

Investigating the asymmetric effect of income inequality on financial fragility in South Africa and selected emerging markets: a Bayesian approach with hierarchical priors

Income
inequality and
financial
fragility

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Abstract

Purpose – This study aims to test the validity of the Rajan theory in South Africa and other selected emerging markets (Chile, Peru and Brazil) during the period 1975–2019.

Design/methodology/approach – In this study, the researchers used time-series data to estimate a Bayesian Vector Autoregression (BVAR) model with hierarchical priors. The BVAR technique has the advantage of being able to accommodate a wide cross-section of variables without running out of degrees of freedom. It is also able to deal with dense parameterization by imposing structure on model coefficients via prior information and optimal choice of the degree of formativeness.

Findings – The results for all countries except Peru confirmed the Rajan hypotheses, indicating that inequality contributes to high indebtedness, resulting in financial fragility. However, for Peru, this study finds it contradicts the theory. This study controlled for monetary policy shock and found the results differing country-specific.

Originality/value – The findings suggest that an escalating level of inequality leads to financial fragility, which implies that policymakers ought to be cautious of excessive inequality when endeavouring to contain the risk of financial fragility, by implementing sound structural reform policies that aim to attract investments consistent with job creation, development and growth in these countries. Policymakers should also be cautious when implementing policy tools (redistributive policies, a sound monetary policy), as they seem to increase the risk of excessive credit growth and financial fragility, and they need to treat income inequality as an important factor relevant to macroeconomic aggregates and financial fragility.

Keywords BVAR, Emerging markets, Financial fragility, Hierarchical priors, Income inequality

Paper type Research paper

1. Background of the study

The outbreak of the 2007–2009 financial crisis in the USA, which ultimately spread widely across many nations, was mainly driven by the interaction of the financial markets in recent decades. The central debate in this field of study is the question of whether the increasing inequality contributes to the excessive accumulation of debt, which then leads to financial fragility. As documented by Fisher (1932), the main driver of this consequence is the private

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sector's explosive degree of indebtedness resulting in the destabilization of the financial markets, thus causing harm to the economy overall. An upsurge in debt leads to financial instability, causing indebted institutions to not be able to meet their liabilities. This output is similar to the conclusion documented by [Minsky \(1975\)](#), which has become well-known as the financial instability hypothesis. It posits that excessive borrowing is the main driver of financial instability. However, these hypotheses are based on investment and cooperative debt rather than consumption and household debt. [Fama \(1998\)](#) argues that such actions do not always follow the efficient-market hypothesis; thus, misdirected investments generate financial losses for many individuals, subsequently marking the beginning of a potential economic downfall.

[Kindleberger \(1978\)](#) documented that the process depends on the asset price evaluation market that becomes the pre-phase of a slump, as the price share of various corporations exceeds their market value. Such investments are driven by credit acquisitions that increase the net debt exposure of the private sector. For this reason, a certain degree of mania overwhelms investment activities, leading to debt-to-income ratios increasing and capital ratios falling. Ultimately, when an incident occurs exposing asset overvaluation, sentiments of panic arise in which investors withdraw their money, especially from liquid assets, in order to avoid losses. Consequently, asset prices collapse, and if the investments have been inefficient, the liabilities may not be repaid. Therefore, rapid economic growth results in speculative activities and risks taken by dramatically increasing the debt-to-income ratio ([Mendoza and Terrones, 2008](#)).

Financial fragility has been defined in various ways by incorporating many factors including bank hand behaviour ([Kindleberger, 1978](#)); the credit policies based on inter-bank dependency as a result of the information problem ([Rajan, 1994](#)); underestimated risks ([Borio et al., 2001](#)); borrowers' limited commitment and loose credit standards ([Dell'Ariccia and Marquez, 2006](#)). Furthermore, various factors have been documented in the literature defining the measured course of the recent global financial crisis, such as the securitization of mortgages, Wall Street's ethically deficient culture, financial deregulation policies and households' excessive borrowing ([Yamarik et al., 2016](#)). However, the emerging strand of studies such as [Rajan \(2010\)](#), [Galbraith \(2012\)](#) and [van Treeck \(2014\)](#) propose that income inequality is the main driver of the recent financial outbreak. Considering the argument made by [Rajan \(2010\)](#), which has lately been supported by various studies, we aim to test whether the *Rajan hypothesis is comparable in the emerging markets*.

The existing literature on this subject is vast and has yielded numerous conflicting results, as some authors discovered the Fisher hypothesis, which argues that the main drivers of fragility are the private sector's explosive degree of indebtedness, resulting in the destabilization of financial markets, thus causing harm to the economy overall ([Bazillier and Hericourt, 2017](#); [Destek and Koksel, 2019](#)), while others found the Minsky hypothesis, which posits that a period of extreme euphoria and growth was followed by financial downfalls as a result of inefficient investment decisions and speculative activities ([Kumhof and Rancière, 2010](#); [Fasianos et al., 2017](#); [Bodea et al., 2021](#)). Others discovered the Rajan hypothesis, which posits that a significant increase in inequality was the major driver of the crisis ([Kumhof et al., 2012](#); [Stiglitz, 2012](#); [Perugini et al., 2013, 2016](#); [El-Shagi et al., 2019](#)). Among these studies, others find the relationship to be inconclusive ([Tridico, 2012](#)). The inconsistency in these results may be attributable, but not limited, to the differing model assumptions, datasets, estimate approaches or degree of economic development in assessing the relationship between income inequality and financial fragility in the existing literature.

The current study extends the existing literature on this subject matter, following the seminal work of [Yamarik et al. \(2016\)](#) who employed the pooled mean group and dynamic fixed-effects analysis in a panel of 50 US countries, following the Rajan hypothesis over the period 1977–2010. In their model, the ratios of bank loans (total and real estate) to

personal income and real estate loans were used to measure credit growth, while the share of personal income earned by the Top 1%, the Theil index and the Gini coefficient was utilized to capture income inequality. Their model controls the logarithm of real wages and earnings. They found that income inequality is positively related to real-estate lending. In their analysis, major macroeconomic and policy variables, such as broad money supply, real interest rate, credit demand financial capital inflows and democratic pressure, that impact the common-man directly or indirectly, were not captured. We then intend to strengthen the argument in the topic by empirically testing *whether monetary policy variables cause inequality-fragility in emerging markets*. Furthermore, the study aim includes *democratic pressure on the inequality-fragility system in order to understand whether democratic pressure triggered the studied subject matter*. In addition, their analysis was conducted in advanced countries. However, our study focuses on South African and other selected emerging economics.

It is because of these contrary views that we strive to fill a vacuum in the literature by including and assessing those macroeconomic and policy variables and their impacts on the income-fragility relationship in South Africa and other emerging countries that most prior studies have ignored. As the current study investigates the asymmetric effect of income inequality on financial fragility in South Africa and selected emerging markets, we build on the spirit of [Kilian and Vigfusson \(2011\)](#) of the asymmetric effect. In their model, they adopted the linear and asymmetric VAR to examine whether the responses of the US economy are asymmetric in energy price increases and decreases. Their VAR model was in a nonlinear context.

However, we fundamentally extend their VAR model by including a Bayesian with hierarchical priors, which then becomes the Bayesian Vector Autoregression (BVAR) with hierarchical priors for South Africa and the selected emerging markets in a linear context, covering the period 1975 to 2019, to test for the existence of the Rajan hypothesis developed by [Rajan \(2010\)](#) and the impact of monetary policy and democratic pressure. We believe that our BVAR with hierarchical priors is useful in accounting for these weaknesses in both income inequality and financial fragility, even in the prior literature. Informative priors are being used to impose additional structure on the model and push it towards established benchmarks. The resulting models display reduced parameter uncertainty and dramatically improved out-of-sample forecasting performance ([Koop, 2013](#)). However, the precise choice and parameterization of these priors pose a challenge that remains at the heart of both debate and critique. A variety of previous selection strategies have been suggested in the literature. [Giannone et al. \(2015\)](#) address this issue by prioritizing formativeness in a data-driven manner, in the spirit of hierarchical modelling. The Bayesian hierarchical technique employs marginal likelihood (ML) to examine the whole posterior hyperparameter space while accounting for uncertainty. This will produce robust inference and will be theoretically sound. Therefore, the BVAR with hierarchical priors will also serve as a contribution to this subject matter.

We included South Africa, along with 14 other emerging markets, in our model. The motivation behind focusing on South Africa is that it is one of the emerging countries with the highest level of income inequality. Since it became independent in 1994, South Africa has experienced a quick growth in black middle-income households, with an accumulation of assets and access to credit. A big drive to get the unbanked to open bank accounts was also successful, through African Bank. Furthermore, South Africa has a very active informal “credit system” through money-lending businesses, which through its informal nature contributes to fragility and even inequality due to the higher cost of informal funding. Even according to the working class, South Africans have high rates of credit, which then leads us to be interested in empirically investigating the asymmetric shock of income inequality on domestic credit. However, the other selected emerging economies

will be selected from 14 emerging countries, which are Argentina, Brazil, China, Chile, India, Indonesia, Malaysia, Mexico, Peru, Philippines, Saudi Arabia, Singapore, Thailand and Turkey. Among these countries, we will select those with a high level of income inequality and compare their results with the ones we generated in the South African context. Comparing these findings will help to understand the nature of the income inequality and financial fragility relationship in order for policy makers to be able to formulate and implement relevant policy recommendations for these countries. Moreover, since the BVAR model is a time-series model, it will only be able to solve problems that are in a time-series context. Therefore, we calculated the mean Gini coefficient by finding countries with a high mean, as they may be regarded as countries with very high levels of inequality. We set 48 (mean of Gini coefficient) as the threshold in order for us to be able to segregate countries with low/middle inequality from very high inequality. We found that Brazil (51.19), Peru (51.19) and Chile (48.53) are the countries with very high Gini coefficient means, but not South Africa as per our assumption. Furthermore, we did a data inspection as presented in Figure 1 by looking at how inequality behaved during every decade from 1975–2019. The data shows that South Africa (SA) is the leading country with the highest level of inequality over all the decades, followed by Brazil, Peru and Chile. The data for SA further illustrate that income inequality is still on the increase, as can be observed from decade 1 (1975–1984) to decade 4 (2005–2019).

While other countries seem to achieve the goal of reducing income inequality, countries like Chile, Peru and Brazil experienced high levels of inequality during decades 1 to 3, giving rise to the question for SA of how these countries managed to experience a reduction in inequality in decade 4 (2005–2019).

We intend to address a vacuum in the research by including and assessing the influence of these macroeconomic and policy factors on financial fragility, which has not been reflected in the existing literature on the subject. Furthermore, our time-series datasets have comparable time coverage to earlier research, making our empirical model robust and valuable for policy decision-making. Finally, the inspiration for this study stems not only from a lack of studies examining the effects of income inequality on financial fragility but also from the fact that this relationship may differ from that which exists in advanced countries due to differences in the smoothness of economic development and the macroeconomic policies that are implemented. Furthermore, our model and the macroeconomics and policy variables incorporated in this study are different from the ones adopted from the existing literature.

