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The Impact of Uncertainty Shocks in South Africa: The Role of Financial Regimes

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Abstract

This article examines the connection between economic uncertainty and financial market conditions in South Africa, documenting that the macroeconomic implications of an uncertainty shock differs across financial regimes. A non-linear VAR is estimated where uncertainty is captured by the average volatility of structural shocks in the economy, and the transmission mechanism is characterised by two distinct financial regimes (i.e. financially stressful versus normal periods). We find that while the deterioration of output following an uncertainty shock is much more prominent during normal periods than during stressful periods, it is much more persistent during stressful financial times. The share of output variance explained by the volatility shocks in good financial times is more than double the share in bad times. Uncertainty shocks are found to be inflationary in both regimes, with the impact being larger in the stress regime. While our estimates reveals that financial frictions do not amplify the impact of uncertainty on real output, it does increase the impact on prices.

Keywords: Uncertainty, Financial regimes, South Africa, non-linear VAR, Stochastic volatility

JEL Classification: C32, E32, E44, G00

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1 Introduction

In 1964 (revisited in 1993) the late well-known Nobel Laureate in Economics, Milton Friedman, proposed the "guitar string" theory or better known "plucking model" for recessions, according to which he postulated that deep recessions are followed by rapid recoveries, just as a guitar string bounces right back after it is pulled and then released (Friedman (1964), Friedman (1993)). However, the economic performance in many economies since the Great Recession of 2008-09 has not followed that proposition, but instead economies globally experienced slow economic recovery. Many economists and policymakers, following the seminal work of Bloom (2009) have highlighted heightened economic uncertainty as the main source of this macroeconomic instability and anaemic recovery.[1] While traditionally, the transmission of uncertainty shocks have been linked to real frictions (Bernanke (1983); Bloom (2009)), recent studies have documented the crucial role of financial frictions in the transmission mechanism (Arellano et al. (2010); Gilchrist et al. (2014); Christiano et al. (2014); Caldara et al. (2016)). However, most of the studies examining the link between financial conditions and country-specific uncertainty have focused on advanced economies only. Against this backdrop and to narrow the gap in literature, our paper examines the 'financial view' of the transmission of uncertainty shocks within a small open emerging market economy, in our case South Africa.

To examine this conjecture, we employ monthly data covering the period between January 1995 and December 2017 to estimate a nonlinear (threshold) vector autoregression (VAR) model with time-varying, stochastic volatilities and quantify the extent to which aggregate financial conditions influence the response of the South African economy to uncertainty shocks. Such a model proposed by Alessandri & Mumtaz (2019), allows the first moment dynamics of the system to be characterised by two distinct financial regimes (i.e. financially stressful versus tranquil/ normal periods) based on the financial stress indicator. The change in regime is abrupt and as a result the

[1] In general, economic uncertainty refers to an environment in which the future state of the economy is unknown. Since uncertainty is a latent variable and presents quantification challenges, most of the measures of uncertainty have focused mainly on macroeconomic uncertainty which include the dispersion in economic forecasts, volatility of stock returns and the count of the term "economic uncertainty" in media.

economy is either in a stressful period or a normal period. Particularly, the stress regime occurs when the estimated threshold variable (financial stress indicator) rises beyond an endogenously estimated threshold value. In this framework, uncertainty is treated as an unobservable state variable, and is estimated as the average volatility of the structural shocks in the economy. As such, our paper contributes to the South African literature on the implications of uncertainty shocks, by estimating a model-based measure of uncertainty (unlike Redl (2018) and Hlatshwayo & Saxegaard (2016) that construct observable proxies for uncertainty) for the country within the framework of a non-linear stochastic volatility in mean VAR to quantify the impact of an uncertainty shock during stressful and tranquil financial periods.

Our estimates reveal that an uncertainty shock has different implications for the South African economy based on the state of financial markets. We find that the response of output is larger in normal times compared to periods characterised by high financial stress. In particular, the peaked contraction in output growth in the stress regime is roughly 5 times larger than the peaked contraction in the tranquil regime. Irrespective of the sign and magnitude of the volatility shock, the responses are much larger in the tranquil regime compared to the stress regime. This suggests that there is not enough room for financial uncertainty to increase further in the stress regime and hence the response of output is smaller, supporting Popescu & Rafael Smets (2010) that the impact of higher economic uncertainty is driven by its ability to increase financial uncertainty. Despite the smaller output response in the stress regime, the deterioration is more persistent than in the tranquil regime. Contrary to the aggregate demand effect, uncertainty shock is inflationary in both regimes with the impact being larger in the high stress regime, lending support to the the precautionary pricing effect following uncertain future demand and marginal costs. While our data reveals that financial frictions do not amplify the impact of uncertainty on real output, it does increase the impact on prices and interest rates. Variance decompositions show that the share of output variance explained by the volatility shocks in good financial times is more than double the share in bad times. Again, this is contrary to evidence provided for advanced economies, highlighting the differing dynamics in these economies compared to developing economies.

The rest of the paper is organised as follows. Section 2 reviews the literature on the role of uncertainty in driving business cycle fluctuations, while Section 3 covers the data used in the model and Section 4 outlines the specification of the non-linear VAR model. Our empirical results are reported and discussed in Section 5 and Section 6 concludes.

2 Literature

The surge in research interest in economic uncertainty has been driven by its role in shaping the prolonged recession following the global financial crisis of 2007. Following the seminal work of Bloom (2009), there has been a growing number of empirical studies that have developed proxies for uncertainty to examine the transmission of uncertainty shocks to the real economy. The majority of these studies lend support to the negative channel in the transmission of uncertainty shocks, consistently proving that such innovations are linked to strong recessionary effects (Bloom (2014)). While traditionally, the transmission of these volatility shocks have been linked to real frictions (Bernanke (1983); Bloom (2009)), recent studies have documented the crucial role of financial frictions in the transmission mechanism (Arellano et al. (2010); Gilchrist et al. (2014); Christiano et al. (2014); Caldara et al. (2016)).

