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Time-Varying Evidence of Predictability of Financial Stress in the United States over a Century: The Role of Inequality

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Abstract

In this paper, we analyze time-varying predictability of financial stress due to growth in income inequality of the United States (US) over the annual period of 1913 to 2016. In order to ensure that we remove the asset price effects on income inequality, and provide incorrect inferences regarding the impact on financial stress, we work with capital-gains excluded six alternative measures of top shares of pretax income and wages. We find that the top 10 percent, the top 10 percent to 5 percent, and the top 5 percent to 1 percent inequality growth rates tend to predict financial stress relatively better than the corresponding inequality growth rates associated with the top 1 percent, top 0.1 percent, and the top 0.01 percent of the income distribution. Moreover, all the six metrics of inequality growth is capable of predicting the heightened financial stress observed during the onset of the Great Depression and the same associated with the recent global financial crisis. Finally, our in-sample evidence of predictability tends to carry over to an out-of-sample forecasting exercise under four out of the six measures of inequality considered, and in particular for the broader measures of inequality – a result consistent with our in-sample analysis.

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

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1. Introduction

Recent studies by Rajan (2010), and Morelli and Atkinson (2015), have pointed out the potential impact of changes in income inequality on financial crises. From a theoretical perspective, Kumhof et al. (2015), show that wealthy individuals used a substantial portion of their income to accumulate financial wealth through loans to finance consumption of households at the lower end of income distribution. However, note, the increased credit intermediation and the lower income of poorer households may raise the likelihood of default and the risk of a crisis. Bordo and Meissner (2012) using a sample of 14 advanced countries found no evidence of the response of credit to changes in income inequality for the period 1920-2000. However, Perugini et al. (2016) arrived at the opposite conclusion, i.e., they found evidence in favor of the implications that increases in income inequality have contributed to upsurges in household indebtedness. Similarly, Yamarik et al. (2016) based on state-level data of the United States (US) over the period 1977 to 2010 confirm that increases in inequality can lead to credit boom. More recently, Destek and Koksel (2019) used a rolling bootstrap causality test on 10 developed countries and found inequality to intermittently cause credit expansion for Australia in 1989, the United Kingdom (UK) in 1991 and 2007, and the US in 1929 and 2007. Kirschenmann et al. (2016), instead of relying on credit growth, which may or may not always increase during crises, showed that changes in the top income shares contain relevant information to directly predict financial crises. To arrive at this conclusion they use a panel logit model for the same set of 14 developed countries considered by Bordo and Meissner (2012), but over the period 1870-2008.

However, as pointed out by Paul (2017), none of the abovementioned papers exclude capital-gains from the income inequality measures, which in fact induce large and volatile changes in the income shares. Since the related assets (for example, equities), are typically held by people at the very top of the distribution, such movements in income inequality may simply reflect asset price effects and not necessarily correspond to an increase in saving of one part of the population. Therefore, it is not possible to be sure, whether the predictive role of income inequality on financial crises documented by previous is not actually contaminated by the movements in asset prices. In light of this, Paul (2017) suggests testing the predictive power of income inequality on financial crisis by using inequality measures that exclude capital gains. Using pretax income share data that exclude capital-gains for 17 advanced economies over the period from 1870 to 2013, Paul (2017) finds evidence that that rising top income shares (and low productivity growth) predicts crises based on a probabilistic model with the log-odds ratio. Hence, in the analysis the author rules out the possibility of asset price effects.[1]

We contribute to this literature, and in particular go beyond the work of Paul (2017), by exploring the time-varying predictive power of the growth in income inequality on a broad index of financial stress for the US. The analysis include six alternative measures of income inequality, which are calculated based on pretax income share data that excludes capital-gains over the annual period of 1913 to 2016.. We use the longest possible data sample that prevents our study from suffering from the sample-selection bias. Further, unlike the above-mentioned papers, which rely on constant parameter models, we use the recently proposed test of time-varying causality in a vector autoregressive (VAR) framework by Wang and Rossi (2019). The method allows us to conduct a state-dependent analysis by accommodating for regime-changes, and in the process detect exact periods of predictability of financial stress due to inequality. This issue is important since financial stress does not always lead to

[1] The role of capital-gains became evident for the trend-cycle decomposition used by Paul (2017), since when capital-gains were not excluded, then it is the cyclical part and not the trend part that explained the predictive power of the top income shares, driven by temporary asset price booms.

crisis, but does so only when it increases beyond a certain "threshold" as witnessed during the "Great Depression" and the recent global financial crisis in the wake of the "Great Recession". The time-varying approach would provide evidence of not only whether the predictive capacity of inequality for financial stress actually increases during episodes of crises, but also whether inequality can also cause financial stress in general during relatively calmer periods of financial turmoil. In addition, in our estimated methods, we account for structural breaks, and hence provide more reliable inference than constant parameter models. Naturally, the accurate prediction of crises due to inequality as a possible factor remains an important issue for policymakers. Note that it is the availability of both historical financial stress and capital-gains excluded inequality data that leads us to choose US as our case study. Besides, the US was the source of the recent global financial crisis that shook the world financial system to its core, and inequality in the country has increased sharply over the past three-and-a-half decades (Chang et al. 2018, 2019).

