Macroeconomic Uncertainty in South Africa

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Abstract

This paper develops a new index of economic uncertainty for South Africa for the period 1990-2014 and analyses the macroeconomic impact of changes in this measure. The index is constructed from three sources: (1) Disagreement among professional forecasters about macroeconomic conditions using novel data from a forecasting competition run by a national newspaper, (2) a count of international and local newspaper articles discussing economic uncertainty in South Africa and (3) mentions of uncertainty in the quarterly economic review of the South African Reserve Bank. The index shows high levels of uncertainty around the period of democratic transition in 1992-4, the large depreciation of the currency in 2001 and the financial crisis of 2008. The uncertainty index is a leading indicator of a recession. An unanticipated increase in the index is associated with a fall in GDP, investment, industrial production and private sector employment. Contrary to evidence for the U.S.A and U.K., uncertainty shocks are inflationary. These results are robust to controlling for consumer confidence and a measure of financial stress. I show that these results are consistent with a simple New Keynesian model subject to volatility shocks in technology. In this model, nominal rigidities induce firms to raise prices as a precautionary measure when future demand becomes more uncertain.

Keywords: economic uncertainty, business cycles, inflation, South Africa
JEL classification numbers: D80, E32, E31, E66, N17

1 Introduction

The Great Recession has renewed interest in the question of the sources of business cycle fluctuations. Traditional sources of fluctuations, such as technology and labour supply shocks, are less plausible explanations of this episode than of previous recessions. I study a new driver proposed by Baker and Bloom (2013): fluctuations in uncertainty. These authors develop a proxy for economic

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policy uncertainty based on news articles discussing policy uncertainty, the number of federal taxes set to expire and disagreement among professional forecasters over the future values of government purchases and inflation. They show, using a vector autoregression, that an increase in their proxy equivalent to the rise seen during the financial crisis is associated with a loss of around 2 million jobs and a decline in industrial production of 2.5% for the U.S.A.. Moreover, Bloom (2009) show that uncertainty rises by around 50% during a typical U.S. recession. Studies following Baker and Bloom (2013) have provided similar evidence that uncertainty shocks are important drivers of the business cycle, e.g. Dendy et al. (2013) for the for the U.K.

Despite some cross-country work relating uncertainty to growth by Baker and Bloom (2013), there is little evidence of the effects of such proxies for economic uncertainty for developing countries. Given that developing countries experience much higher levels of realised volatility than developed nations (Fernandez-Villaverde et al. (2011b) and Bloom (2014)) it is plausible that fluctuations in uncertainty are important drivers of business cycles in these regions. It has been argued by Leduc and Liu (2012) that shocks to uncertainty have a central role to play in understanding business cycles as they are prototypical aggregate demand shocks, with lower output and inflation. However, recent papers by Popescu and Smets (2010) and Gilchrist et al. (2013a) have challenged the relevance of uncertainty shocks once their correlation with credit spreads is accounted for, suggesting that uncertainty shocks only matter when acting through a financial channel. Extending studies of uncertainty beyond developed nations can help disentangle the effects of financial shocks from uncertainty shocks. During the Great Recession many developing countries experienced increases in uncertainty, as the impact of a large recession in trading partner countries took hold, yet they did not experience the same levels of financial stress and instability as in the developed world.

This paper contributes to this literature in three ways. Firstly, it extends the evidence that uncertainty shocks generate drops in real activity to a developing country. Secondly, it provides evidence that uncertainty shocks have real effects even when controlling for financial stress (credit spreads). Thirdly, it provides new empirical and theoretical evidence against the argument that uncertainty shocks are in fact aggregate demand shocks.

I construct an index of economic uncertainty following Dendy et al. (2013) for the period 1990-2014. The index is constructed from three sources: (1) Disagreement among professional forecasters about macroeconomic conditions using novel data from a forecasting competition run by a national newspaper, (2) a count of international and local newspaper articles discussing economic uncertainty in South Africa and (3) mentions of uncertainty in the quarterly economic review of the South African Reserve Bank (SARB). The index is positively correlated with other proxies for uncertainty, i.e. realised and option implied volatility of the stock market. The index shows high levels of uncertainty around the period of democratic transition in 1992-4, the large depreciation of the currency in 2001 as well as the financial crisis of 2008.

To measure the impact of uncertainty shocks I use a structural VAR. The results show that economic uncertainty is a leading indicator of a recession in South Africa. An unanticipated increase in the index is associated with a fall in GDP, investment, industrial production, capital inflows and private sector employment. Contrary to evidence for the U.S.A. and U.K., uncertainty shocks are inflationary. I show that this result is robust to the inclusion of a proxy for credit spreads as well as alternative methods of construction for the index.

To further support the empirical results regarding inflation, I show that a simple New Keynesian model can generate inflation under volatility shocks regarding technological progress. Firms unable to adjust their price each period (Calvo nominal rigidities) raise prices when uncertainty increases as insurance against large positive shocks hitting the economy and generating high levels of demand when they cannot increase prices. This is the same result found by Fernandez-Villaverde et al. (2011a) in their study of fiscal volatility shocks.

The remainder of the paper is organised as follows. Section 1.1 reviews the literature on uncertainty shocks. Section 2 describes the construction of the index and compares it to alternative proxies in South Africa. Section 3 presents the VAR results and robustness checks. Section 4 describes the theoretical results from the New Keynesian Model and section 5 concludes.

1.1 Literature

Why should uncertainty matter? There are (at least) three broad reasons identified in the literature: real options, risk aversion and growth options effects (Bloom (2014)).

The real options approach to uncertainty (Bernanke (1983)) envisages firms face a number of projects which they may pause if prospects diminish. However, for this to have macroeconomic effects a number of preconditions are needed: firms must be subject to fixed costs or partial irreversabilities in investment, be able to wait to bring its products to market (e.g. not in a patent race with other firms) and operate in an environment where today's investment decision affects tomorrows actions e.g. through decreasing-returns-to-scale technology. These effects have the potential to weaken productivity-enhancing reallocation of resources as productive firms expand less and unproductive firms contract less as both wait for uncertainty to clear. This can generate pro-cyclical productivity as in Bloom et al. (2012) and link these shocks to the business cycle.

Greater uncertainty directly increases risk premia if investors are risk averse and will increases the probability of default among lenders, leading to higher default premia. An important channel through which uncertainty operates is through its ability to generate and amplify financial stress (Arellanon et al. (2012); Christiano et al. (2014); Gilchrist et al. (2013a)). Risk averse households respond with precautionary savings which is contractionary in the short run but may stimulate long run growth . For small open economies much of this savings flows abroad leading to large reductions in domestic demand (Fernandez-Villaverde et al. (2011b)). If nominal rigidities are strong, the drop in demand will not be met with sufficiently reduced prices leading to a recession even in large economies (Leduc and Liu (2012); Fernandez-Villaverde et al. (2011a)).

It is not clear why an increase in uncertainty should be interpreted always as equivalent to bad news. Growth options refer to the idea that entrepreneurs can only lose their investment but the upside of an increase in potential outcomes is unbounded. Thus uncertainty creates call option effects. However, the empirical literature has consistently found non-positive responses to increases in uncertainty on a macroeconomic level. A potential reason for the bad news interpretation of increased uncertainty is that agents are "ambiguity averse". Such agents cannot assign a probability distribution over the future and respond by assuming the worst-case-scenario of the possible distributions they consider (Ilut and Schneider (2014)). Thus any increase in the possible range of outcomes acts only to worsen expectations of the future.

The large increases in uncertainty during the 2008 recession has stimulated research into better proxies to measure uncertainty. These focus on macroeconometric estimates of time varying volatility, cross-sectional dispersion of firms earnings or productivity, and direct measures of perceived uncertainty in the form of forecast distributions from surveys of professional forecasters.

The literature developing proxies for uncertainty was initiated by Bloom (2009) who uses large shifts in U.S. stock market volatility as a proxy for exogenous changes in uncertainty. He finds this measure is a leading indicator for declines in industrial output and employment with a short recessionary effect and a subsequent period of recovery and positive catch-up growth. This pattern is explained as due to drops in real activity as investment and hiring plans are paused in response to higher uncertainty but can be quickly rekindled as this uncertainty dissipates. Baker et al. (2012) develop an economic policy uncertainty index for the U.S. comprised of a a frequency count of news stories on uncertainty about the economy or fiscal and monetary policy, the number and revenue impact of scheduled federal taxes set to expire, and the extent of disagreement among economic forecasters over future government purchases and future inflation. Dendy et al. (2013) pursue a similar methodology for the U.K. focusing on economic rather than policy uncertainty with an index composed of a newspaper search, variation in forecasts of economic variables and mentions of uncertainty in the Bank of England Monetary Policy Committee (MPC) minutes and Financial Stability Reports (FSRs). Both studies find similar results to Bloom's original study, although without the positive growth catch-up phase, with large negative real effects on employment and industrial production which peak after 1 year to 18 months, respectively, after the shock.

Studies that make exclusive use of forecaster disagreement from surveys of professional forecasters include Dovern et al. (2012), who find that these measures matters more for nominal than real variables in the G7, Bachmann et al. (2013), who use German business climate surveys and find significant (but short lived) decline in production, and Leduc and Liu (2012) who measure perceived uncertainty directly as the fraction of respondents in surveys of businesses and consumers indicating uncertainty about the future as a factor limiting their spending plans (cars for consumers or capital expenditure for firms). The latter find evidence that uncertainty shocks are prototypical aggregate demand shocks with delayed declines in inflation, employment and short term interest rates.

Other studies aim to measure the role of uncertainty through econometric techniques to estimate the time varying volatility of macroeconomic time series. Mumtaz and Zanetti (2013), studying U.S. data, augment a standard SVAR model to allow for time variation in the volatility of identified monetary policy shocks where the level of endogenous variable included in the VAR and this time varying volatility dynamically interact. They find similar results to Leduc and Liu (2012) with a demand shock like response of falling output, interest rates and inflation. Mumtaz and Surico (2013) extended this to measures of fiscal policy uncertainty using the same methodology. They find that uncertainty about public debt sustainability, government spending and tax changes all have significant contractionary effects on GDP. Using a more structural econometric approach Fernandez-Villaverde et al. (2011a) estimate volatility of government spending and taxes and feed this series of volatility estimates into a general equilibrium model finding similar contractionary patters for real variables, however, their model indicates that fiscal uncertainty shocks have potentially inflationary effects. Using a similar methodology, Fernandez-Villaverde et al. (2011b), study time-varying volatility in the real interest rates of four emerging small open economies: Argentina, Ecuador, Venezuela, and Brazil. They find that real interest rate volatility leads to a fall in output, consumption, investment, and hours worked. A recent alternative econometric approach pursued by Jurado et al. (Forthcomming) measures macroeconomic and financial uncertainty as the conditional variance of the unforecastable component common to a large number of firm-level, macroeconomic and financial variables. This approach indicates uncertainty episodes are less common than the above proxies tend to indicate but that when spikes in uncertainty do occur they are larger and more persistent. These authors find the real macroeconomic effects of their measure of uncertainty lead to a large and protracted drop in real activity (production, hours, employment) without the growth catch-up period found in Bloom (2009). Their results do agree with the results of Bloom (2009); Bloom et al. (2012) in finding a countercyclical pattern to cross-sectional dispersion in firm earnings and productivity however they only find a recessionary effect for an increase in productivity dispersion.