In general, the 'real view' of the transmission mechanism, commonly known as 'real options', is based on the "wait and see" approach by investors and firms in the face of high uncertainty pertaining to economic conditions. This view relies on important irreversible costs in firms' hiring and investment decision, which puts pressure on agents to postpone these decisions, consequently dampening productivity and economic activity (Baker et al. (2016)). On the other hand, the 'financial view' of the transmission mechanism, or commonly known as the 'risk-premium effect', puts financial frictions in the form of credit aggregates and asset prices at the centre of the propagation of uncertainty shocks to the real economy. According to the view, high uncertainty which raises the probability of defaulting, results in an increase in risk premium or external finance, raising the cost of borrowing and negatively impacting firms' investment. In this context, uncertainty works through its ability in amplifying financial stress. Consistent with the 'financial view', Gilchrist et al. (2014) suggests that innovations to uncertainty affect macroeconomic outcomes mainly via financial distortions, while Carrière-Swallow & Céspedes (2013) find evidence of strong correlation between economic dynamics and the depth of financial markets, in particular, United States (US) uncertainty shocks have a larger negative impact on emerging market economies with underdeveloped financial markets. Similarly, more recent studies including Gupta et al. (2020) and Bhattarai et al. (2019) document heterogeneity in the transmission of US uncertainty to emerging market economies dependent on country-specific factors including financial vulnerability and monetary policy stance, respectively. According to Caldara et al. (2016), the strong correlation between economic uncertainty and financial uncertainty makes it difficult to empirically discriminate between the two. To overcome this setback, these authors makes use of a penalty function and find evidence that the financial channel is crucial in the transmission of uncertainty shocks, while the uncertainty channel is negligible in the transmission of financial shocks. Similarly, Popescu & Rafael Smets (2010) find that once a measure of financial stress (i.e. credit spread) is included in a VAR framework, the independent role of uncertainty shocks (proxied by forecaster dispersion) becomes minimal.

Most of the studies examining the link between financial conditions and uncertainty have focused on advanced economies only (more so on the US), with the exception of Carrière-Swallow & Céspedes (2013), Gupta et al. (2020), and Bhattarai et al. (2019). However, these three studies have documented the importance of the financial channel in the international spillover of US uncertainty and not country-specific uncertainty shocks.[2] To narrow this gap in literature, we examine the 'financial view' of the transmission of uncertainty shocks within a small open emerging market economy, in our case South Africa. Specifically, we follow the approach by Alessandri & Mumtaz (2019) in estimating the state-dependent link between economic uncertainty and financial conditions in South Africa, within a non-linear VAR model.[3] In this way, we are able to examine whether

[2]Gupta et al. (2020) examines the relative importance of the exchange rate, trade and financial channel in the transmission of US uncertainty shocks on the dynamics of a panel of advanced economies and emerging market economies, and finds that in both cases the financial channel plays the most prominent role in the transmission mechanism.

[3]van Roye (2014), Aboura & van Roye (2017), Hubrich & Tetlow (2015), Hollo et al. (2012), Chatterjee et al.

the impact of uncertainty changes over time in relation to the state of South African financial markets. Previous South African studies, including Redl (2018), Hlatshwayo & Saxegaard (2016), and Kisten (2020) have provided evidence in support of the 'real view' of the transmission of uncertainty shocks, documenting the recessionary effects of uncertainty shocks. However, Redl (2018) does find that the estimated results are robust to the inclusion of a measure of financial stress. While Kisten (2020) does examine the time-varying transmission of uncertainty shocks, documenting that the impact of an uncertainty shock on key macroeconomic variables have declined systematically over time (supporting evidence for advanced economies by Mumtaz & Theodoridis (2018), Mumtaz (2016), and Beetsma & Giuliodori (2012)), the author does not consider the interdependence between financial conditions and uncertainty supported by the financial view of the transmission mechanism. Attempts in this regard are more evident, but considerably limited, for advanced economies (Lhuissier et al. (2016) and Alessandri & Mumtaz (2019) focus on the US). Employing a Markov-switching VAR, Lhuissier et al. (2016) find that uncertainty shocks (proxied by the VIX index) are more powerful during financial stress regimes than during tranquil regimes. Alessandri & Mumtaz (2019) find similar evidence, but make use of a non-linear VAR where economic uncertainty is approximated by the average volatility of the structural shocks in the economy, rather than being proxied by observable measures. In line with this, our paper contributes to the South African literature on the implications of uncertainty shocks, by estimating a model-based measure of uncertainty (unlike Redl (2018) and Hlatshwayo & Saxegaard (2016) that construct observable proxies for uncertainty) for the country within the framework of a non-linear stochastic volatility in mean VAR to quantify the impact of an uncertainty shock during stressful and tranquil financial periods.

(2017), and Balcilar et al. (2016) have documented differing economic dynamics during stressful and normal times in the financial system, however, specifically examining the impact of financial shocks

3 Data

Monthly data covering the period 1995 to 2017 is employed in our study. We obtain data on the industrial production index (*IP*) and the three-month treasury bill rate (*R*) from the South African Reserve Bank historical database, while data on headline consumer price index (*CPI*) is sourced from Statistics South Africa.[4] The estimation uses growth rates for industrial production and the price index, and therefore these variables enter our model as log first differences. Other variables, including the interest rate and the financial stress indicator, which is elaborated on below, remain untransformed. We use a broad recently constructed financial stress index (called $SAFSI$) by Kisten (2019) to capture the state of financial markets. $SAFSI$ comprises seventeen financial indicators emanating from six major markets in South Africa (i.e. credit market, equity market, money market, housing market, foreign exchange market, and commodity market). These indicators were aggregated based on information weights and time-varying cross-correlations between market segments, representing a technical improvement over past measures (see Gumata et al. (2012), Thompson et al. (2015), Kasaï & Naraidoo (2013), and Kabundi & Mbelu (2017) that construct financial condition indexes (FCIs) for South Africa).[5] As such, $SAFSI$ has the advantage of capturing the interconnectedness of financial markets, allowing indicators to be assessed in terms of their systemic importance. Indicators included in the $SAFSI$ were selected based on their ability to capture key episodes of stress in the South African financial system. The procedure in which the index is constructed reduces the risk of combining informationally redundant data that would over emphasise a given market segment at any point in time. The end result is a parsimonious index that captures the dynamics of a relevant set of financial indicators.

