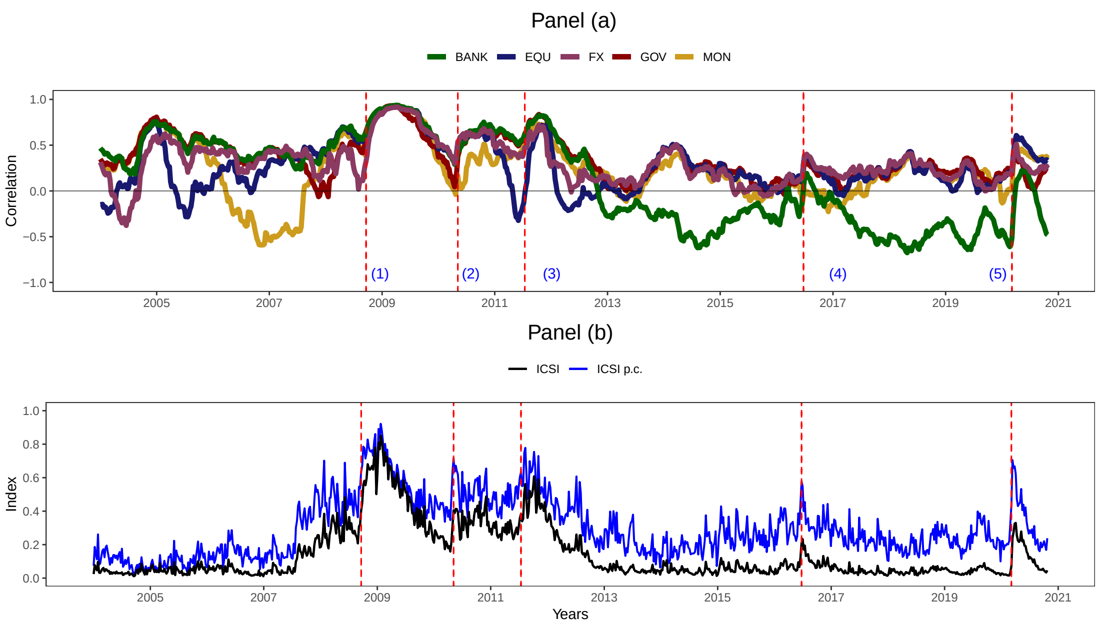
Notes. The figure displays the financial market sub-indices obtained by aggregating (through arithmetic average) the standardized raw stress indicators. In particular, the stress indicators are grouped as follows: 1) Vol.Euribor and Int.rate spread (MON); 2) Vol. 10YR Govt, 10YR Swap spread and 10YR IR-DE Spread (GOV); 3) Vol. Non-Fin. DS, CMAX Non-Fin and Stock-Bond corr. (EQU); 4) Vol. Bank and CMAXinvPB Fin. (BANK); 5) Vol. EURO/USD, Vol. EURO/GBP and Vol. EURO/YEN (FX). See Table 1 for a detailed description of the raw stress indicators.

Figure 4: Irish Composite Stress Indicator (ICSI) (weekly frequency). 1999M1 – 2020M10.



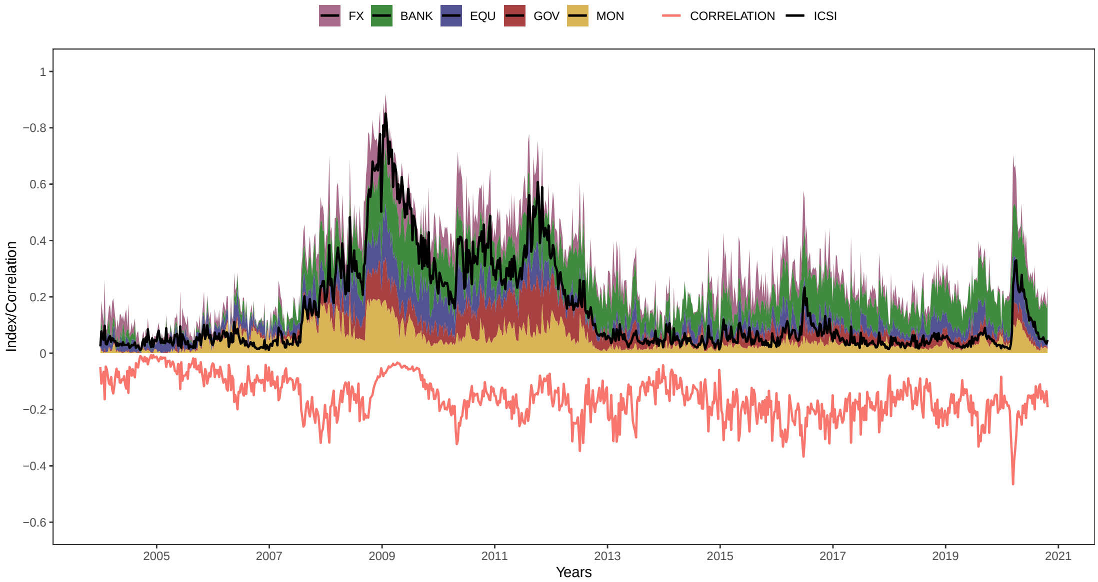
Notes. The figure shows the ICSI computed over the period 1999M1 – 2020M10 (black line). Financial market stress episodes are also reported (vertical red dashed lines). In particular, the list of financial market stress events includes: 1) the Dot-com bubble (around March 2000); 2) the September 11 attacks; 3) the collapse of Lehman Brothers (15 September 2008); 4) the Greek financial support programme (May 2010); 5) the downgrade of the Irish government bonds ratings (July 2011); 6) the Brexit referendum (23 June 2016); 7) the COVID-19 outbreak (first cases of Coronavirus registered in the Republic of Ireland in early March 2020).