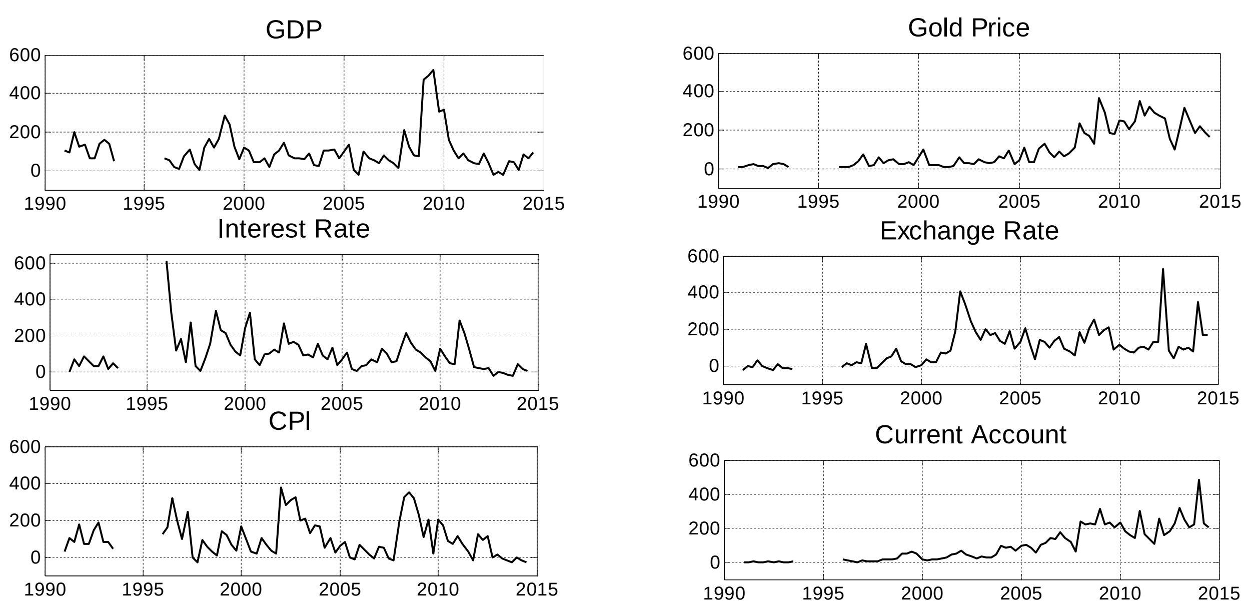
The above results have been challenged by Popescu and Smets (2010) and Gilchrist et al. (2013a), who argue that once a measure of financial stress, as proxied by credit spreads, is included in these regressions the independent role of uncertainty shocks becomes minimal. Popescu and Smets (2010), studying German data, use a VAR with forecaster dispersion as a proxy for uncertainty and credit spreads (corporate and mortgage bond rates to government bonds rates) as a measure of financial stress. They show that the real effects of financial stress are much larger and persistent than those of uncertainty with lower inflation and GDP, and higher unemployment.

In contrast to the findings above, they find uncertainty shocks are inflationary once financial stress is controlled for. Similarly, Gilchrist et al. (2013a) seek to discriminate between financial and uncertainty shocks role in the business cycle. Their identification procedure uses a penalty function method of Uhlig (2005) to (1) extract the shock explaining the largest forecast error variance of corporate credit spreads (adjusted for predictable default) then (2) do the same for an uncertainty proxy (realised volatility of cross-sectional stock market returns) conditional on the financial shock identified in the first step. They then repeat this procedure but reversing the order of shocks. The first identification strategy makes it hard for uncertainty shocks to matter, but it extracts the most powerful financial shock in the system and the second strategy delivers the most powerful uncertainty shock by minimizing the role played by financial shocks. They find that financial shocks are important drivers of the business cycle but that uncertainty shocks are not unless they have their effect through a financial channel i.e. by tightening credit conditions.

2 Measuring macroeconomic uncertainty

I construct an index of economic uncertainty following Dendy et al. (2013) for the period 1990-2014. The index is constructed from three sources: (1) Disagreement among professional forecasters about macroeconomic conditions, (2) a count of international and local newspaper articles discussing economic uncertainty in South Africa and (3) mentions of uncertainty in the quarterly economic review of the SARB.

Figure 1: Forecaster Disagreement



Source: *Die Beeld* Newspaper Economist of the Year Competitions. Normalised standard deviation of forecasts across forecasters. Normalised to have a mean and standard of 100 for each variable for the sample period of 1990-2014.

2.1 Forecaster disagreement

I use a novel data source to capture forecaster disagreement. Since 1988 the South African national daily newspaper *Die Beeld* has run a forecasting competition for professional forecasters from the private and public sector. Contestants are asked to make nowcasts (estimates of current year) and forecasts (estimates for next year) for real GDP growth, CPI inflation, the short term interest rate, gold price, Rand/Dollar exchange rate and the level of current account. The newspaper reports both the mean and standard deviation of across forecasters. I use the reported standard deviation for nowcasts across forecasters as my measure of forecaster disagreement. I use nowcasts since one year ahead forecasts are only available for GDP and CPI from 1996. Gaps in availability of the monthly publication of this data is overcome by aggregating to quarterly through averaging. Unfortunately there remain gaps in this data for 1990 and 1993Q4-1995Q4. To make these comparable I standardise each series to have a mean and standard deviation of 100: $y_q = 100 + 100\left(x_q - \overline{x}\right)/\sigma_x$. Where x_q is the quarterly data, y_q is the standardised value; $\overline{x}$ is the mean and σ_x the standard deviation calculated from the entire sample.

Forecaster disagreement is higher across all variables during the 2008 recession with the most pronounced response for GDP, CPI inflation and the Gold Price (see figure 1). The Asian crisis of 1999 and subsequent financial distress associated with Russia's default on its sovereign debt along with the collapse of Long Term Capital Management had a contagion effect on the Rand with a substantial depreciation in 2001. This appears to introduce greater exchange rate and inflation uncertainty in the next 5 years following this episode. While domestic uncertainty (that over GDP, Interest rates and CPI) has decreased after the great recession, external uncertainty (Gold Price, Exchange Rate, Current Account) remains elevated. The pattern in uncertainty in the gold price and current account mimics the levels of these variables[1].

Two alternative methods of construction were explored. The first considered use of forecasts instead of nowcast estimates which resulted in a highly similar series (see appendix) and almost no change in the final index to measure uncertainty. The second was using the adjustment of Dovern et al. (2012) to convert the fixed event forecasts in the data to approximate fixed horizon forecasts which are better suited to the notion of uncertainty. Fixed event forecasts are forecast made regarding a fixed event, such as GDP growth in 1992 and forecasters are surveyed as they approach this date. Fixed horizon forecasts are when forecasters give an estimate a fixed time horizon away e.g. forecasters give their estimate for GDP growth 1 year from the time the are surveyed regardless of when they are surveyed. I describe the approximation in the appendix and show that the results are very similar.

[1]The gold price rose from lows of around \$300 in the early 2000s to over \$1750 in 2011, falling thereafter back down to \$1250 by the end of 2014. Similarly the current account to GDP ratio has deteriorated from a surplus of in the early 1990s to a consistent deficit since with a declining trend (around -5% in 2014). Similar depreciation trend is relevant for the Rand with a spike in 2001 and 2009.

2.2 News and policy uncertainty

To measure economic uncertainty by news stories I use the Nexis U.K. database of national and international newspapers. I searched for stories based on inclusion of the word stem "econ*" within 10 words of the stem "uncert*" within 10 words of "South Africa"[2]. An informal audit of these results showed that the stories were, in general, about economic uncertainty in South Africa rather than unrelated stories that happen to contain these words. Since the number of articles produced and archived varies over time I normalise the number of articles found in the previous step by the number of articles found that include the term "today" within 10 words of "South Africa". This is similar to the normalisation used in Baker et al. (2012) where they normalise by the number of articles in the database each month and Dendy et al. (2013) who normalise by the use of the key word "the" for the U.K. newspapers in their archive. This series is normalised to have a mean and standard deviation of 100 as before.

The results show peaks in uncertainty around 1992Q2,1996Q1, 1999Q1, 2003, 2008Q3 and 2010Q1 (see figure 2). The spike in 1992Q2 relates to news about political and economic change surrounding the end of Apartheid and its potential to extend the protracted recession that began 1989Q4. The rise in 1996Q1 relates to EU/South African free trade area talks, 1999Q1 relates to sharp movement in the Rand, 2003 relates to stagflation induced by the large and persistent exchange rate depreciation in 2001. The spike in 2008Q3 relates to political uncertainty surrounding the resignation of President Thabo Mbeki and potential corruption charges for the leading candidate to succeed him, Jacob Zuma; as well concerns about global financial developments affecting the domestic economy. News in 2010Q1 was dominated by discussion relating to economic recovery after the 2008 global financial crisis, further deterioration of neighbouring Zimbabwe and concerns over political stability under President Jacob Zuma.

Uncertainty from the perspective of policy makers is measured by searching for mentions of the word stem "uncert*" in the Quarterly Economic Review found in the Quarterly Bulletin of the SARB for 1990-2014. Although published by the monetary authority, this review is broad and covers a range of developments including domestic production, labour markets, housing markets, foreign trade and payments, financial markets and public finance[3]. This is done using the free text analysis software AntConc (Anthony (2014)). This series is normalised to have a mean and standard deviation of 100 as before.

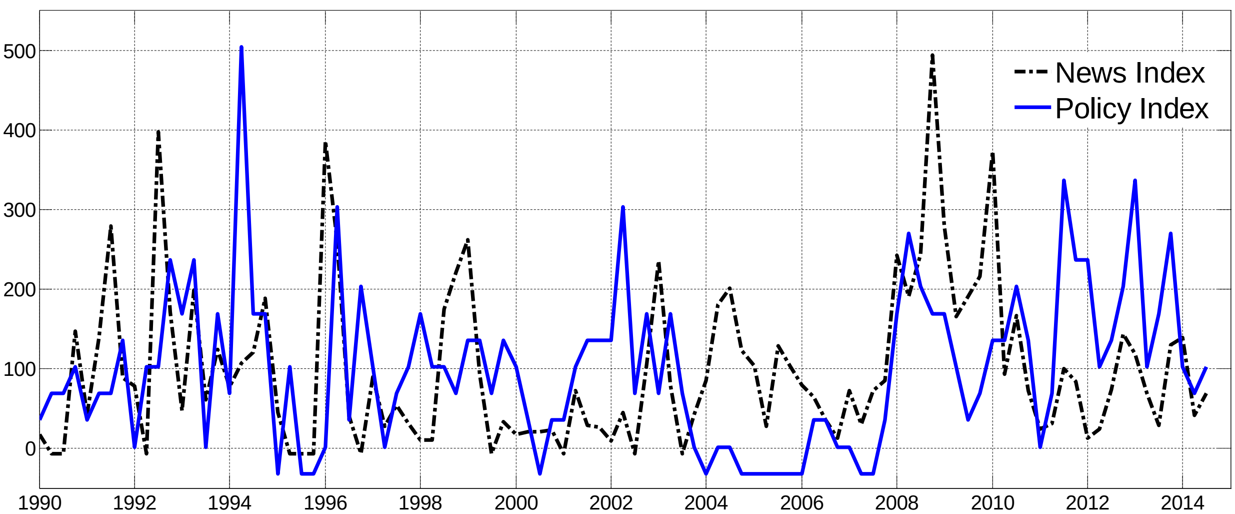
Periods of outstanding uncertainty are 1994Q2, 1996, 2002Q1, 2008Q2 and the period from 2011Q2 onward (see figure 1). April 1994 saw the first democratic elections in South Africa. Unsurprisingly, policy makers were unsure of the political and regulatory environment to follow. 1996 saw elevated levels of turbulence in the demand for South African sovereign bonds, leading to

[2]The use of the stem econ* means that terms like uncertain, uncertainty,uncertainties, etc. will all be included in the search.