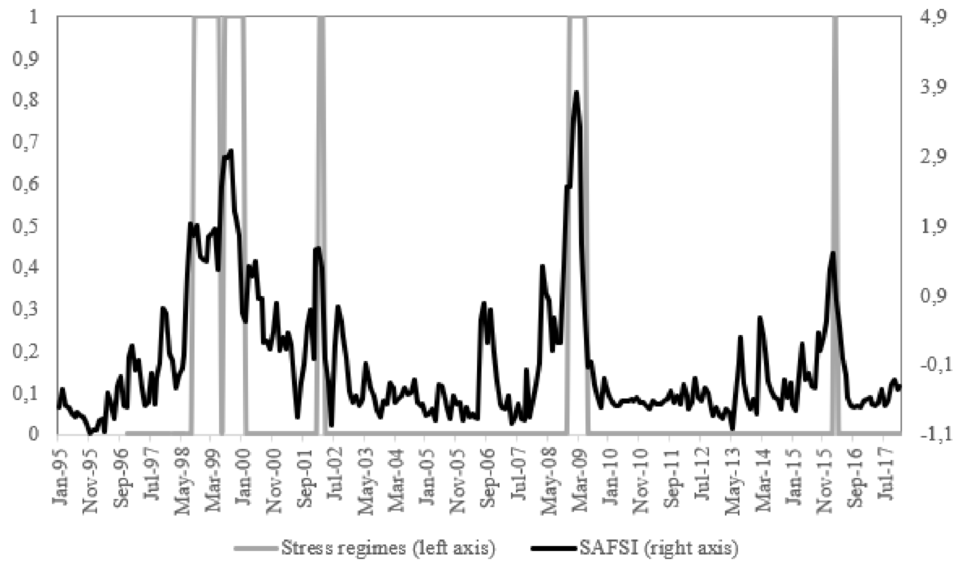
Figure 1 displays the $SAFSI$ along with the estimated stress regimes over the period 1995 - 2017.[6] The stress regimes are defined as periods when the the threshold variable (which is the

[4]The industrial production index covers real output in the manufacturing sector only.

[5]We do not distinguish between financial condition indexes (FCIs) and financial stress indexes (FSIs) in this paper, since the difference between them are negligible. While FCIs are aggregates of a variety of financial variables that aid in characterising the state of financial markets, FSIs similarly monitors financial instability by aggregating financial variables that indicate increased likelihood of a crisis.

[6]The construction of the $SAFSI$ will not be covered in this paper. Please refer to Kisten (2019) for detail pertaining

Figure 1: The SAFSI and estimated stress regimes



Notes: The stress regimes are periods when the South African economy is estimated to have experienced high financial stress, which according to the threshold VAR model is defined as a state in which the index exceeds an estimated threshold. This threshold was estimated to be 1.38.

d_{th} lag of the financial stress index ($SAFSI$) denoted as Y_{t-d}) rises beyond an estimated critical threshold value Y^*. Our model estimates the optimal delay parameter to be two months. The threshold VAR model is able to capture the main episodes of financial stress in South African history, as the estimated stress regimes are consistent with the benchmark episodes identified in Kisten (2019). In particular, the estimated regimes captures the currency crisis experienced by the economy in 1998 following the East Asian financial crisis of 1997 and the Russian financial crisis of 1998; liquidity pressures experienced by smaller to mid-sized banks in 1999; the banking crisis of 2002 following the imposition of curatorship over Saambou Bank Limited (7th largest bank in SA) in February 2002 and the subsequent takeover of BOE Bank Limited by Nedbank Limited; the financial and economic impact of the 2008-2009 global financial crisis; and more recently the financial market turmoil at the beginning of 2016, following the political turmoil that lead to the axing of former Finance Minister Nhlanhla Nene.

to the identification of the key periods of financial stress in the South African economy, selection and list of stress indicators that comprise the $SAFI$, and the corresponding construction methodology.

4 Model specification

We quantify the impact of innovations to economic uncertainty on the South African economy during different financial states by estimating a Threshold VAR model with time-varying, stochastic volatilities. Such a model proposed by Alessandri & Mumtaz (2019), which allows the first moment dynamics of the system to be characterised by two distinct financial regimes (i.e. financially stressful versus tranquil/ normal periods), is defined as

$$Y_t = \left[c_1 + \sum_{j=1}^{P} \beta_{1j} Y_{t-j} + \sum_{k=0}^{K} \theta_{1k} lnh_{t-k} + v_t\right] \tilde{R}_t + \left[c_2 + \sum_{j=1}^{P} \beta_{2j} Y_{t-j} + \sum_{k=0}^{K} \theta_{2k} lnh_{t-k} + v_t\right] (1 - \tilde{R}_t) \tag{1}$$