To the best of our knowledge, this paper is the first study to analyze time-varying predictability of financial stress of the US based on growth in income inequality, using over a century of data. 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

Our analysis consists of two variables, namely a newspaper-based index of financial stress and six alternative available measures of inequality, which exclude capital-gains. The corresponding historical news-based financial stress data is derived from Püttmann (2018). The author constructs the Financial Stress Index (FSI) from the titles of articles published in five US newspapers (the Boston Globe, Chicago Tribune, Los Angeles Times, Wall Street Journal and Washington Post), by following three steps: Püttmann (2018) defines eleven topics ("bonds", "business", "central banks", "economy", "general", "gold or silver", "inflation", "railroads", "stocks", "trade", and "trouble") comprised of 120 words. If a title contains one of these 120 words, he classifies the article as pertaining to financial markets. Püttmann (2018) then uses four sentiment dictionaries to measure the sentiment of each title flagged in the first step. For a given dictionary, the author treats a title as having a net negative connotation if it includes more negative than positive words. This approach yields a raw monthly FSI for each newspaper-dictionary combination,[2] and; Finally Püttmann (2018) standardizes the raw monthly FSI for each newspaper dictionary combination to a mean of 100 and a unit standard deviation from 1889 to 2016. Averaging across all 20 such combinations by month yields the monthly FSI, which we convert into annual frequency by taking a twelve-month average.[3]

As far as the inequality data is concerned, it is derived from Piketty and Saez (2003), who build new homogeneous series on top shares of pretax income and wages (with and without capital-gains) in the US starting in 1913. These new series are based primarily on tax returns data published annually by the Internal Revenue Service (IRS) since the income tax was instituted in 1913, as well as on the large micro-files of tax returns released by the IRS since 1960. The six measures of income inequality that

[2] Specifically, the raw indicator value for a given newspaper-dictionary-month is (the number of titles pertaining to financial markets) times (the share of such titles with a net negative connotation) divided by (the number of all titles).
[3] Further details and the data is available for download from: http://www.policyuncertainty.com/financial_stress.html.

are available corresponds to the top decile (denoted by Top10), and for a number of higher fractiles within the top decile: the top 10 percent-5 percent (Top10-5), the top 5 percent to 1 percent (Top5-1), the top 1 percent (Top1), the top 0.1 percent (Top01), and the top 0.01 percent (Top001). We use the version of each measure that does not include capital-gains, as suggested by Paul (2017).[4] The first three measures start in 1917, while the next 3 begin at 1913.

Note, there are other FSI measures available for the US, but they cover only the post-World War II period. In this study, we only rely on Püttmann (2018) historical measure of financial stress to match the time-span of our inequality data. Using the longest possible data sample prevents our study from suffering from a sample-selection bias. Since our econometric approach, which we describe below, requires us to work with stationary data, we convert the inequality measures into their corresponding growth rates. FSI is left untransformed as it is found to be mean-reverting.[5] Inequality growth measures are depicted as: GI*j*, *j*=1..6, corresponding to the six measures of income inequalities (Top10, Top10-5, Top5-1, Top1, Top01, and Top001). Due to the transformations, our effective sample starts from 1918 to 2016 for the cases involving Top10, Top10-5, Top5-1, and from 1914 to 2016 for Top1, Top01, and Top001, with the start date driven by the availability of the inequality measures and the end date corresponding to the last data point for the FSI. All variables are plotted in Figure A1 (Appendix).

2.2. Methodology

Given that we use a long span of historical data on FSI and GI, which is likely to be (and as we show below that it indeed is) associated with structural breaks in their relationship, we use the recently proposed full-fledged time-varying Granger causality test of Wang and Rossi (2019). We use Wang and Rossi's (2019) approach to analyze the time-varying impact of GI*j*, *j*=1,…,6, on FSI 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:

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

where $\Psi_{j,t}\ , j = 1, \dots p$ are functions of time varying coefficient matrices, $y_t = [y_{1,t}, y_{2,t}]'$ is an $(2x1)$ 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, FSI and GI*j*, *j*=1,…,6, in a bivariate set-up. We test the null hypothesis that GI*j* does not Granger cause FSI for all *t* where the null hypothesis is $H_0: \phi_t = 0 \text{ for all } t = 1,2,\dots,T$, given that ϕ_t is appropriate subset of $vec\ (\Psi_{1,t}, \Psi_{2,t}, \dots, \Psi_{p,t})$. To this end, Wang and Rossi (2019) suggest four alternative test statistics namely: the exponential Wald (*ExpW*), mean Wald (*MeanW*), Nyblom (*Nybolm*) and Quandt Likelihood Ratio (*SupLR*) tests. Based on the Schwarz Information Criterion (SIC), the VAR model is estimated using 1 lag. We use an end-point trimming of 5% in the bivariate set-up, which in turn amounts us to losing 5 observations from both ends.