The rest of the paper is organized as follows. Section 2 briefly surveys the related literature. Section 3 presents an overview of the model, the different sectors it is composed of and its features. Section 4 discusses the results of the BVAR model. Section 5 provides concluding remarks and discusses policy implications.

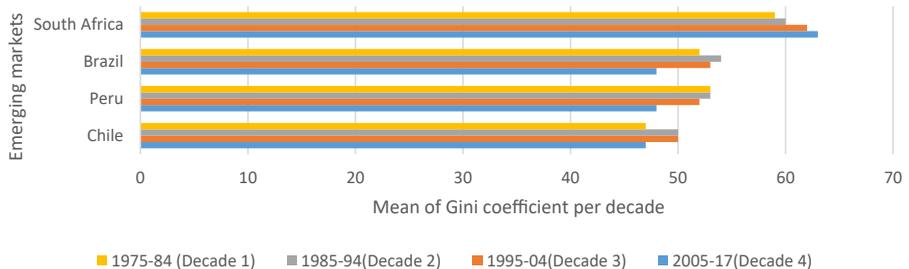


Figure 1.
The mean Gini coefficient after every decade from 1975–2019

Source(s): Author's calculation based on SWIID data (Solt, (2014))

2. Literature review

2.1 *Theoretical review of inequality, indebtedness and financial fragility*

In the literature, the relationship between income inequality and financial fragility is not new. However, the channels through which inequality links to economic fragility are still debatable and not clear. This argument becomes noticeable from the study by Fisher (1932), which posits that the main driver of this consequence is the private sector's explosive degree of indebtedness, resulting in the destabilization of the financial markets, thus harming the economy overall. An upsurge in debt accumulation leads to financial instability, causing indebted institutions not to meet their liabilities. The financial instability hypothesis documented by Minsky (1975) posits that the major driver of indebtedness is the financial system, which then leads to a high possibility of a Ponzi scheme, where institutions and individuals are not able to meet their liabilities. This significant contribution documented by Minsky's hypothesis was based on the argument that income inequality impacts financial fragility through the indebtedness channel. However, Raghuram Rajan, in his 2010 book titled "Fault Lines", added a great deal of momentum to the existing inequality-fragility debates, by arguing that the increasing inequality in the USA puts pressure on the governments of all political encouragement to pass policies meant to improve the lives of the middle- and low-income voters, but not succeeding. He points out that, in the polarized world of American politics, the usual recourse of governments in such circumstances, namely, the redistribution of income via social spending and taxes, is politically poisonous. The government then chooses to placate the voters by implementing policies that would expand their access to credit – a solution that attracts far less political attention and is, therefore, far more palatable to both sides of the political divide. Among these policies are the deregulation of credit and the reassurance of state-owned mortgage agencies to increase lending to low-income households. This generates an excessive amount of credit that households obligingly absorb as a supernumerary for increasing income, as they endeavour to achieve a high standard of living. The consequent credit bubble forms the foundation for the subsequent crisis. The logic behind this is that, when income and wealth are concentrated among a few people, there will be social inefficiency, since the investment decisions may be non-productive. In a nutshell, the Rajan hypothesis was based on the argument that, in the USA, politicians tried to redistribute income by giving middle- and low-income groups access to credit. With the lack of sufficient regulations, such policies lead to volatile indebtedness as borrowing has become the solution to maintaining acceptable standards of living. That is how this bubble led to the 2007–2009 financial crisis.

The above-mentioned theories are based on the US experience, as the global financial crises of 2007–2009 started in the USA, where studies such as Rajan (2010) claim that the interplay between increasing inequality and the US politics caused the credit boom, which then led to the subsequent crisis, as a result of the deregulation of the financial markets. We believe that this indirect explanation is compatible with the US experience only, and there is no solid proof that the relationship would hold in different countries or at different times. More general lines of reasoning should therefore be applied to explain how rising inequality might be linked to an abnormal increase in household indebtedness.

2.2 *Review of empirical literature*

After scrutinizing the empirical literature on this subject, we found that the existing studies build on three strands, the Fisher hypothesis, the Minsky hypothesis and the Rajan hypothesis. Among these strands a strong paradox emerged, since the Fisher hypothesis argues that the main drivers of the fragility are the private sector's explosive degree of indebtedness resulting in the destabilization of the financial markets, thus causing harm to the economy overall. The Minsky hypothesis argues that a period of extreme euphoria and

growth was followed by financial downfalls as a result of inefficient investment decisions and speculative activities undertaken by the private sector, and ultimately, the Rajan hypothesis posits that a significant increase in inequality was the main driver of the crisis. A number of authors have suggested that increasing inequality may have played a crucial role in the recent global financial crisis of 2007–2009, rekindling interest in this problem. This is covered by a number of popular authors (e.g. [Rajan, 2010](#); [Reich, 2010](#); [Galbraith, 2012](#)) as well as opinion editorials penned by prominent economic commentators (e.g. [Wade, 2010](#)) and policy-focused papers (e.g. [Stiglitz, 2009](#)). Moreover, there is a growing body of academic research to formally analyse the theoretical and empirical relationships in this subject matter ([Kumhof and Ranci re, 2010](#); [Tridico, 2012](#); [Bordo and Meissner, 2012](#); [Kumhof et al., 2012](#); [van Treeck, 2014](#); [Lim, 2019](#); [El-Shagi et al., 2019](#); [Balcilar et al., 2020](#); [Bodea et al., 2021](#)).

[Kumhof and Ranci re \(2010\)](#) built a closed-economy Dynamic Stochastic General Equilibrium (DSGE) model. In their model, two economic agents feature: workers who earn only wage income and use this only for consumption; and investors who are defined as the top 5% of earners who own all of the capital, earn only capital income and save and invest as well as consume. Their findings documented that when a shock reduces the bargaining power of workers relative to investors, the workers who are then faced with declining real wage growth borrow in order to maintain their desired level of consumption. On the other hand, investors lend to the workers out of their rising incomes via financial intermediaries. As inequality increases, the workers become increasingly indebted to the investors, who overwhelm them with claims. The saving and borrowing behaviour of these two groups then leads to an increased demand for financial intermediation, and the size of the financial sector grows relative to the rest of the economy. All this while, leverage of the household and financial sector increases, thus increasing the probability of a financial crisis.

[Kumhof et al. \(2012\)](#) build on [Kumhof and Ranci re \(2010\)](#) to investigate the same subject in a panel of 18 Organization for Economic Co-operation and Development (OECD) countries over the period 1968–2006. Their model adopted the financial liberalization shocks, as it addressed the concerns raised in the existing literature. To the original closed-economy model, they added foreign agents who both work and invest, like before, following a bargaining shock that causes the income share of the workers to decline while strengthening the profit share of the investors. The latter reacts by lending a portion of their increased income back to the workers, who thus seek to maintain their regular consumption. In an open economy, investors also profit from being able to mediate the savings of foreigners to domestic workers. Calibrating the model to UK data, simulations show that increased inequality endogenously leads to credit expansion, increased leverage and increased current account deficits, which in turn increase the probability of a systemic financial crisis. Their findings show that income concentration (indicated by the top 1% and 5% income shares) is a statistically significant predictor of external deficits. The empirical findings in the study by [Stiglitz \(2012\)](#) on the global crisis, social protection and jobs in the USA support the argument that increases in income inequality among high earners with a high propensity to consume, leading to a financial crisis.

[Perugini et al. \(2013\)](#) studied the same subject in the case of an unbalanced panel of 18 OECD countries over the period 1970–2007, using a Generalized Method of Moments (GMM) estimator. In their model, domestic credit to the private sector (as % of GDP) was adopted as a proxy for financial fragility, while the share of total income earned by the top 1% of earners was adopted as a proxy for income inequality. However, their model controlled for portfolio investments (as a % of GDP), current account balance (as a % of GDP) and real interest rate. Their study documented a positive relationship between income concentration and private-sector indebtedness when controlling for conventional credit determinants.

[Perugini et al. \(2016\)](#) replicated the study documented by Mahmoud and Niguez. What makes their study to differ slightly from that of Mahmoud and Niguez is that they use binary

indicators coded as 1 (crises occurred) and 0 otherwise, following [Laeven and Valencia \(2013\)](#), while credit growth is captured by the credit-to-GDP ratio. What draws attention is that their findings contradict the findings reported by [Bordo and Meissner \(2012\)](#), while the study by [Yamarik et al. \(2016\)](#) on a panel of 50 provinces in the USA over the period 1977–2010, using the autoregressive distributed lag, contradicts the findings reported by [Perugini et al. \(2016\)](#). However, the empirical literature still supports the Rajan hypothesis.

[Bazillier and Hericourt \(2017\)](#) conducted a survey on this subject but included leverage in the model. Their survey was based in China, India and South America. Their findings contradicted the aforementioned studies as they found the results ambiguous. The study by [Fasianos et al. \(2017\)](#) contradicted the findings reported by [Perugini et al. \(2016\)](#) and [Bazillier and Hericourt \(2017\)](#), as they supported the Rajan hypothesis. [Amountzias \(2018\)](#) studied the inequality crises covering the period 1995–2015 in a panel of 33 OECD countries, following the Minsky hypothesis using a panel VAR framework analysis. Their findings supported a positive relationship between income inequality and financial fragility. [Destek and Koksel \(2019\)](#) supported the literature that relied on a positive relationship in this subject by using a bootstrap rolling window in 10 selected countries, which are the USA, Canada, Norway, Australia, Finland, the UK, Denmark, France, Sweden and Japan. In the same year, the argument was taken forward by [El-Shagi et al. \(2019\)](#) for Russian regions and [Lim \(2019\)](#) on a panel of 42 countries. The Russian study adopted Russian regions to test the Rajan hypothesis using the data from 75 highly heterogeneous regions between the Russian crisis and the introduction of inter-national sanctions from 2000 to 2012. While the study by [Lim \(2019\)](#) used the heterogeneous approach on a panel of 42 countries covering the period 1970–2015, utilizing the panel VAR. Their findings show that rising income inequality is likely to have implications for financial stability, then leading to financial crises. The studies by [El-Shagi et al. \(2019\)](#) and [Lim \(2019\)](#) are in line with the findings reported by [Destek and Koksel \(2019\)](#) and others. However, they contradict the study published in 2021 by [Bodea et al. \(2021\)](#). The study by [Bodea et al. \(2021\)](#) finds the Rajan hypothesis to not hold in the case of 66 countries covering the period 1960–2009 since their data on whether crises are associated with diverging incomes are weak and plagued by (1) the potential of a reverse impact, (2) the persistent nature of income inequality and (3) significant measurement errors in both the dependent and independent variables. They used the market Gini coefficient to measure income inequality in their analysis, and bank crises were coded following significant events, such as (1) bank runs that resulted in the closure, merger or takeover of one or more financial institutions by the public sector; or (2) where no runs occurred, the closure, merger, takeover or large-scale government assistance of an important financial institution (or group of institutions) that marked the beginning of a string of similar outcomes for other financial institutions.