In our framework Y_t represents a $N \times 1$ vector of endogenous variables including industrial production growth (IP), consumer price inflation (CPI), three-month treasury bill rate (R), and the financial stress index ($SAFSI$). The parameters of the VAR system are represented by c_i, β_i, θ_i, and $v_t \sim N(0, \Omega_{it})$ for $i = 1, 2$, allowing us to capture the change in economic dynamics during stressful and tranquil financial conditions. In this setup, uncertainty is treated as an unobservable state variable, represented by h_t, and is estimated as the average volatility of the structural shocks in the economy. The inclusion of h_t in Equation (1) allows the economic variables (output, prices, and interest rates) to adjust endogenously to the different states of financial markets. As is common with monthly data, we set the number of lags of the endogenous variables in the system P to 2 based on the Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC), and K which is the lag length of uncertainty is set to 1. $\tilde{R}_t$ allows for the possibility of two regimes which switches endogenously through the dynamics of some threshold variable. In our case, the threshold variable is the d_{th} lag of the financial stress index ($SAFSI$) denoted as Y_{t-d}. We define $\tilde{R}_t = 1$ ($\tilde{R}_t = 0$ otherwise) as the stress regime if and only if the threshold variable rises beyond an unobserved threshold value Y^*, which we let the data decide. Equation (1) shows all parameters are allowed to change across regimes. This is motivated by our interest in capturing changes in the transmission of uncertainty shocks between financially good and bad times, consistent with the spirit of Alessandri & Mumtaz (2019), but applied to the South African economy.

The covariance matrix of the error term v_t i.e. Ω_{it} has time-varying elements and is critical to our analysis. It is defined as $\Omega_{it} = A_i^{-1} H_t A_i^{-1'}$, depending on the economic regimes, $H_t = h_t S$ where $S = diag(s_1, \ldots s_N)$, and A_i are lower triangular matrices with each non-zero element evolving as a random walk (Primiceri (2005)). The volatility process, which we take to represent economic uncertainty, evolves as an AR(1) process and is defined as

$$lnh_t = \alpha + F lnh_{t-1} + e_t,\ VAR(e_t) = Q \tag{2}$$

The above specification does not distinguish between the common and idiosyncratic component in volatility and h_t is a convolution of both components. Importantly, in estimating volatility h_t, all structural shocks implicitly carry the same weight. In this framework, a shock to volatility or uncertainty i.e. $e_t \geq 0$ raises h_t, shifting the covariance matrix of innovations v_t upwards, reducing the accuracy with which agents can predict future economic outcomes i.e. Y_{t+m}.

A natural conjugate prior with dummy observations, following Banbura et al. (2010), is imposed on the VAR parameters $B_i = c_i, \beta_{i_{i=1,2}}$ in the two regimes, given that the sample can be relatively short in the stress regime.[7] We estimate AR(1) regressions for each endogenous variable in the system using a pre-sample, and use the OLS coefficients as the prior means. Following Canova (2007), the hyperparameter that controls the overall tightness of the prior on the VAR coefficients τ is set to 0.2 a loose prior on the VAR coefficients and we choose a loose prior on the constant with $c = 10^5$. A normal fairly loose prior is assumed for the threshold value Y^* where $Y^* \sim N(\bar{Y}, \bar{V})$ with $\bar{Y}$ denoting the sample mean of the financial stress indicator and $\bar{V} = 10$. We assume a flat prior for the delay parameter d and limit its value between 1 and 2. The posterior

[7] Technicalities pertaining to appending the data with dummy or artificial observations can be found in Banbura et al. (2010)

distribution of the parameters and the state variable h_t are approximated using a Gibbs sampling algorithm.[8] In essence, given a draw of the state variable, the variables in the system are transformed to remove the heteroscedasticity, after which the model collapses to a standard threshold VAR and the conditional posterior distribution of the VAR parameters in both regimes, the delay parameter, and threshold are given by Alessandri & Mumtaz (2017).[9] In particular, the conditional distribution for the VAR coefficients is given by $N(B_i^*, \bar{\Omega}_i \otimes (X_i^{*'} X_i^*)^{-1})$ in each financial regime, where $B_i^* = (X_i^{*'} X_i^*)^{-1})(X_i^{*'} Y_i^*)$, Y_i^* and Y_i^* are the transformed data appended with dummy observations, and $\Omega_i = A_i^{-1} S A_i^{-1'}$. Given a draw for the VAR parameters, the threshold, and h_t, the conditional posterior distribution for A and the variance S is normal and inverse Gamma respectively. Given all of these parameters, the model takes on a non-linear state space framework, wherein the state variable h_t is drawn via a independence Metropolis Hastings algorithm for stochastic volatility models, following Jacquier et al. (2002).

We run 20,000 iterations of the Gibbs sampler to ensure convergence and discard the first 10,000 as burn-in, using the last 10,000 for inference. Generalised impulse response functions as specified in Koop et al. (1996) are used to study the potential differences in the propagation of uncertainty shocks under the specific financial regimes (i.e. tranquil versus stressful). The impulse responses are captured using Monte Carlo integration and defined as

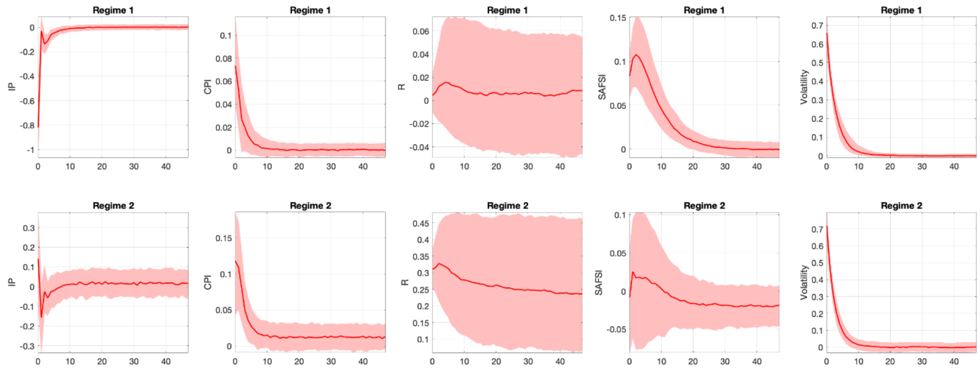
$$IRF_t^{\tilde{R}} = E(Y_{t+m} | \xi_t, Y_{t-1}^{\tilde{R}}, \mu) - E(Y_{t+m} | \xi_t, Y_{t-1}^{\tilde{R}}) \tag{3}$$

where ξ_t represents all the parameters and hyperparameters of the VAR model, m is the horizon under consideration, $\tilde{R} = 0, 1$ denotes the regime and μ is the shock (i.e. increase in uncertainty or volatility, in our study). Equation (3) states that the impulse responses are computed as the