3. Results

[4] The data is downloadable from the website of Professor Emmanuel Saez at: https://eml.berkeley.edu/~saez/.

[5] Complete details of the unit root tests are available upon request from the authors. In addition, using growth rate of the FSI does not affect the qualitative conclusions of our results reported in the next section, and are again available upon request from the authors.

In Table 1, to analyze the predictive ability of GI*j*, *j*=1,…,6, on FSI in a bivariate set-up, we start with the standard constant-parameter Granger causality test and find that none of the inequality measures Granger causes the FSI even at the 10% level of significance. However, based on the powerful *UDmax* and *WDmax* tests of Bai and Perron (2003), which we use to detect 1 to *M* structural breaks in the FSI equation of the various VAR(1) models, allowing for heterogenous error distributions across the breaks and 5% trimming. We find evidence of several structural breaks: 4 (1930, 1935, 1980, 2012); 5 (1929, 1935, 1973, 2007, 2011); 5 (1929, 1935, 1973, 2007, 2012); 4 (1930, 1935, 1980, 2012); 2 (1980, 2012), and; 2 (1980, 2012) under including GI*j*, *j*=1,…,6, respectively. The break points correspond to the Great Depression (1929-1939), the oil shock of 1973, the recession of 1980 following the energy crisis in 1979, the Great Recession (2007-2009), and the European sovereign debt crisis which started in 2010 and deepened around 2012. 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.[6] As can be seen, the null of no-Granger causality from including GI*j*, *j*=1,…,6 to FSI is overwhelmingly rejected at the highest possible level of significance across all the four tests, and the six measures of inequality growth used as predictors by turn. In other words, the predictive ability of including GI*j*, *j*=1,…,6 for FSI is in fact time-varying and strong, even though no evidence of causality is observed from the constant parameter model.

[INSERT TABLE 1]

Next, in Figure 1 to 6, we present the whole sequence of the Wald statistics over time, which gives more information on when the Granger causality occurred. As can be seen, GI1, and GI3 consistently predict FSI, over the entire sample period, barring early part of the sample and for a few years after 1940, with strong evidence of causality post-2000. In comparison, GI4, GI5 and GI6 predict FSI for the early part of the Great Depression and then from mid-to late-1980s, i.e., the period post financial liberalization in the US. Again, strong evidence of causality is observed during the Great Recession. However, among all the six measures, strongest evidence of causality for FSI emanates from GI2, which corresponds to inequality associated with the top 10 percent-5 percent of the income distribution, with the time-varying test statistic having an upward trend.[7] In general, we can draw two main conclusions from these results: First, broader measures of inequality growth predict to the top 10 percent, the top 10 percent to 5 percent, and the top 5 percent to 1 percent tends to cause FSI relatively better than the narrower measures of top 1 percent, top 0.1 percent, and the top 0.01 percent[8]. Second, all the six inequality metrics tend to cause the heightened financial stress during the recent turbulent episodes associated with the Great Recession and the European sovereign debt crisis (which slowed down the US equity market through decline in demand for its exports from Europe), and at least the onset of the Great Depression.[9]

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[6] All time-varying estimations were based on the STATA codes available for download from the research segment of the website of Professor Barbara Rossi at: https://sites.google.com/site/barbararossiwebsite/Barbara-Rossi-research.

[7] The time-varying estimates of the lagged inequality growth is found to be positively related with FSI over the entire sample period, barring the case of GI6. This suggests that historically, higher inequality growth generally leads to increased financial stress in the US economy as suggested by theory. Complete details of these results are available upon request from the authors.

[8] Using the nonparametric causality-in-quantiles test of Jeong et al. (2012), we obtained similar results, which are available upon request from the authors.

[9] Quite a few single and cross-country based studies (see for example, Roine et al. (2009), Wolff (2013), Callan et al. (2014), Grabka (2015), and Gokmen and Morin (2019)), have suggested that financial crises can impact inequality.

[INSERT FIGURES 1 TO 6]

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 model with stochastic volatility (TVP-VAR-SV) along the lines of Huber et al., (forthcoming).[10] Note that, global-local priors are used to induce shrinkage TVP models as they tend to be over-parameterized. Even though the estimates produced by these priors can still have appreciable uncertainty, sparsification has the potential to reduce this uncertainty and improve forecasts. Given this, we use the approach of Huber et al., (forthcoming), who develop computationally simple methods which both shrink and sparsify TVP models. Since all the measures of inequality growth generally tends to predict within-sample the FSI during the recent global financial crisis and the period thereafter, we conduct an one-step-ahead out-of-sample forecasting over 2007 to 2016. The analysis are based on a TVP-VAR(1)-SV model (which includes both FSI and the inequality growth rates in turn) and the performance is compared relative to a TVP-AR(1)-SV model of the FSI. The results have been reported in Table 2, where we present the relative root mean squared errors (RRMSE) of the TVP-VAR(1)-SV model relative to the TVP-AR(1)-SV model. Understandably, if RRMSE is less than one, then adding lagged information from the inequality growth rates improve the forecast of FSI out-of-sample, compared to when we just consider a lag of the FSI. As can be seen from the table, RRMSE is less than one under GI1, GI2, GI3 and GI5, with strongest gains obtained under GI3 followed by GI2, i.e., for growth of Top10-5, and Top5-1. The forecasting results are consistent with our in-sample finding that stronger predictability for financial stress is observed under broader measures of inequality growth.