As the current work aims to investigate the asymmetric effect of income inequality on financial fragility, we give a brief summary of the studies that build on the asymmetric context. However, we found that there are studies that examined the asymmetric effect in the current subject matter. We then borrowed from other studies in order to construct an argument about the asymmetric effect in our study. Following the work documented by [Kilian and Vigfusson \(2011\)](#), our study builds on the spirit of the asymmetric effect by using linear and nonlinear asymmetric VAR to examine whether the responses of the US economy are asymmetric in energy price increases and decreases. [Oguzhan \(2019\)](#) used structural vector autoregression (SVAR) to examine the asymmetric effects on exchange market pressure: empirical evidence from developing countries.

3. Methodological methods and data used in this study

3.1 Justification of variables

The study employed annual time series covering the period 1975–2019 to estimate a BVAR model with hierarchical priors for four emerging markets [1]. We adopted the level of

domestic credit to the private sector (as % of GDP) to capture financial fragility, as this variable includes credit from banks and other financial institutions. Focusing on bank credit alone can be misleading as our study is concerned with financial fragility. According to [Elekdag and Wu \(2011\)](#), while seeking to understand financial fragility, the choice of the credit aggregate is critical. A variable that includes credit extended by non-deposit-taking institutions is preferred, as credit booms can occur as a result of funds provided by these institutions, particularly during periods of high financial innovation and deregulation. The choice to evaluate total credit (as a percentage of GDP) in terms of levels rather than changes is justified by the fact that all of the research emphasizes how excessive credit availability in the economy leads to a financial crisis ([Bordo and Meissner, 2012](#)). On the other hand, whether or not greater rates of credit growth lead to a financial crisis is determined by the initial amount of credit accessible in the economy because the same growth rate might translate into quite different levels of credit and risk. Therefore, the measure adopted in this study is preferable. For income concentration, we adopted the Gini coefficient as disposable income to measure income inequality. The concept of disposable income (post-tax and transfers) is preferable in this study, compared to market income (pre-tax and transfers), as it has a robust impact on the individual borrowing decision, investment and consumption. We then used a different measure of income inequality from SWIID ([Solt, 2020](#)).

While our model controls for a monetary policy shock through broad money supply (BMS) (M2 over GDP) and real interest rate (INR) (lending rate adjusted by the GDP deflator) following the argument by [Elekdag and Wu \(2011, p. 9\)](#), the interest rate alone may represent the level of global financial liquidity accurately, especially in the environment of an unconventional monetary policy. Therefore, to address this issue, we adopted the interest rate series by a metric of broad money supply. We controlled for credit demand and financial capital inflows following [Mendoza and Terrones \(2008\)](#) by using portfolio investments (PIG) (as a % of GDP). This was due to the credit demand being based on the transactions in debt securities, external liabilities and equity. However, studies such as [Adarov and Tchaidze \(2011\)](#) among others, argue that the overall level of economic development captured by GDP per capita (GDPp) is a major predictor of credit availability and financial progress. We then controlled for economic development and the pro-cyclicality of credit, following [Borio et al. \(2001\)](#). Lastly, we controlled for demographic pressures. The democratic pressure indicator evaluates pressures on the state resulting from the population or its surroundings. The indicator takes demographic factors such as pressures from high population growth rates into account. It considers pressures resulting from extreme weather occurrences (hurricanes, floods, etc.) in addition to population pressures ([Davis and Carother, 2010; Lipsy, 2018](#)). Our variables were obtained from the World Development Indicators (WDI, 2020), Fund for Peace, and SWIID ([Solt, 2020](#)). All our variables were selected in line with the theoretical foundations and empirical literature underpinning the relationship under investigation.

3.2 Bayesian VAR model: model specification

To achieve the objective of the study, we built a Bayesian VAR approach, following [Bańbura et al. \(2010\)](#). However, our BVAR model accommodates hierarchical priors for various reasons. Reflect on the following VAR(p) model:

$$y_t = \alpha_0 + A_1 y_{t-1} + \dots + A_p y_{t-p} + \epsilon_t \text{ with } \epsilon_t \sim N(0, \Sigma), \quad (1)$$

where $y_t = \text{Cred}_t, \text{Gini}_t, \text{DP}_t, \text{PIG}_t, \text{INR}_t, \text{BMS}_t, \text{GDPp}_t$ is a 7×1 column vector of 7 endogenous variables in the BVAR system, while α_0 denotes a 7×1 vector of the intercept. A_j ($j = 1, \dots, p$) denotes a 7×7 matrix of autoregressive coefficients of regressors, while p is the order of the BVAR and lastly, ϵ_t is a 7×1 vector of Gaussian exogenous shocks with a zero mean and variance-covariance (VCOV) matrix Σ . The $7 + 7_p^2$ are the number of

coefficients to be estimated, rising quadratically with the number of included variables and linearly in the lags order. In such parameterization, some lead to inaccuracies with regard to structural inference and out-of-sample projecting, especially for higher-dimensional models. This phenomenon is normally referred to as the curse of dimensionality.

The good fit of the VAR estimated through the Bayesian approach is that it tackles this limitation by an impressive extra structure in the model, which includes the priors which have been shown to be effective in mitigating the curse of dimensionality and allowing for a large model to be estimated (Doan *et al.*, 1984). They push the model parameters towards a parsimonious benchmark, reducing estimation errors and improving out-of-sample prediction accuracy (Koop, 2013). This shrinkage is associated with frequentist regularization approaches (Mol *et al.*, 2008). Our approach is flexible and significant in accommodating a varied range of naturally evolved prior information, economic issuing and the issuing of data and it is also powerful in mitigating uncertainty through hierarchical modelling.

3.3 Selection of priors and specification

Properly informing prior beliefs is critical and thus the subject of much research. The flat priors come from the multivariate context which posits that the priors aim to impose a certain belief, which aims to yield poor inference (Bańbura *et al.*, 2010) and inadmissible estimators. Going far back, the study by Litterman (1980) contributed to the argument of the priors set-up by setting the hyperparameters in a way that maximizes out-of-sample predicting performance over a pre-sample, while the study by Del-Negro and Schorfheide (2004) chose values that maximize the marginal data density. The study by Bańbura *et al.* (2010) adopted a slightly different approach, following Litterman (1980), by controlling for overfitting and using an in-sample fit as a decision. Economic theory is an ideal foundation for the prior information, but it is lacking in many settings particularly to high-dimensional models. Villani (2009) rebuilt the model by placing the priors in a steady state, which was then better understood theoretically by economists. The study by Giannone *et al.* (2015) suggested setting hyperparameters in a data-based fashion by treating them as additional parameters. In their approach, the uncertainty surrounding the choice of prior hyperparameters which is acknowledged explicitly, by invoking Bayes' Law, can be expressed as follows:

$$p(\gamma|y) \propto p(y|\theta, \gamma)p(\theta|\gamma)p(\gamma), \quad (2)$$

$$p(Y|\gamma) = \int p(y|\theta, \gamma)p(\theta|\gamma)d\theta, \quad (3)$$

where $y = (y_{p+1}, \dots, y_T)^\top$, while the variance and autoregressive parameters of the VAR are indicated by θ , and the set of hyperparameters by γ . The first part of Eq. 1 is marginalized with respect to the parameters θ in Eq. 2. This produces a density of data as a function of the hyperparameters $p(y|\gamma)$, as well as the ML. The quantity is conditional to the hyperparameters γ , but marginal with respect to parameters θ . A decision criterion for the maximization and hyperparameter choice is derived from the results of the ML test, which constitutes an empirical Bayes method, with a clear frequentist interpretation (Giannone *et al.*, 2015). In our approach, the ML is adopted to explore the full posterior hyperparameter space, by acknowledging the uncertainty surrounding them. According to Giannone *et al.* (2015), this produces results that are robust and theoretically grounded, if implemented in an efficient manner. The authors established a high accuracy of forecasts and impulse response functions, with the model performing competitively compared to factor models. Since then, their approach has been used widely in applied research (Altavilla *et al.*, 2019). Their contribution emphasizes conjugate prior distributions, precisely of the Normal-inverse-Wishart (NIW) family. Conjugacy involves that

the ML is available in closed form, allowing competent computation, where the NIW family embraces numerous of the most frequently used priors, with some notable exceptions. These include the Dirichlet-Laplace prior, the steady-state prior and the Normal-Gamma prior. The recent contributors in this argument focus on accounting for heteroskedastic error structures. This may improve model performance, but is not possible within the conjugate setup and, moreover, would confuse inference. In the selected NIW framework, we approach the model in Eq. 1 by letting $A = [a_0, A_1, \dots, A_p]^T$ and $\beta = \text{vec}(A)$. Then, the conjugate prior setup reads as:

$$\beta | \Sigma \sim \kappa(b, \Sigma \otimes \Omega) \tag{4}$$

$$\Sigma \sim IW(\Psi, d) \tag{5}$$

where b, Ω, Ψ and d are functions of a lower dimensional vector of hyperparameters γ . Giannone *et al.* (2015) considered three priors in their study, which were called the sum-of-coefficients prior, the single unit-root prior and the Minnesota prior which is used as a baseline. The study by Litterman (1980) adopted the Minnesota prior and imposed the hypothesis that individual variables all follow random walk processes. This parsimonious specification typically performs well in forecasts of macroeconomic time series (Kilian and Lütkepohl, 2017) and is often used as a benchmark to evaluate accuracy. The prior is characterized by the following moments:

$$E[(A_s)_{ij} | \Sigma] = \begin{cases} 1, & \text{if } i = j, s = 1 \\ 0, & \text{and otherwise} \end{cases}, \tag{6}$$

$$\text{cov}[(A_s)_{ij} (A_r)_{kl} | \Sigma] = \begin{cases} \lambda^2 \frac{1}{s^\sigma} \frac{\Sigma_{jk}}{\Psi_j / (d - M - 1)} & \text{if } l = j \text{ and } r = s \\ 0, & \text{and otherwise} \end{cases}, \tag{7}$$

where λ is the key parameter that controls the tightness of the prior and, therefore, weighs the relative significance of data and prior. When the priors are imposed precisely, that will follow $\lambda \rightarrow 0$, while when $\lambda \rightarrow \infty$, the posterior estimates will approach the ordinary least squares (OLS) estimates. Finally, ψ controls the prior's standard deviation on lags of variables other than the dependent. The Minnesota prior is normally applied as an additional prior in the model, in an attempt to reduce the significance of the deterministic component implied by the VAR model's estimated conditioning in the initial observations. The study by Doan *et al.* (1984) included the sum-of-coefficients (SOC) prior by imposing the notion that a no-change projection is optimal at the beginning of a time series. It is implemented via the Theil mixed estimation by adding artificial dummy observations to the data matrix, which are constructed as follows:

$$y^+_{M \times M} = \text{diag} \left(\frac{\bar{y}}{\mu} \right) + x^+_{M \times (1+Mp)} = [0, y^+, \dots, y^+] \tag{8}$$

in Eq. 8 where \bar{y} is a $M \times 1$ vector of the averages over the first p observations of each variable. The variance is controlled by the key parameter μ and, therefore, due to the tightness of the prior for $\mu \rightarrow \infty$, the prior becomes uninformative. For $\mu \rightarrow 0$, the model is pulled towards a form with as many unit roots as variables, and no cointegration. This inspires the single unit-root (SUR) prior (Sims and Zha, 1998), which allows for cointegration relations in the data. The prior pushes the variables either towards them or towards the presence of at least a one-unit root or unconditional mean. These kinds of priors are associated with the following dummy observations:

$$Y_{1 \times M}^{++} = \frac{\bar{y}}{\delta} + \frac{x^{++}}{1 \times (1+Mp)} = \left[\frac{\bar{y}}{\delta}, y^{++}, \dots, y^{++} \right] \quad (9)$$

where \bar{y} is again distinct as above. Likewise, δ is the key parameter, governing the tightness of the SUR prior. A number of heuristics have been proposed, as setting this parameter of these priors has been discussed by various studies including [Doan et al. \(1984\)](#) and [Banbura et al. \(2010\)](#). The study by [Giannone et al. \(2015\)](#) noted that, from a Bayesian point of view, this choice of parameters is theoretically identical to other parameters of the model. They show that it is possible to treat the model as a hierarchical one, with the ML of the data, given the prior parameters, available in closed form for VAR models with conjugate priors. Estimating these hyperparameters via maximization of the ML is an empirical Bayes method with a clear frequentist interpretation ([Giannone et al., 2015](#)).

