Time-Varying Predictability of Financial Stress on Inequality in United Kingdom[#]

*Edmond Berisha (Montclair State University, Montclair, New Jersey, USA)

David Gabauer (Johannes Kepler Universitat Linz, Linz, Austria)

Rangan Gupta (University of Pretoria, Pretoria, South Africa)

Jacobus Nel (University of Pretoria, Pretoria, South Africa)

* Corresponding author: Edmond Berisha can be contacted at: berishae@montclair.edu

Abstract

Purpose: Existing empirical evidence suggests that episodes of financial stress (crises) can act as driver of growth of inequality. Consequently, in this study, the authors explore the time-varying predictive power of an index of financial stress for growth in income (and consumption) inequality in the UK. The authors focus on the UK since income (and consumption) inequality data are available at a high frequency, i.e. on a quarterly basis for over 40 years (June, 1975 to March, 2016).

Design/methodology/approach: The authors use Wang and Rossi's approach to analyze the time-varying impact of financial stress on inequality. Hence, the method provides a more appropriate inference of the effect rather than a constant parameter Granger causality method. Besides, understandably, the time-varying approach helps to depict the time-variation in the strength of predictability of financial stress on inequality.

Findings: This study's findings point that financial distress correspond to subsequent increases in inequality, with the index of financial stress containing important information in predicting growth in income inequality for both in and out-of-sample periods. Interestingly, the strength of the in-sample predictive power is high post the period of the global financial crisis, as was observed in the early part of the sample. The authors believe these findings highlight an important role of financial stress for inequality – an area of investigation that has in general remained untouched.

Originality/value: Accurate prediction of inequality at a higher frequency should be more relevant to policymakers in designing appropriate policies to circumvent the wide-ranging negative impacts of inequality, compared to when predictions are only available at the lower annual frequency.

JEL Code: C32, C53, D31, G01
Keywords: Financial Stress; Inequality; Time-Varying Predictions

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1. Introduction

Literature shows that fluctuations in financial sector can act as a source of business cycles. Jermann and Quadrini (2012) emphasize that a model driven only by productivity shocks fails to explain observed business cycles in the United States. The model that incorporates financial shocks generates more realistic dynamics of real business cycle quantities, especially labor. Similarly, Caldara et al (2016) find that financial shocks have a significant adverse effect on economic outcomes, especially since the mid-1980s. Earlier studies, such as, Christiano, Motto & Rostagno (2008), Gilchrist, Yankov & Zakrajsek (2009) and Kiyotaki & Moore (2008) suggest that shocks that originate from the financial sector could play an important role as a source of macroeconomic fluctuations. In this study, we examine the distributional consequences of financial shocks. We believe that understanding the distributional impact of financial shocks is a crucial prerequisite for optimal policy design, especially in the aftermath of the recent global financial crisis.

Financial shocks can have distributional effects based on differing responses of labor and capital income, relative price changes, and heterogeneous change in the availability of credit across the income distribution (Acemoglu, 2011; Kuhn et al., 2018).[1] Few single- and cross-country-based recent studies have provided evidence of the predictive role of financial shocks on income inequality (see for example, Roine et al., (2009), Wolff (2013), Callan et al., (2014), Grabka (2015), Baeten (2016), Destek and Koksel (2019), and Gokmen and Morin (2019)). However, the sign of distributional impact of financial shocks is not straightforwardly predictable. Many complexities in sign predictions arise from the metrics used to measure economic well-being (Jenkins et al (2012)).

We contribute to this literature by exploring the time-varying predictive power of financial shocks for growth in income (and consumption) inequality in the United Kingdom (UK) over the quarterly period of 1975:2 to 2016:1. Unlike the above-mentioned papers, which rely on constant parameter models based on low-frequency (annual) data, we conduct a time-varying, i.e., state-dependent analysis which allows us to accommodate for regime-changes, using relatively high-frequency (quarterly) data. These issues are important since accurate prediction of inequality, which accounts for structural breaks, and is conducted at a higher frequency should be more relevant to policymakers than at the lower annual frequency. It is this availability of quarterly measures of inequality that motivates us to consider the UK in our study. In addition, in the last four decades the UK has experienced dramatic increases in income inequality (Mumtaz and Theophilopoulou (2017)) and is considered to be an outlier of extreme inequality in the European context (Dorling, 2015), with income (consumption) inequality growth between 1975:2 to 2016:1 being 13.63% (11.19%) in our data set. Simultaneously, the UK has also witnessed periods of heightened financial stress, as observed from the plot of the Financial Stress Index (FSI), maintained by the European Central Bank (ECB), in Figure A1 in the Appendix of the paper. In particular, the FSI is observed to have increased on and after the mid-1970s due to bank failures as a result of excessive credit growth and leverage, during the early 1990s when a quarter of the small- and medium-sized banks failed triggered by the closure of Bank of Credit and Commerce International, and of course more recently as a result of the global financial crisis of 2007-2009 (Chatterjee et al., 2017).

[1] See also the Financial Times (2016, 2017).

To the best of our knowledge, this paper is the first study to analyze time-varying predictability of (country-level) financial shock, as captured by an index of financial distress (in equity, bond and foreign exchange markets), on growth in income (and consumption) inequality based on a high-frequency data set. In this regard, from an econometric perspective, we use the recently proposed (multivariate) test of time-varying causality in a vector autoregressive (VAR) framework by Wang and Rossi (2019), which is robust to the presence of instabilities. A paper that is somewhat related to our work is the rolling-window causality method used by Destek and Koksel (2019). They analyze the relationship between inequality and credit growth for ten advanced (Australia, Canada, Denmark, Finland, France, the United Kingdom, Japan, Norway, Sweden, and the United States) economies, and in turn detect virtually no evidence of credit boom in causing inequality.[2] However, unlike us, Destek and Koksel (2019) used annual data and a rolling-window approach, results from which are known to be sensitive to the size of the window, which is not the case in our full-fledged time-varying model. In addition, though the time-varying predictability is the primary focus of our paper, causality tests are silent about the sign of the impact (if any). Thus, we use time-varying impulse response functions to analyze the effect of a shock to the FSI on the growth of inequality in a time-varying parameter VAR model. Finally, we also examine the out-of-sample forecastability of the growth in income inequality from the variation in the FSI.

We are aware that shocks in financial sector are correlated with overall increases in economic uncertainty (Caldara et al (2016)) and actions of monetary policy makers. Thus, to single out the distributional consequences of financial shocks, in our analysis we incorporate a financial stress index that captures returns and (realized) volatility of three financial market segments, i.e., equity, bond and foreign exchange and we use real GDP and real interest rate to control for the overall economic conditions and variation in monetary policy. To preview, results indicate that the FSI has strong predictive power on growth in income (and to some extent consumption) inequality in the UK, though the strength of the effect is indeed time-varying. Moreover, increases in financial stress corresponds to a subsequent increase in the growth of income inequality. In addition, the FSI is found to produce forecasting gains for the growth of income inequality over an out-of-sample period, primarily at medium to long-runs. The rest of the paper proceeds as follows: Section 2 discusses the data and the methodology, Section 3 presents the empirical results, and Section 4 concludes.

2. Data and Methodology

2.1. Data

We use quarterly data from 1975:Q1 to 2016:Q1, based on availability of measures of inequality. The income inequality data is taken from Mumtaz and Theophilopoulou (2017). To construct income inequality measures they use income equivalized by dividing with the square root of the number of people in a household. The inequality measures are computed using survey data on income and consumption from the family expenditure survey (FES).[3] Mumtaz and Theophilopoulou (2017) provide an extensive documentation of the construction of the data and the survey. Note that, while

[2] In fact, this paper detected relatively stronger evidence of causality running from inequality to credit growth, something we too analyse and discuss in our paper later in the Appendix.

[3] The data is downloadable from: https://discover.ukdataservice.ac.uk/series/?sn=200016 and https://discover.ukdataservice.ac.uk/series/?sn=2000028.

the surveys are recorded at an annual frequency, Mumtaz and Theophilopoulou (2017) assign households to different quarters within a year based on the date of the survey interviews, which, in turn, allows them to calculate the measures of inequality at a quarterly frequency. Note that, these authors remove any households reporting zero or negative income, when constructing the income-based measures of inequality.[4] In our main analysis, we consider the Gini coefficient of income inequality. However, as part of additional analyses, we also present the results involving the Gini coefficient of consumption inequality (for total consumption per capita of a household), as well as, the standard deviation (of the data in natural logs), and the difference between the 90th and 10th percentile (with the data in natural logs) associated with both income and consumption. These five additional measures of inequality is also sourced from Mumtaz and Theophilopoulou (2017).