Figure 5: Synchronization of stress in the Irish financial markets (weekly frequency). 2004M1 – 2020M10.



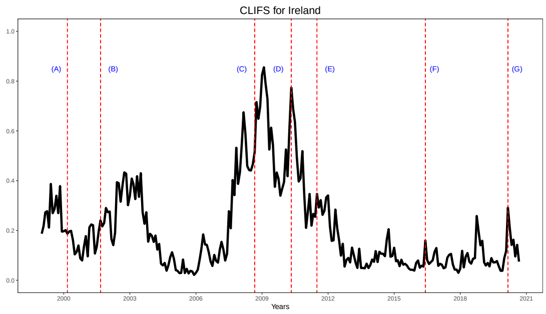
Notes. The figure displays the time-varying average pairwise cross-section correlations computed across the sub-market indices, that is money (MON), sovereign bonds (GOV), equity (EQU), banking (BANK) and foreign exchange (FX) markets (panel a) and two versions of the ICSI, i.e. the ICSI described in Section 3 (black line) and the ICSI computed under a perfect correlation scenario (ICSI$_{p.c.}$) (blue line) (see panel b). The average cross-correlations are computed as follows: $\bar{\rho}_{it} = \left(\sum_{j=0}^{5} \rho_{ijt} - 1\right)/(5-1)$, for $i, j = 1, \ldots, 5$, $i \neq j$ and $t = 1, \ldots, T$. Financial market stress episodes are also reported (vertical red dashed lines): 1) the collapse of Lehman Brothers (15 September 2008); 2) the Greek financial support programme (May 2010); 3) the downgrade of the Irish government bonds ratings (July 2011); 4) the Brexit referendum (23 June 2016); 5) the COVID-19 outbreak (first cases of Coronavirus registered in the Republic of Ireland in early March 2020).

Figure 6: Decomposition of the Irish Composite Stress Indicator (ICSI) (weekly frequency). 2004M1 – 2020M10.

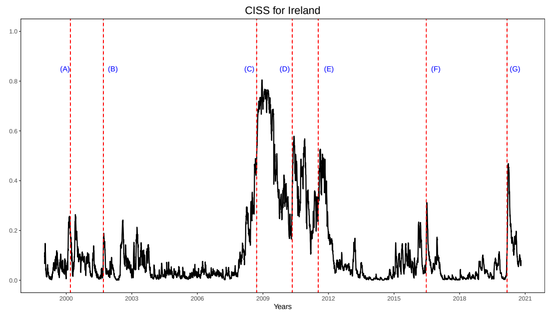


Notes. The figure shows the contribution from the financial market sub-indices (coloured stacked areas) and from all the cross-correlations jointly (red line) to the dynamics of the ICSI (black line). The sum of the contributions equals the financial stress index under a perfect correlation scenario ($\text{ICSI}_{p.c.}$). The contribution from a specific sub-index (V_{it}) is computed as follows: 1) $s_{it} = (S_{it} \times w_i)^2 / \sum_{i=1}^{5} (S_{it} \times w_i)^2$, where S_{it} is the i-th financial market sub-index, with $S_{it} \in (S_{MON,t}, S_{GOV,t}, S_{EQU,t}, S_{BANK,t}, S_{FX,t})$; 2) $V_{it} = s_{it} \times \text{ICSI}_{p.c.}$. The contribution from the cross-correlations is computed as the difference between the ICSI and the $\text{ICSI}_{p.c.}$ (see Holló *et al.*, 2012; Miglietta & Venditti, 2019, for more details).

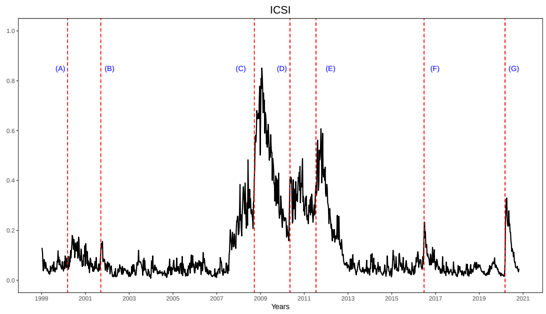
Figure 7: Comparison of the ICSI with alternative measures of financial market distress for Ireland.