4. Empirical analysis and interpretation results

This section discusses the empirical results of the study. The findings of the study will be robust to policy-makers in understanding the inequality-fragility relationship in South Africa and other selected emerging markets. As part of the preliminary analysis, we used the function developed by [Kuschning and Vashold \(2019\)](#) for data transformation and the stationarity test, as it is one of the most important tasks to be performed before estimating the BVAR model. Furthermore, the ordering of the variables is critical prior to estimating the VAR model. As a result, we began by executing the machine learning established by [Breiman \(2001\)](#) utilizing the random forest (RF) in this study to determine the variable that contributes the most to financial fragility among all variables adopted in this study. The main aim of running the machine learning using the RF is to find the ordering of the variables that will be estimated in a BVAR. We increased the number of trees within the RF to 15,000 in order to better anticipate the RF. The results of the RF show that Gini contributes the most to financial fragility, followed by DP, PIG, INR, BMS and lastly, GDPp. We then used the results drawn from the LM to specify the ordering of variables in our BVAR model as follows: DP, PIG, INR, BMS and GDPp.

4.1 Data transformation and stationarity

The descriptive statistics of the different variables for all countries are reported in [Appendix A \(Table A1\)](#). Developing a BVAR model, using the function *bvar* (), requires the data to be coercible to a rectangular numeric matrix with no missing data points. We used seven variables in our BVAR model, these variables being: Cred, Gini, DP, INR, BMS, PIG and GDPp. GDPp is given in billions of 2010 dollars, while other variables are in rates, except for Gini which is an index. Following [Kuschning and Vashold \(2019\)](#), we transformed GDPp into log levels using the function developed by [Kuschning and Vashold \(2019\)](#) in order to demonstrate dummy priors. This function supports the transformation that appeared in [McCracken and Ng \(2016\)](#) and can be accessed via their transformation codes and automatic transformation. We then used the codes argument derived from the direct-transformation codes to specify a log transformation for GDPp with code 4 and no transformation for the other variables, which were set to code 1. We adopted two-unit root tests, the Augmented Dickey–Fuller test (DF) and the Phillips–Perron test (PP). Testing of unit roots is crucial for determining whether the time series needs to be differentiated and, if so, the number of times such differences should be taken. The stationary results are reported in the Appendix, [Table A2](#). As indicated in [Table A2](#), the tests exhibit that all variables are non-stationary in levels and stationary after the first differencing. After

finding that all variables are stationary after first differencing, we adopted code 2 in instructing the system to transform all the variables into 1st differences after finding that our variables are stationary at 1st difference. Doing this helped us to choose 5 log differences for GDPp and 2 for all variables (for 1st differences). As the current study is dealing with time-series data, before estimating the BVAR model, we tested for the possibility of homogeneity in order to determine whether the relationship under investigation is nonlinear or linear using the Terasvirta Sequential tests by applying the Smooth Transition Regression (STAR) model. The study utilized the STAR model using the Terasvirta sequential tests developed by [Teräsvirta \(1998\)](#) to access the existence of the nonlinearity, as this test produces accurate results for the nonlinearity. Testing for the nonlinearity in the variable is primitive to avoiding false detections of important transitions caused by model errors. The Terasvirta sequence tests the null hypothesis, which states that the model is linear, against the alternative of nonlinearity. The null hypothesis would be rejected if the F-statistic is insignificant, implying that the relationship is nonlinear. The linearity test results based on the Terasvirta sequential tests indicate that the nonlinear model is rejected at the conventional level. This result implies that the relationship between income inequality and financial fragility in the adopted emerging economy is indeed linear, as shown in [Table A3](#) in the appendix. Therefore, the study proceeds with the estimation of a BVAR to detect the asymmetric effect of income inequality on financial fragility. We then set the number of lags to 2 for annual differences from our data. The results of the lag selection are reported in [Table A4](#) in the appendix.

4.2 Prior setup and configuration

The traditional maximum likelihood VARs (TML-VAR) suffer two measured defects, using data from middle- and low-income countries where the quality of the data is questionable and typically insufficient. They are over-parameterized – with too many lags being included in the model, leading to a significant loss in the degree of freedom. Therefore, prior selection is useful in a BVAR to account for this weakness. After preparing the data, we then specify priors and configure our model by following [Kuschnig and Vashold \(2019\)](#) prior setting function, which holds the arguments for Minnesota and dummy-observation priors, as well as the hierarchical treatment of their hyperparameters. We begin by adjusting the Minnesota prior. The prior hyperparameter λ has a Gamma hyperprior and is handed upper and lower bounds for its Gaussian proposal distribution in the MH step. As a result, we start by not treating α hierarchically. Following [Kuschnig and Vashold \(2019\)](#), we let Ψ be set automatically to the square root of the innovation variance, after fitting $AR(p)$ models to each of the variables. We then include a SOCs in a SUR prior, where we pre-construct three dummy observation priors. The hyperpriors of their key parameters are assigned Gamma distributions, with specifications working similar to λ . In this version of the BVAR, this will be equivalent to providing the character vector $c(Lambda, Soc, Sur)$ after setting the configuration of the model's priors and the MH.

4.3 Estimation of the model

As mentioned in Section 4.1, the model function of the BVAR model developed by [Kuschnig and Vashold \(2019\)](#) requires data preparations and transformations in the system by setting the order of p as an argument. It is also mandatory for the for the BVAR function to pass the customization setup with respect to the argument. We defined the total number of initial iterations to discard with a number of burn set to 1,500,000 and the number of iterations which is draws set to 500,000. We set the verbose to be true following [Kuschnig and Vashold](#)

(2019), as this function enables a progress bar during the Markov chain Monte Carlo (MCMC) step. [Table 1](#) indicates the results of the posterior ML.

The return value of the BVAR function is an object of a class of BVAR which produces several outputs, including the parameters of interest which are hierarchically treated hyperparameters, the VCOV matrix and the posterior draws of the VAR coefficients. The object of the BVAR also contains the values of the ML [2] for each draw, prior settings provided and starting values of the prior hyperparameters obtained from optima, as well as ones set automatically, and the original call to the BVAR function.

4.3.1 Result of the convergence of Markov chain Monte Carlo in a BVAR model. In this section, we access the overview and convergence of the MCMC algorithm of our estimation, which is significant for its stability.

[Table 2](#) provides a summary of the BVAR model, where the coefficients of lambda, soc and sur are 1.67, 0.15 and 0.46 for SA; 1.75, 0.31 and 0.50 for Brazil; 1.58, 0.22 and 0.39 for Chile; and 1.89, 0.21 and 0.40 for Peru, respectively, while the iter (burnt/thinning):1,500,000 (500,000/1) and the acpt draws (rate) are found to be 35%, 33%, 40% and 39%, respectively. The arguments *var_response* and *var_impulse* provide a concise alternative way of retrieving autoregressive coefficients. We then use the type argument to choose a specific type of plot (as shown in [Figure 1a](#) in the appendix) that provides plots of the density, trace of the ML and hierarchically treated hyperparameters. The graphical inspection of density and trace plots signifies the convergence of the key hyperparameters in the estimated BVAR model for all countries. The chain appears to be exploring the posterior rather well; no glaring outliers are recognizable.

South Africa	Brazil	Chile	Peru
Optimization concluded			
PMK: -412.01	PMK: -750.99	PMK: -597.65	PMK: -699.4
Hyperparameters:	Hyperparameters:	Hyperparameters:	Hyperparameters:
<i>lambda</i> = 1.678	<i>lambda</i> = 1.753	<i>lambda</i> = 1.589	<i>lambda</i> = 1.890
<i>soc</i> = 0.156	<i>soc</i> = 0.312	<i>soc</i> = 0.220	<i>soc</i> = 0.215
<i>sur</i> = 0.467	<i>sur</i> = 0.509	<i>sur</i> = 0.398	<i>sur</i> = 0.409
Finished MCMC after	Finished MCMC after	Finished MCMC after	Finished MCMC
13.33 min	8.74 min	17.02 min	after
			15.51 min

Note(s): PMK is the posterior marginal likelihood

Source(s): Author's calculation based on [WDI \(2020\)](#) and [SWIID \(Solt, 2020\)](#) data

Table 1.
Posterior marginal
likelihood

South Africa	Brazil	Chile	Peru
	BVAR consists of 36 observation, 7 variable and 2 lags		
Hyperparameters:	Hyperparameters:	Hyperparameters:	Hyperparameters:
<i>lambda, soc, sur</i>	<i>lambda, soc, sur</i>	<i>lambda, soc, sur</i>	<i>lambda, soc, sur</i>
HV after optimization:	HV after optimization:	HV after optimization:	HV after optimization:
1.67, 0.15, 0.46. Iter	1.75, 0.31, 0.50. Iter	1.58, 0.22, 0.39. Iter	1.89, 0.21, 0.40. Iter
(burnt/thinn): 1,500,000	(burnt/thinn): 1,500,000	(burnt/thinn): 1,500,000	(burnt/thinn): 1,500,000
(500,000/1) Acpt draws	(500,000/1) Acpt draws	(500,000/1) Acpt draws	(500,000/1) Acpt draws
(rate): 3,561 (0.35).	(rate): 338,082 (0.33).	(rate): 404,302 (0.40).	(rate): 389,708 (0.39).
Finished after: 13.7 min	Finished after: 8.74 min	Finished after: 17.02 min	Finished after: 15.51 min

Note(s): HV means hyperparameter values, and iter refers to iterations, while Acpt means accepted

Source(s): Author's calculation based on [WDI \(2020\)](#) and [SWIID \(Solt, 2020\)](#) data

Table 2.
Summary of the
BVAR model

4.3.2 Impulse responses of the Bayesian VAR. This study aims to find an inequality-fragility relationship in SA and other selected emerging markets and to examine whether the shock is persistent over the period 1975–2019, using a BVAR with hierarchical priors selection. [Figure 2](#) depicts the IRFs derived from the BVAR by means of hierarchical selection, where the coefficients for the dynamic impact of Gini, DP, INR, BMS, PIG and GDPp on financial fragility have been given a tighter hierarchical priors distribution. The shaded areas refer to the 16% and the 84% credible sets.