Financial Stress Index (FSI) is derived from the Statistical Data Warehouse of the ECB [5]. The index includes six market-based financial stress measures that capture returns and (realized) volatility of three financial market segments, i.e., equity, bond and foreign exchange. In addition, when aggregating the sub-indices, the FSI takes the co-movement across market segments into account. For further details, the reader is referred to Duprey et al., (2017). Given that developments in overall economic conditions and monetary policy is likely to affect both income (consumption) inequality and financial conditions (Berisha, 2017; Berisha and Meszaros, 208; Berisha et al., 2018), we use real Gross Domestic Product (GDP) for the UK to capture current economic conditions, and real interest rate (nominal three-month Treasury bill rate less the Consumer Price Index (CPI)-based inflation rate) as a measure of the stance of monetary policy, as additional controls in our VAR model as part of robustness checks.[6] The data source used to derive the two controls is the Main Economic Indicators database of the Organisation for Economic Co-operation and Development (OECD).

Since our econometric approach, which we describe below requires us to work with stationary data, we convert all data, barring the FSI, into their corresponding growth rates,[7] and depict them as: GI*j*, *j*=1..6, corresponding to the six measures of income and consumption inequalities (Gini coefficient, the standard deviation, and the difference between the 90th and 10th percentile) respectively; FSI: financial stress index; GRGDP: growth of real GDP, and; RIR: real interest rate. Due to the transformations, our effective sample starts from 1975:Q2 to 2016:Q1, giving us a total of 164 observations. All variables have been plotted in Figure A1 in the Appendix of the paper.

2.2. Methodology

The simplicity of the classical linear Granger causality test makes it one of the most commonly used methods for testing in-sample predictability. However, VAR model-based analyses face major technical difficulties in handling macro-economic data that are subject to instabilities, thereby causing the associated estimates of VARs to be also sensitive to instabilities (Boivin and Giannoni, 2006; Clark and McCracken, 2006; Rossi, 2013). Moreover, the traditional Granger-causality test requires stationarity of the variables, which in turn may lead to an erroneous inference in the presence of instabilities. In order to overcome these problems, Wang and Rossi (2019) propose a robust causality

[4] We would like to thank Professor Haroon Mumtaz for kindly sharing the inequality data.

[5] The data can be downloaded from: https://sdw.ecb.europa.eu/quickview.do;jsessionid=244C179E1D35ED03C386D97A5CE499B0?SERIES_KEY=383.CLIFS.M.GB._Z.4F.EC.CLIFS_CI.IDX.

[6] The FSI, CPI and the Treasury bill rate data are available monthly, which we convert to quarterly frequency by taking three month averages comprising a quarter.

[7] Complete details of the unit root tests are available upon request from the authors.

test, which is more powerful than the traditional Granger-causality test, following the time-varying methodologies suggested by Rossi (2005). Given that we find statistical evidence of regime-changes in our data, we use Wang and Rossi's approach to analyze the time-varying impact of FSI on GI*j*, *j*=1,…6, and hence, provide a more appropriate inference of the effect rather than a constant parameter Granger causality method. Besides, understandably, the time-varying approach helps us to depict the time-variation in the strength of predictability.

In this study, we consider the following VAR model with time-varying parameters:

$$y_t = \Psi_{1,t} y_{t-1} + \Psi_{2,t} y_{t-2} + \cdots + \Psi_{p,t} y_{t-p} + \varepsilon_t \tag{1}$$

where $\Psi_{j,t}$, $j = 1, \ldots p$ are functions of time varying coefficient matrices, $y_t = [y_{1,t}, y_{2,t}, \ldots, y_{n,t}]'$ is an $(nx1)$ vector and the idiosyncratic shocks ε_t are assumed to be heteroscedastic and serially correlated.

The variables included in our VAR constitutes of two endogenous variables namely, GI*j*, *j*=1,…6, and FSI in a bivariate set-up, and then later GRGDP and RIR as controls in the multivariate (four variables) model. We test the null hypothesis that FSI does not Granger cause GI*j* for all *t* where the null hypothesis is H_0: $\phi_t = 0$ for all $t = 1,2, \ldots, T$, given that ϕ_t is appropriate subset of $vec\ (\Psi_{1,t}, \Psi_{2,t}, \ldots, \Psi_{p,t})$. To this end, Rossi (2005) suggested four alternative test statistics namely: the exponential Wald (*ExpW*), mean Wald (*MeanW*), Nyblom (*Nybolm*) and Quandt Likelihood Ratio (*SupLR*) tests. Based on the Akaike Information Criterion (AIC), the VAR model is estimated using 2 lags. We use an end-point trimming of 5% in the bivariate set-up, which in turn amounts us to losing 8 observations from both ends. However, a trimming of 10%, i.e., loss of 16 observations from both ends of the sample, is required to estimate the four-variable system.

3. Results

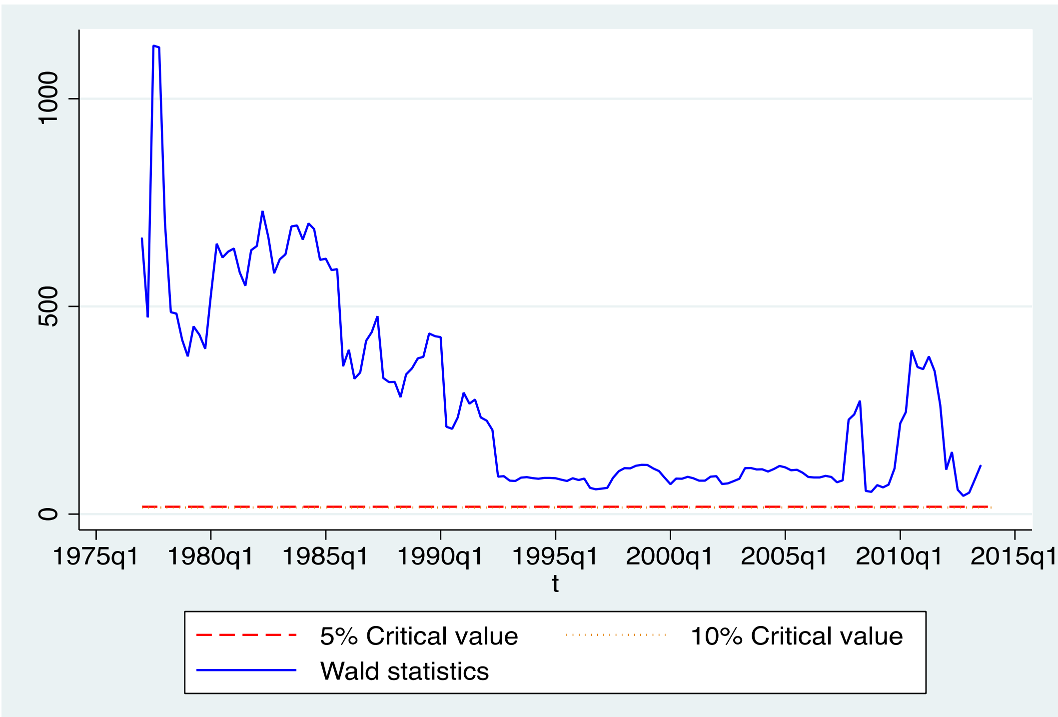
In Table 1, to analyze the predictive ability of financial stress indicator (FSI, hereafter financial stress) on the income Gini coefficient growth rate (GI1, hereafter income inequality growth), we first started with the standard constant parameter Granger causality test and found that financial stress does not Granger cause income inequality growth at the 5% level of significance, but does so at the 10% level. However, based on the powerful *UDmax* and *WDmax* tests of Bai and Perron (2003), used to detect 1 to *M* structural breaks in the income inequality growth equation of the VAR(2) model, allowing for heterogenous error distributions across the breaks and 5% trimming, yielded 3 break points at: 1990:4, 2005:4, 2008:1, corresponding to episodes of heightened financial stress (as can be seen from Figure A1). Given this evidence of instability, the results from the constant parameter model is not robust, and hence to obtain reliable inference, we look at the *ExpW*, *MeanW*, *Nyblom*, and *SupLR* tests of Wang and Rossi (2019) based on the time-varying VAR also reported in Table 1. As can be seen, the null of no-Granger causality from financial stress to income inequality growth is overwhelmingly rejected at the highest possible level of significance across all the four tests. In other words, the predictive ability of financial stress for income inequality growth is in fact time-varying and exceptionally strong, even though weak evidence of predictability can also be derived from the constant parameter model.

Table 1. Constant parameter and time-varying parameter Granger causality tests

	$\chi^2(2)$	*ExpW*	*MeanW*	*Nyblom*	*SupLR*
Test Statistic	5.5134	559.0112	276.9320	5.9693	1127.8030
p-value	0.0635	0.0000	0.0000	0.0000	0.0000

Note: Null hypothesis is the FSI does not Granger cause GI1 in a constant or time-varying VAR(2). GI1: growth of Gini coefficient corresponding to income inequality; FSI: financial stress index.

Figure 1. Time-varying Wald statistics with VAR(2) under AIC, testing whether FSI Granger-causes GI1



Note: See Notes to Table 1; tq: corresponds to quarterly data; and the vertical axis measure the test statistic.