[INSERT TABLE 2]

The recent study by Destek and Koksel (2019) is somewhat related to our work, given that they use a time-varying method as well. In this study, we generally provide stronger evidence of predictability of financial stress by using a more robust full-fledged time-varying approach rather than the window-size sensitive rolling-window method. In addition, we use measures of inequality that excludes capital-gains, and hence eliminate possible asset price effects. In addition, we go beyond the in-sample-based work, by providing an out-of-sample forecasting exercise, which as noted above is a more robust way of determining predictability.

4. Conclusion

Existing empirical evidence is mixed regarding the impact of inequality on financial crises. Consequently, in this study we explore the time-varying causal impact of the growth in six alternative measures of income inequality, on a broad index of financial stress of the US over the annual period of 1913 to 2016. Using the longest possible data span allows our study to be unbiased from the perspective of sample-selection. Simultaneously, utilizing the time-varying method makes our inferences robust by accounting for regime changes, which we show to exist, in the relationship between financial stress and inequality over the century of data used in our analysis.

Given this, when we ran the causality tests the other way round, we detected strong evidence of FSI causing GI1, GI3, GI4, GI5 and GI6 over our entire data coverage, and GI2 towards the beginning and end of the sample period. Complete details of these results are available upon request from the author.

[10] The estimations were done based on the R codes available for download from the computer codes segment on the website of Professor Florian Huber at: https://sites.google.com/site/fhuber7/computer-codes?authuser=0.

Our findings show that measures of inequality growth corresponding to the top 10 percent, the top 10 percent to 5 percent, and the top 5 percent to 1 percent tends to predict FSI relatively better than measures of top 1 percent, top 0.1 percent, and the top 0.01 percent. Moreover, the growth in all of the six metrics of inequality predicts the heightened financial stress observed with the start of the Great Depression, and the same associated with the recent global financial and European sovereign debt crises. Finally, our in-sample results also tends to hold over an out-of-sample forecasting exercise for four out of the six measures of inequality growth.

Our results have important policy implications. Recall, Rajan (2010) argues that governments in the US with voting anxiety, instead of implementing policies to actually reduce income inequality, have facilitated credit access for voters in low- and middle-income groups based on deregulation policies in credit markets and encouraging state-owned mortgage agencies to loan to these segments. As a result of these subsidized loans, the situation became unsustainable, resulting in a credit bubble and the subsequent crisis in 2007. This line of reasoning is indeed supported by our analysis, suggesting that policy measures to facilitate credit access among low-income segments by deregulating certain sectors will basically increase repayment risks and create pressure on the financial system, and hence is not an optimal policy decision. Rather, as also suggested by Destek and Koksel (2019), a progressive taxation policy or investments to accumulate human capital to raise the level of education of low-income people, and in the process help this segment to find work with higher wages, and eventually reduce the income inequality in the long-run.

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

	Test Statistic				
Predictor	$\chi^2(1)$	*ExpW*	*MeanW*	*Nyblom*	*SupLR*
GI1	1.1581	64.3864*	25.3240*	14.9115*	137.7320*
GI2	2.3202	209.8598*	148.6203*	8.6571*	428.6786*
GI3	1.2331	193.4630*	54.9477*	6.5716#	394.7929*
GI4	0.1801	87.6372*	25.1259*	14.6454*	184.3136*
GI5	0.1149	92.7942*	23.6528*	17.8010*	194.6276*
GI6	0.0171	47.4707*	18.9932*	18.5761*	103.9726*