[Figure 2](#) in Plots I and II depicts that income inequality appears to be more instrumental in creating the risk of financial fragility in both countries, following a 1% standard deviation shock to policy shock Gini and attaining a maximum impact of 0.35 four years after the shock on Gini, which then converges immediately, reversing to the steady state region and dying after 6 years. For Brazil, on the other hand, it reaches a maximum impact of 0.51 in 5 years. However, with Brazil the impact is more insignificant in the first 2 years than in year 3, when it takes a sharp turn and becomes significant, but then converges after 5 years, reversing to the steady state region and dying in year 11.

The results in both countries are plausible and consistent with the Rajan hypothesis and with the study by [Kumhof et al. \(2012\)](#) on a panel of 18 OECD countries, [Yamarik et al. \(2016\)](#) on a panel of 50 US states, [Perugini et al. \(2016\)](#) on a panel of 18 OECD countries, [Bazillier and Hericourt \(2017\)](#) in a survey of China, India and South America, [Lim \(2019\)](#) on a panel of 42 countries, [El-Shagi et al. \(2019\)](#) on a panel of 75 highly heterogeneous regions in Russia and [Balciar et al. \(2020\)](#) in the USA. The argument behind income inequality being a source of financial fragility is based on the argument made by [Rajan \(2010\)](#). The Rajan hypothesis posits that a significant increase in inequality was the main driver of the global financial crisis.

In the South African context, a further increase was reported in financial fragility following a 1% standard deviation shock to policy shock DP and attaining a maximum impact of 0.5, three years after the shock on DP. This then converged immediately, reversing to the steady state region and dying after 6 years. For Brazil, on the other hand, its financial fragility gradually declined and attained a maximum impact of -0.04 five years after the DP shock, then converging after 4 years, reversing to the steady-state region and dying. The findings are empirical and plausible in the existing literature such as the study by [Davis and Carothers \(2010\)](#) and [Lipsy \(2018\)](#).

Financial fragility responds negatively and reaches a maximum of -0.10 two years after the shock on GDPp. The effect declines gradually and becomes statistically insignificant after 4 years. For Brazil financial fragility responds positively, reaching a maximum of 0.25 two years after the shock on GDPp, after which the effect declines gradually and becomes statistically insignificant after 3 years. In a nutshell, economic development has an asymmetric impact on financial fragility. The empirical findings in this context support the findings documented by [Gartmann \(2011\)](#) and [Loayza et al. \(2017\)](#).

Financial fragility increases, following a 1% standard deviation shock to monetary policy (INR, and attains a maximum impact of 0.18% after 3 years, which then converges immediately, reversing to the steady-state region and dying after 8 years. In Brazil, on the other hand, financial fragility gradually declines and reaches a maximum of -0.22 three years after the monetary policy shock. The effect declines gradually and becomes statistically insignificant after 8 years. This supports the findings reported by [Kirschenmann et al. \(2016\)](#).

Surprisingly, following a 1% standard deviation policy shock (BMS), financial fragility responds positively and attains a maximum impact of 0.10 two years after the BMS shock, which then converges after 4 years, reversing to the steady-state region and dying. This supports the findings reported by [Elekdag and Han \(2015\)](#). For Brazil, on the other hand, financial fragility declines gradually and attains a maximum impact of -0.10 two years after the BMS shock, which then converges immediately, reversing to the steady state region and

(continued)

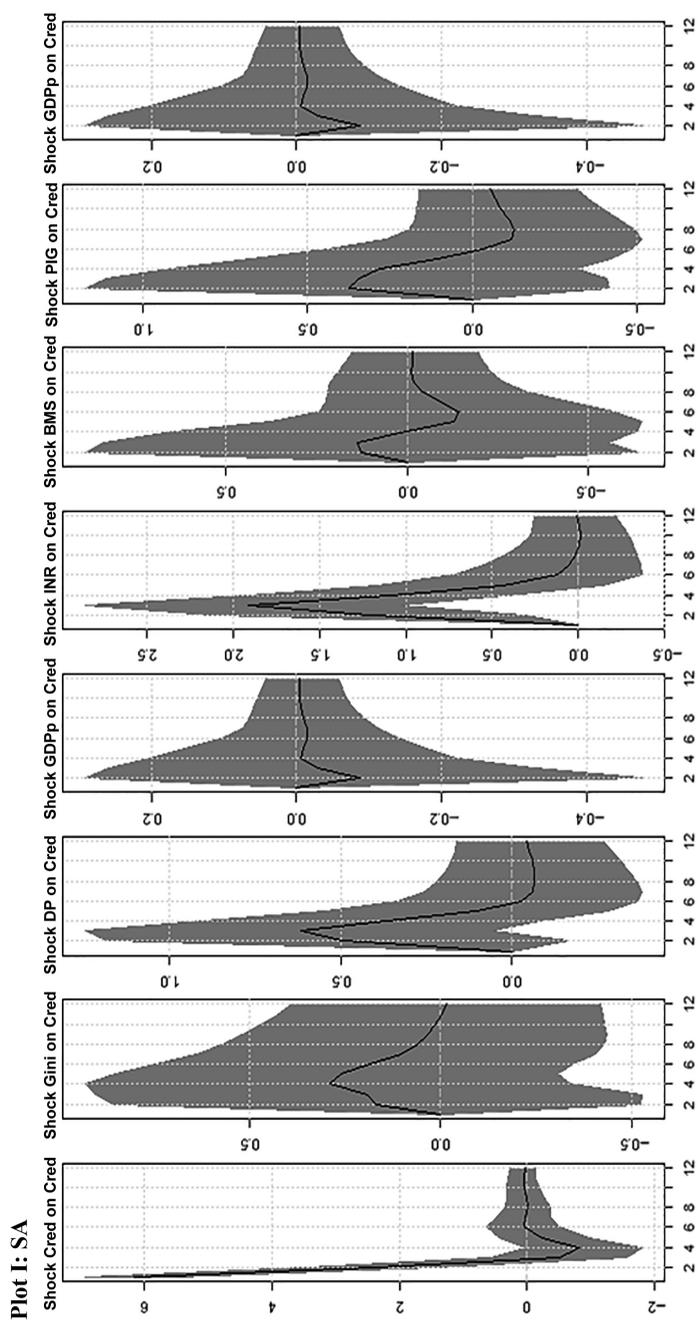


Figure 2.
Generated impulse
responses of the
Bayesian VAR

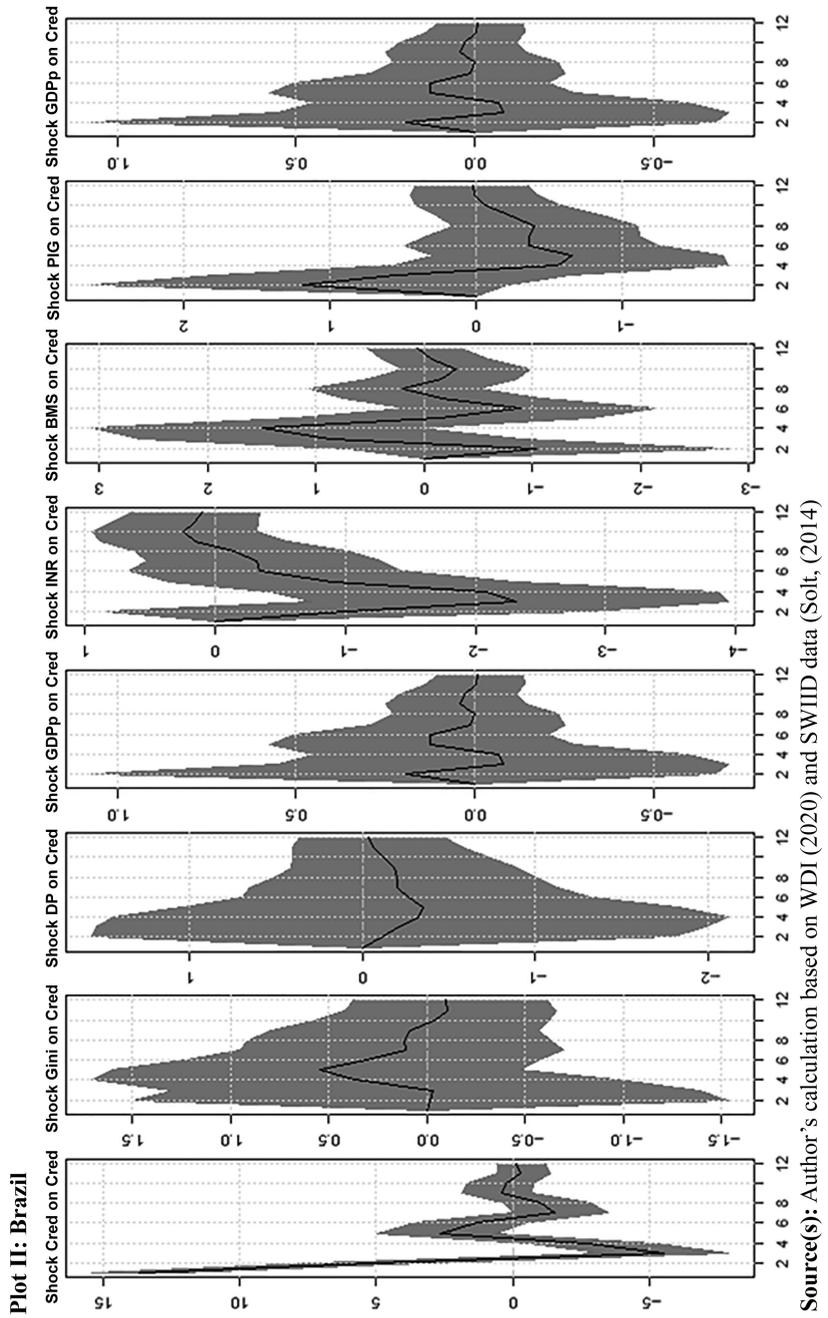


Figure 2.

dying. The overall impact of BMS on financial fragility is asymmetric and persistent. The results are in line with the study documented by [Boissay et al. \(2021\)](#).

Lastly, for both countries financial fragility responds positively, following a 1% standard deviation shock on PIG and attains a maximum impact of 0.4 after 2 years, which then converges immediately, reversing to the steady state region and dying after 6 years. For Brazil, it reaches a maximum level of 0.12 and converges immediately, reversing to the steady state region and dying after 4 years. The overall impact of PIG on financial fragility is asymmetric and persistent ([Oguzhan, 2019](#)).