Next, in Figure 1, we present the whole sequence of the Wald statistics across time, which gives more information on when the Granger-causality occurs. As can be seen, financial stress consistently predicts income inequality growth, with the effects being particularly strong during the early period of the sample corresponding to heightened financial stress, and also following the global financial crisis. Given that some studies have found that inequality can predict financial crises (see for example, Rajan (2010), Bordo and Meissner (2012), Kumhof et al., (2015), Morelli and Atkinson (2015), Kirschenmann et al., (2016), Perugini et al., (2016), and Paul (2017)), in Figure A2 in the Appendix of the paper, we plot the time-varying Wald statistics of income inequality growth Granger causing financial stress. A similar picture to the effect of financial stress on income inequality growth emerges, with causality consistently running from income inequality growth to financial stress.[8] Furthermore in Figures A3 to A7, we provide the evolution of the Wald statistics over time based on a VAR(2) model

[8] Interestingly, the constant parameter-based Granger causality test could not detect causality running from income inequality growth to financial stress even at the 10% level of significance, though *ExpW*, *MeanW*, *Nyblom*, and *SupLR* tests all overwhelmingly rejected the null of no time-varying predictability at the highest level of significance. Complete details of these results are available upon request from the authors.

with 5% trimming, whereby we test the time-varying causality from financial stress to growth rates for standard deviation of income (GI2) and consumption (GI5), difference between 90th and 10th percentile of income (GI3) and consumption (GI6), consumption Gini coefficient (GI4). As can be seen from the figures, financial stress consistently causes the alternative measures of income and consumption inequalities over the entire sample period, though the effect on consumption inequalities is somewhat intermittent, but increases tremendously post the global financial crisis.

As is well-known, causality tests are sensitive to the lag-length, so we revisit our results by re-conducting the Wang and Rossi (2019) test by using a VAR(1) model as suggested by the Schwarz Information Criterion (SIC), which in turn also allows us to use a trimming of only 2.5%. This might be due to the usage of one lag, besides the usual 5% trimming used above. Figures 2(a) and 2(b) show the evolution of the Wald statistics over time based on a VAR(1) model with 5% and 2.5% trimming. As can be seen from Figure 2(a), under a trimming of 5%, strong evidence of causality from financial stress to income inequality growth in general holds for the entire sample period with strong predictability observed at the two ends of the sample period. Interestingly, when we use a 2.5% trimming as shown in Figure 2(b), strong causality from financial stress to income inequality growth is primarily observed towards the end of the sample period, but not very strongly otherwise. This weak evidence possibly is a result of the very low trimming. It is important to understand that the impact of financial stress is likely to take time to affect the real economy, and hence inequality (Pierdzioch et al., 2019). Thus, it probably makes more sense to rely on results under longer lags, which in turn provides a more accurate description of the relationship between growth in inequality due to episodes of financial crises.

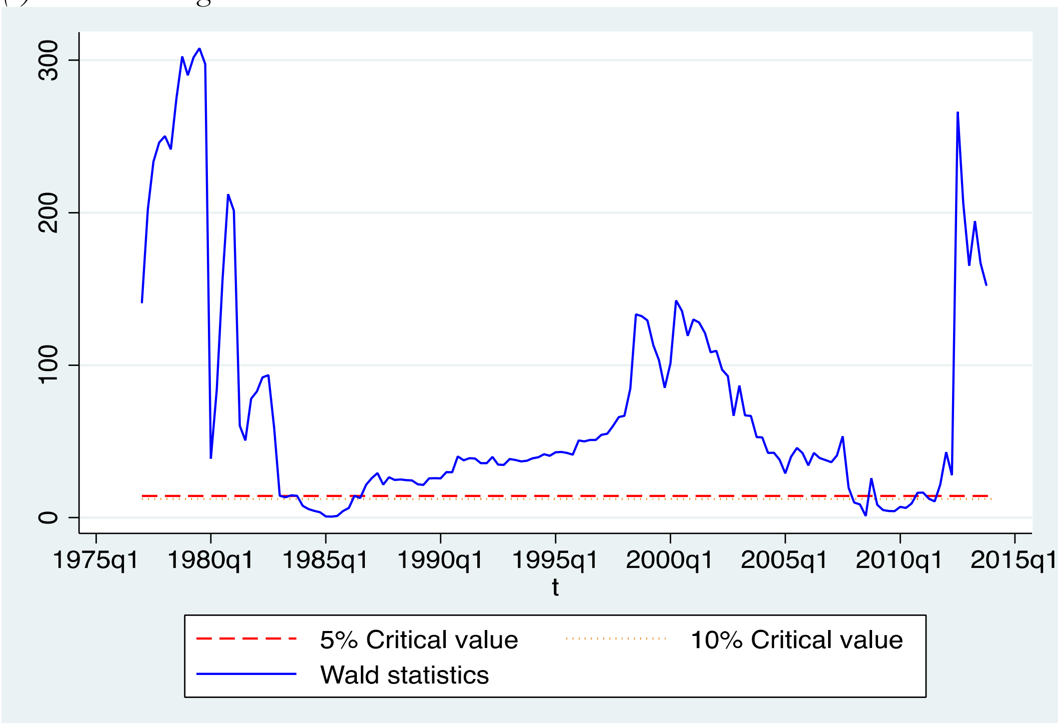
As a robustness check, we extend our bivariate model to include growth in real GDP (GRGDP, hereafter GDP growth) and real interest rate (RIR) to control for possible omitted variables, and revisit the causality from financial stress to income inequality growth. Using a VAR(2) model with a trimming of 10% required to accommodate the four variables, we find that the pattern of results derived under the bivariate model continues to hold in the extended model, as seen from Figure 3. In other words, our two-variable model (in Figures 1 with 5% trimming and 3(b) with 10% trimming) does not suffer from omitted variables bias, and financial stress indeed causes income inequality growth over the entire sample period in a time-varying manner, and particularly in the early part of the sample, and post the global financial and the European sovereign debt crises.

While the time-varying predictive analysis is the focus of our paper, causality tests are silent about the sign of the impact of financial stress on income inequality growth. Given this, we next estimate a time-varying parameter VAR model with stochastic volatility (TVP-VAR-SV) as developed by Primiceri (2005), and Del Negro and Primiceri (2015) with 2 lags, and analyze the time-varying impact on income inequality growth following a shock to financial stress. We rely on a Cholesky decomposition-based impulse response function, whereby income inequality growth is ordered first, followed by the financial stress .[9] The TVP-VAR model is estimated using Markov-Chain Monte-Carlo (MCMC) methods with Bayesian inference, based on 40,000 draws after an initial burn-in of 40,000 (i.e., we use a total of 80,000 iterations). The MCMC method assesses the joint posterior distributions of the parameters of interest based on certain prior probability densities that we set in advance, which in turn, are identical to those used in Primiceri (2005), Del Negro and Primiceri (2015). Once the model is estimated, we can produce time-varying impulse response functions of the variables in the model

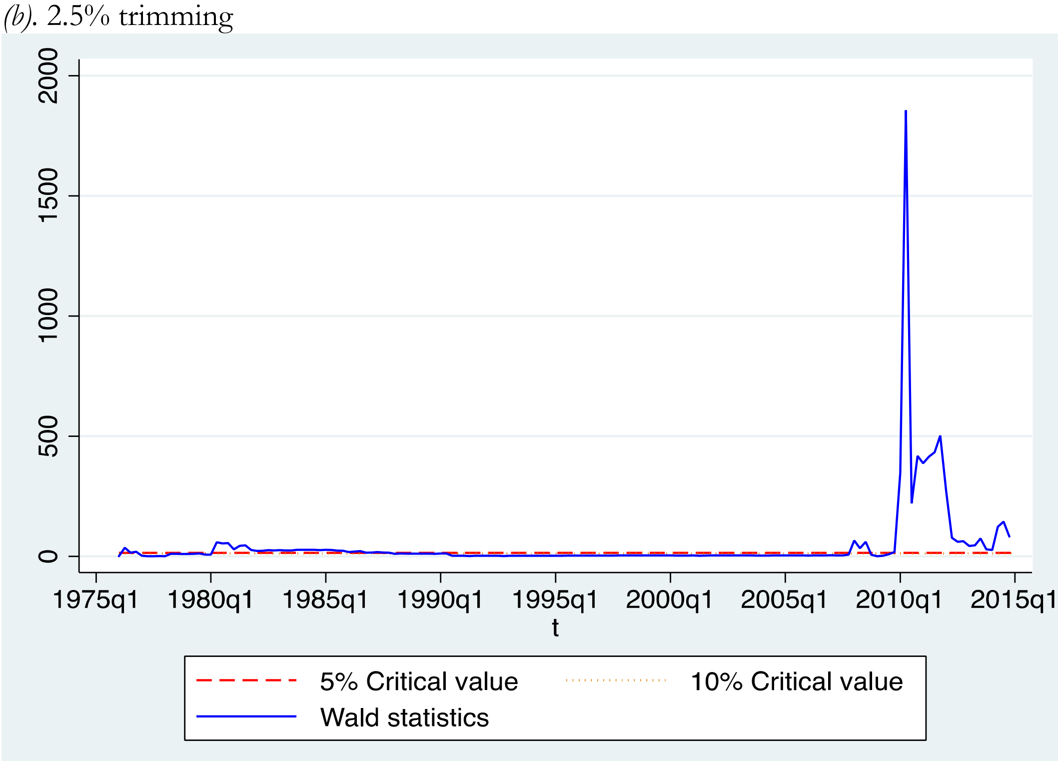
[9] Generalized impulse response functions reported in Figure A10 in the Appendix of the paper, produces a qualitatively similar result, though the peak is more on impact.