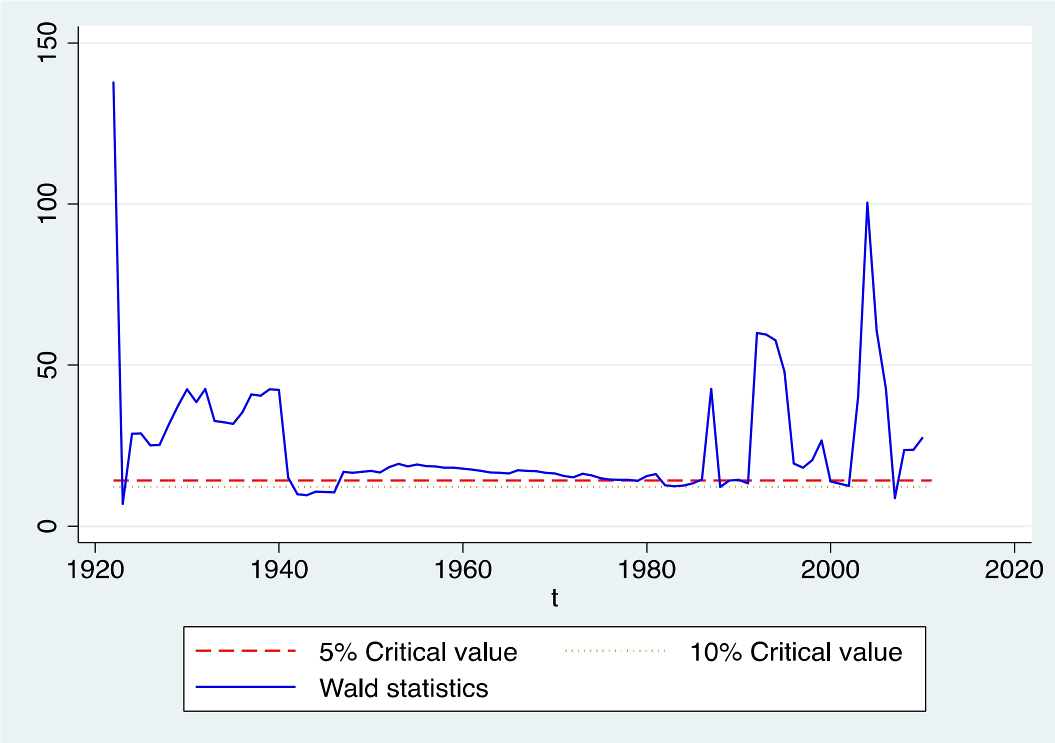
Note: Null hypothesis is GI1/GI2/GI3/GI4/GI5/GI6 does not Granger cause FSI in a constant or time-varying VAR(1). FSI: financial stress index; GI*j*, *j*=1,..6, corresponds to the growth rate of the six measures of income inequality, i.e., Top10, Top10-5, Top5-1, Top1, Top01 and Top001 respectively; * and # indicates significance at the 1% and 5% levels respectively.

Table 2. Out-of-sample forecasting of results for the financial stress index

	Forecasting Models					
	Model1	Model2	Model3	Model4	Model5	Model6
RRMSE	0.9691	0.9475	0.9398	1.0083	0.9986	1.0177

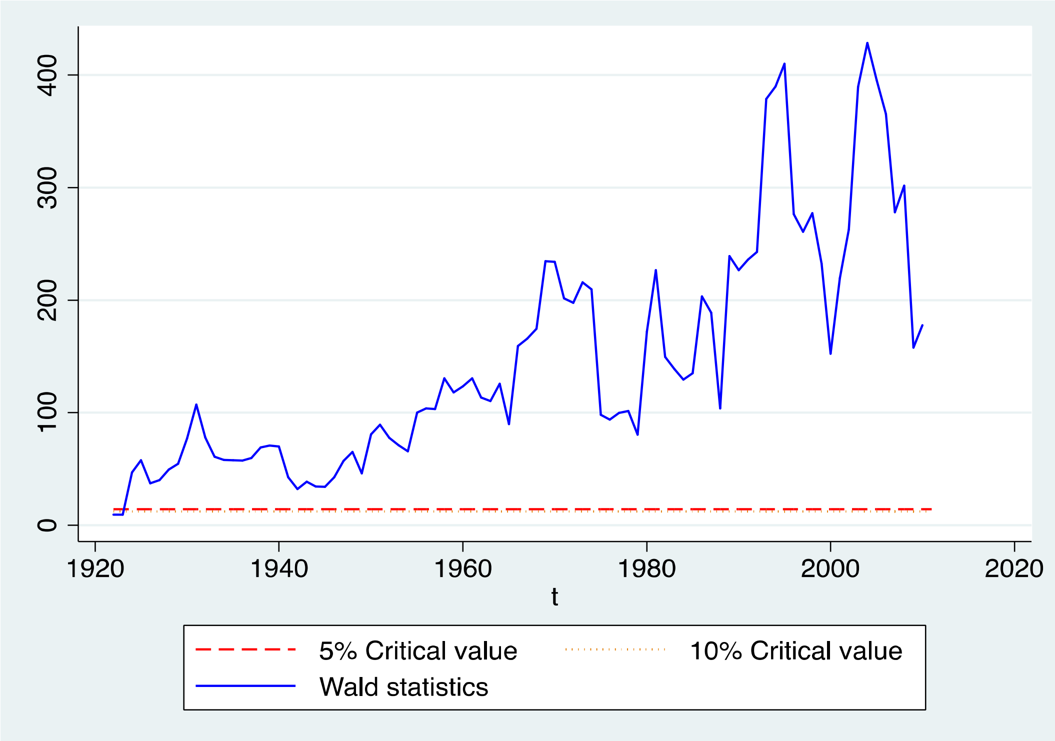
Note: See Notes to Table 1; RRMSE is the ratio of RMSE of the TVP-VAR(1)-SV model of FSI and GI1, GI2, GI3, GI4, GI5 or GI6 relative to the RMSE of the TVP-AR(1)-SV model of FSI; Model1: FSI and GI1; Model2: FSI and GI2; Model3: FSI and GI3; Model4: FSI and GI4; Model5: FSI and GI5; Model6: FSI and GI6.