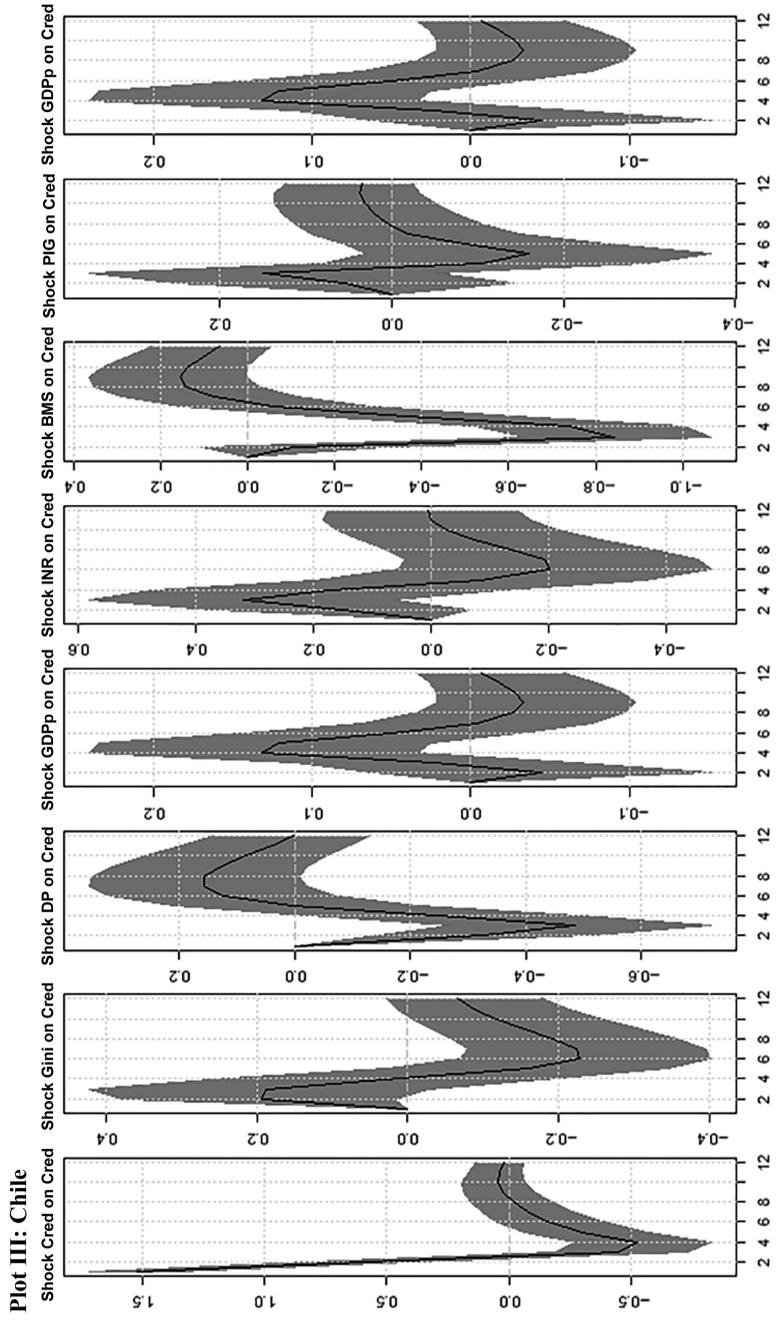
[Figure 3](#) in Plots III and IV depicts mixed results for the impact of Gini on financial fragility, as it shows that, following a 1% standard deviation shock on Gini, it appears to be more effective in stimulating the risk of financial fragility in Chile and attains a maximum level of 0.19 after 2 years, which then converges immediately, reversing to the steady-state region and dying after 5 years. The results in both countries are plausible and consistent with the Rajan hypothesis and with the study by [Kumhof et al. \(2012\)](#) on a panel of 18 OECD countries, [Yamarik et al. \(2016\)](#) on a panel of 50 US states, [Perugini et al. \(2016\)](#) on a panel of 18 OECD countries, [Bazillier and Hericourt \(2017\)](#) in a survey of China, India and South America, [Lim \(2019\)](#) on a panel of 42 countries, [El-Shagi et al. \(2019\)](#) on a panel of 75 highly heterogeneous regions in Russia and [Balcilar et al. \(2020\)](#) in the USA. The argument behind income inequality being a source of financial fragility is based on the argument made by [Rajan \(2010\)](#). The overall impact of income inequality on financial fragility is asymmetric and persistent in Chile. For Peru, on the other hand, it appears to be effective in reducing the risk of financial fragility and attains a maximum level of -0.08 after 2 years. It then reverses to the steady-state region and dies after 7 years. Empirical findings for Peru contradict the Rajan hypothesis ([Rajan, 2010](#)), however, support the findings documented by [Bodea et al. \(2021\)](#). We believe that the argument behind the contradiction emanates from the fact that Peru is one of those countries with a high level of government debt. According to the [Fisher \(1932\)](#) hypothesis, the main driver of this consequence is the private sector's explosive degree of indebtedness, resulting in the destabilization of the financial markets and thus harming the economy overall.

The results for Chile are plausible and consistent with the theory of [Rajan \(2010\)](#), as well as the existing literature such as Mahmoud and Niguez for a panel of 18 OECD countries, and [Yamarik et al. \(2016\)](#) for a panel of 50 US states.

In both countries, DP is found to have a gradually declining impact on financial fragility, following a 1% standard deviation shock on DP after the shock reaches a minimum level of -0.45 in 3 years, while for Peru, it reaches a minimum level of -0.06 in 4 years, then converges reversing to the steady state region and dying after 4 years for Chile and 8 years for Peru. The overall impact of DP on financial fragility is asymmetric and persistent.

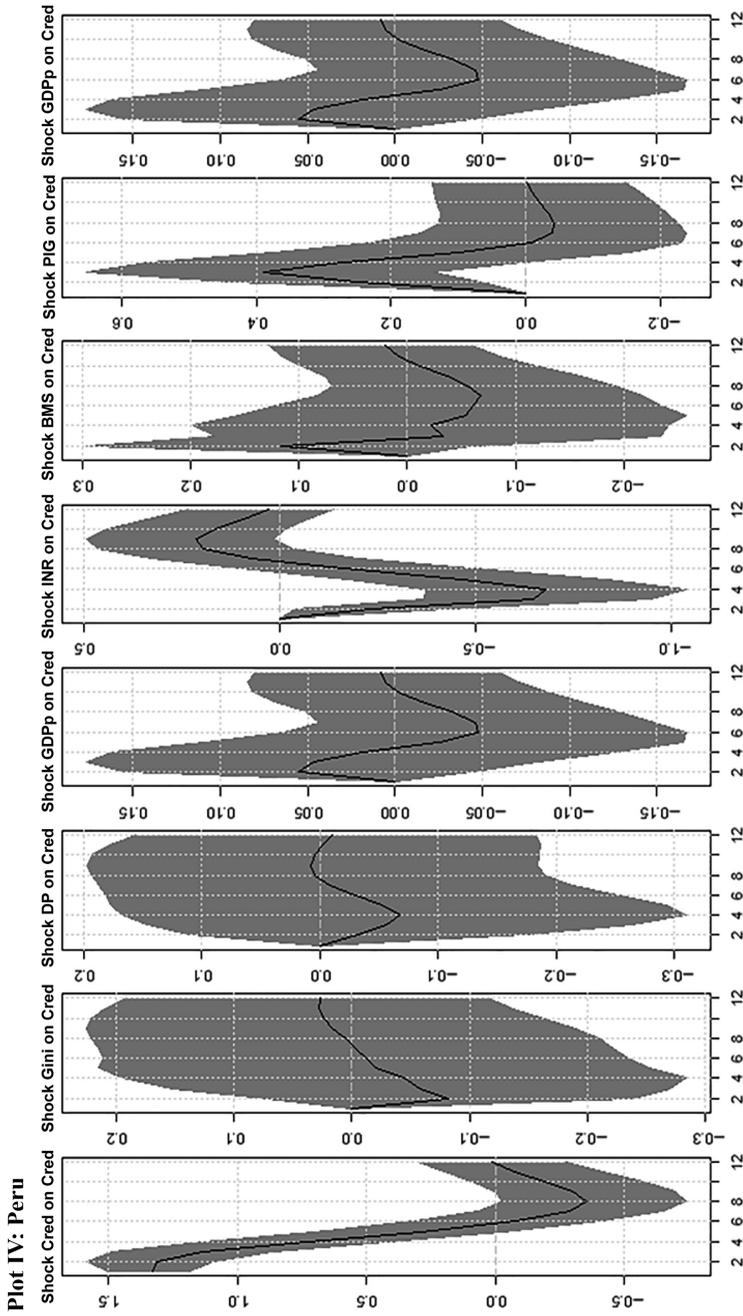
Financial fragility gradually declines, following a 1% standard deviation shock on GDPp, and attains a maximum impact of -0.04 three years after the shock on GDPp. The effect declines gradually and becomes statistically insignificant after 3 years. The empirical findings in this context support the findings documented by [Gartmann \(2011\)](#) and [Loayza et al. \(2017\)](#). For Peru, on the other hand, financial fragility responds positively, reaching a maximum of 0.06 two years after the shock on GDPp, and the effect declines gradually, becoming statistically insignificant after 3 years. In a nutshell, GDPp has an asymmetric impact on financial fragility in both countries.

Following a 1% standard deviation shock on the monetary policy shock (INR), financial fragility responds positively and reaches a maximum of 0.35 three years after the monetary policy shock. The effect declines gradually and becomes statistically insignificant after 6 years, then converges immediately, reversing to the steady state region and dying after 4 years. For Peru, on the other hand, it declines gradually and attains a maximum impact of -0.18% after 3 years. This then converges immediately, reversing to the steady state region and dying after



(continued)

Figure 3.
Generated impulse responses of the Bayesian VAR for Chile and Peru



Source(s): Author's calculation based on WDI (2020) and SWIID (Solt, 2020) data

Figure 3.

6 years. The overall impact of a policy shock on financial fragility is asymmetric and persistent in both countries. This supports the findings reported by [Kirschenmann et al. \(2016\)](#).

Financial fragility gradually declines, following a 1% standard deviation shock on the policy shock (BMS) and attains a maximum impact of -0.80 three years after the shock on BMS, which then converges immediately, reversing to the steady-state region, and dying after 6 years. For Peru, financial fragility responds positively and reaches a maximum of 0.11 two years after the BMS shock, then converges after 3 years, reversing to the steady-state region, and dying. The overall impact of BMS on financial fragility is asymmetric and persistent in both countries the result for Peru supports the findings reported by [Elekdag and Han \(2015\)](#).

Lastly, financial fragility initially improves, following a 1% standard deviation shock on fiscal policy (PIG) in both countries. The impact reaches a maximum level of 0.15 after 3 years for Chile, while in Peru, it reaches a maximum level of 0.39, then converges immediately, reversing to the steady-state region and dying after 6 years in both countries. The overall impact of a fiscal policy shock on financial fragility is asymmetric and persistent. The result supports the findings reported by [Perugini et al. \(2016\)](#).