(a) CLIFS for Ireland



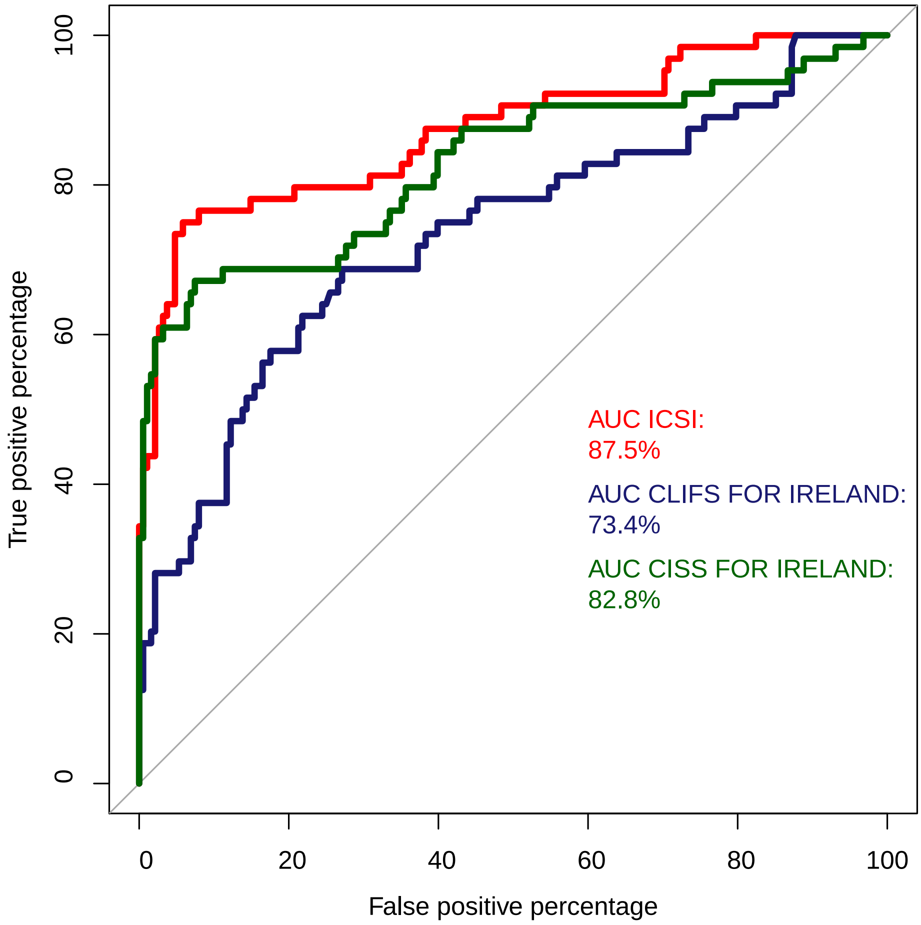
(b) CISS for Ireland



(c) ICSI

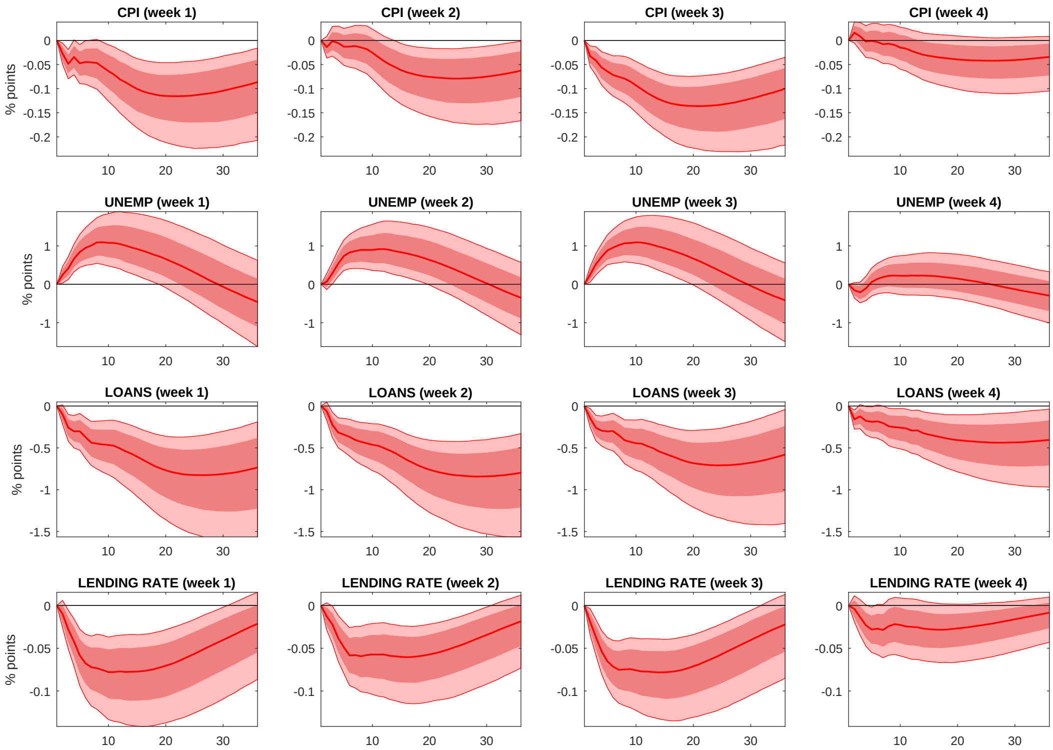
Notes. The figure shows three measures of financial market stress for Ireland. Panel (a) shows the CLIFS (Country-Level Index of Financial Stress) over the period 1999M1–2020M9. It is a monthly index developed by the study of Duprey *et al.* (2017) and it is updated by the ECB at the end of each month, reporting values for the previous month. The series of CLIFS for Ireland is available at https://sdw.ecb.europa.eu/browse.do?node=9693347. Panel (b) displays the daily New CISS (Composite Indicator of Systemic Stress) for Ireland introduced by Chavleishvili & Kremer (2021). The series is downloaded from the Statistical Data Warehouse (SDW) of the ECB (available at https://sdw.ecb.europa.eu/browse.do?node=9689686). Panel (c) shows the ICSI (Irish Composite Stress Indicator).
Financial market stress episodes are also reported, including A) the Dot-com bubble (around March 2000); B) the September 11 attacks; C) the collapse of Lehman Brothers (15 September 2008); D) the Greek financial support programme (May 2010); E) the downgrade of the Irish government bonds ratings (July 2011); F) the Brexit referendum (23 June 2016); G) the COVID-19 outbreak (first cases of Coronavirus registered in the Republic of Ireland in early March 2020).