Figure 2. Time-varying Wald statistics with VAR(1) under SIC, testing whether FSI Granger-causes GI1

(a). 5% trimming



(b). 2.5% trimming



Note: See Notes to Table 1 and Figure 1.

Figure 3(a). Time-varying Wald statistics with VAR(2) under AIC, testing whether FSI Granger-causes GI1 with additional controls

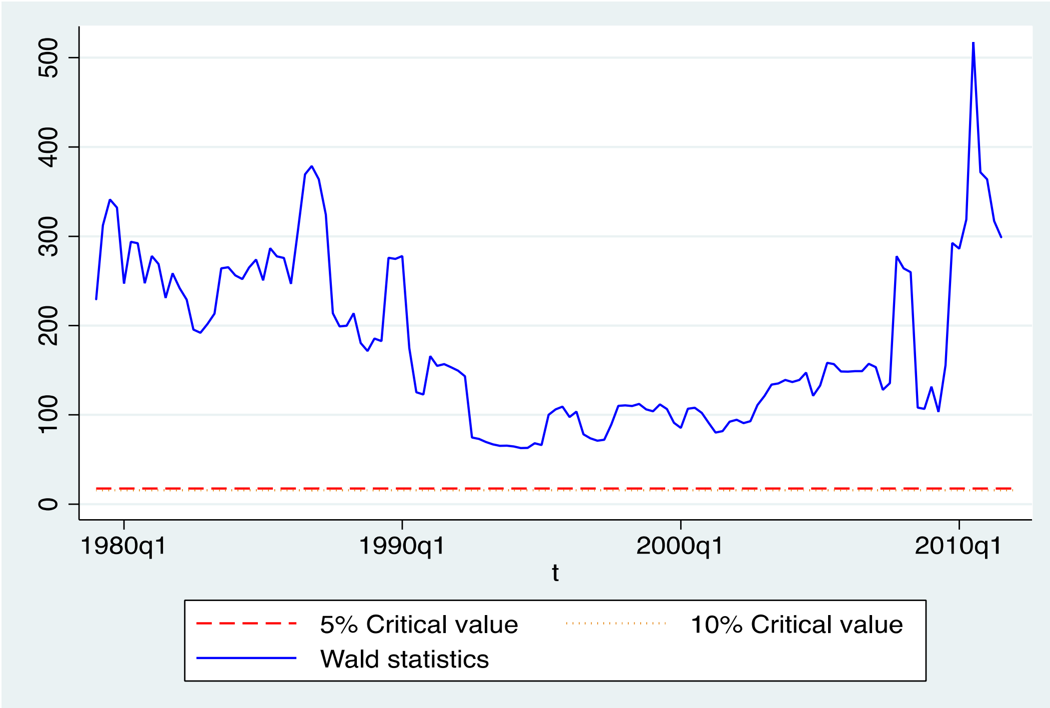
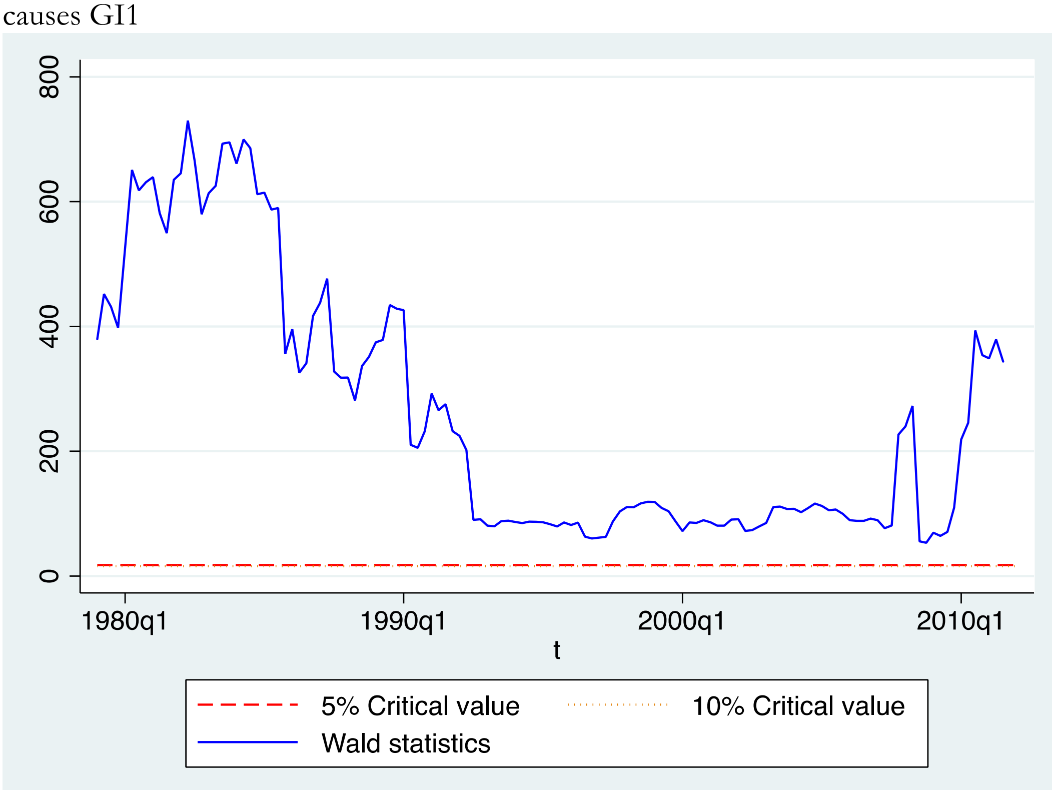


Figure 3(b). Time-varying Wald statistics with VAR(2) under AIC, testing whether FSI Granger-causes GI1

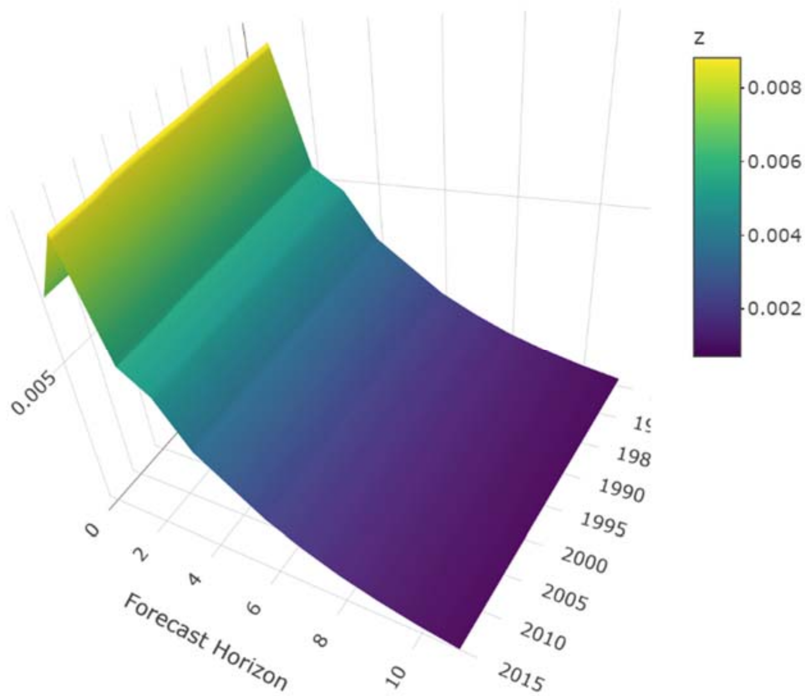


Note: See Notes to Table 1 and Figure 1; the two additional controls are: GRGDP: growth of real GDP; and; RIR: real interest rate.

following the one standard deviation of the financial stress shock. In Figure 4, we present the time-varying response of income inequality growth over a horizon of 12 quarters. In essence, the impact of the financial stress on income inequality growth is positive and persistent, and peaks in the first-quarter following the shock, throughout the sample period, with the effect monotonically decreasing over the 12 quarters. Based on the suggestion of an anonymous referee, we also considered a five-variable VAR comprising of GDP growth, inflation rate, the short-term interest rate, income inequality growth and financial stress, and analyze in Figure 5, the effect of the financial stress shock identified again by Cholesky decomposition.[10] As can be seen, compared to Figure 4, now we observe much more variability in terms of the effect on income inequality growth over time, at the shorter-horizons, with the impact tending to increase over time, in line with the time-varying causality results. The finding is also confirmed by the time-varying variance decomposition of income inequality growth due to financial stress in Figure 6, as well as in Figure 7, where we compare the average (i.e., over 1 to 12-quarter-ahead) time-varying variance decomposition of income inequality growth due to GDP growth, inflation, interest rate and financial stress. As can be seen, from Table 2, where we report the percentage of income inequality growth explained, averaged over both the forecast horizon and the time-dimension, stands at nearly 1.5%, which is higher than that of the interest rate (0.40%), but lower than GDP growth (at 4.7%) and inflation (2.2%). Variability in income inequality growth is explained mostly, i.e., 91%, by itself. But consistent with the IRFs, towards the end of the sample, we can see that financial stress now tends to predict nearly 2.5% of the variance in income inequality growth.