5. Concluding remarks and policy recommendations

This study aims to test the Rajan hypothesis in emerging economies. We believe that the indirect explanation in his book “Fault Lines” is compatible with the US experience only, or the experiences of developed countries, and there is no solid evidence that the relationship would hold in different countries or at other times. Therefore, more general lines of reasoning are needed to explain the mechanism by which rising inequality might be linked to an irregular increase in household indebtedness. The view that income inequality may drive credit demand and indebtedness, which then leads to financial fragility, is evident in high-income countries, but not in middle- and low-income countries. No studies have, as yet, investigated the impact of income inequality on financial fragility in emerging markets.

Our results for all countries except Peru confirmed the Rajan hypothesis, showing that financial fragility improves after a 1% standard deviation shock on inequality, which implies that income inequality has a distinct role as a driver of credit demand and indebtedness, then leading to financial fragility, and ultimately resulting in a financial crash once its conventional determinants have been controlled for. This is plausible and consistent with the empirical literature of [Yamarik et al. \(2016\)](#) for a panel of 50 US states, and [Amountzias \(2018\)](#) for 33 OECD countries. Thus, in the case of emerging markets, the view that income inequality may drive credit demand and indebtedness, which then leads to financial fragility, is evident. Theoretically, the findings of the study may be explained in terms of herd behaviour, as explained by [Rajan \(1994\)](#).

We controlled for a monetary policy shock and found the results differing country-specific. We found that the policy shock, using the broad money supply as a monetary policy tool (meaning more money coming in) drives credit expansion in Peru and South Africa, leading to an increase in financial fragility ([Elekdag and Han, 2015](#)), while for Brazil and Chile, it reduces the level of credit growth. The real interest rate shows that it is credit-driven for South Africa and Chile, while for Brazil and Peru, it reduces credit growth, which then leads to a reduction in financial fragility. This supports the findings reported by [Kirschenmann et al. \(2016\)](#), which in a period of higher fiscal sovereign risk the interest rate is associated with an increase in credit expansion; which then shows that, *ceteris paribus*, interest rates are considerably more sensitive to indebtedness in the wake of such a crisis.

We then controlled for credit demand and financial capital inflows, finding that our results supported the evidence documented by [Perugini et al. \(2016\)](#), namely, that credit demand increases credit growth, resulting in financial fragility in all countries. However, this contradicts the findings reported by [Mendoza and Terrones \(2008\)](#) and [Perugini et al.](#)

(2013). Lastly, after controlling for economic development and pro-cyclicality, as argued in the literature that GDP per capita is a major predictor of credit availability and financial progress, we found the results differing country-specific. For Brazil and Peru, we found that financial fragility responds positively after a 1% shock on economic development, while for South Africa and Chile, the shock impact was very small, showing that an improvement in GDP per capita did not play a significant role in containing the credit demand and indebtedness.

The findings suggest that increasing inequality leads to financial fragility, implying that policymakers should be wary of excessive inequality when attempting to contain the risk of financial fragility through the implementation of sound structural reform policies that aim to attract investments consistent with job creation, development and growth in these countries. Policymakers should also be cautious when implementing policy instruments (redistributive policies, a sound monetary policy), as they appear to raise the risk of excessive credit growth and financial fragility, and they should treat income inequality as a significant factor influencing macroeconomic aggregates and financial fragility.

The limitation of the study is data unavailability, especially for income inequality. As the data for the Gini coefficient ends in 2019, the author suggests that future research should focus on a comparative study where advanced or emerging countries are compared to undeveloped countries. This would aid in determining whether the Rajan hypothesis holds true at all levels of development or only in emerging and advanced countries. Furthermore, a more in-depth explanation of why Peru is different from the adopted countries is needed, as the results for Peru seem to contradict the Rajan hypothesis. Another significant contribution can be made by comparing regions as well, such as Asia, Europe and African countries, to test the three hypotheses.

Notes

1. South Africa, Brazil, Chile and Peru
2. Marginal likelihood

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Vari	South African					Brazil					Chile					Peru				
	Mean	Std.d	Min	Max	J-B stat	Mean	Std.d	Min	Max	J-B stat	Mean	Std.d	Min	Max	J-B stat	Mean	Std.d	Min	Max	J-B stat
CredGG	9.89	7.319	19.76	19.15	2.54	6.38	17.07	29.38	67.06	2.77	5.73	2.64	8.73	-7.41	1.28	6.28	2.90	-5.42	7.12	2.11
Gini	61.28	1.47	59.10	63.50	2.00	51.45	2.68	46.200	55.00	2.17	48.52	1.75	50.700	45.60	1.14	51.18	2.82	45.00	53.30	2.10
DP	7.46	1.08	5.77	8.96	1.49	6.92	1.710	2.800	10.42	1.54	4.94	1.37	7.93	3.35	2.03	6.49	0.68	5.130	7.89	1.89
INR	4.75	3.15	0.12	12.99	2.01	52.03	11.87	27.39	86.36	1.29	20.06	13.42	51.39	4.55	1.07	19.01	62.07	15.74	42.04	2.04
BMS	59.82	10.14	45.50	80.79	2.45	47.25	28.54	10.08	11.32	2.45	52.01	23.52	88.22	13.88	2.45	28.45	8.56	16.27	48.20	2.22
PIG	20.77	1.73	17.96	23.42	1.87	20.11	3.06	14.50	24.35	2.94	19.98	1.47	22.49	15.63	8.02	18.94	1.47	13.30	20.83	1.20
GDPp	8.77	0.09	8.61	8.93	2.20	9.06	0.21	8.13	9.39	1.21	8.94	0.44	9.60	8.19	2.03	8.21	0.24	7.85	8.74	3.04

Note(s): * $p < 0.1$, ** $p < 0.05$ & *** $p < 0.01$. While lev and inter denote level and integration, respectively. J-B stat and Std.d denote the Jarque-Bera statistics and standard deviation

Source(s): Author's illustration based on SWIID (Solt, 2020; WDI, 2020)

Table A1.
Descriptive Statistics
per country

Table A2.
Unit root test per country

Vari	South African			Brazil			Chile			Peru		
	ADF test 1St	Intr	PP test 1St									
CredGG	-4.55**	I(1)	-2.45**	-2.00**	I(1)	-5.35**	-3.05**	I(1)	-5.30**	-3.44***	I(1)	-4.56**
Giml	-8.23*	I(1)	-4.56**	-5.99***	I(1)	-2.65**	-4.95**	I(1)	-2.60**	-8.45***	I(1)	-1.99*
DP	-4.65**	I(1)	-2.05*	-8.87***	I(1)	-2.34**	-4.40**	I(1)	-3.40**	-6.78*	I(1)	-4.57**
INR	-6.10***	I(1)	-4.43**	-4.11**	I(1)	-4.45*	-2.04***	I(1)	-4.73*	-5.67***	I(1)	-6.45**
BMS	-4.52**	I(1)	-5.89**	-2.75**	I(1)	-5.55**	-3.98**	I(1)	-2.43**	-2.67*	I(1)	-3.87**
PIG	-2.29***	I(1)	-3.78**	-3.01***	I(1)	-3.78**	-4.65**	I(1)	-4.84**	-5.54***	I(1)	-9.89**
GDpp	-5.64**	I(1)	-6.56**	-6.55**	I(1)	-4.47**	-2.62*	I(1)	-2.00**	-2.43**	I(1)	-8.79*

Note(s): * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$. While lev and intr denote level and integration, respectively
The authors reported the important results of the unit root test
Source(s): Author's illustration based on SWIID (Solt, 2020; WDI, 2020)

Income
inequality and
financial
fragility

South Africa			
Terasvirta sequential tests			
Hull hypothesis	<i>F</i> -statistics	df	<i>p</i> -value
$H3 : b3 = 0$	0.043891	(1.49)	0.887
$H2 : b3 = 0 b3 = 0$	2.098621	(1.76)	0.787
$H1 : b1 = 0 b2 = b3 = 0$	0.012392	(1.38)	0.965
Brazil			
Terasvirta sequential tests			
Hull hypothesis	<i>F</i> -statistics	df	<i>p</i> -value
$H3 : b3 = 0$	0.091292	(1.10)	0.930
$H2 : b3 = 0 b3 = 0$	1.909398	(2.76)	0.207
$H1 : b1 = 0 b2 = b3 = 0$	1.000273	(1.92)	0.598
Chile			
Terasvirta sequential tests			
Hull hypothesis	<i>F</i> -statistics	df	<i>p</i> -value
$H3 : b3 = 0$	1.899209	(2.23)	0.129
$H2 : b3 = 0 b3 = 0$	1.022789	(1.00)	0.698
$H1 : b1 = 0 b2 = b3 = 0$	1.898124	(2.50)	0.130
Peru			
Terasvirta sequential tests			
Hull hypothesis	<i>F</i> -statistics	df	<i>p</i> -value
$H3 : b3 = 0$	0.089839	(1.39)	0.798
$H2 : b3 = 0 b3 = 0$	2.939002	(2.19)	0.252
$H1 : b1 = 0 b2 = b3 = 0$	2.008929	(2.00)	0.140

Note(s): All the tests are based on the third-order Taylor expansion ($b4 = 0$). Nonlinear model is rejected at all levels

Source: Author's illustration based on SWIID (Solt, 2020; WDI, 2020)

Table A3.
STAR model: Testing
for non-linear
dependencies in time
series

Lag	MBIC	MAIC	MQIC
1	-472.77	-114.04	-197.83
2	-559.74	-192.75	-239.78
3	-347.62	-72.38	-182.65
4	-232.59	-49.09	-122.61
5	-114.01	-22.27	-59.02
6

Source(s): Author's illustration based on SWIID (Solt, 2020; WDI, 2020)