Figure 8: AUROC for alternative measures of financial market stress for Ireland.



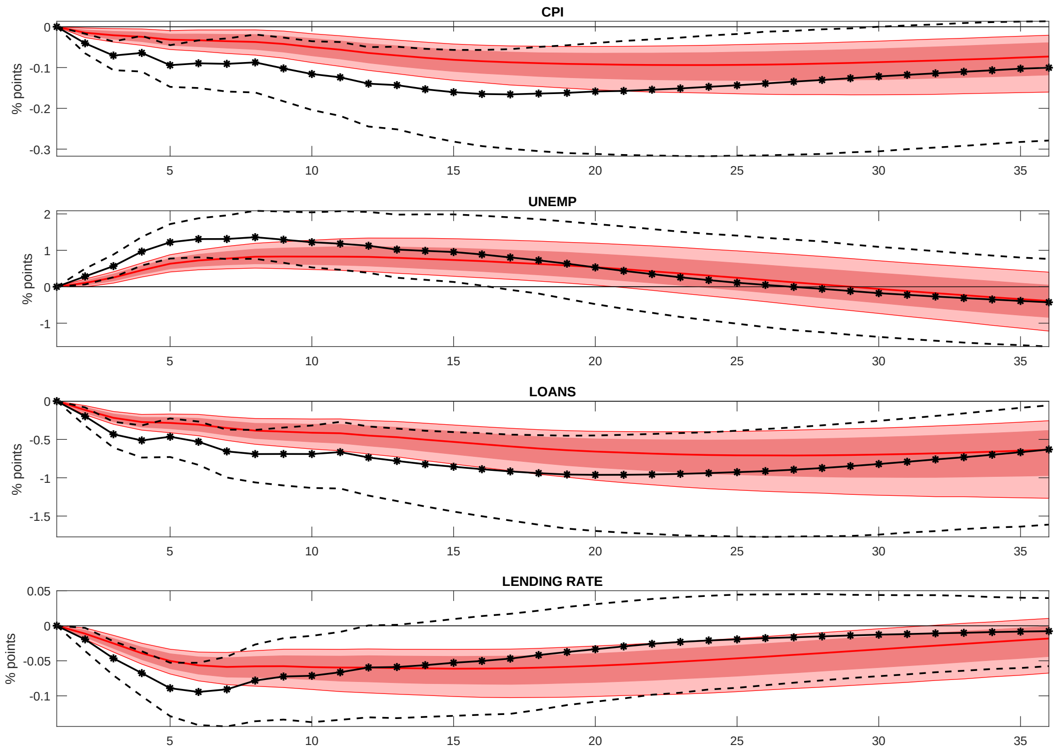
Notes. The figure shows the receiver operating characteristic (ROC) curve computed for three different measures of financial market stress for Ireland: ICSI (red line), CLIFS (blue line) and New CISS (green line). The area under the receiver operating characteristic (AUROC) curve in percentage is also reported: ICSI (87.5%), CLIFS (73.4%) and CISS (82.8%). The chart displays, for each value of the threshold (see Section 4.2, for technical details), the percentage of false positive (i.e. Type II error) (horizontal axis) and the percentage of true positive (i.e. $1-$ Type I error) (vertical axis). The 45-degree diagonal line corresponds to an uninformative indicator.

Figure 9: Weekly responses of macroeconomic and banking variables to financial market distress.