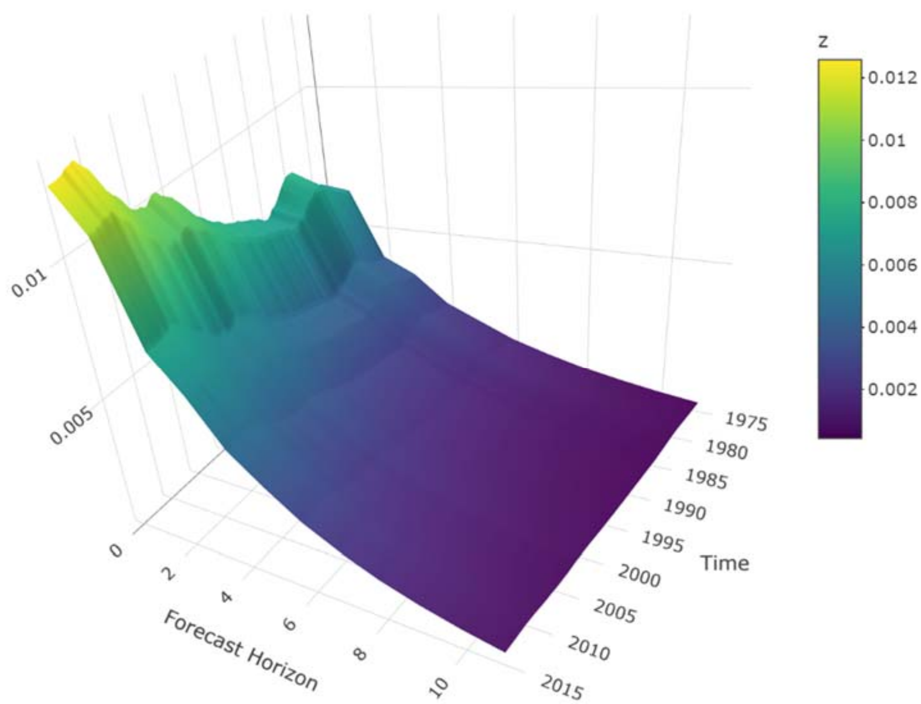
[10] Figures A8 and A9 in the Appendix plots the identified FSI shock and its associated SV respectively. As can be seen from these two Figures, in line with the FSI variable in Figure A1, both the shock and its SV tend to have relatively higher values at the beginning of the sample period, and in and around the global financial crisis.

Figure 4. Cholesky decomposition-based impulse response of GI1 to a one standard deviation FSI shock in the 2-variables TVP-VAR model



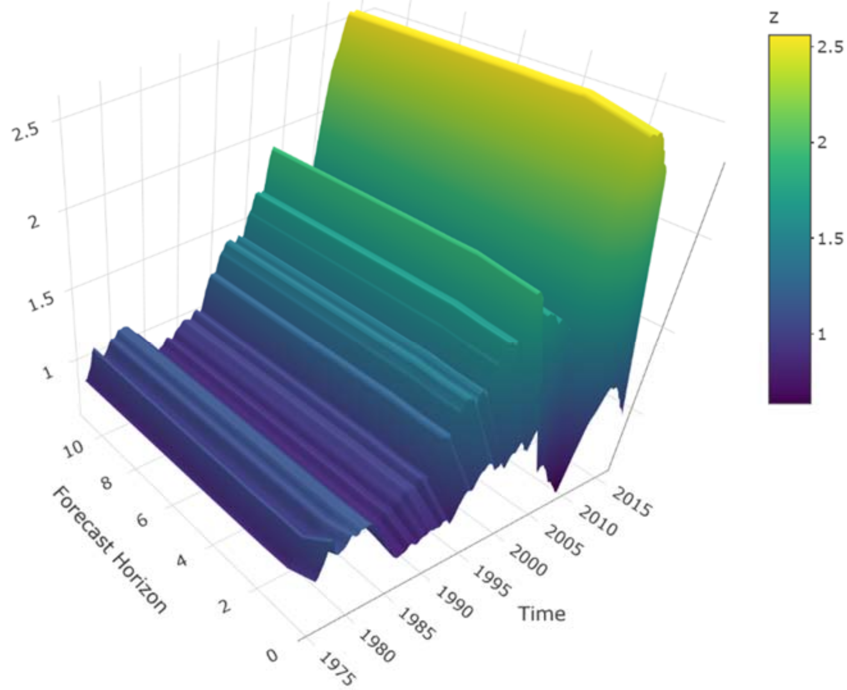
Note: See Notes to Table 1 and Figure 1.

Figure 5. Cholesky decomposition-based impulse response of GI1 to a one standard deviation FSI shock in the 5-variables TVP-VAR model



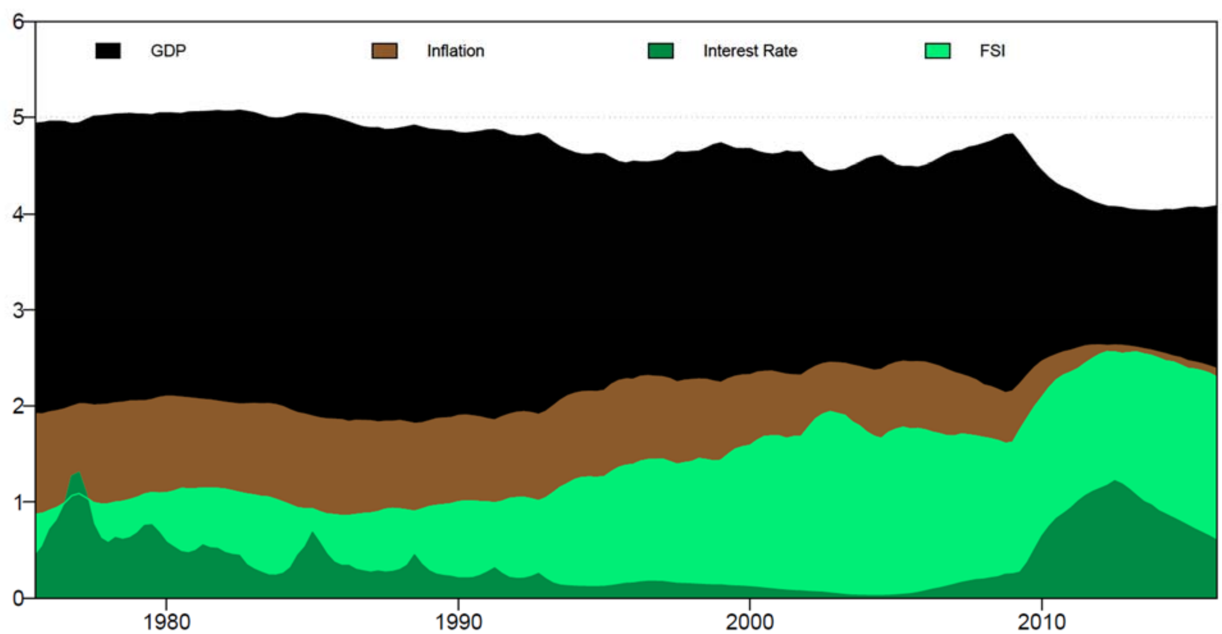
Note: See Notes to Table 1 and Figure 1.

Figure 6. Time-varying variance decomposition of GI1 due to FSI in the 5-variables TVP-VAR model



Note: See Notes to Table 1 and Figure 1.

Figure 7. Average (1-to-12-quarter-ahead) time-varying variance decomposition of GI1 in the 5-variables TVP-VAR model



Note: See Notes to Table 1 and Figure 1.

Table 2. Variance decomposition results from the 5-variables TVP-VAR

	Variance explained by				
Variable	GRGDP	Inflation	Interest Rate	GI1	FSI
GRGDP	67.1191	25.6234	2.0817	2.0606	3.1152
Inflation	25.8087	60.1106	6.5675	1.7093	5.8038
Interest Rate	14.6557	4.5721	75.7172	0.3801	4.6748
GI1	4.6878	2.1866	0.3929	91.2723	1.4605
FSI	19.8890	5.1474	3.6760	0.3223	70.9653

Note: The entries corresponds to the variance decomposition of the variable in the row as explained by the variable in the column, so that the entries in a particular row adds up to 100%.