Table A4.
Lag selection criteria

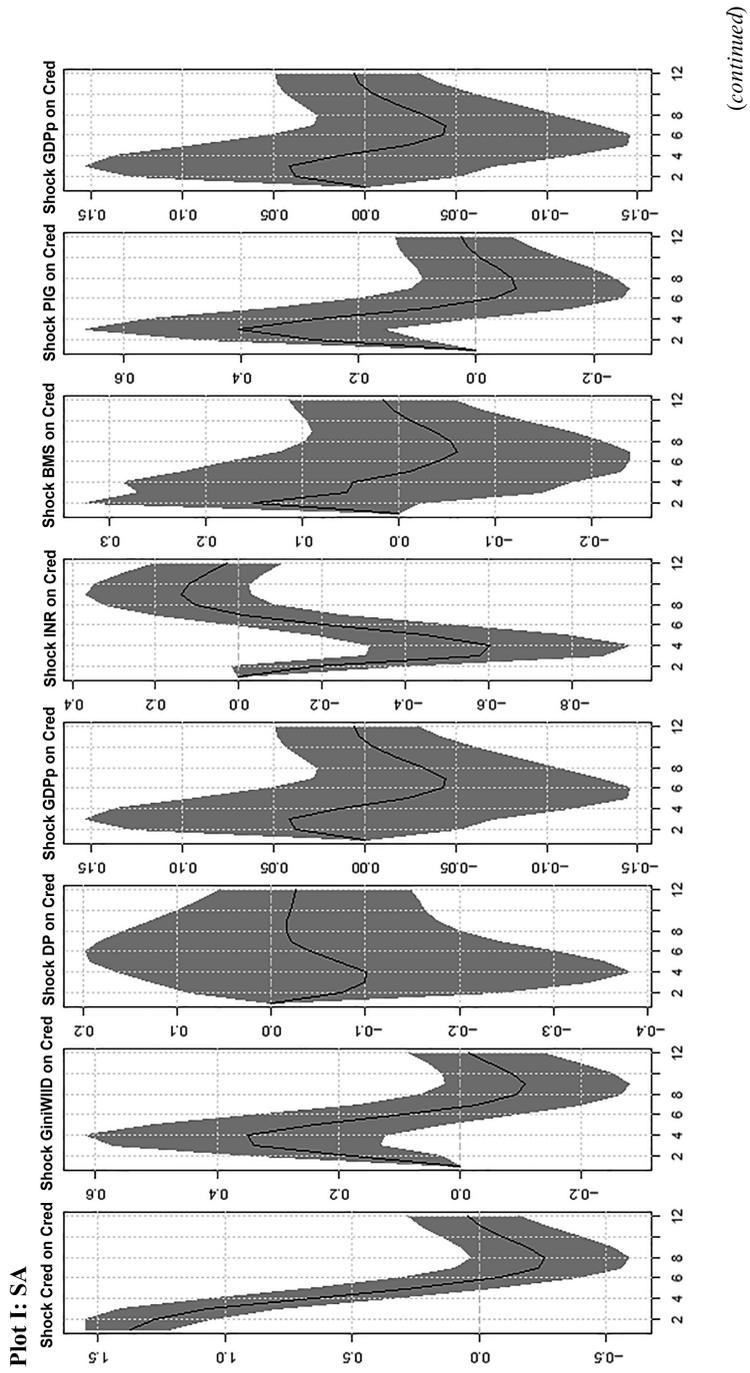


Figure A1.
Robustness model

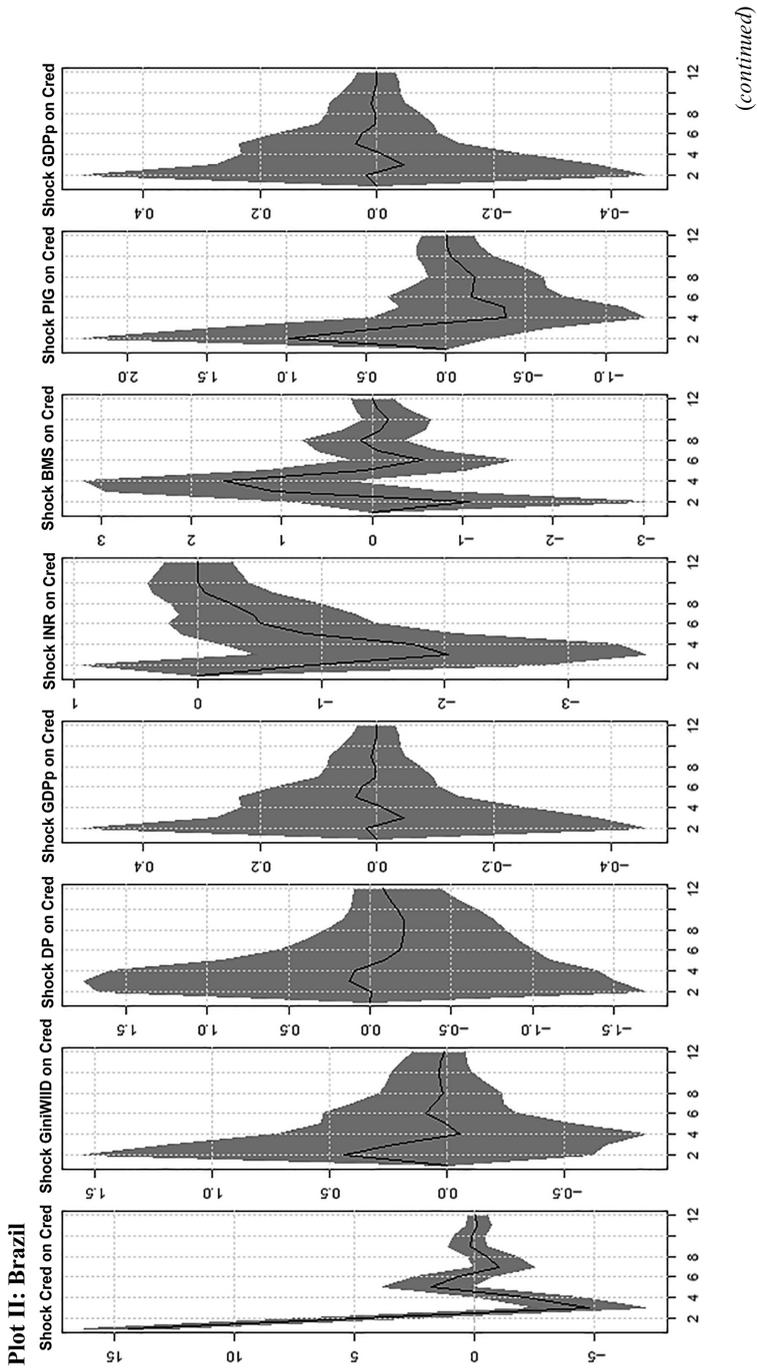


Figure A1.

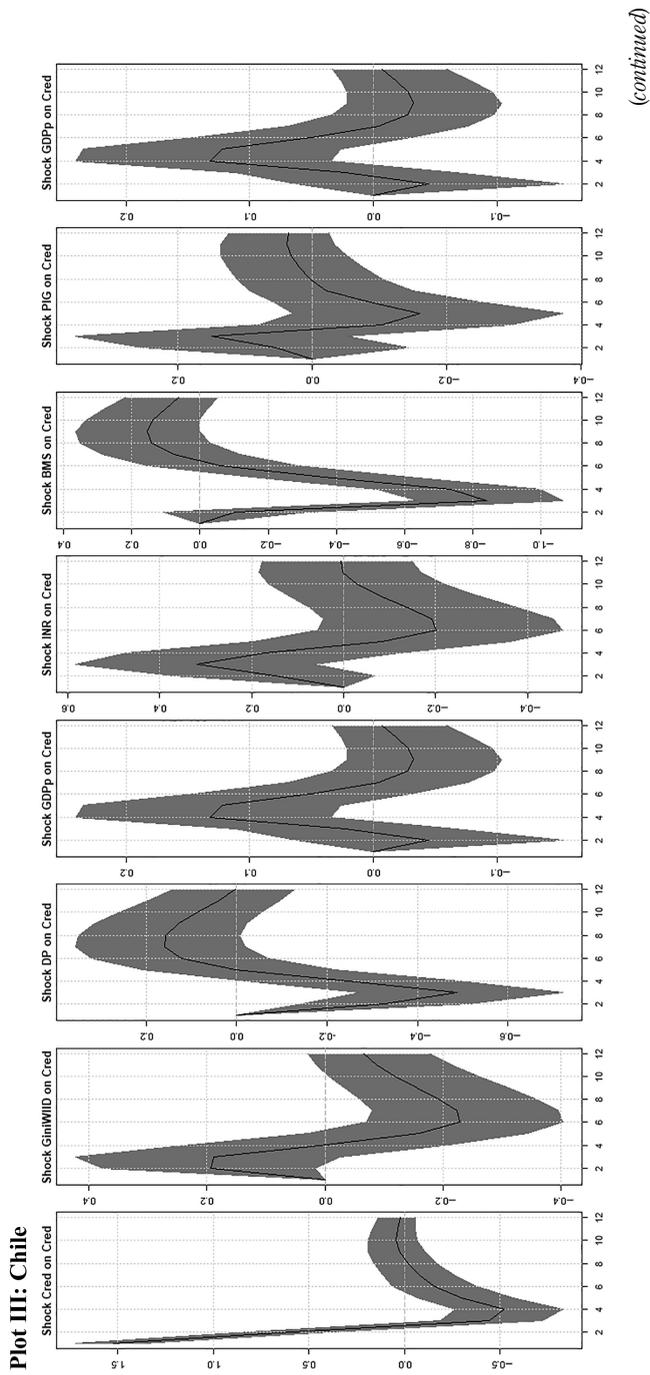
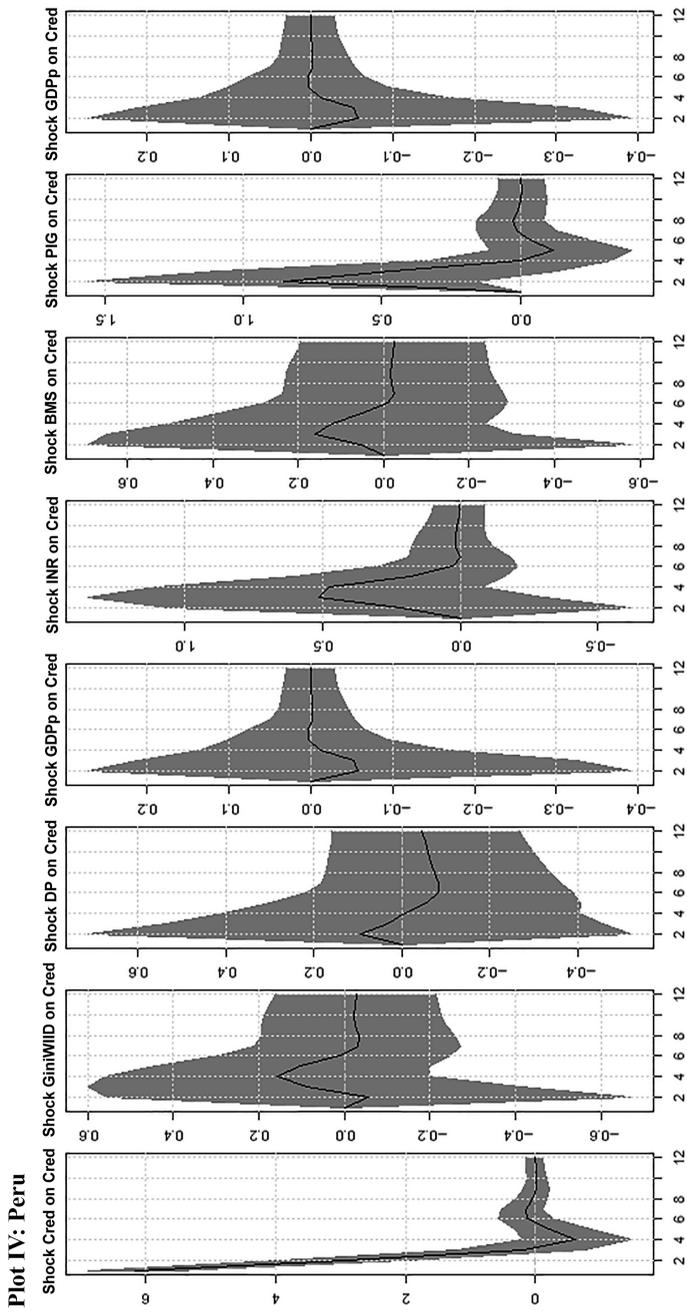


Figure A1.



Source(s): Author's calculation based on WDI (2020) and SWIID (Solt, 2020) data

Figure A1.