[8]See Alessandri & Mumtaz (2019) for detail regarding the implementation of each step in the algorithm. This is beyond the scope of our paper, as we focus more on the results rather than the technicalities

[9]Due to the analytical intractability of the posterior distribution of Y^*, a random walk Metropolis Hastings step, following Chen & Lee (1995) is used to draw the threshold value in each simulation i.e. $Y_{new}^* = Y_{old}^* + \phi^{1/2}\varepsilon$, where $\varepsilon \sim N(0,1)$ and $\phi^{1/2}$ is a scaling factor which is set so as to ensure that the acceptance rate lies in the 20-40% interval. The acceptance probability is given by $\frac{f(Y_t|Y_{new}^*,M)}{f(Y_t|Y_{old}^*,M)}$ where $f(.)$ represents the posterior density and M denotes all other parameters in the model. The delay parameter d is then sampled conditional on the threshold value and its conditional posterior is a multinomial distribution with probability $\frac{L(Y_t)}{\Sigma^d L(Y_t)}$ where $L(.)$ is the likelihood function.

Figure 2: Impulse responses to a positive uncertainty shock



Notes: The figure shows the median responses of industrial production growth (IP), consumer price inflation (CPI), interest rate (R), and SAFSI to a positive one standard deviation model-based volatility (or uncertainty) shock during tranquil financial times or low stress regime (Regime 1) and stressful financial times or high stress regime (Regime 2). Median responses are reported within 68% confidence bands. The estimation period is 1995M1-2017M12, and horizontal axis reports time which is measured in month.

difference between two conditional expectations: The first term is the forecast of the endogenous variables conditional on one of the structural shocks μ; the second term being the baseline forecast i.e. where the shock equals zero. The impulse responses fully account for abrupt endogenous changes in regimes and the conditional expectations are approximated via a stochastic simulation of the VAR model (Alessandri & Mumtaz (2017)).

5 Empirical results

In this section we report the change in macroeconomic and financial dynamics during good financial times (Regime 1) and bad financial times (Regime 2), following an exogenous increase in uncertainty. Regime 2 occurs when the estimated threshold variable goes beyond the estimated threshold value. As mentioned previously, the SAFSI is used as the threshold variable, which is a measure of financial stress in the South African financial sector. In our framework, the change in regime is abrupt and as a result the economy is either in a stressful period (Regime 2) or a normal period (Regime 1).

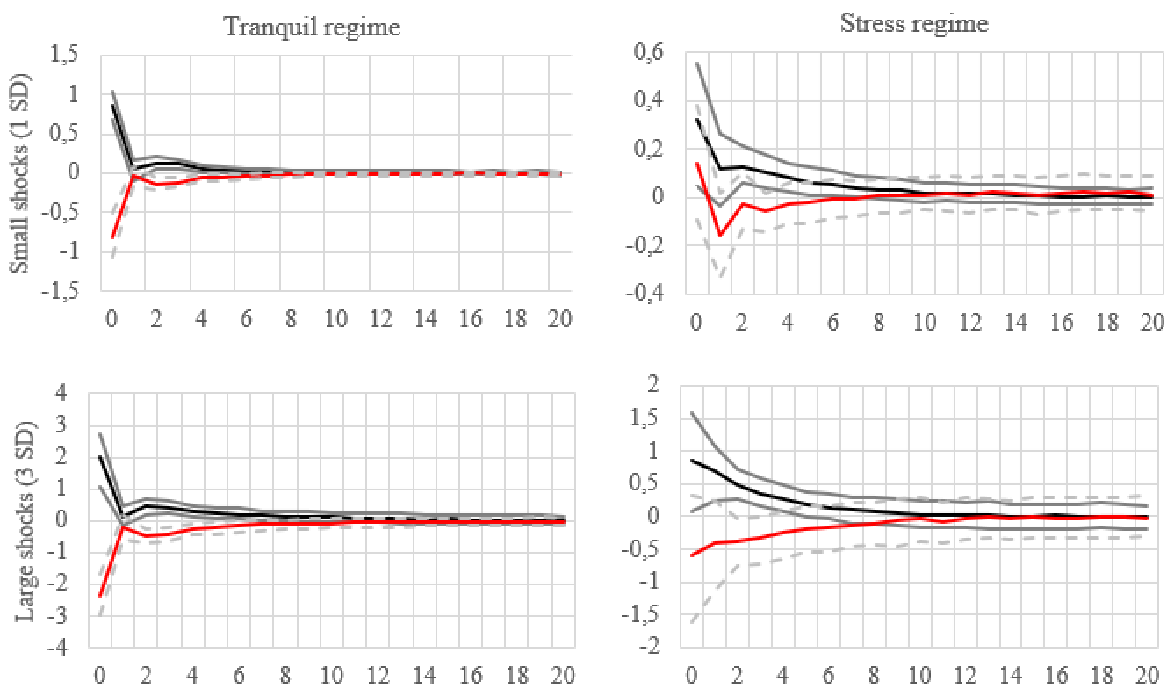
Figure 2 reports the impulse responses of the South African economy following an increase in uncertainty, represented as a positive one standard deviation shock to the volatility process h_t in Equation 2. In response to an uncertainty shock, there is an immediate deterioration in real output growth (IP)[10] and financial conditions, indicated by an immediate jump in our financial stress index SAFSI. We find a larger and statistically significant impact on output and financial conditions in the low stress Regime 1 compared to the high stress Regime 2. In particular, the peaked contraction in output growth in the stress regime is roughly 5 times larger than the peaked contraction in the tranquil regime. While there is an immediate short-lived positive impact on output in Regime 2, this impact is not evident once we impose a larger uncertainty shock, as is seen in Figure 3 below. Despite the smaller output response in the stress regime, the deterioration is more persistent than in the tranquil regime. In spite of this persistent impact, we do not find evidence of the amplification impact of an uncertainty shock on economic activity during episodes of financial distress as predicted by the 'financial view' of the transmission mechanism (the crucial role of financial frictions in the transmission mechanism has been supported by Arellano et al. (2010); Gilchrist et al. (2014); Christiano et al. (2014); Caldara et al. (2016)); and more recently Alessandri & Mumtaz (2019) for advanced economies). One possible explanation for this contradictory evidence found when using South African data could be that there is not enough space for financial uncertainty to increase further in the high financial stress regime, and hence impact on output from economic uncertainty is smaller than the regime where financial uncertainty is low. Hence economic uncertainty increases financial uncertainty more in the low stress regime and depresses output more.[11]