[3]Fiscal policy documents, such as the annual budget, and analysis from international organisations, such as the IMF Article IV country reports, are not available at the required frequency (quarterly) and for the sample period.

a SARB injection of liquidity by taking 2/3 of a Treasury Bill tender in May. Political uncertainty and labour market unrest helped amplify these concerns leading to bond yield and exchange rate volatility. Uncertainties surrounding the U.S recession, domestic equity market volatility and the large depreciation of the currency are responsible for the peak in 2002Q1. 2008Q2 relates to concerns due to the global financial crisis. The period after 2011 is driven by the chicanery around raising the U.S. federal debt ceiling, the earthquake in Japan, continued uncertainty regarding the stability of the Euro and concerns over the impact of future rises in interest rates in the U.S..

Figure 2: News and policy based measures of uncertainty

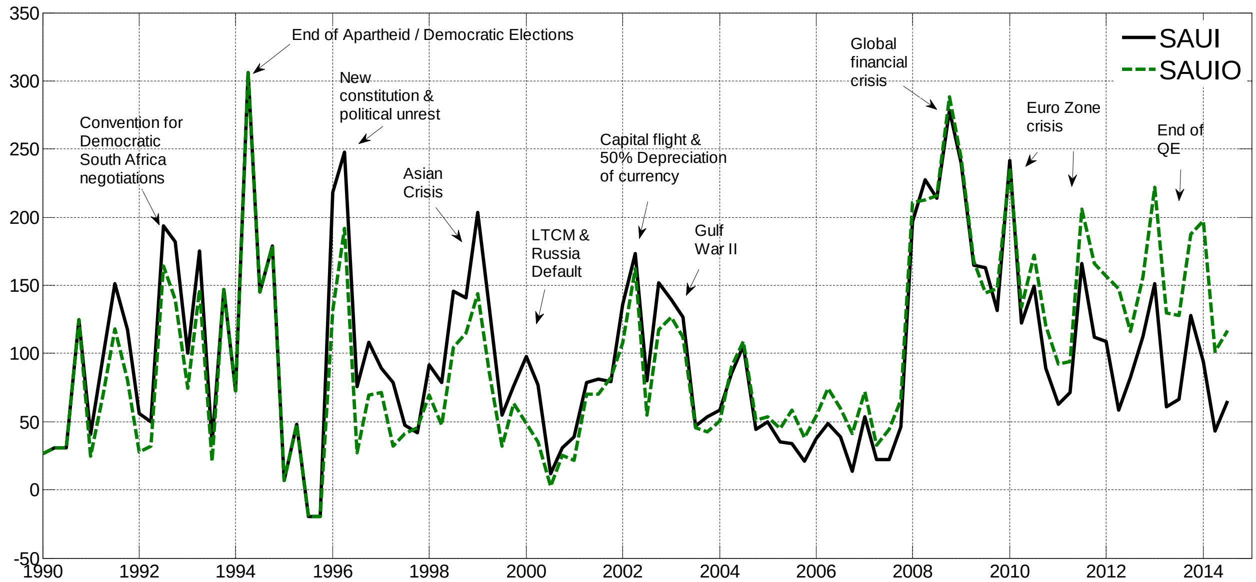


Sources: Nexis U.K. newspaper archive (News) , SARB Quarterly Bulletins (Policy). The News index is a count of articles with the word stem "econ*" within 10 words of the stem "uncert*" within 10 words of "South Africa" for international and South African Newspapers normalised by a count of articles with the term "today" within 10 words of "South Africa". The policy index is a count of the word stem "uncert*" in the Quarterly Economic Review found in the Quarterly Bulletin of the SARB. Both series are normalised to have a mean and standard deviation of 100.

2.3 Macroeconomic uncertainty index

I construct 2 indices of macroeconomic uncertainty. The first uses an equally weighted average of the (standardised) values of forecaster disagreement over GDP, CPI and interest rates and the second, disagreement over the gold price, exchange rate and the current account balance. The first captures domestic issues, the second has more focus on open economy developments. Each index is an equally weighted average of forecaster disagreement with the (standardised) values of news uncertainty and policy uncertainty mentioned above (see figure 3). I label the index with domestic focus SAUI and the open economy analogue SAUIO.

Figure 3: Macroeconomic Uncertainty Indices



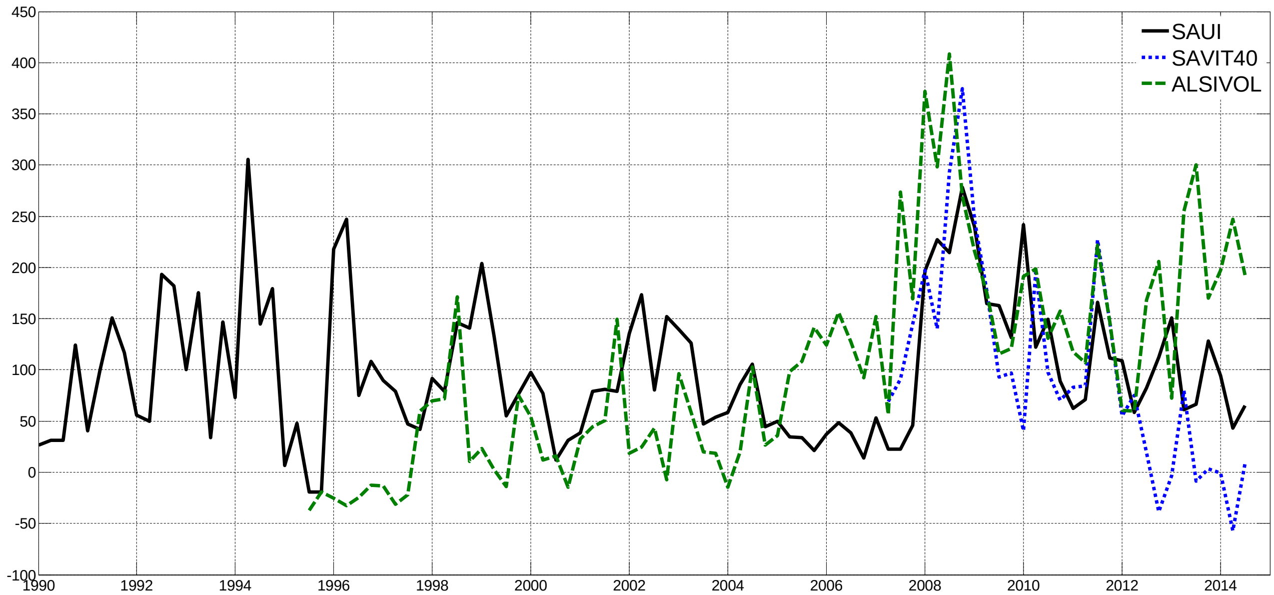
SAUI is an equally weighted average of the normalised values of (1) forecaster disagreement over GDP, CPI and interest rates; (2) News index; (3) Policy index. SAUIO is identical except the first term is (1) forecaster disagreement over the gold price, exchange rate and the current account balance

The two peak periods of uncertainty effectively identify the key drivers of uncertainty in the first half and second half of the 1990-2014 period. The first peak in 1994, and the period of the 1990s, is principally driven by political uncertainty. The second peak around the 2008 global financial crisis is typical of the period after 2000 when developments in global economy have a contagion effect on South Africa. The 1990s was the most politically turbulent in modern South African history with the unbanning of political organisations, the release of political prisoners along with violent political unrest e.g. around the negotiations to end Apartheid at the Convention for a Democratic South Africa (CODESA). The period after 2000 saw a depreciation of the currency of almost 50% from 2000 to 2002 due to capital flight associated with destabilising effects of the earlier Asian crisis and collapse of Long Term Capital Management in 2000. The period of 2002-2007 saw the highest levels of post-Apartheid GDP growth, off high consumption levels and strong house price growth that ended with the contagion effects of the global financial crisis in 2008. Continued external uncertainty relating to the protracted recovery from the episode, especially surrounding the eurozone (South Africa's largest trading partner) and the potentially destabilising effects of the large interest rate differential with developed markets closing when central banks raise base rates above zero for the first time in half a decade. Due to little independent variation in the two indices, I use the SAUI index for the empirical section below.

This measure of uncertainty accords well with other proxies for uncertainty: realised daily volatility of the Johannesburg Stock Exchange All Share index (ALSIVOL) and a measure of option implied volatility based on the 40 largest shares by market value on the JSE index (SAVIT40) -

see figure 4.

Figure 4: Comparison with realised and implied stock market volatility



Sources: Bloomberg, author's calculations. SAUI is the index described in section 2.3, ALSIVOL is the standard deviation of the daily JSE All Share index over each quarter, SAVIT40 is a weighted average of call and put options on JSE Top 40 (i.e. the 40 largest shares on the JSE All Share index) expiring within 3 months and is thus a measure of expected equity market volatility. All series are normalised to have mean and standard deviation of 100.

3 Impact of uncertainty shocks

3.1 VAR model

The benchmark model estimated below is:

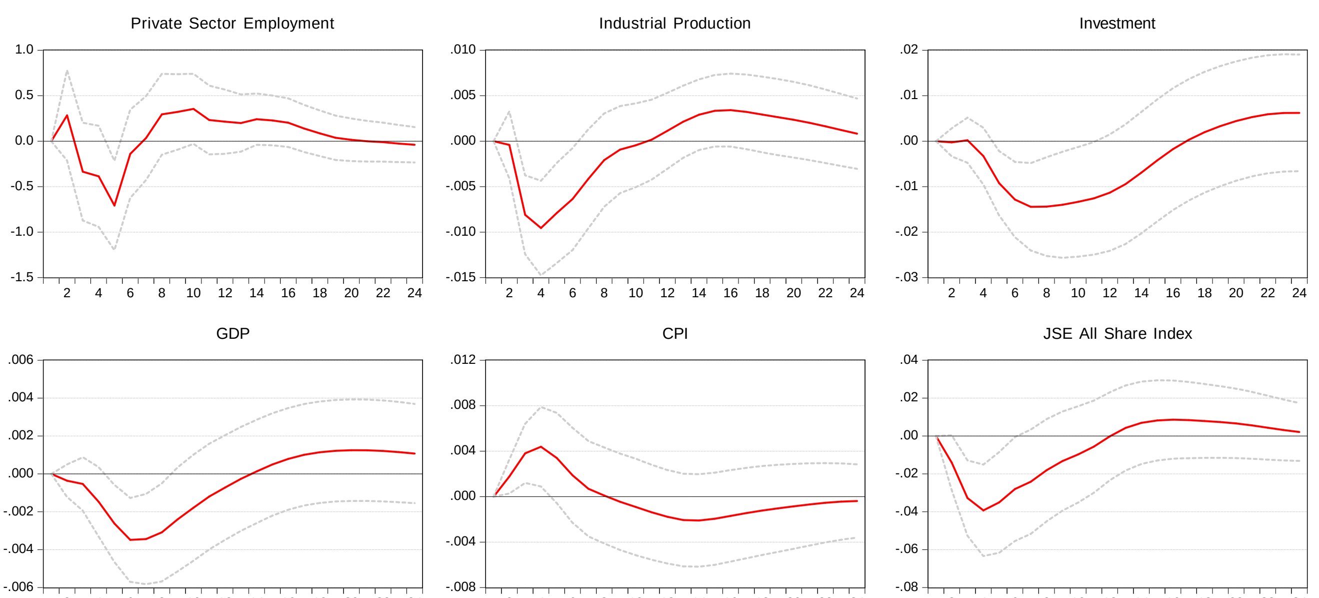
$$\mathbf{Y_t} = \mathbf{A_0} + \mathbf{A_1 t} + \mathbf{B(L)Y_{t-1}} + \mathbf{e_t}$$

Where $\mathbf{B(L)}$ is a matrix lag polynomial of coefficients which are estimated with OLS, $\mathbf{t}$ is a linear time trend, and $\mathbf{e_t} \sim \mathcal{N}(0, \Sigma)$. The variables included in the matrix $\mathbf{Y_t}$ are private sector employment rate, log of Industrial production, log of investment, log of GDP, log of the CPI index, log of the JSE All Share Index, 10 year government bond yield, Repurchase rate of the Reserve Bank and the SAUI index. The sample is quarterly and runs from 1990 to 2013Q4. The Schwarz information criteria calls for only 2 lags however I extend this to a lag lenth of 3 based on tests of no serial correlation and normality of the error term $\mathbf{e_t}$.