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



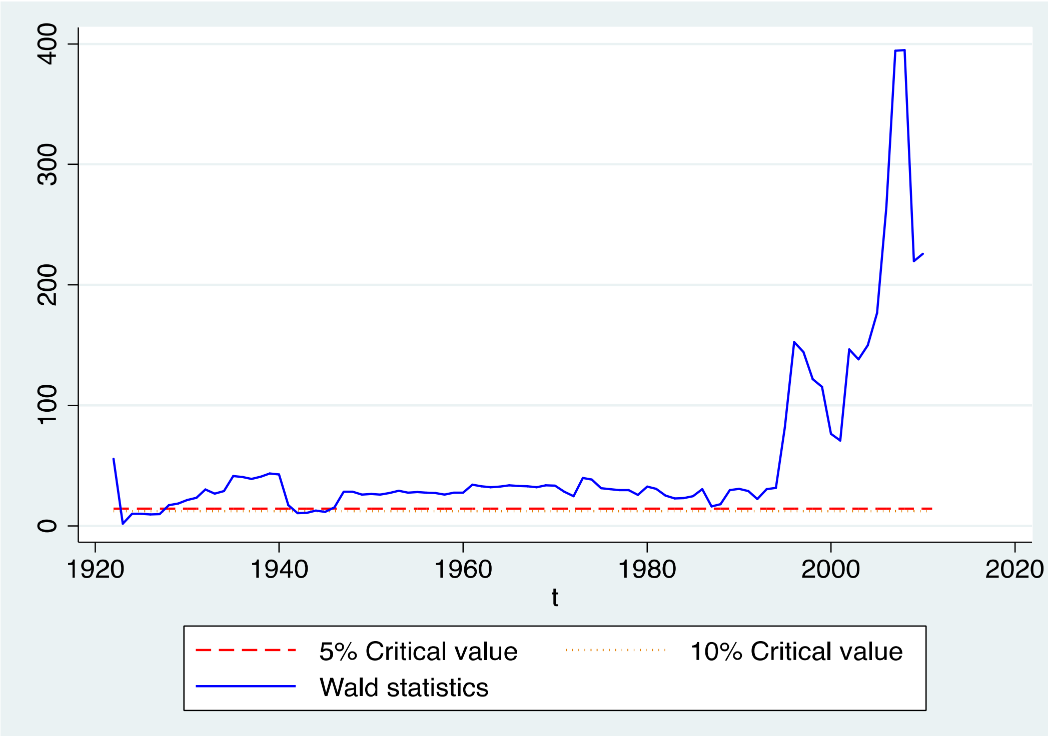
Note: See Notes to Table 1; t: corresponds to annual data; and the vertical axis measure the test statistic.

Figure 2. Time-varying Wald statistics with VAR(1) under SIC, testing whether GI2 Granger-causes FSI



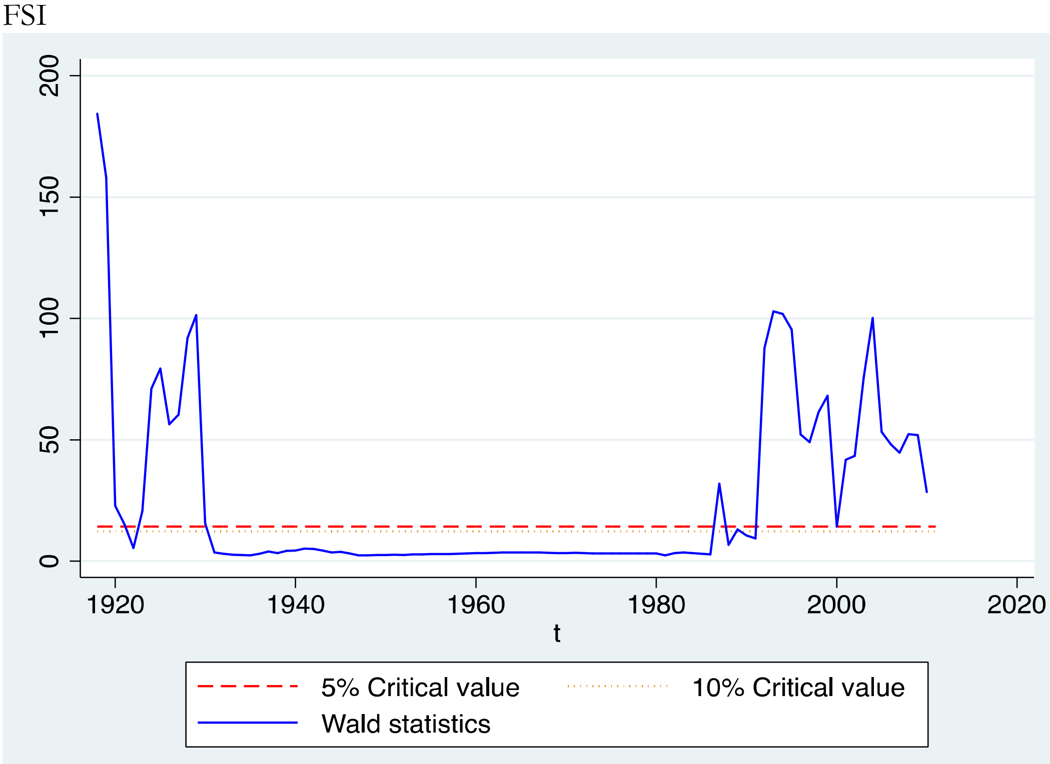
Note: See Notes to Table 1 and Figure 1.