Since the stochastic volatility process is not regime-dependent, the volatility dynamics are identical across good and bad financial times as shown in the last column of Figure 2. Increases in uncertainty are generally associated with a negative demand shock in the economy i.e. reducing prices, interest rate, and output in accordance with the 'wait and see' behaviour of economic agents

[10] A similar sharp decline was also noted when we used the generalised stochastic volatility in mean VAR model of Mumtaz (2018), as reported in Appendix B. The variables contained in the model was industrial production growth (*IP*), consumer price inflation (*CPI*), and a measure of financial stress (*SAFSI*), and the uncertainty shock was identified using a Cholesky decomposition with the variables ordered as h_{1t}, h_{2t}, h_{3t}, $SAFSI$, IP, CPI.

[11] Popescu & Rafael Smets (2010) suggest that high uncertainty matters to the extent that it increases credit spreads and risk levels, otherwise its impact on the real economy relatively modest.

Figure 3: Output response following uncertainty shocks of different sizes and signs



Notes: The first row shows the responses of industrial production growth following a one standard deviation or small uncertainty shock during tranquil financial times (or Regime 1) and stressful financial times (or Regime 2). Median responses are reported within 68% confidence bands with the red solid line corresponding to positive uncertainty shocks and the black solid line to negative shocks. Similarly, the second row depicts the response of output growth to a three standard deviation (or large) uncertainty shock during the tranquil and stress regime. The estimation period is 1995M1-2017M12, and horizontal axis reports time which is measured in month.

(Bloom (2009)). However, our estimation reveals that an uncertainty shock is inflationary in both regimes with the impact being larger in the high stress regime as illustrated in column 2. While this result contradicts the aggregate demand effect of an uncertainty shock, it lends support to the the precautionary pricing effect following uncertain future demand and marginal costs pointed out by Fernández-Villaverde et al. (2015), Mumtaz & Theodoridis (2015), and Redl (2018).[12] According to Klein (2011), price mark-ups are countercyclical in South Africa, in contrast to international experience, and therefore the recessionary effect of a positive uncertainty shock on production may translate to higher mark-ups introducing a rise in inflation.[13] Since price stability is one of the main goals of monetary policy in South Africa, the understanding of which propagation mechanism holds in the data is imperative. In line with this, we notice that although the short-term interest rates (R) does not respond significantly to the volatility shock, we nevertheless note that the immediate jump in interest rates in the high stress Regime 2 points to the procyclical behaviour of monetary policy as output falls but prices rise. While our data reveals that financial frictions do not amplify the impact of uncertainty on real output, it does increase the impact on prices and interest rates.

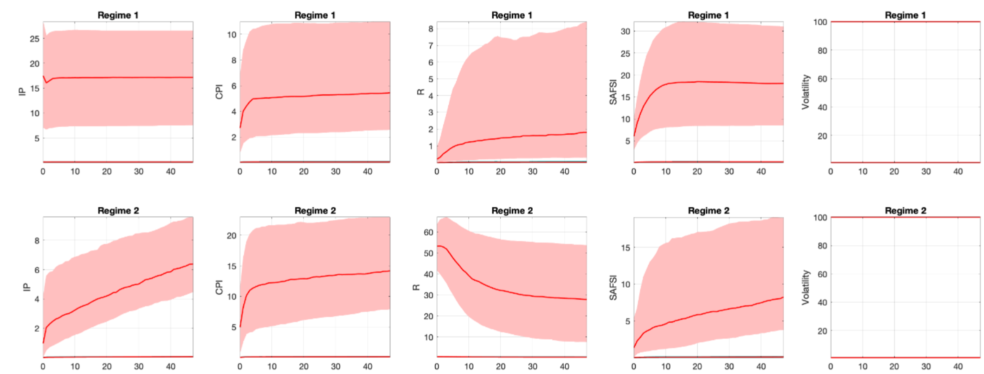
The real implications of a change in uncertainty might be dependent on the size and sign of the shock, given the non-linearity inherent in the model. Figure 3 compares the response of industrial production growth in good and bad financial times following uncertainty shocks of different magnitude (i.e. one and five standard deviation (SD) shocks) and sign (i.e. positive and negative volatility shocks). [14]The left column shows that the response of output in the tranquil regimes where financial conditions are loose are symmetrical in the size and sign of the shock. Irrespective of the sign and magnitude of the volatility shock, the responses are much larger in the tranquil regime compared to the stress regime in column 2. This is contrary to the findings of Alessandri

[12] Unlike in Alessandri & Mumtaz (2019), we do not find evidence of the aggregate demand effect on prices in the high stress regime as the precautionary mechanism appears to dominate in both regimes in the South African economy.