To identify the structural shocks I use a Cholesky decomposition of $\hat{\Sigma}$ using a ordering as described above. This identification assumption follows the convention in the VAR literature of assuming that the slower moving macro variables are ordered before fast moving financial variables (for example Popescu and Smets (2010)). The macro bloc is ordered with quantities first and the price level afterwards. I order uncertainty last since it is predominately a measure of agents expectations (which can change very quickly). The results are robust to alternative orderings (see appendix).

An unanticipated rise in the uncertainty index is associated with a decline in output, employment, asset prices and investment in the future (see figure 5). The effects are most pronounced for industrial production and investment with a peak fall in industrial production of almost 1% after 1 year and 1.5% after 1.5 years for investment. These results are broadly in line with the findings in the literature where a strong response of industrial production to uncertainty (Baker et al. (2012); Dendy et al. (2013); Leduc and Liu (2012)). Similarly the strong response of investment accords with the real options view of uncertainty whereby higher levels of uncertainty have a significant effect on investment decisions of firms (Bernanke (1983); Bloom (2009); Bloom et al. (2012)). The effects on GDP and the employment rate are more moderate but still significant with a peak impact of 0.6% and 0.37% after a year and a half, respectively. Asset prices respond with a peak decline of around 4% after a year. Similar negative responses to asset prices have been found for the U.K., although with much less persistence (Dendy et al. (2013)). In contrast to the studies of (Leduc and Liu (2012)) for the U.S. who find that uncertainty shocks are deflationary, I find that they are associated with 0.45% increase in the price level after about 1 year. Variance decompositions show that almost 25% of the forecast error variance of industrial production is explained by uncertainty shocks (figure 6). Similarly, the index is an important component of the variance of the stock market and investment as well as GDP

Figure 5: Impulse Responses to SAUI

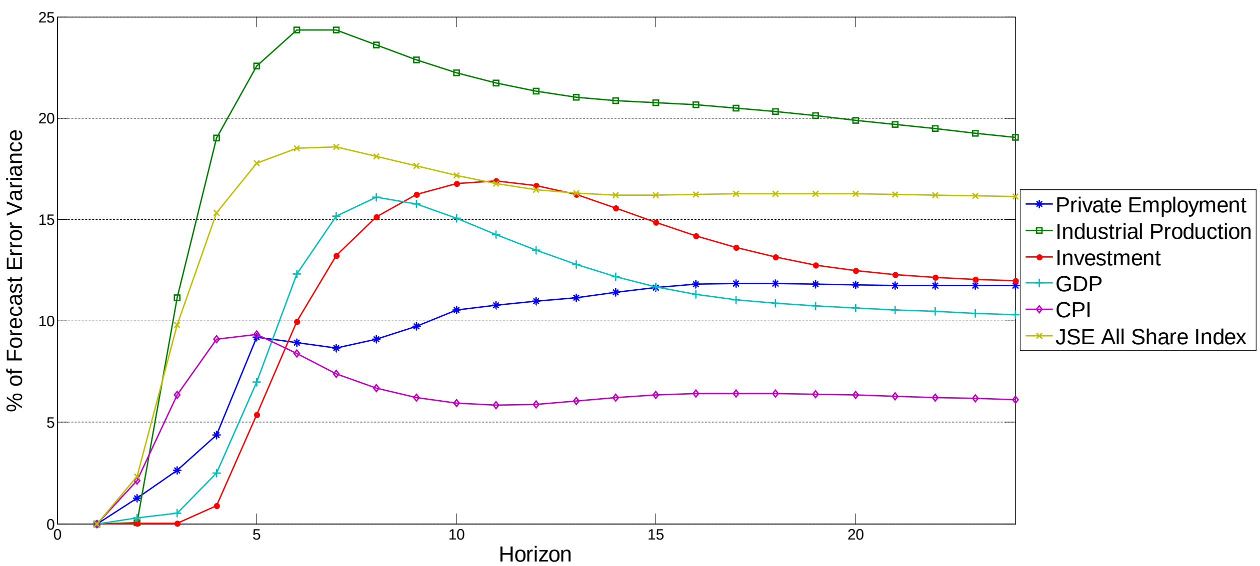


Response to Cholesky One S.D. Innovations ± 2 S.E. Sample is from 1990Q1-2013Q3. Cholesky ordering is the baseline: (1) Private Employment Rate (2) log(Industrial Production) (3) log(Investment) (4) log(GDP) (5) log(CPI) (6) log(All Share Index) (7) 10 Year Government Bond Yield (8) Repo Rate (9) Uncertainty Index SAUI

3.2 Robustness

These results extend the findings for developed nations that uncertainty shocks are an important source of business cycle fluctuations. In order to test the robustness of these results I augment the VAR above to include consumer confidence and a measure of the financial stress, in the form of a bank lending credit spread. The first robustness check follows Baker et al. (2012), who include consumer confidence in order to disentangle uncertainty (a mean-preserving increase in the variance of macro variables) from that of bad news (a change in the mean). Consumer confidence is the OECD consumer opinion survey composite indicator. The second is motivated by the recent debate in the literature that the effects of uncertainty shocks are primarily through their impact on financial conditions, i.e. higher uncertainty matters because it raises risk levels and credit spreads, but have little effect in themselves. Gilchrist et al. (2013b), studying the U.S., and Popescu and Smets (2010), looking at German data, find that once credit conditions are controlled for the impact of uncertainty shocks on the real economy is relatively modest. Those authors used the spread of corporate to government bond yields as a proxy for financial stress.

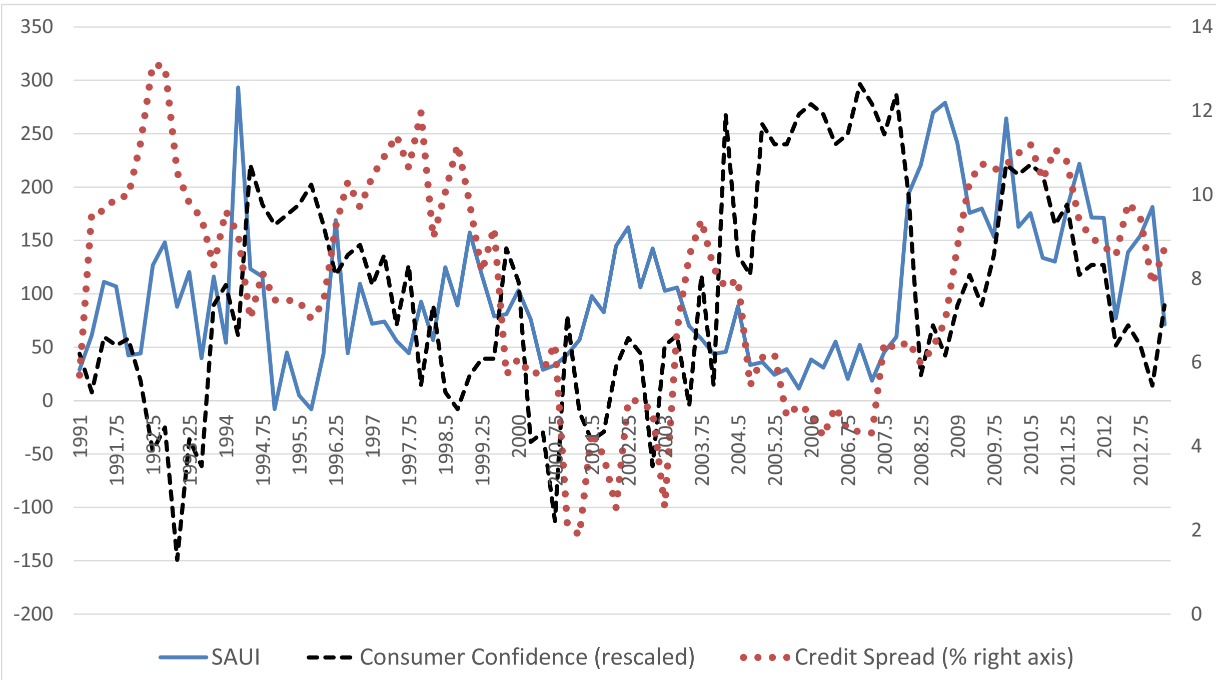
Figure 6: Contribution of SAUI to Forecast Error Variance



Sample is from 1990Q1-2013Q3. Cholesky ordering is the baseline: (1) Private Employment Rate (2) log(Industrial Production) (3) log(Investment) (4) log(GDP) (5) log(CPI) (6) log(All Share Index) (7) 10 Year Government Bond Yield (8) Repo Rate (9) Uncertainty Index SAUI

Unfortunately, the bond market in South Africa is dominated by government instruments, and features only a small number of (mostly state owned) firms (Hassan (2013)). Thus using a market based measure of corporate spreads would be undesirable. Instead, I construct a measure of the bank lending conditions facing firms as the spread on new fixed-rate instalment sale credit over the 3 month Negotiable Certificate of Deposit rate at banks. The first measures credit conditions facing firms and households seeking credit on movable property and the second is closely tied to the South African Benchmark Overnight Rate (Sabor) used for interbank lending, however a longer series is available for the Negotiable Certificate of Deposit rate. Both series are available from the SARB.

Figure 7: Uncertainty, Consumer Confidence and Credit Spreads



Source: Authors calculations, SARB, FRED database of St. Louis Federal Reserve. Consumer confidence is the OECD consumer opinion survey composite indicator from FRED (CSCICP02ZAQ460N). Credit Spread is the difference between the bank lending rate on new fixed-rate instalment sale credit (KBP1181M) less the NCD rate (KBP1411W).

Consumer confidence and uncertainty are negatively correlated (see figure 7). Consumer confidence improves during the boom years of the early 2000s and collapses in 2008 as the financial crisis hits, uncertainty follows the inverse pattern. Credit spreads are weakly positively correlated with uncertainty (28%) with generally lower spreads during boom years and a spike in rates as the global financial crisis hits South Africa. Interestingly, this spike only happens about a year after the spikes in uncertainty and consumer confidence. It took about a year for the contagion effects of dislocation in credit markets in the U.S. and Europe to translate into a recession in South Africa. This is reflected in lending conditions. This timing is helpful to distinguish the role of uncertainty from financial stress in that these two were not as highly correlated as in the markets where the global financial crisis originated.

The baseline results are robust to the inclusion of both consumer confidence and the credit spread measure. However, the size of the effects of uncertainty on industrial production, GDP and CPI are moderated (to about 2/3 of the decline found in the baseline). This result is noteworthy as, for example, Bachmann et al. (2013) finds that effects of uncertainty shocks are not robust to the inclusion of consumer confidence. Moreover, the evidence in developed markets that uncertainty only matters as a proxy for financial stress is not supported by these findings. Robustness to Cholesky ordering is shown in the appendix.