Finally, since in-sample predictability does not guarantee out-of-sample predictive gains (Campbell, 2008), we conduct a full-fledged forecasting exercise, by estimating a TVP-VAR models along the lines of Primiceri (2005), Del Negro and Schrofheide (2013), and Del Negro and Primiceri (2015). In particular, we estimate a TVP-VAR(2) containing income inequality growth and financial stress (Model 1), and compare the forecasting performance of this model with the benchmark TVP-AR(2) model of income inequality growth (Model 0). Understandably, if the first model produces lower mean square forecast errors (MSFEs) relative to the first model for income inequality growth, then clearly financial stress contains out-of-sample predictive information for the future path of the growth in income inequality. Given that our first break date is at 1990:4, we design our forecasting experiment to have an in-sample period of 1975:2 to 1990:3, with the models estimated recursively over the out-sample covering 1990:4 to 2016:1, i.e., the period which includes all the regime changes in income inequality growth associated with financial stress, and hence can be considered as an unstable period. The relative MSFEs (RMSFEs), i.e., the ratio MSFE of Model 1 to Model 0 has been reported in Table 3 for forecast horizons of one-, two-, three-, and four-quarters-ahead. Understandably, if the RMSFE is less than one, then the financial stress produces out-of-sample forecasting gains for income inequality growth over and above the latter's own two lags. As observed from the table, RMSFEs is less than one for horizons (h) of two-, three-, and four-quarters-ahead, and is virtually the same for h=1. However, an important question is whether the forecasting gains produced by financial stress, i.e., Model 1 is statistically significant relative to Model 0. Since Model 1 nests Model 0, we use the *MSE-F* test statistic of McCracken (2007) to establish this point. Note that, the *MSE-F* statistic tests the null hypothesis that the restricted (Model 0) and unrestricted (Model 1) models have equal forecasting ability, against the one-sided alternative hypothesis that the MSFE for the unrestricted model is less than the MSFE for the restricted model forecasts. As depicted in Table 2, the *MSE-F* statistic was found to be significant at the 5% level of significance for h = 2, 3 and 4. Overall then, financial stress can produce significant forecasting gains for income inequality growth, especially for medium- to long-runs.

In sum, financial stress has time-varying in- and out-of-sample predictive content, particularly in the early and towards the end of the sample period, for income inequality growth, with the sign of the effect being positive over the entire sample period.

Table 3. Out-of-sample forecasting of results of growth in income inequality (Gini coefficient)

	Forecasting Horizon (*h*)			
	1	2	3	4
RMSFE	1.007	0.9786	0.9823	0.9808
MSE-F	-0.7816	2.2067*	1.7996*	1.9425*

Note: See Notes to Table 1; RMSFE is the ratio of MSFE of Model 1 to Model 0, where Model 1 is a TVP-VAR(2) model of GI1 and FSI, and Model 0 is a TVP-AR(2) model of GI1; * corresponds to significance of the *MSE-F* test statistic at 5% level, given the critical value of 1.7520.

4. Conclusion

Existing empirical evidence suggests that episodes of financial stress (crises) can act as driver of growth of inequality. Consequently, in this study we explore the time-varying predictive power of an index of financial stress for growth in income (and consumption) inequality in the UK. We focus on the UK since income (and consumption) inequality data are available at a high frequency, i.e., on a quarterly basis for over 40 years (June, 1975 to March, 2016). Given that inequality is not only a problem in itself, but it also has negative economic, social, and health implications (Chang et al., 2019), we consider the usage of quarterly data to be of tremendous importance. Accurate prediction of inequality at a higher frequency should be more relevant to policymakers in designing appropriate policies to circumvent the wide-ranging negative impacts of inequality, compared to when predictions are only available at the lower annual frequency.

Our findings point that financial distress correspond to subsequent increases in inequality, with the index of financial stress containing important information in predicting growth in income inequality for both in and out-of-sample periods. Interestingly, the strength of the in-sample predictive power is high post the period of the global financial crisis, as was observed in the early part of the sample. We believe these findings highlight an important role of financial stress for inequality – an area of investigation that has in general remained untouched.

Given that financial stress across economies can spill over (Gil-Alana et al., 2020), as part of future research, it would be interesting to compare the role of international financial stress on UK's inequality, relative to domestic financial distress. Further, it would be interesting to use mixed data sampling (MIDAS) methods to predict the future path of low-frequency (annual) inequality growth based on data of high-frequency data of financial stress available for many economies around the world.

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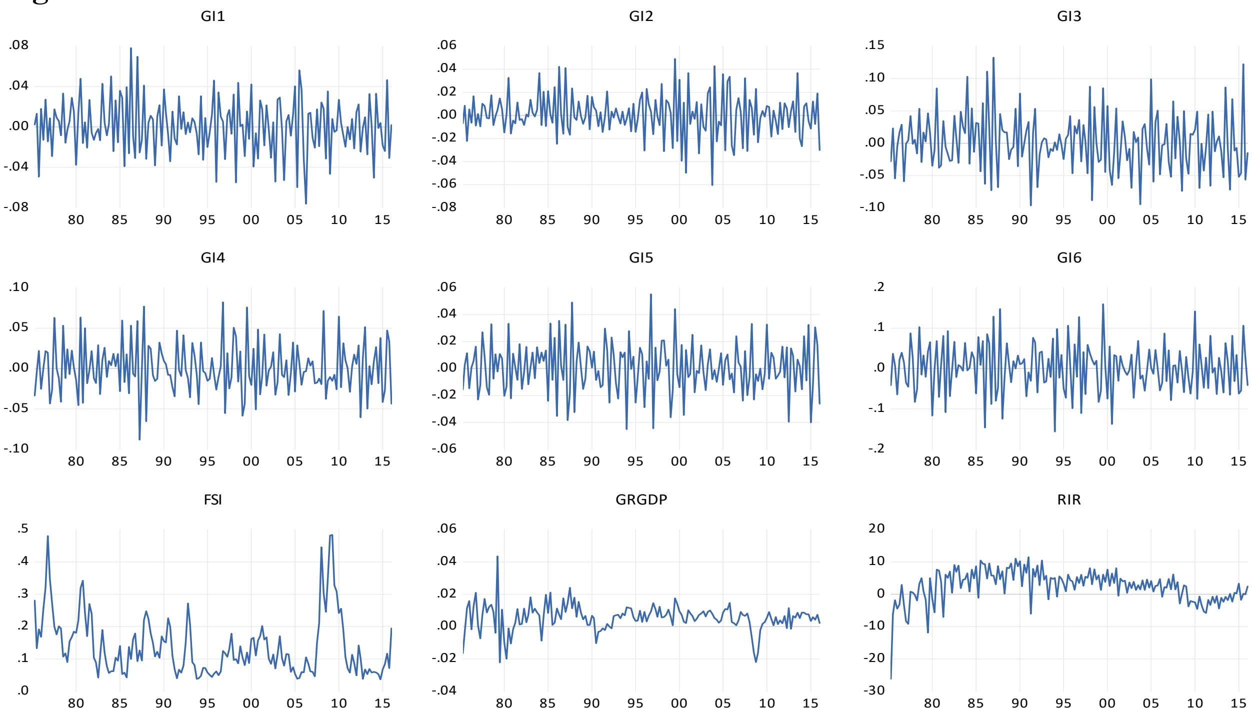
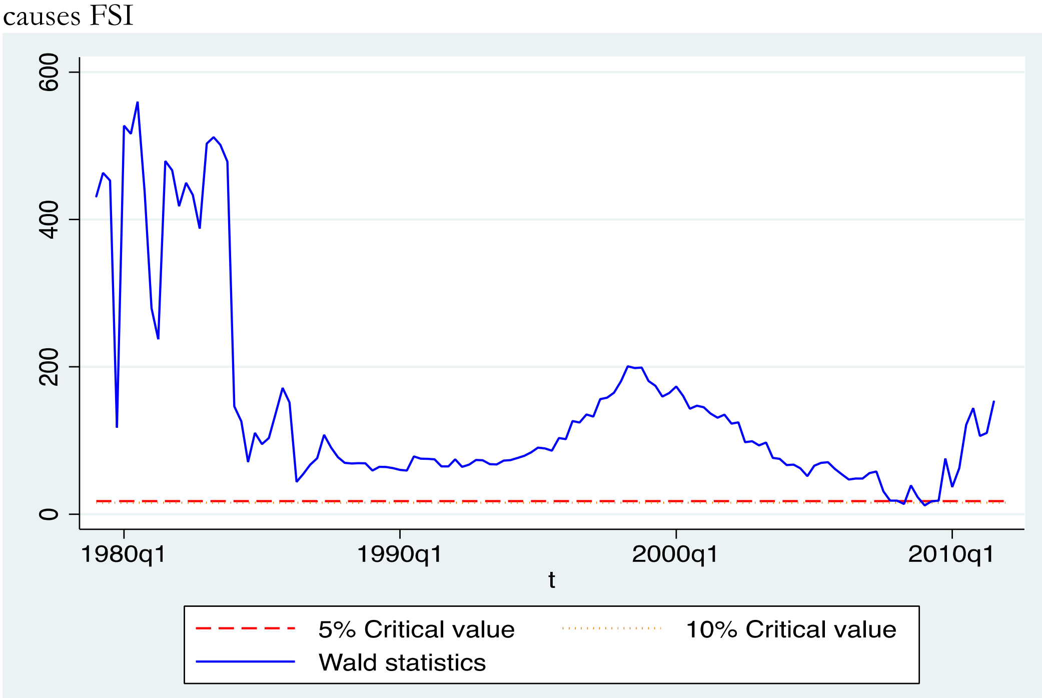
APPENDIX:

Figure A1. Data Plots



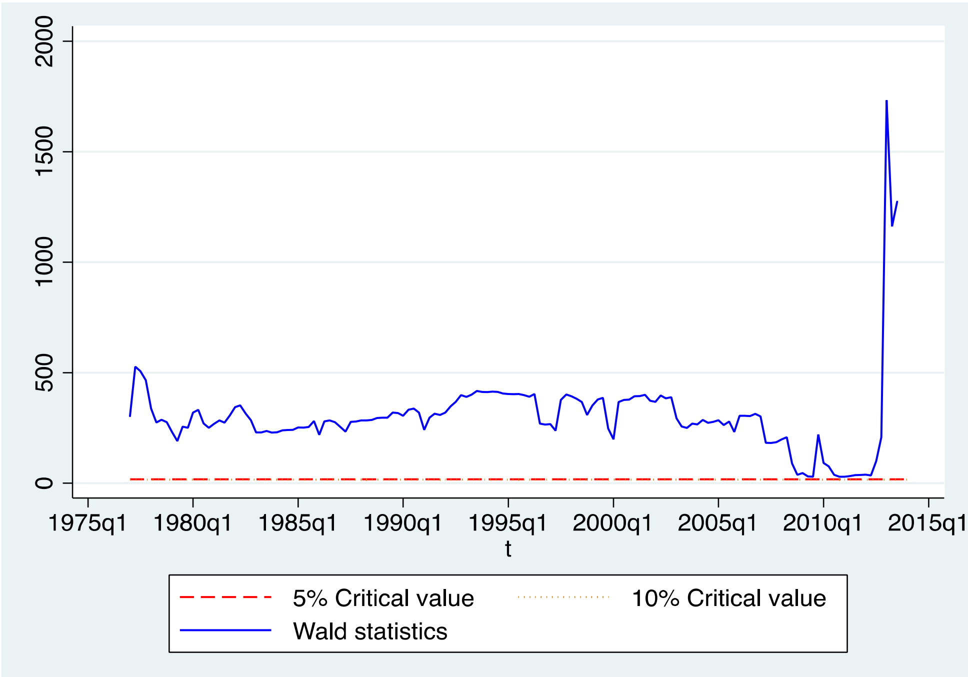
Note: GI*j*, *j*=1,..6, corresponds to the six measures of income and consumption inequality (Gini coefficient, the standard deviation, and the difference between the 90th and 10th percentile) respectively; FSI: financial stress index; GRGDP: growth of real GDP; and; RIR: real interest rate.

Figure A2. Time-varying Wald statistics with VAR(2) under AIC, testing whether GI1 Granger-causes FSI



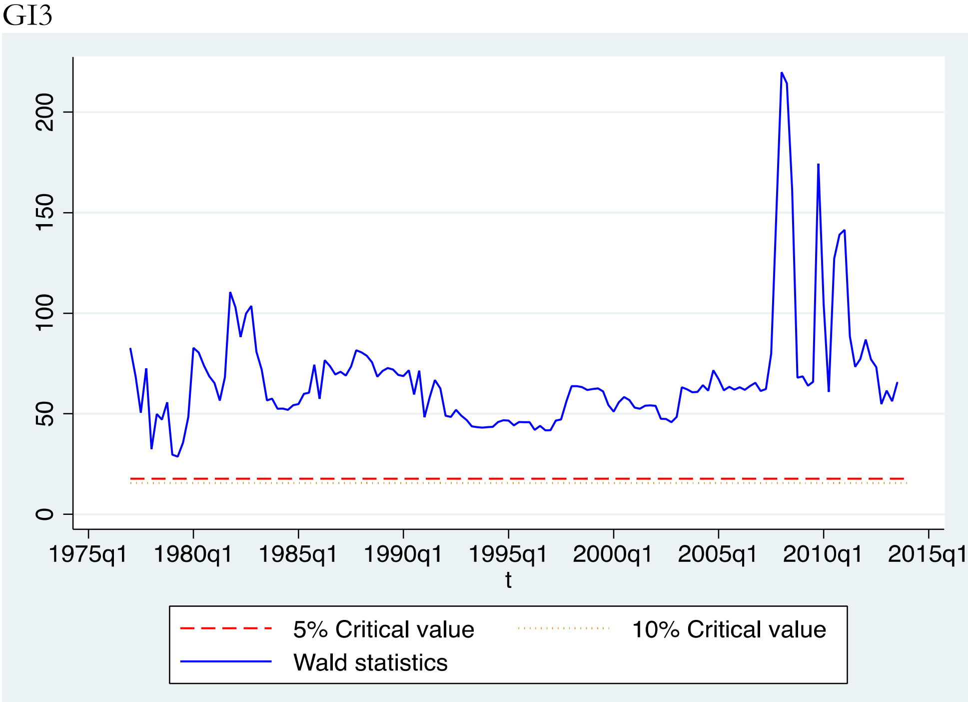
Note: See Notes to Figure A1; tq: corresponds to quarterly data; and the vertical axis measure the test statistic.

Figure A3. Time-varying Wald statistics with VAR(2) under AIC, testing whether FSI Granger-causes GI2



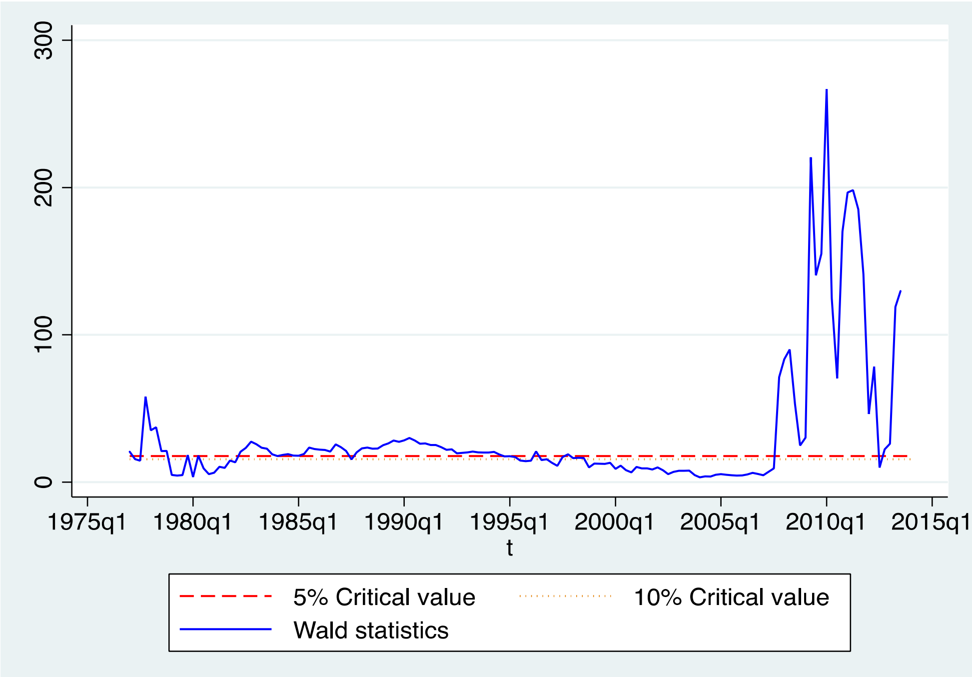
Note: See Notes to Figure A1 and Figure A2.

Figure A4. Time-varying Wald statistics with VAR(2) under AIC, testing whether FSI Granger-causes GI3



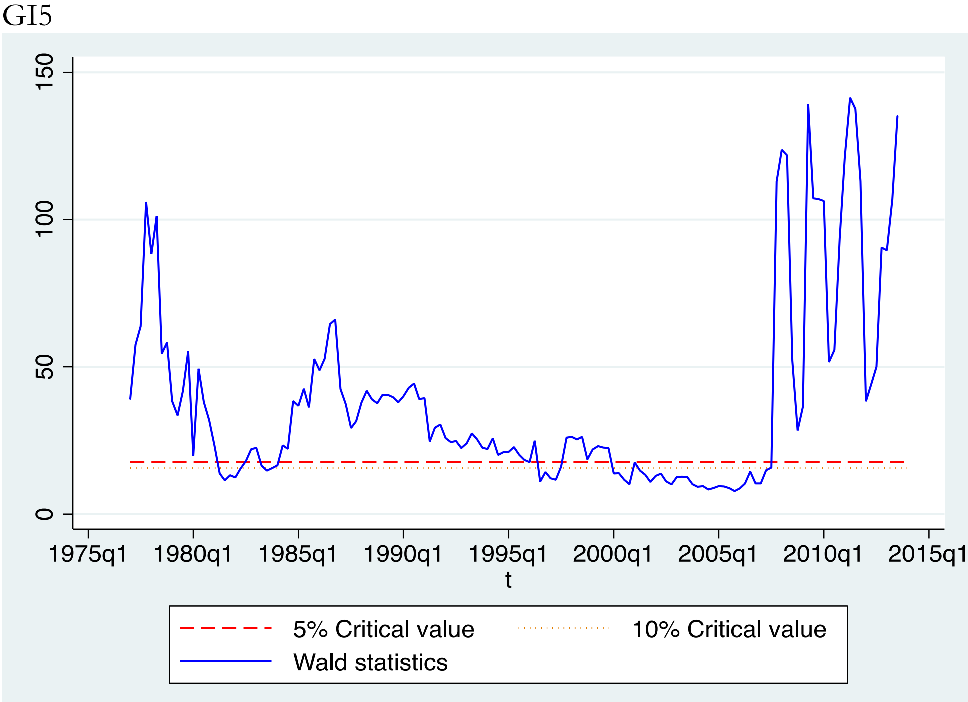
Note: See Notes to Figure A1 and Figure A2.