[13] Oh (2020) provides an in-depth theoretical explanation of firms' precautionary pricing motive within a standard New Keynesian model with Calvo-type price rigidities. In the Calvo model, output decreases and inflation rises following an uncertainty shock. By contrast, in a Rotemberg-type setup, only the aggregate demand effect is operative for firms as an uncertainty shock reduces both output and prices.

[14] Responses of the other endogenous variables to uncertainty shocks of different sizes and signs are shown in Appendix A.

Figure 4: Forecast error variance decomposition



Notes: The figure shows the contribution of volatility shocks to the variance of each endogenous variable (i.e. industrial production growth (IP), consumer price inflation (CPI), interest rate (R), and SAFSI) as specified in the Threshold VAR outlined in Section 4. Regime 1 corresponds to tranquil financial times and Regime 2 to stressful financial times. The horizontal axis reports the forecast horizon which is measured in month.

& Mumtaz (2019) that financial frictions amplify the impact of uncertainty shocks, irrespective of its direction and size. However, we note that the responses of output are much more persistent in the stress regime. This suggests that an uncertainty shock in a tight credit environment has a more prolonged impact on the real economy, lasting for about six months, compared to the short-lived response in the tranquil regime. Interestingly, there is a sign asymmetry in the stress regime for both large and small shocks. Contrary to the evidence for the US economy provided by Alessandri & Mumtaz (2019), we find that for the South African economy a drop in volatility causes a larger change in output than a rise in volatility of equal magnitude. Our data reveals that volatility shocks in the stress regime matters more on the way down than on the way up, reaffirming our earlier assertion that there is not enough room for financial uncertainty to increase further in this regime and supporting Popescu & Rafael Smets (2010) that the impact of higher economic uncertainty is driven by its ability to increase financial uncertainty.

Variance decompositions shown in Figure 4 show the contribution of volatility shocks to the variance of the endogenous variables in the Threshold VAR outlined in Section 4, allowing us to gauge the overall role of macroeconomic uncertainty in the business cycle. The Figure reveals that uncertainty shocks play a much more prominent role in the variance of output (column 1) and financial conditions (column 4) in the low stress Regime 1, accounting for more than double their variance in the high stress regime. This is contrary to evidence provided for the US economy by Alessandri & Mumtaz (2019), highlighting the differing dynamics in advanced and developing economies. However, for inflation and interest rate, uncertainty shocks are more relevant in stressful financial times.

6 Concluding remarks

In this paper we document the connection between economic uncertainty and financial market conditions, specifically that the macro-financial implications of an uncertainty shock differ across financial regimes. Using monthly South African data over the period 1995 to 2017, we estimate a non-linear VAR where uncertainty is captured by the average volatility of structural shocks in the economy. Regime shifts are abrupt and the economy shifts to a high stress regime characterised by tight financial condition when the financial stress indicator breaches an endogenously estimated threshold. We find that while the deterioration of output following an uncertainty shock is much more prominent during normal periods than during stressful periods, it is much more persistent during stressful financial times. Our findings support the proposition of Popescu & Rafael Smets (2010) that the impact of higher economic uncertainty is driven by its ability to increase financial uncertainty, and since there is not enough room for financial uncertainty to increase further in the stress regime, the response of output is smaller. Contrary to the aggregate demand effect and in support of the precautionary pricing effect, uncertainty shocks are inflationary in both regimes, with the impact being larger in the stress regime. Since price stability is one of the main goals of monetary policy in South Africa, the understanding of which propagation mechanism holds in the data is imperative. In line with this, we notice that although interest rates do not respond significantly to the volatility shock, we nevertheless note that the immediate jump in interest rates in the high stress regime points to the procyclical behaviour of monetary policy as output falls but prices rise. While our data reveals that financial frictions do not amplify the impact of uncertainty on real output, it does increase the impact on prices and interest rates. Our results suggest that policymakers could limit the propagation of uncertainty shocks by implementing appropriate macroprudential and monetary policy in line with the state of financial markets.

South Africa is a small open economy and hence is likely to be subjected to a variety of shocks from major global economies, as highlighted with regard to monetary policy shocks from the US recently by Meszaros & Olson (2020). Now given that, monetary policy shocks have been shown to generate significant macroeconomic uncertainty in the US (Mumtaz & Theodoridis (2019)), the possibility of spillover of US uncertainty to domestic uncertainty in South Africa via monetary policy shocks in the US (and other channels as outlined in Gupta et al. (2020)), cannot be ignored. Given this as part of future research, it would be interesting to analyze the role of foreign uncertainty, conditional on financial regimes, on macroeconomic variables of South Africa.