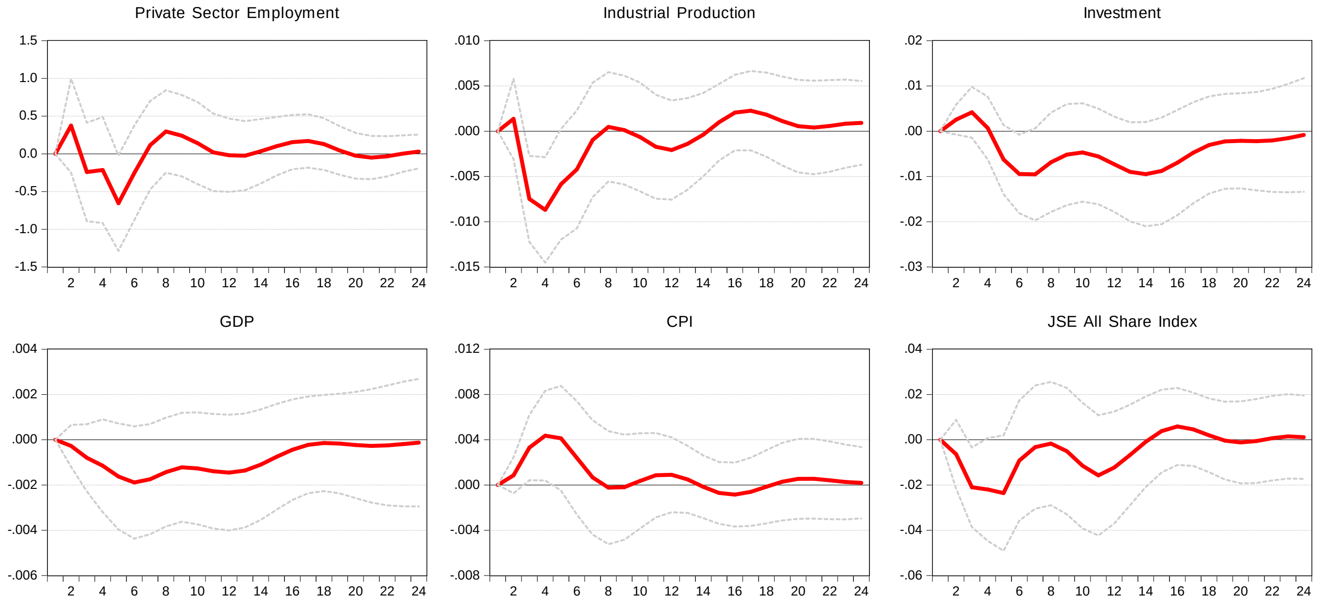
Figure 8: Impulse Responses to SAUI

Response to Cholesky One S.D. Innovations ± 2 S.E.

Response to Cholesky One S.D. Innovations ± 2 S.E. Sample is from 1990Q1-2013Q3. Cholesky ordering is : (1) Private Employment Rate (2) log(Industrial Production) (3) log(Investment) (4) log(GDP) (5) log(CPI) (6) Credit Spread (7) log(All Share Index) (8) 10 Year Government Bond Yield (9) Repo Rate (10) Confidence Index (11) Uncertainty Index SAUI

The series for forecaster disagreement has missing data for 1992,1994 and 1995. Thus the uncertainty index is comprised only of news and policy uncertainty for these years. To check the robustness of the results to this I repeat the baseline regressions for 1996-2013. This drop in sample size from (96 to 72) mechanically increases the width of confidence intervals and makes it harder for the results to be significant. Despite this all the baseline results hold with the exception of GDP, which is not significant although the response is otherwise similar (see figure 9).

Figure 9: Response to SAUI with shorter sample



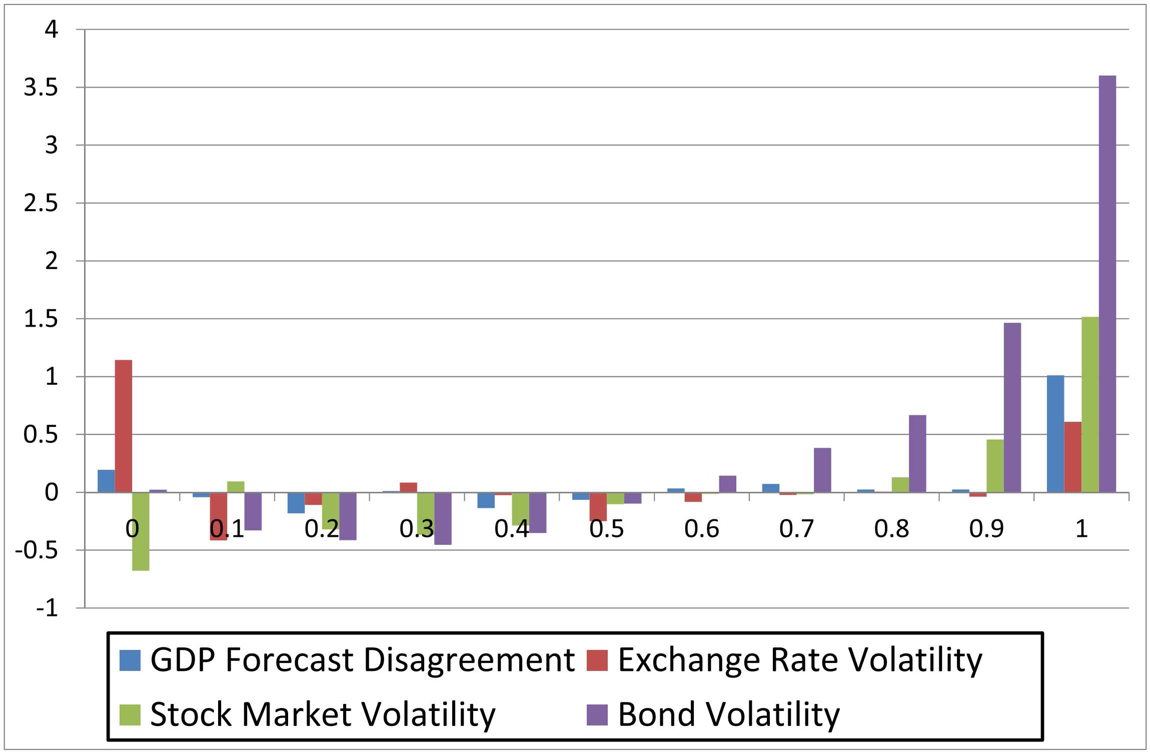
Response to Cholesky One S.D. Innovations ± 2 S.E. Sample is from 1996Q1-2013Q3. Cholesky ordering is the baseline: (1) Private Employment Rate (2) log(Industrial Production) (3) log(Investment) (4) log(GDP) (5) log(CPI) (6) log(All Share Index) (7) 10 Year Government Bond Yield (8) Repo Rate (9) Uncertainty Index SAUI

3.3 Discussion: are uncertainty shocks inflationary?

It is uncommon to find that uncertainty shocks are deflationary in VAR studies (Baker et al. (2012); Dendy et al. (2013); Leduc and Liu (2012); Mumtaz and Zanetti (2013)). However, Popescu and Smets (2010), controlling for credit spreads, do find evidence of inflation following an uncertainty shock for Germany. In this section I provide suggestive evidence that this association is plausible from a cross-country perspective. I augment the cross-country dataset of Baker and Bloom (2013) to include inflation. This data covers 60 developed and developing countries from the years 1980-2013 and four proxies for uncertainty: macro and micro stock volatility, exchange rate volatility, bond yield volatility and GDP forecast disagreement[4]. Figure 10 presents the average levels of each normalised uncertainty proxy (mean of zero and standard deviation of 1) conditional on the inflation decile for the group of countries. For example, the group of countries collected in bin 0.2 have average inflation rates form 1980-2013 in the 3rd decile of the 60 country group. The figure provides evidence that uncertainty and inflation may well be positively related, at least in terms of long run averages. However, this doesn't provide causal evidence in favour of this relationship. In the next section I use a standard New Keynesian model to explore causality further.

[4]Proxies are not available for all regions, esp. for the GDP forecast disagreement measure. For example, none is present for South Africa. The dataset can be accessed at http://www.stanford.edu/~nbloom/bakerbloom2.zip

Figure 10: Inflation deciles and proxies for uncertainty for 60 countries



Source: Baker and Bloom (2013), World Bank.

Each bin is a decile for the average inflation rate 1980-2013 for the group of countries. Thus the 0 bin represents the 10% of countries with the lowest inflation. Each measure of uncertainty is normalised to have a mean of 0 and standard deviation of 1 over the entire 60 counrty dataset.

4 Model

Exploring the impact of uncertainty shocks with a SVAR has the appealing feature that it imposes minimal restrictions on the data (in contrast with estimating a fully specified DSGE model). This comes at the costs of the causal channels through which uncertainty has its effects being less clear. In order to better understand these channels, I study the effects of volatility shocks in a simple New Keynesian DSGE model. This simple model is the basis for most medium scale models used in central bank and policy work (for example Smets and Wouters (2003)) and is based on Woodford (2010). I augment the model to include shocks to the volatility of exogenous technology. The introduction of time-varying volatility necessitates the use of higher order solutions to the model since a linear solution cannot capture the inherently non-linear relationship between volatility shocks and the endogenous variables. I solve the model using a third-order perturbation about the steady state and study the results computing impulse responses as deviations from the ergodic steady state following Fernandez-Villaverde et al. (2011b). The model consists of a representative household, a continuum of monopolistically competitive firms each producing a different variety of goods and setting prices subject to nominal rigidities as per Calvo (1983), and a monetary policy maker.

4.1 Households

The economy is populated by identical infinitely-lived households who choose their consumption, labour supply and holdings of nominal bonds to solve:

$$\max_{\{C_t,H_t,B_t\}_{t=t_0}^{\infty}} U_{t_0} = E_0 \sum_{t=t_0}^{\infty} \beta^{t-t_0} \left\{ \frac{C_t^{1-\frac{1}{\sigma}}}{1-\frac{1}{\sigma}} - \frac{H_t^{1+\frac{1}{\psi}}}{1+\frac{1}{\psi}} \right\} \tag{1}$$

$$s.t. \;\; P_t C_t + Q_{t,t+1} B_t \leq B_{t-1} + W_t H_t + \Upsilon_t + T_t$$

C_t is an index of aggregate consumption, H_t is hours of labour supplied, W_t is the nominal wage, T_t are net government transfers, Υ_t are profits from firms. Households have access to complete asset markets where they can trade one-period bonds, B_t, at a price $Q_{t,t+1}$. Aggregate consumption, C_t, and the price level, P_t, are defined with the Dixit-Stiglitz aggregator over individual consumption good varieties, $C_t(i)$, and their prices, $P_t(i)$:

$$C_t = \left[\int_0^1 C_t(i)^{\frac{\epsilon-1}{\epsilon}} di \right]^{\frac{\epsilon}{\epsilon-1}} \qquad P_t = \left[\int_0^1 P_t(i)^{1-\epsilon} di \right]^{\frac{1}{1-\epsilon}} \tag{2}$$

Where ϵ is the elasticity of substitution between varieties of goods. The solution to the households problem, (1), entails the following intra-temporal labour supply condition and bond price:

$$\frac{W_t}{P_t} = \frac{v_h}{u_c} = C_t^{\frac{1}{\sigma}} H_t^{\frac{1}{\psi}} \tag{3}$$

$$Q_{t,t+1} = \beta E_t \left(\frac{C_t}{C_{t+1}} \right)^{\frac{1}{\sigma}} \frac{P_t}{P_{t+1}} \tag{4}$$

4.2 Firms

There is a continuum of monopolistically competitive firms where each variety of good, indexed by $i \in [0,1]$, is supplied by a single producer. The i^{th} firms buys labour hours, $N(i)$, from households on a competitive labour market. The productivity of workers depends on the aggregate level of exogenous technology, A_t, which is subject to time-varying volatility:

$$\log A_t = \rho_a \log A_{t-1} + \sigma_t^A \epsilon_t$$

$$\log \sigma_t^A = (1-\rho_\sigma)\log \sigma^A + \rho_\sigma \log \sigma_{t-1}^A + \nu \eta_t \tag{5}$$