Figure 3. Time-varying Wald statistics with VAR(1) under SIC, testing whether GI3 Granger-causes FSI



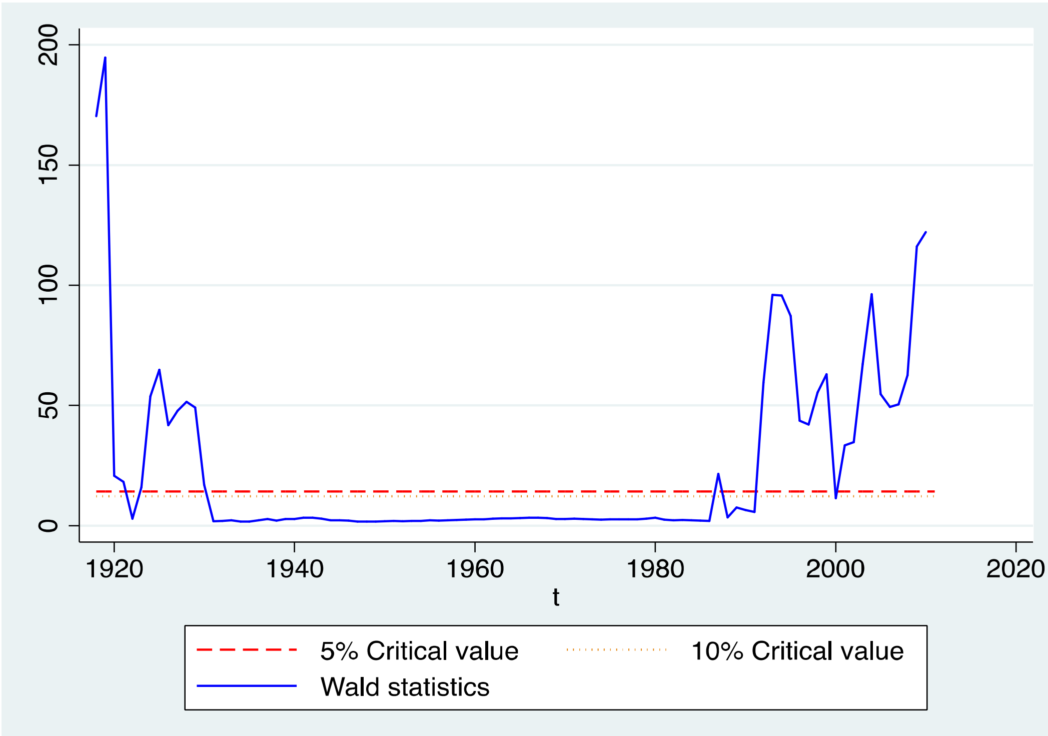
Note: See Notes to Table 1 and Figure 1.

Figure 4. Time-varying Wald statistics with VAR(1) under SIC, testing whether GI4 Granger-causes FSI



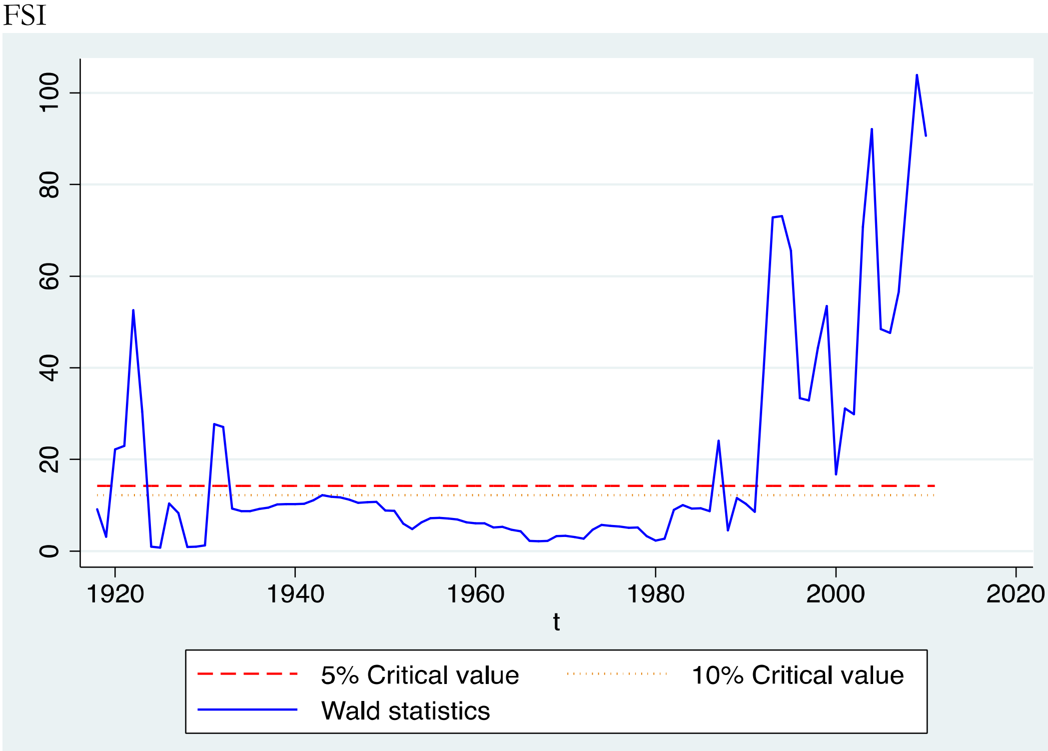
Note: See Notes to Table 1 and Figure 1.