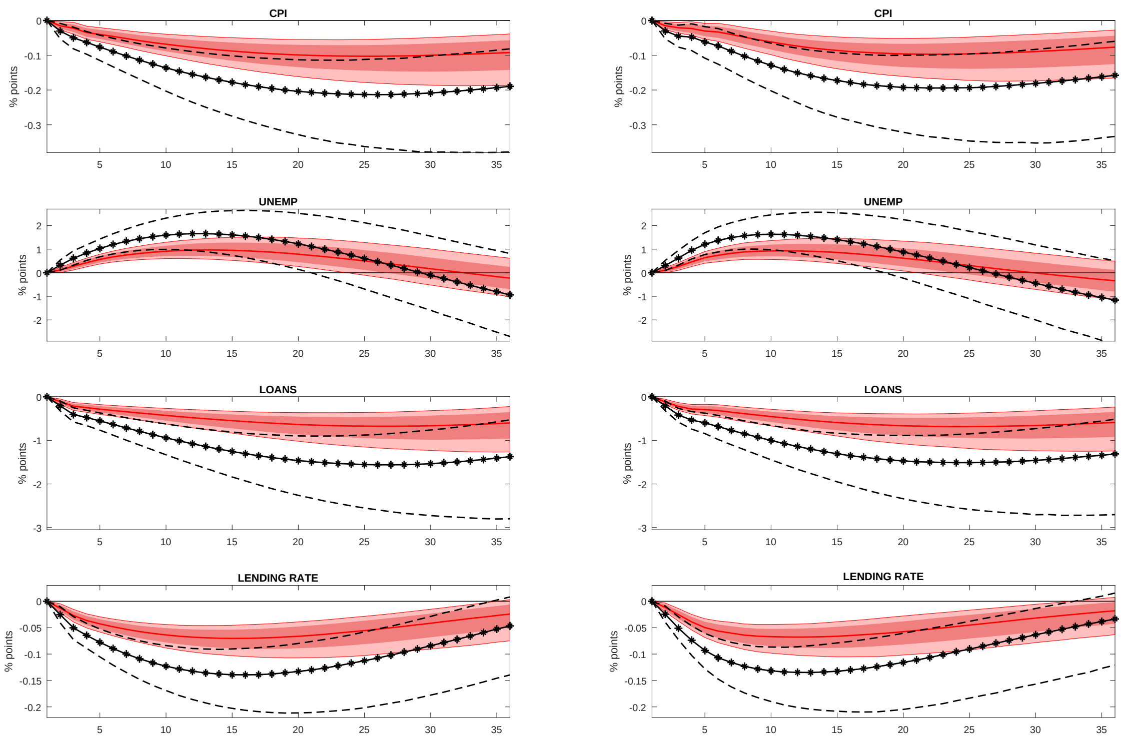
Notes. Impulse responses of the consumer price index (CPI), unemployment (UNEMP), loans and lending rate levels to a one standard deviation ICSI shock (in percentage points), obtained from the estimation of the MF-VAR(13) (see Section 5.1). Each row displays the response of the variable of interest to shocks occurring in week 1, week 2, week 3 and week 4. Each chart shows the median response (red line) and the corresponding 68% and 90% credibility intervals (red shading).

Figure 10: Aggregated responses of macroeconomic and banking variables from MF-VAR to financial market distress.



Notes. Impulse responses of the consumer price index (CPI), unemployment (UNEMP), loans and lending rate levels to a one standard deviation ICSI shock (in percentage points). Each chart shows the aggregated median responses from the MF-VAR(13) and the corresponding 68% and 90% credibility intervals (red shading). The aggregated impulse responses are obtained by averaging out the weekly responses (see Section 5.3). The median responses from a CF-VAR (black line) and the associated 90% credibility intervals (black dashed lines) are also reported.

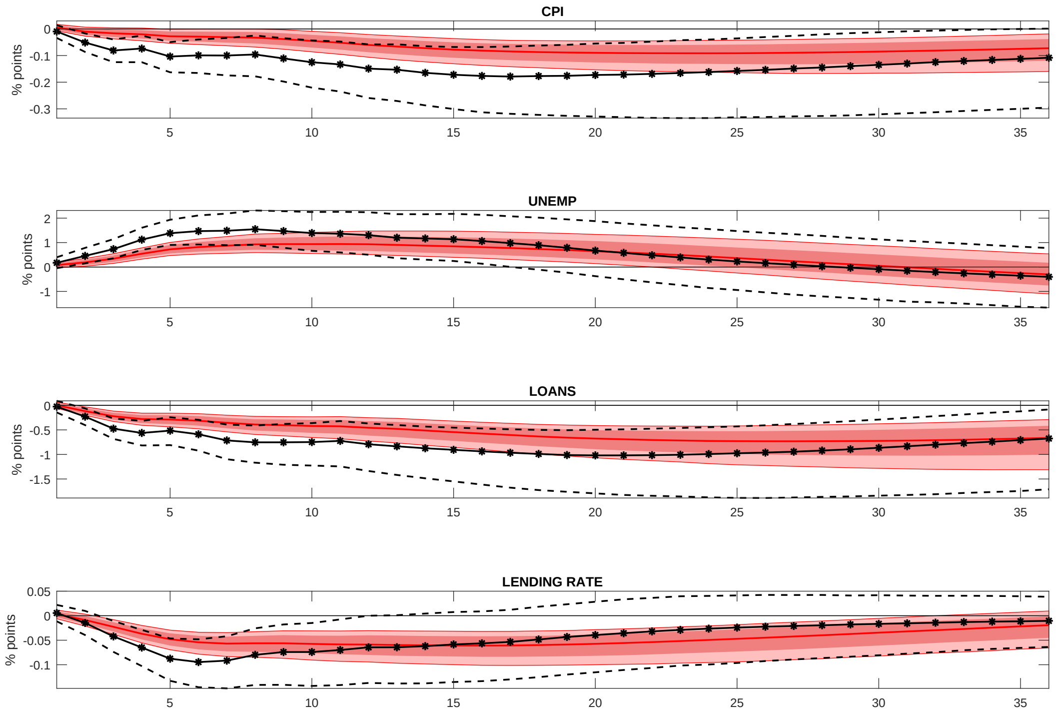
Figure 11: Aggregated responses of macroeconomic and banking variables from MF-VAR to financial market distress. Different lag structures.