Where $\epsilon_t \sim \mathcal{N}(0,1)$ and $\eta_t \sim \mathcal{N}(0,1)$. The mean level of the log of volatility in technology is σ^A and the size of volatility shocks is parametrised by ν. Firms face diminishing marginal returns to labour, governed by α, where $Y_t(i) = A_t(N_t(i))^{1-\alpha}$. Each producer faces a downward sloping demand curve for their variety of goods based on the Dixit-Stiglitz preferences described above:

$$Y_t(i) = \left(\frac{P_t(i)}{P_t}\right)^{-\epsilon} Y_t \tag{6}$$

Y_t is the aggregate demand for the consumption basket C_t defined in (2). Producers are subject to Calvo (1983) price rigidities which implies that $P_t(i)$ need not equal the aggregate price level P_t as only a subset of firms are able to reset prices each period giving rise to a measure of cross-sectional price dispersion:

$$\Delta_t \equiv \int_0^1 \left(\frac{P_t(i)}{P_t}\right)^{-\epsilon(1+\eta)} di \ \geq 1 \tag{7}$$

Where $\eta = \frac{\alpha}{1-\alpha}$. Producers face a fixed probability, ω, of being able to reset their price each period. Thus each firm takes into account that the price chosen today, t, has a probability of survival of ω^{T-t}, after T periods have passed. Thus a firm able to reset their price at time t will solve the following problem:

$$\max_{\{P_t(i)\}_{t=t_0}^{\infty}} E_t \sum_{T=t}^{\infty} \omega^{T-t} Q_{t,T} \Upsilon(P_t(i), P_T, Y_T; A_T) \tag{8}$$

Where $Q_{t,T}$ is the value placed on nominal profits returned to the household T periods hence (see equation (4)) and Υ is nominal profits. The first order conditions for profit maximisation is:

$$E_t \sum_{T=t}^{\infty} \omega^{T-t} Q_{t,T} \Upsilon_1(P_t(i), P_T; Y_T, A_T) = 0 \tag{9}$$

All firms able to reset their price will make the same choice (as they are identical) thus $P_t(i) = P_t^*$. Given the assumptions made above a convenient closed form relationship characterising aggregate supply in the economy can be derived:

$$\left(\frac{P_t^*}{P_t}\right) = \left(\frac{F_t}{K_t}\right)^{\frac{-1}{1+\epsilon\eta}} \tag{10}$$

F_t captures the expected future nominal (marginal) revenue and K_t captures expected future nominal (marginal) costs. These functions are the key forward looking variables in the model that lead to the New Keynesian Phillips curve. They are defined by:

$$F_t = f(Y_t) + \omega\beta E_t \Pi_{t+1}^{\epsilon-1} F_{t+1} \tag{11}$$

$$K_t = k(Y_t, X_t, \Delta_t; A_t) + \omega\beta E_t \Pi_{t+1}^{\epsilon(1+\eta)} K_{t+1} \tag{12}$$

Where $f(Y_T) = (1-\tau)Y_T^{1-\frac{1}{\sigma}}$ and $k(Y_T, X_T, \Delta_T; A_T) = \mu\,(1+\eta)\left(\frac{Y_T}{A_T}\right)^{1+\chi}(\Delta_T)^{\frac{1}{\psi}}$ and μ is firms desired steady state mark-up, $\frac{\epsilon}{\epsilon-1}$. The Calvo scheme entails that the price index evolves according to:

$$P_t^{1-\epsilon} = (1-\omega)\left(P_t^*\right)^{1-\epsilon} + \omega P_{t-1}^{1-\epsilon} \tag{13}$$

Which can be used in conjunction with (10) to yield an equation governing the behaviour of inflation each period, analogous to an aggregate supply relation:

$$\frac{1-\omega\Pi_t^{\epsilon-1}}{1-\omega} = \left(\frac{F_t}{K_t}\right)^{\frac{\epsilon-1}{1+\epsilon\eta}} \tag{14}$$

This description of the firms price setting problem does not rely on linearising the model. This is important since the model must be solved to a third order to study the role of time-varying volatility [5].A law of motion linking cross-sectional price dispersion, Δ_t, to aggregate inflation, Π_t, can be derived from (7) and (13):

$$\Delta_t = \omega\Delta_{t-1}\Pi_t^{\epsilon(1+\eta)} + (1-\omega)\left(\frac{1-\omega\Pi_t^{\epsilon-1}}{1-\omega}\right)^{\frac{\epsilon(1+\eta)}{\epsilon-1}} \tag{15}$$

4.3 Monetary policy

There is a large body of literature showing that a simple linear rule for setting the short term interest rate as a function of output and inflation approximates real world central bank practice (Taylor (1993); Clarida et al. (1997)). Thus I assume monetary policy is conducted using such a Taylor rule:

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{\gamma_0}\left(\frac{Y_t}{Y}\right)^{\gamma_1}\left(\frac{\Pi_t}{\Pi}\right)^{\gamma_2} \tag{16}$$

Where R_t is the gross interest rate $1+i_t$, and R, Y and Π are the steady state levels of the interest rate, output and inflation. The parameters γ_i capture the policy makers desire to smooth interest rate changes (γ_0), respond to deviations in output (γ_1) and inflation (γ_2).

[5]However, this description is equivalent to the New Keynesian Phillips Curve (NKPC) if one log-linearises (11),(12) and (14) , see section 4.5

4.4 Equilibrium, Solution and Calibration

A competitive equilibrium in this economy is a sequence of allocations and prices such that markets clear and household's utility (1) and firms profits (8) are maximised. This is summarised by $\{F_t, K_t, \Delta_t, \Pi_t, Y_t, i_t\}_{t=0}^{\infty}$ satisfying the households optimality conditions (3) and (4); the definition of the forward looking measures of marginal costs and revenue for firms (11) and (12); the firms first order condition summarised in aggregate supply relation (14); the law of motion for price dispersion (15) together with the description for the A_t process (5) and the behaviour of monetary policy (16).

Table 1: Calibration

Parameter	**Value**	**Reference**
β	0.99	Consistent with 4% annual interest rate
α	0.33	Consistent with a labour share of $\frac{2}{3}$
σ	0.8	Attanasio (1999).
ψ	1	Dyrda et al. (2012)
ϵ	11	Leith et al. (2012)
ω	0.75	Average price duration of 4 quarters, Klenow and Malin (2010)
γ_0	0.89	Smets and Wouters (2007)
γ_1	0.13	Smets and Wouters (2007)
γ_2	2.03	Smets and Wouters (2007)
ρ_a	0.95	Fernández-Villaverde et al. (2010)
σ^A	0.02	Fernández-Villaverde et al. (2010)
ρ_σ	0.24	Fernández-Villaverde et al. (2010)
ν	0.80	Fernández-Villaverde et al. (2010)

The model is calibrated to quarterly frequency.

The solution to this equilibrium is found via a third-order perturbation method using Dynare 4.4.3 [6]. This is necessary since a first order solution results in certainty equivalence where an increase in the variance of a shock has no effect. A second-order solution would only include the shocks to the *variance* of technology as a cross-products with the shock to the *level* of technology, thus the variance of technology has no impact unless the level of technology is being changed at the same time. Only a third-order solution allows me to study the effect of a mean-preserving increase in the variance of technology, the appropriate proxy for an increase in uncertainty. However, higher order solutions can induce explosive terms when the model is simulated. In order to resolve this I use the pruning solution in Dynare which follows Andreasen et al. (2013). Pruning solves this problem leaving out terms in the solution that have higher-order effects than the approximation order. For example, this would occur when a second order solution to one variable is substituted into the policy function for another which is also approximated by a quadratic function of the state variables, resulting in terms of 3rd and 4th order. Pruning removes these terms from the solution

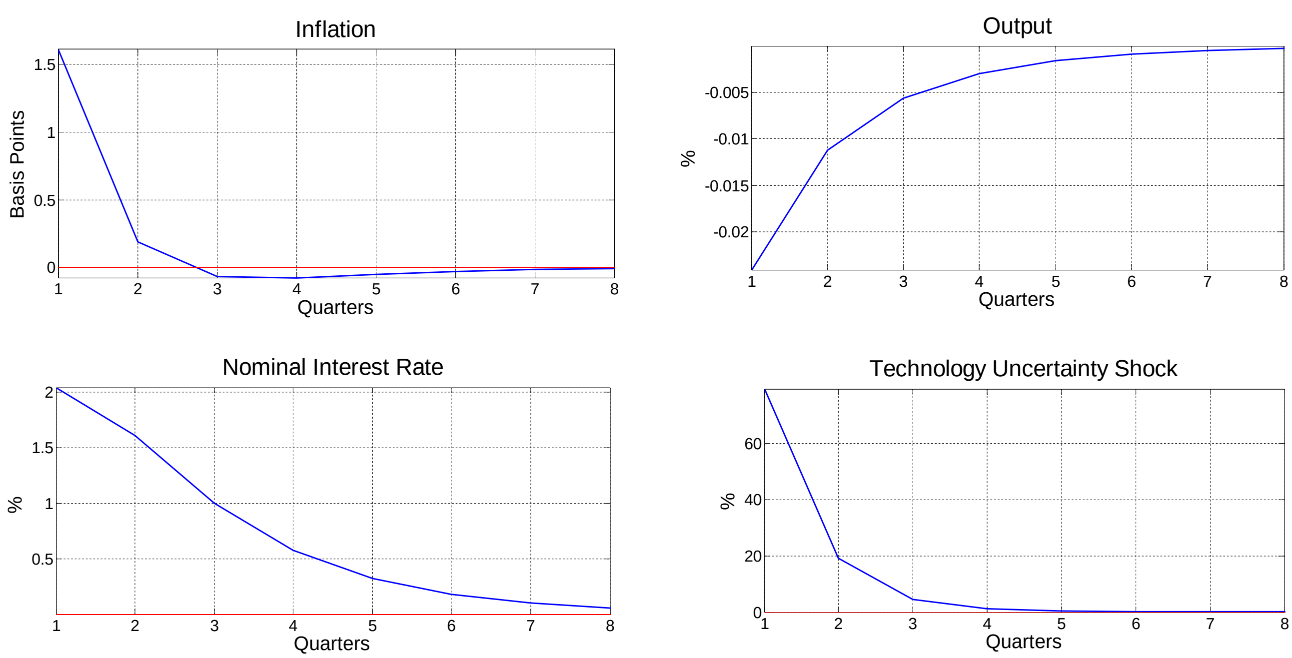
[6] Dyanre is a toolbox for Matlab (or Octave) which performs these calculations easily, see http://www.dynare.org/

inducing stability.

To study the impact of a one standard deviation increase in the volatility of technology (η_t) I follow Fernandez-Villaverde et al. (2011b) in calculating the impulse response functions. This involves calculating the deviation of the model from the ergodic steady state after a one standard deviation shock to η_t. This is preferable to the deviation from the deterministic steady state since the unconditional moments of variables solved under higher-order approximations are, in general, not equal to their steady state values since these solutions include non-linear terms that correct for uncertainty (see Andreasen et al. (2013)). The computation proceeds as follows. I simulate the model with all shocks set to zero for 2048 periods starting at the deterministic steady state. I take the ergodic mean as the value each variable has converged to after 2000 iterations. I then use the last 48 periods to find the response with the volatility shock by setting the volatility shock (η_t) to one standard deviation and simulating the for 48 periods, starting at the ergodic means. The impulse responses are reported as the deviations from the ergodic mean of each variable.