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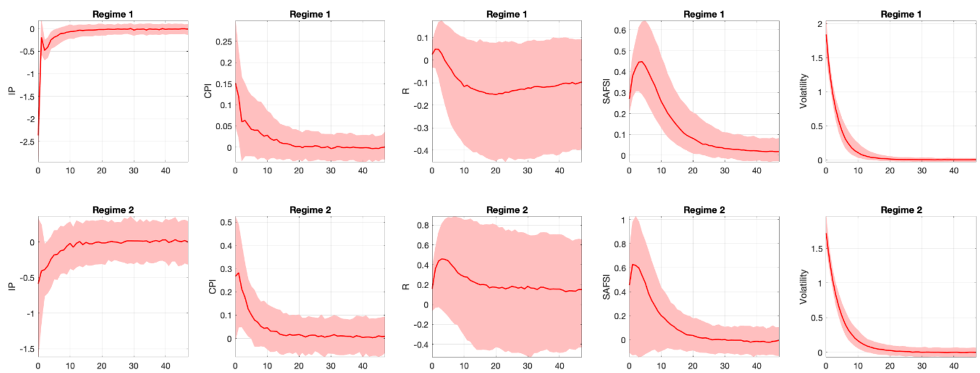
Appendix

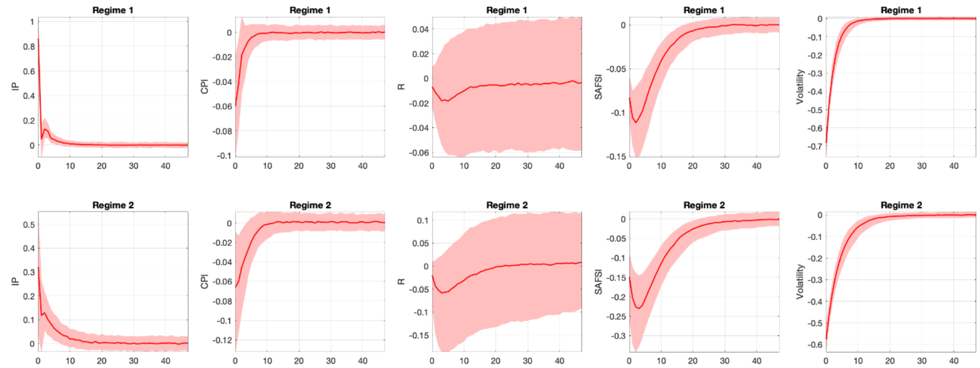
A Impulse responses to uncertainty shocks of different sizes and signs

Figure A.1: Impulse responses to a large positive uncertainty shock



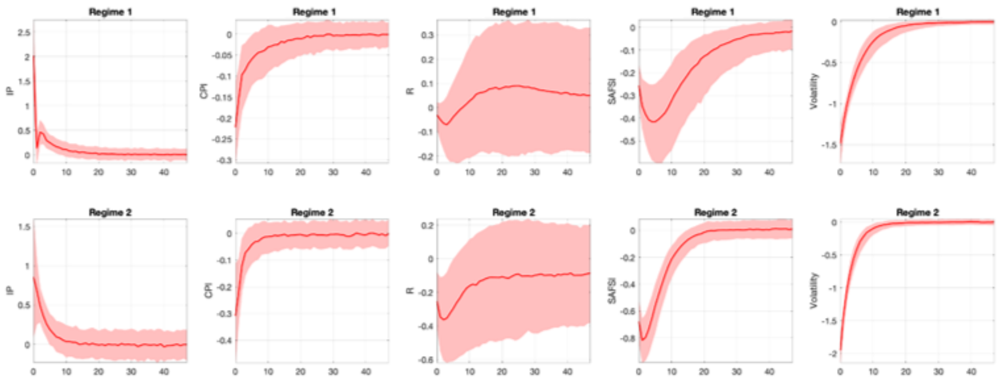
Notes: The figure shows the median responses of industrial production growth (IP), consumer price inflation (CPI), interest rate (R), and SAFSI to a positive three standard deviation model-based volatility (or uncertainty) shock during tranquil financial times or low stress regime (Regime 1) and stressful financial times or high stress regime (Regime 2). Median responses are reported within 68% confidence bands. The estimation period is 1995M1-2017M12, and horizontal axis reports time which is measured in month.

Figure A.2: Impulse responses to a small negative uncertainty shock



Notes: The figure shows the median responses of industrial production growth (IP), consumer price inflation (CPI), interest rate (R), and SAFSI to a negative one standard deviation model-based volatility (or uncertainty) shock during tranquil financial times or low stress regime (Regime 1) and stressful financial times or high stress regime (Regime 2). Median responses are reported within 68% confidence bands. The estimation period is 1995M1-2017M12, and horizontal axis reports time which is measured in month.

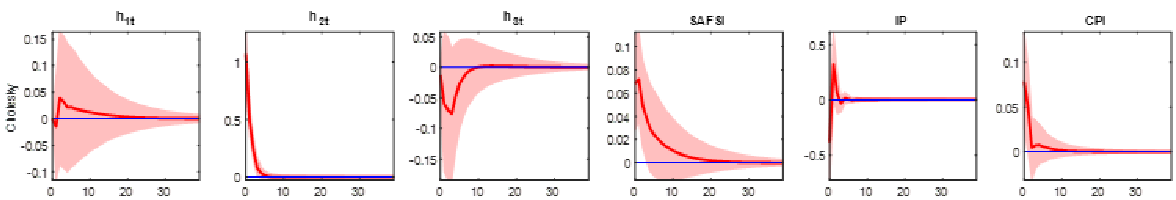
Figure A.3: Impulse responses to a large negative uncertainty shock



Notes: The figure shows the median responses of industrial production growth (IP), consumer price inflation (CPI), interest rate (R), and SAFSI to a negative three standard deviation model-based volatility (or uncertainty) shock during tranquil financial times or low stress regime (Regime 1) and stressful financial times or high stress regime (Regime 2). Median responses are reported within 68% confidence bands. The estimation period is 1995M1-2017M12, and horizontal axis reports time which is measured in month.

B Impact of macro uncertainty shocks on the South African economy

Figure B.1: Impulse response to a output uncertainty shock



Notes: The figure reports the median responses of financial uncertainty (h_{1t}), output uncertainty (h_{2t}, inflation uncertainty (h_{3t}), SAFSI, industrial production growth (IP), and consumer price inflation (CPI) to a positive one standard deviation output uncertainty shock. Median responses are reported within 68% confidence bands. The estimation period is 1995M1-2017M12, and horizontal axis reports time which is measured in month.