(a) 3 lags **(b)** 6 lags

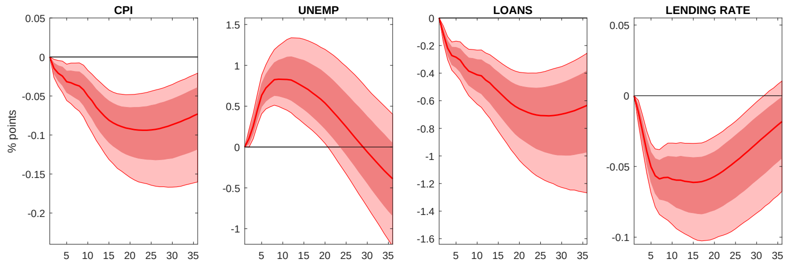
Notes. Impulse responses of the consumer price index (CPI), unemployment (UNEMP), loans and lending rate levels to a one standard deviation ICSI shock (in percentage points), obtained from the estimation of a MF-VAR with 3 (Panel a) and 6 lags (Panel b). Each chart shows the aggregated median response from the MF-VARs and the corresponding 68% and 90% credibility intervals (red shading). The aggregated impulse responses are obtained by averaging out the weekly responses. The median responses from a CF-VAR (black line) and the associated 90% credibility intervals (black dashed lines) are also reported.

Figure 12: Aggregated responses of macroeconomic and banking variables from MF-VAR to financial market distress. ICSI ordered first.

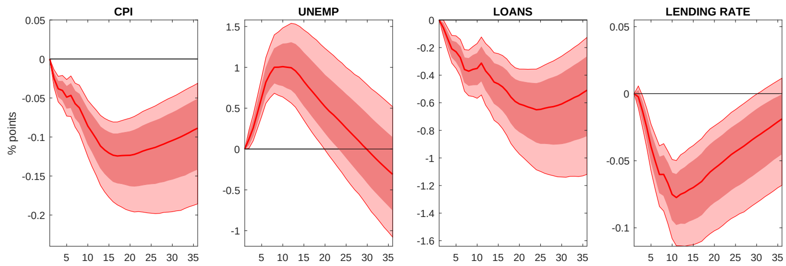


Notes. Impulse responses of the consumer price index (CPI), unemployment (UNEMP), loans and lending rate levels to a one standard deviation ICSI shock (in percentage points). The IRFs are obtained from the estimation of a MF-VAR(13) with the ICSI placed before the block of macroeconomic and banking variables. Each chart shows the aggregated median response from the MF-VAR and the corresponding 68% and 90% credibility intervals (red shading). The aggregated impulse responses are obtained by averaging out the weekly responses. The median responses from a CF-VAR (black line) and the associated 90% credibility intervals (black dashed lines) are also reported.

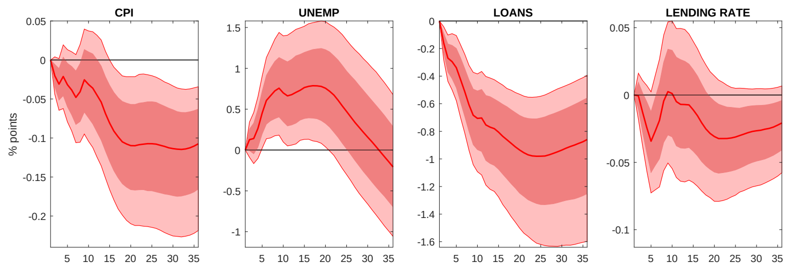
Figure 13: Responses of macroeconomic and banking variables using alternative measures of financial market stress for Ireland.



(a) Proxy of financial stress: ICSI.



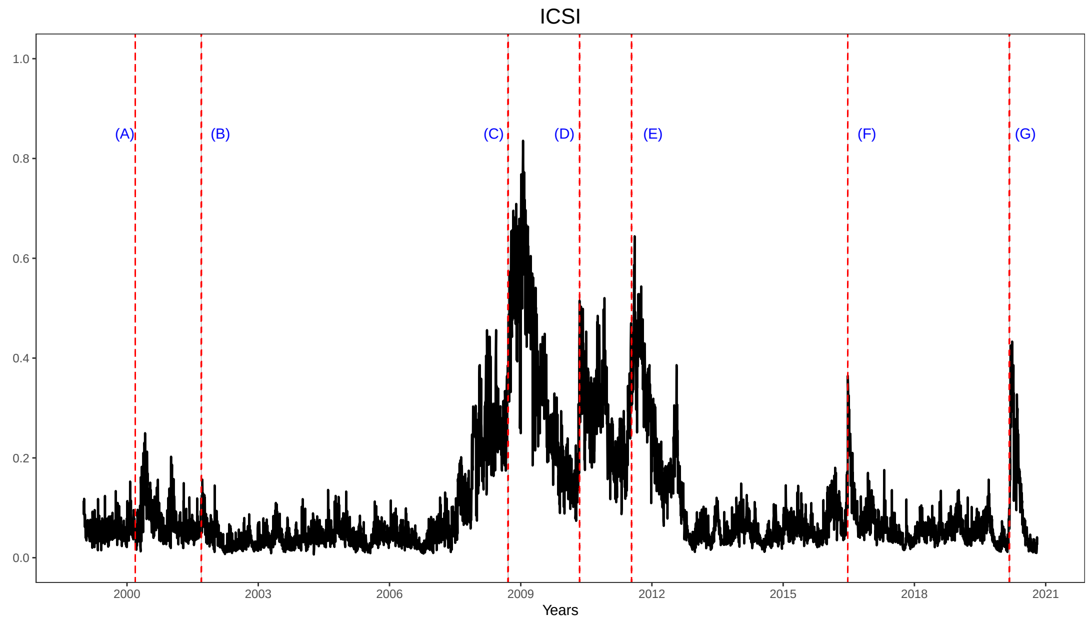
(b) Proxy of financial stress: New CISS for Ireland.