4.5 Results

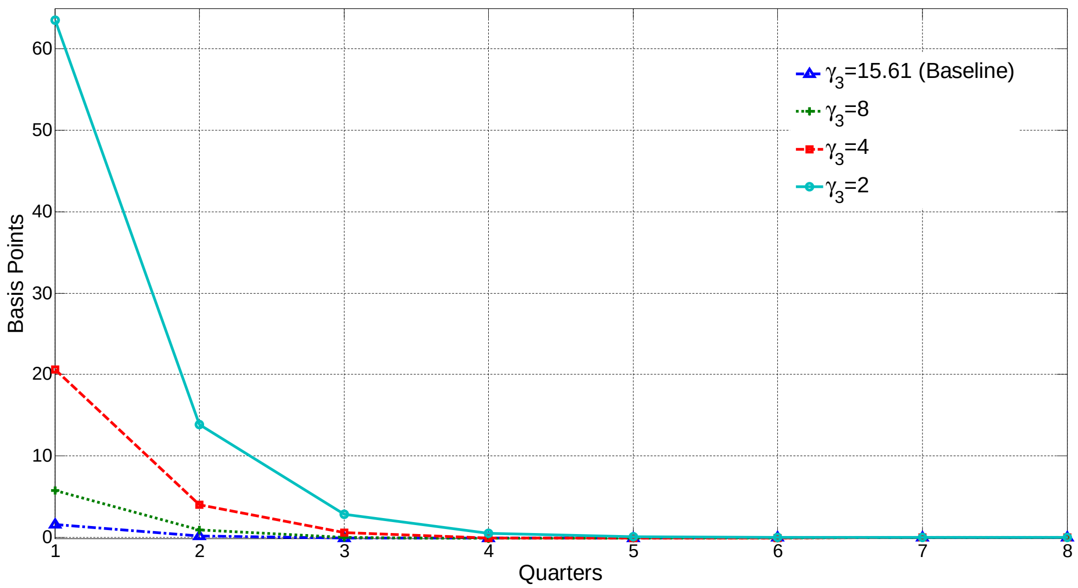
Figure 11: IRFs from a volatility shock to technology in simple New Keynesian Model



All figures depict the deviation of the variable from its ergodic steady state. Inflation is in basis points. Inflation and the Nominal Interest Rate are annualised. The shock is a one standard deviation increase in the volatility of technology.

The results show that an uncertainty shock is consistent with a drop in real output and a rise in inflation as found in the empirical section (see figure 11). However, the response of inflation is very small at only 1.6 basis points. This is due to the strong response of the inflation-targetting central bank with a high weight on inflation relative to output in the Taylor rule ($\gamma_3 = \gamma_2/\gamma_1 = 15.61$) raising interest rates 2% above the steady state rate. If the central bank has a higher weight on output than this then inflation can rise to the levels comparable to the empirical finding of around 50 basis points, see figure 12 (that is, if movements in inflation are only twice as important output variations,$\gamma_3 = 2$).

Figure 12: IRFs of Inflation under alternative Taylor Rules



The response of inflation is measured under alternative Taylor Rules: $\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{\gamma_0}\left(\frac{Y_t}{Y}\right)^{\gamma_1}\left(\frac{\Pi_t}{\Pi}\right)^{\gamma_2}$ where $\gamma_3 = \gamma_2/\gamma_1$.

An increase in uncertainty leads to precautionary savings on the part of households which reduces demand and should induce firms to reduce prices. This is the mechanism leading to lower inflation in the studies of stochastic volatility of Leduc and Liu (2012) and Mumtaz and Zanetti (2013). In contrast, Fernandez-Villaverde et al. (2011a) study a New Keynesian model with stochastic volatility in capital taxation and find higher inflation following an a rise in uncertainty. They show that in addition to this aggregate demand channel there is an upward pricing bias channel. The latter refers to firms raising prices because future demand and thus marginal cost become more uncertain. Firms face a Dixit-Stiglitz demand function (as in equation (6)) which makes profits fall much more quickly when the firms relative price, $\frac{P_t(i)}{P_t}$, is too low than when it is too high [7]. Thus firms raise prices today to insure against the risk that the economy rebounds and they are caught with low prices. Clearly, this effect depends on firms being subject to nominal rigidities. In the study of Fernandez-Villaverde et al. (2011a) firms face quadratic (Rotemberg) adjustment costs to changing their price. This means that they want to set a higher price today

[7]In steady state the period profit function is $\Upsilon = \left(\frac{P_t(i)}{P_t}\right)^{1-\epsilon} Y - \frac{\epsilon-1}{\epsilon}\left(\frac{P_t(i)}{P_t}\right)^{-\epsilon} Y$. This is maximised at $\frac{P_t(i)}{P_t} = 1$ but falls much more quickly when $\frac{P_t(i)}{P_t} < 1$ then when $\frac{P_t(i)}{P_t} > 1$. See figure 3 in Fernandez-Villaverde et al. (2011a)

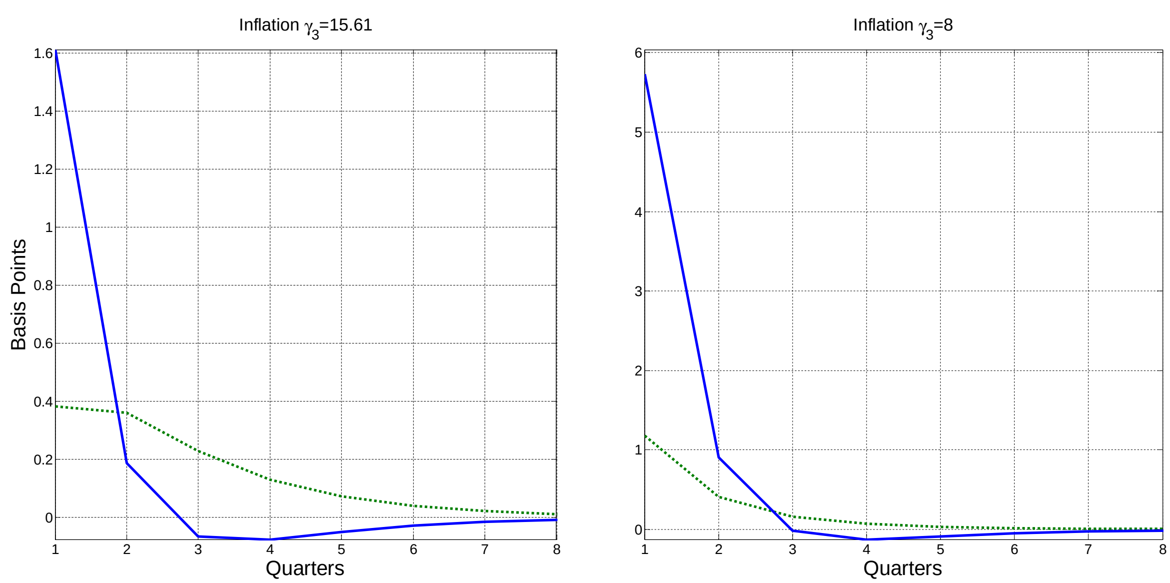
to make any future upward adjustment (which is proportional to $P_{t+1}(i)/P_t(i)$) less costly. The Calvo scheme used here induces similar incentives: firms that are able to reset their price today (ω% of them) know that this opportunity may not be available again for some time, exposing them to relative prices that are too low. Thus, they accept lower profits today (by having a high relative price) to insure against the potentially large drop in profits if relative prices are too low tomorrow.

To measure the relative contribution of the upward pricing bias channel I follow Fernandez-Villaverde et al. (2011a) in removing the impact of volatility from the firms pricing decision by using a log-linear approximation to (11),(12) and (14) which yields the familiar New Keynesian Phillips Curve (NKPC)[8]:

$$\pi_t = \kappa \left[\hat{Y}_t - (1+\chi)\hat{A}_t \right] + \beta E_t \pi_{t+1}$$

Where $\chi \equiv (1+\frac{1}{\psi})(1+\eta) - 1$ and $\kappa = \frac{(1-\omega)(1-\omega\beta)(\chi+\sigma^{-1})}{\omega(1+\epsilon\eta)}$; and $ln\,(\Pi_t/\Pi) = \pi_t$, $\hat{Y}_t = ln(Y_t/Y)$, $\hat{A}_t = ln(A_t/A)$. This means firms pricing decisions ignore changes in the volatility of A_t (since this requires a higher order approximation) but inflation will still respond to the aggregate demand channel through $\hat{Y}_t$. The results show that a substantial proportion of the rise in inflation in response to a volatility shock is driven by the upward pricing bias channel and that this effect is stronger the higher the relative weight on output, γ_3 (see figure 13).

Figure 13: IRFs from a volatility shock to technology: the role of the upward pricing bias channel



Inflation response is measured in annualised basis points. The response is measured under two alternative weights for inflation relative to output in the central bank's Taylor: $\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{\gamma_0} \left(\frac{Y_t}{Y}\right)^{\gamma_1} \left(\frac{\Pi_t}{\Pi}\right)^{\gamma_2}$ where $\gamma_3 = \gamma_2/\gamma_1$. The baseline model refers to the model outlined in section 4 with a non-linear pricing decision of firms. The linear NKPC is the identical model but where the non-linear pricing rules have been log-linearised to produce a linear New Keynesian Phillips Curve (NKPC).

[8]For details on this derivation see Redl (2015)

5 Conclusion

This paper develops a new index of macroeconomic uncertainty in South Africa using (1) forecaster disagreement among professional forecasters about macroeconomic conditions, (2) newspaper articles about uncertainty and (3) uncertainty from the perspective of policy makers. The impact of unanticipated increases in uncertainty is studied using a Structural VAR. These results provide evidence that a rise in uncertainty is important for the business cycle in South Africa, as has been found for the U.S.A. and the U.K., with a decline in GDP, investment, industrial production and private sector employment. However, in contrast to those developed market studies, I find that uncertainty shocks are inflationary. This effect is robust to controlling for financial stress in the form of a credit spreads, measured by bank lending rates relative deposit rates, and consumer confidence - a proxy to disentangle the effect of higher uncertainty from bad news. To explore the channels generating the results I study a simple New Keynesian model where uncertainty is measured through time varying volatility of technology. The results are consistent with lower output and higher inflation. The degree of inflation is strongly dependent on the relative weight of output to inflation in the monetary policy maker's Taylor Rule. For inflation consistent with the empirical results output needs to have a weight of approximately half that of inflation (empirical estimates of Taylor rules typically find a weight around 1/16). The dominant mechanism driving higher inflation in this model is precautionary increases in prices by firms. Firms face asymmetric costs in choosing their price: pricing too low is much more costly than pricing too high. Higher uncertainty makes future demand (and thus marginal costs) harder to predict. Since firms are subject to nominal rigidities they may not be able raise prices in the near future if demand picks up. As an insurance policy they raise prices today.

These results suggest that both fiscal and monetary policy makers should monitor the levels of economic uncertainty as this may foreshadow a decline in economic activity. Moreover, the empirical and theoretical results show that uncertainty shocks are particularly pernicious for inflation targeting central banks in that they have stagflation effects. Thus it may be worthwhile for South African policy makers to survey professional forecasters as is done in the U.S.A. (Survey of Professional Forecasters by the Philadelphia Federal Reserve), U.K. (Forecasts for the UK economy by HM Treasury) and the E.U. (Survey of Professional Forecasters by the ECB). This would allow for a richer study of uncertainty, for example perceived subjective uncertainty in the form of forecast distributions by individual forecasters.

Future empirical research could formally explore the ability of this index to forecast economic activity, study firm level data to test the theoretical mechanism of precautionary pricing and develop measures of uncertainty more focused on policy and political uncertainty. Future theoretical work could study whether different sources of time varying volatility (e.g. cost push shocks, labour supply) generate stagflation and extend the results here to a more fully specified model of a small open economy to study the effects of time varying volatility on the exchange rate and capital flows.