Figure A5. Time-varying Wald statistics with VAR(2) under AIC, testing whether FSI Granger-causes GI4



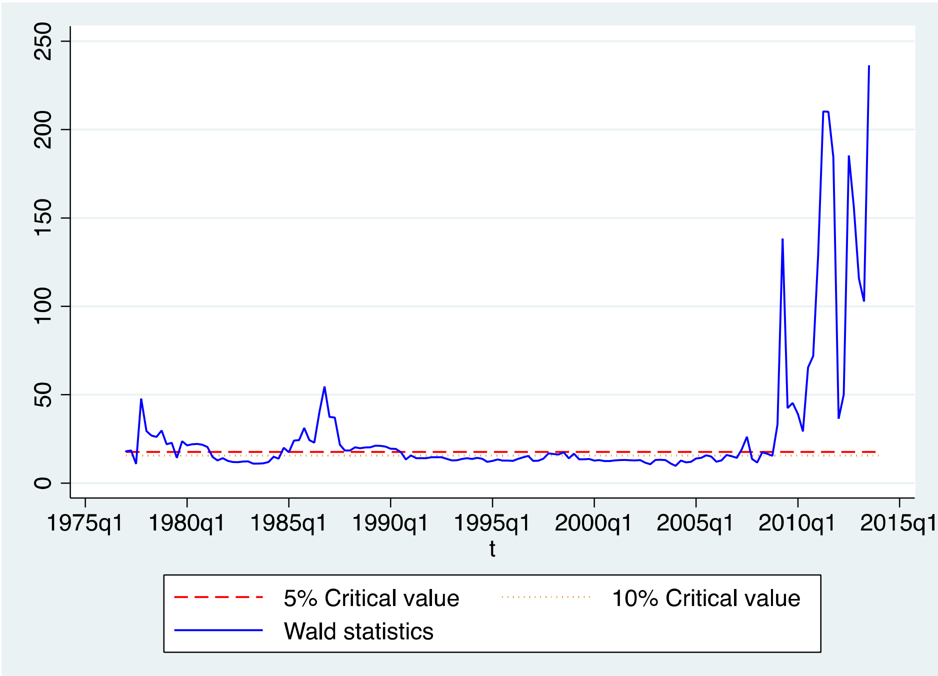
Note: See Notes to Figure A1 and Figure A2.

Figure A6. Time-varying Wald statistics with VAR(2) under AIC, testing whether FSI Granger-causes GI5



Note: See Notes to Figure A1 and Figure A2.

Figure A7. Time-varying Wald statistics with VAR(2) under AIC, testing whether FSI Granger-causes GI6



Note: See Notes to Figure A1 and Figure A2.

Figure A8. Identified FSI shock

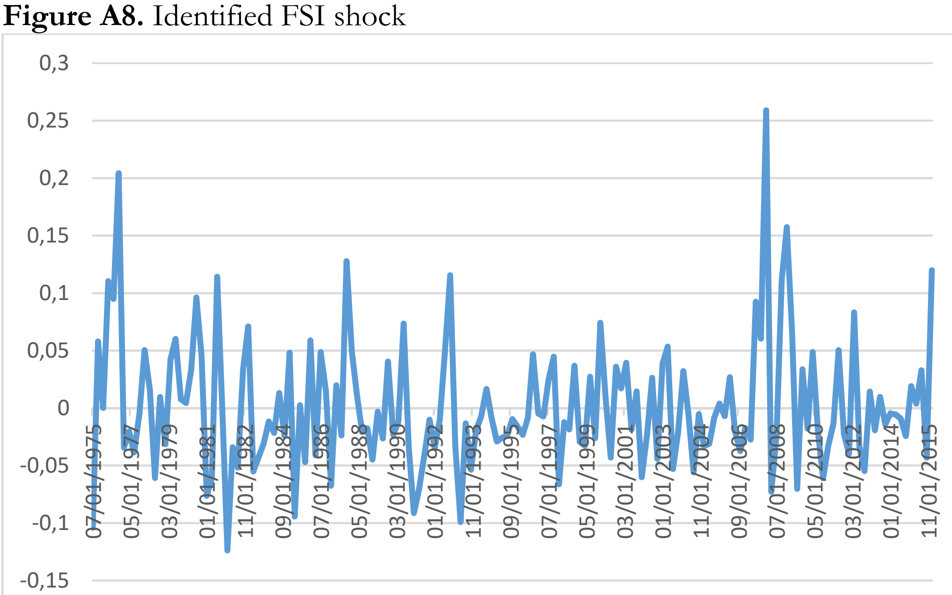


Figure A9. Stochastic volatility of identified FSI shock

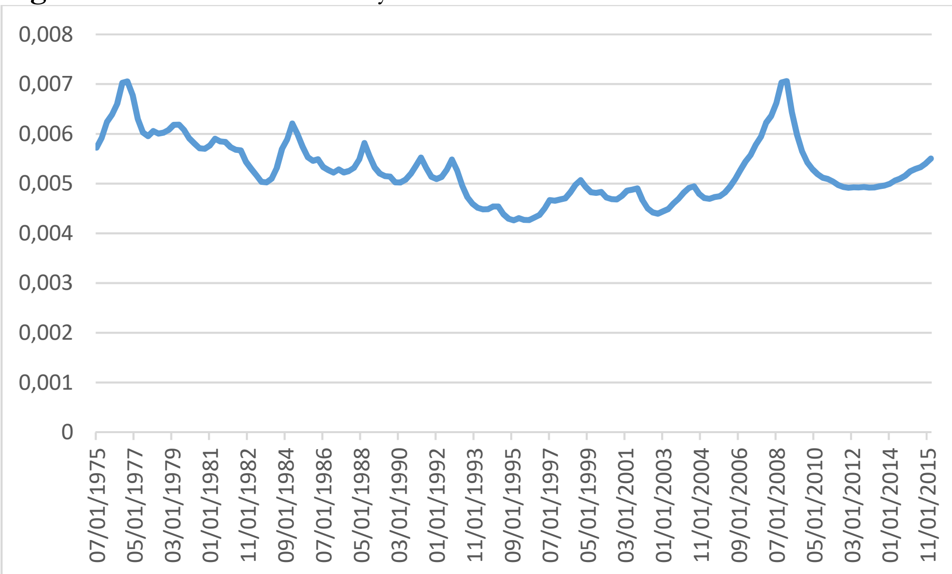
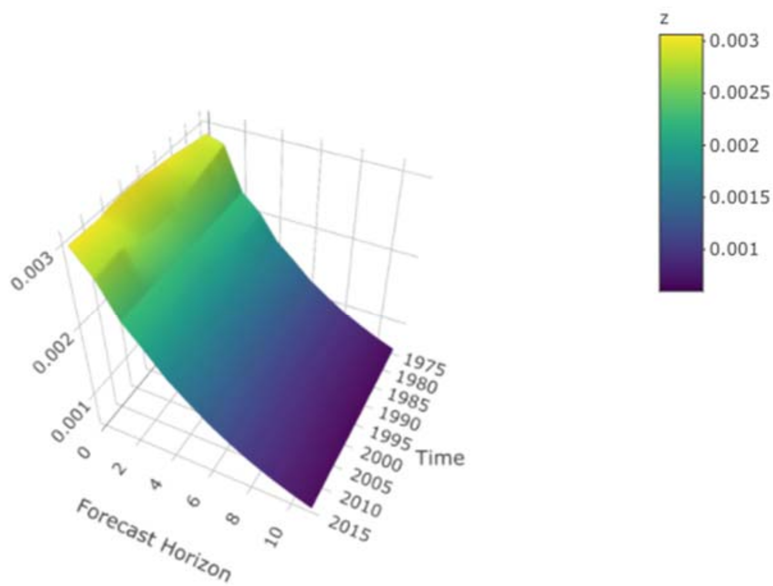


Figure A10. Generalized Impulse Response of GI1 to a one standard deviation FSI shock in the 2-variables TVP-VAR model



Note: See Notes to Table 1 and Figure 1.

Computer Programs and Data Availability Statement

The STATA and MATLAB codes, and data that support the findings of this study are available from the corresponding author upon reasonable request.