Figure 5. Time-varying Wald statistics with VAR(1) under SIC, testing whether GI5 Granger-causes FSI



Note: See Notes to Table 1 and Figure 1.

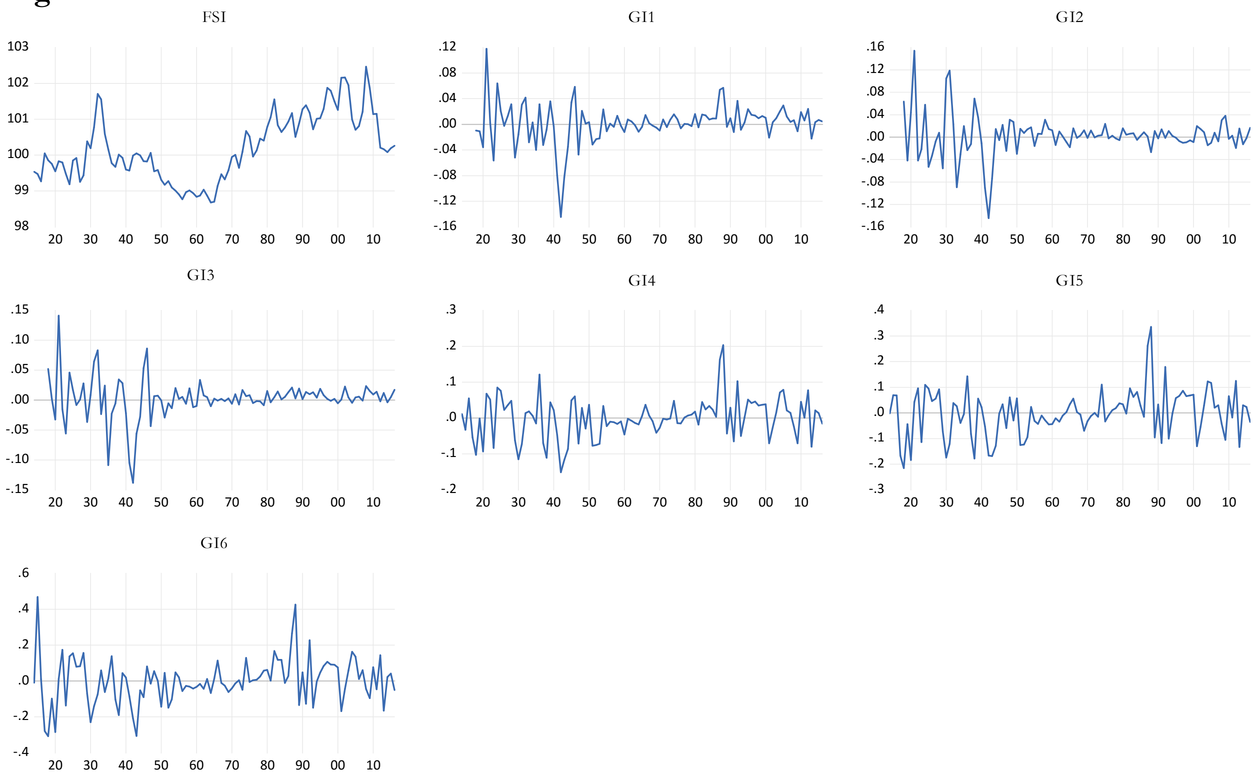
Figure 6. Time-varying Wald statistics with VAR(1) under SIC, testing whether GI6 Granger-causes FSI



Note: See Notes to Table 1 and Figure 1.

APPENDIX:

Figure A1. Data Plots



Note: FSI: financial stress index; GI*j*, *j*=1,..6, corresponds to the growth rate of the six measures of income inequality, i.e., Top10, Top10-5, Top5-1, Top1, Top01 and Top001 respectively.