(c) Proxy of financial stress: CLIFS for Ireland.

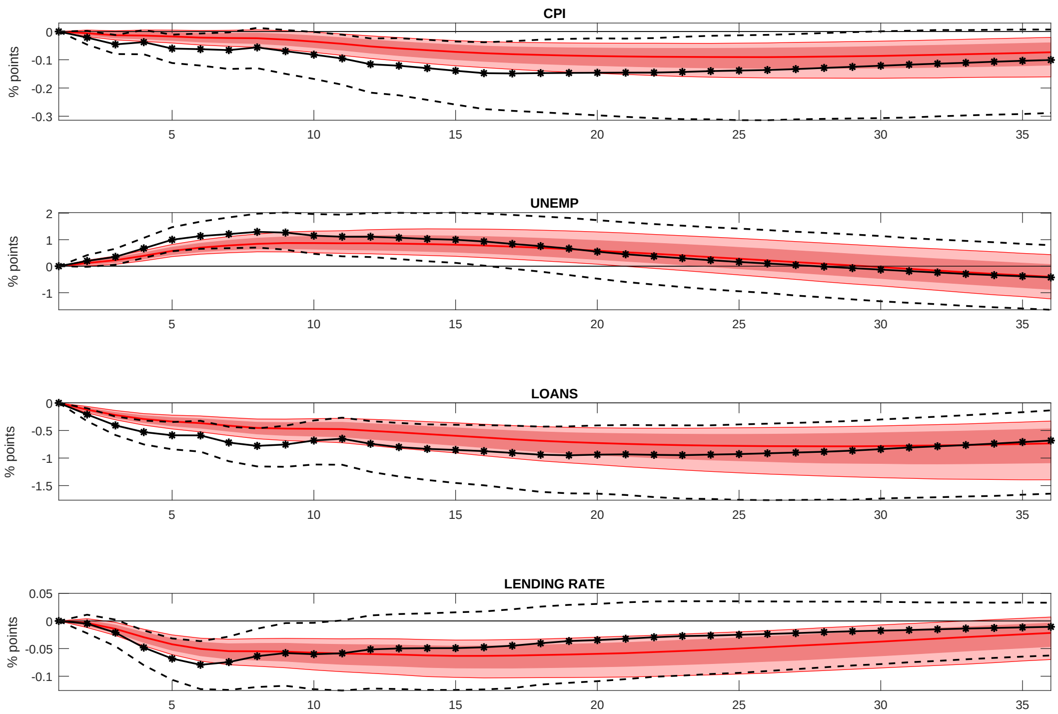
Notes. Impulse responses of the consumer price index (CPI), unemployment (UNEMP), loans and lending rate levels to a one standard deviation financial shock proxied by alternative measures of financial market stress (in percentage points). Panel a shows the responses obtained from the estimation of a MF-VAR fitted to weekly series of ICSI. Panel b shows the responses obtained from the estimation of a MF-VAR with financial distress proxied by the weekly series of New CISS (see Section 5.4). Finally, Panel c shows the responses obtained from the estimation of a monthly VAR using the CLIFS as a measure of financial market stress. The models are estimated using a lag length equal to 13. Each chart shows the median response (aggregated for MF-VARs) and the corresponding 68% and 90% credibility intervals (red shading).

Figure A.1: Irish Composite Stress Indicator (ICSI) at a daily frequency. 1999M1 – 2020M10.



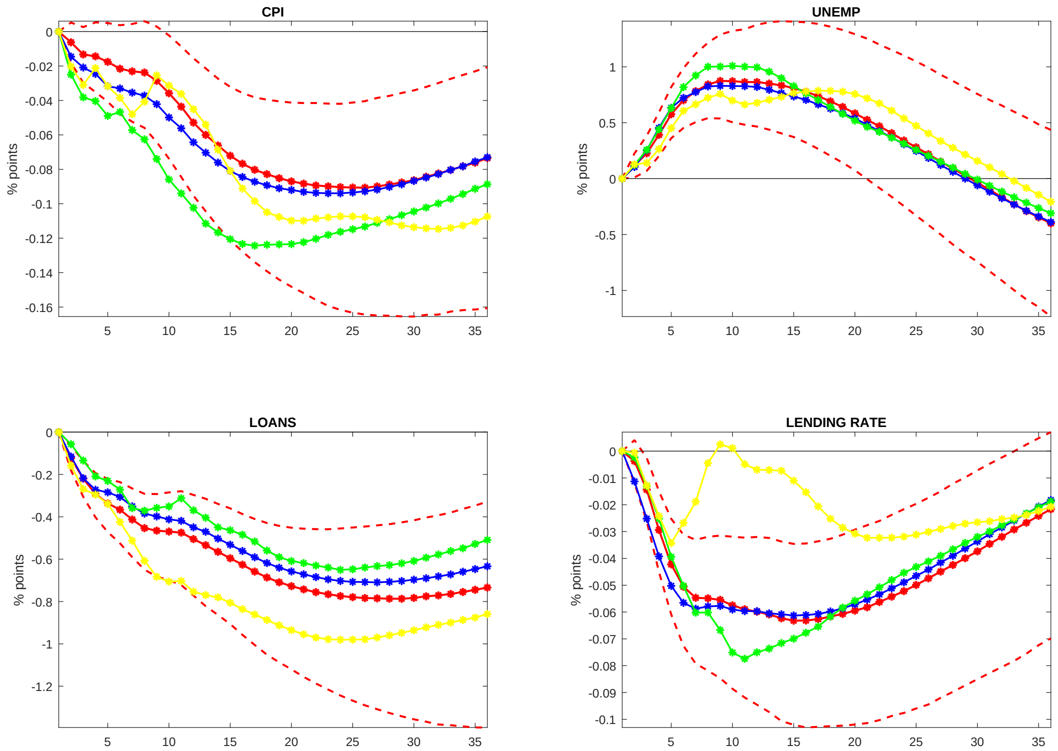
Notes. The figure shows the ICSI computed at a daily frequency over the period 1999M1 – 2020M10 (black line). The financial market series entering the index are the same of those described in Table 1. Financial market stress episodes are also reported (vertical red dashed lines). In particular, the list of financial market stress events includes: A) the Dot-com bubble (around March 2000); B) the September 11 attacks; C) the collapse of Lehman Brothers (15 September 2008); D) the Greek financial support programme (May 2010); E) the downgrade of the Irish government bonds ratings (July 2011); F) the Brexit referendum (23 June 2016); G) the COVID-19 outbreak (first cases of Coronavirus registered in the Republic of Ireland in early March 2020).

Figure A.2: Aggregated responses of macroeconomic and banking variables from MF-VAR using the daily series of ICSI.



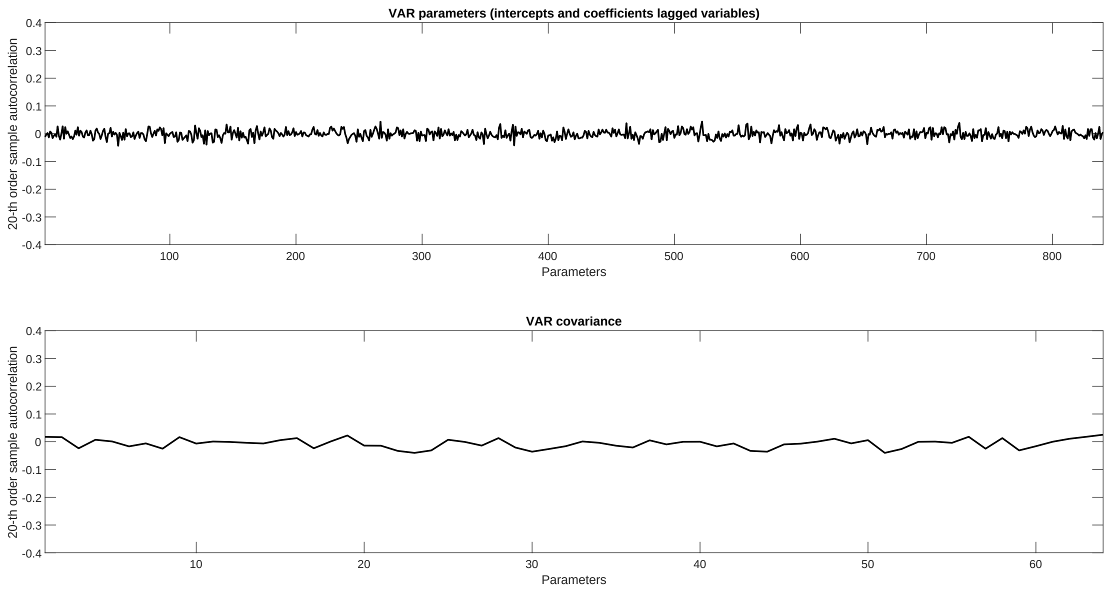
Notes. Impulse responses of the consumer price index (CPI), unemployment (UNEMP), loans and lending rate levels to a one standard deviation ICSI shock (in percentage points). Each chart shows the aggregated median response from a MF-VAR(13) and the corresponding 68% and 90% credibility intervals (red shading). The aggregated impulse responses are obtained by averaging out the weekly responses (see Appendix A). The median responses from a CF-VAR (black line) and the associated 90% credibility intervals (black dashed lines) are also reported.

Figure A.3: Responses of macroeconomic and banking variables using alternative measures of financial market stress.



Notes. Impulse responses of the consumer price index (CPI), unemployment (UNEMP), loans and lending rate levels to a one standard deviation financial market shock (in percentage points). Each chart shows the aggregated median response from a MF-VAR(13) (red line) and the corresponding 68% and 90% credibility intervals (red dashed lines) using the (aggregated) daily series of ICSI. The median responses from a MF-VAR(13) using the weekly ICSI (described in Section 3) (blue line), from a MF-VAR(13) using the Irish CISS (green line) and from a monthly CF-VAR(13) using the CLIFS (yellow line) are also reported.

Figure C.1: Convergence diagnostics for VAR coefficients and residual covariance matrix.



Notes. 20th order sample autocorrelation of the retained draws (i.e. 5000) computed for the 840 VAR coefficients (slope coefficients and constant terms) (upper panel) and for the 64 elements entering the residual covariance matrix (lower panel). The VAR parameters and the residual covariance matrix are obtained from the estimation of the baseline MF-VAR (see Section 5.1).

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