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6 Appendix

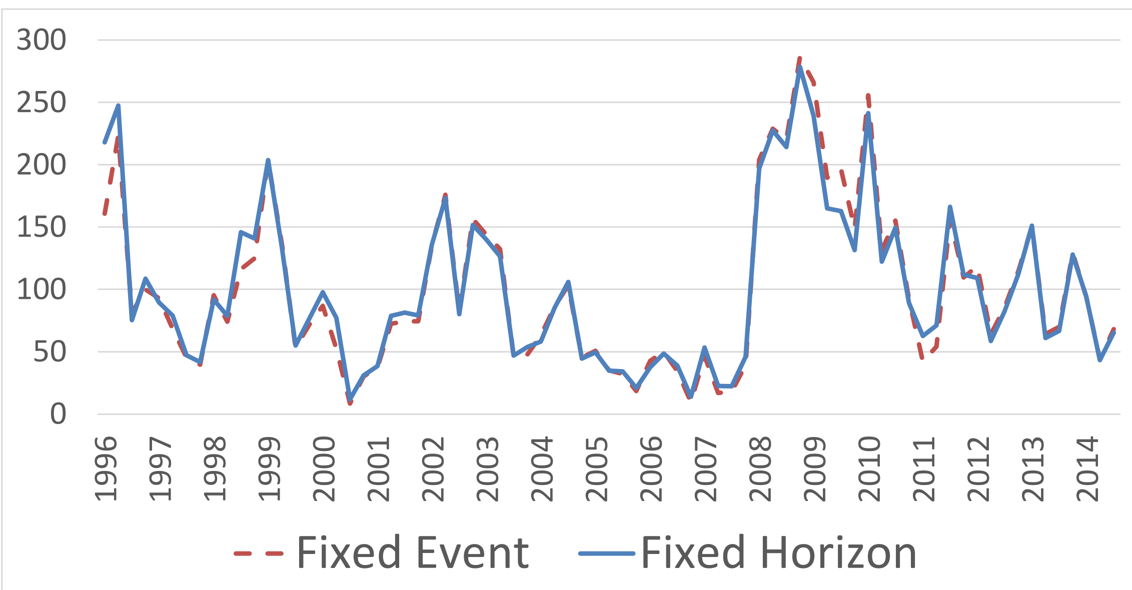
6.1 Fixed event and fixed horizon forecasts

The data contains fixed event forecasts: each forecast is based on expectations over the current calendar year as opposed to a forecast for the value of a variable 1 year ahead (a fixed horizon forecast). For example, a forecast of GDP growth in quarter 1 of 1992 and quarter 4 of 1992 are both expectations of GDP growth for the year 1992[9]. Since forecasts made closer to the data of the forecast year have more information there is likely to be both less forecaster uncertainty and this may be manifest in greater seasonality in the series for forecaster dispersion. To address this issue I follow Dovern et al. (2012) in re-weighting the forecast data to approximate fixed horizon forecasts. Let $S^{fe}_{y0,q,y1}(x)$ denote the fixed event forecast for the variable x in year $y1$ which is made in the previous year $y0$, $y0 = y1 - 1$, and quarter q. For example the forecast for 1992 made in quarter 1 of 1992 is $S^{fe}_{1992,1,1992}(x)$ and forecast for 1993 made in quarter 1 of 1992 $S^{fe}_{1992,1,1993}(x)$. The fixed horizon forecast is approximated as:

$$S^{fh}_{y0,q,y1}(x) = \frac{4-q+1}{4} S^{fe}_{y0,q,y0}(x) + \frac{q-1}{4} S^{fe}_{y0,q,y0+1}(x)$$

For example, the forecast of GDP growth between Q4 1992 and Q4 1993 is approximated by the sum of $S^{fe}_{1992,4,1992}(GDP)$ and $S^{fe}_{1992,4,1993}(GDP)$ with weights of $\frac{1}{4}$ and $\frac{3}{4}$, respectively, since the first forecast has a 1 quarter horizon for the forecaster surveyed and the second has 3 quarter horizon. Ideally this could be done on the raw data for each forecasters for each quarter. Unfortunately, there are too many data gaps to pursue this approach and consequently I have to perform this adjustment with the standard deviations across forecasters which is available for every quarter [10].

Figure 14: Fixed event and fixed horizon forecasts



[9]The official data for Q4 GDP growth would only be released in Q1 1993, at the end of February

[10]A significant portion of the forecast data was recovered from archives at the National Library of South Africa. These archives are both incomplete and require ordering a physical copy of each newspaper where the data is expected to be found. Since it is not known which day of the month the competition results for that month will be published, it is a challenge to find even one table of this data. Happily the task of recovering the standard deviations across forecasters was made feasible by the fact that the last table of the year included this standard deviation data for all previous months. However it does not include individual forecast data for each month.

6.2 Nowcasts vs. forecasts

Figure 15: GDP nowcasts vs. forecasts (+1)

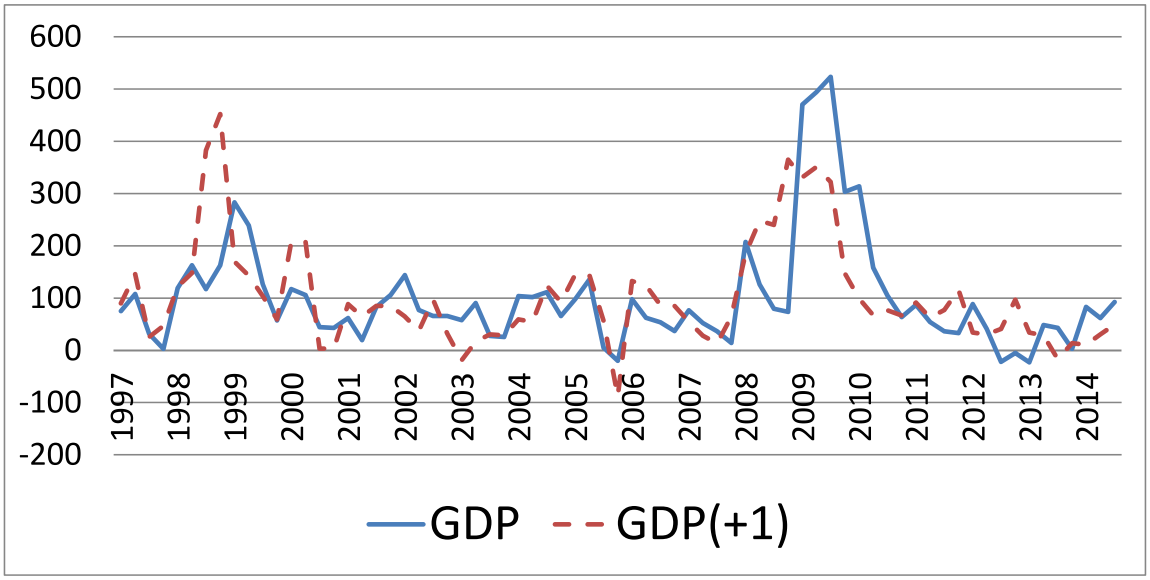
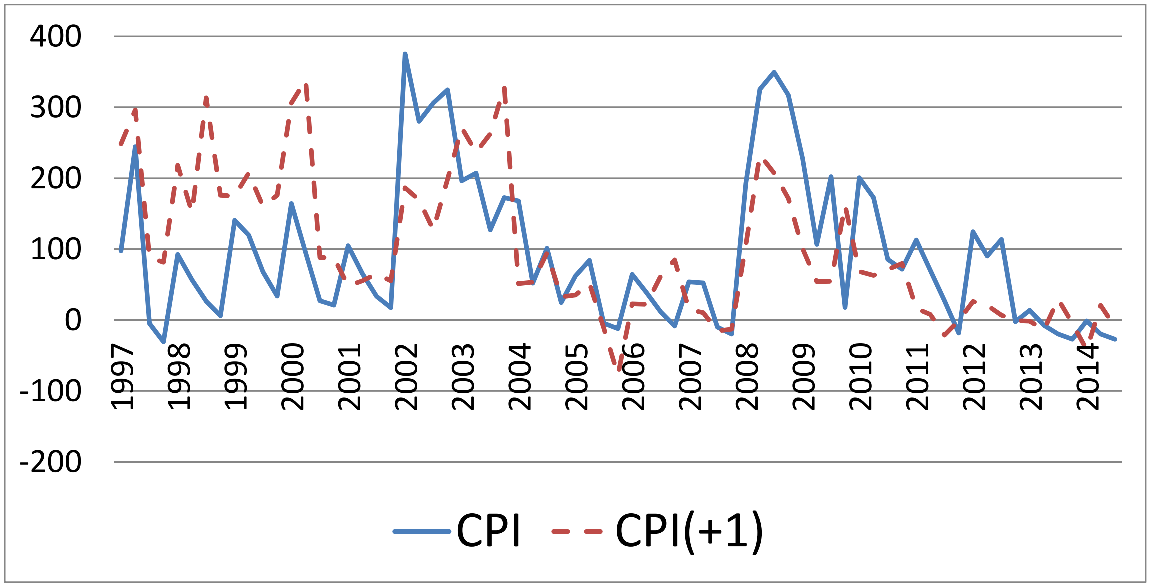


Figure 16: CPI nowcasts vs. forecasts (+1)

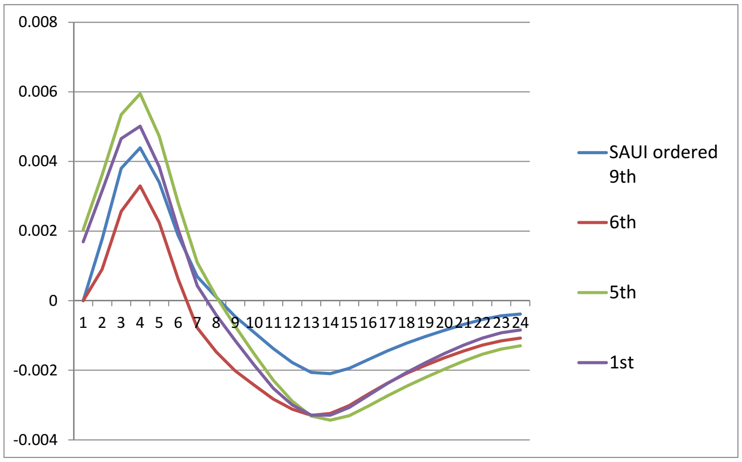


6.3 Alternative Identification

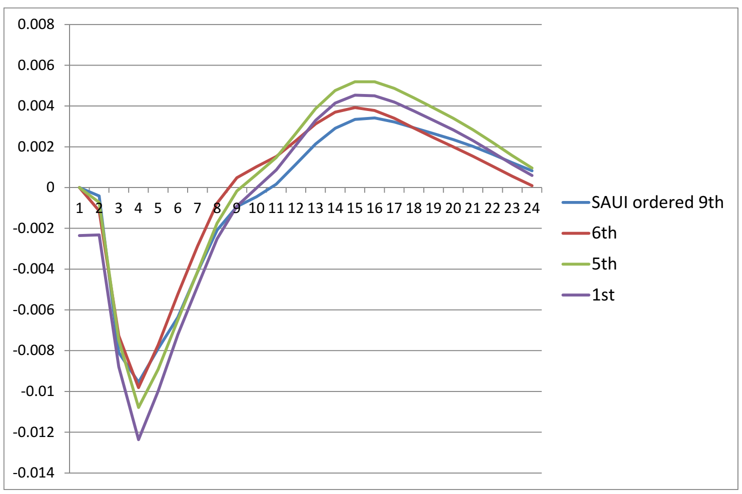
Figure 17: Alternative Cholesky Orderings for Baseline Model

Baseline: (1) Private Employment Rate (2) log(Industrial Production) (3) log(Investment) (4) log(GDP) (5) log(CPI) (6) log(All Share Index) (7) 10 Year Government Bond Yield (8) Repo Rate (9) Uncertainty Index SAUI

(a) CPI Inflation



(b) Industrial Production



(c) Private Sector Employment Rate

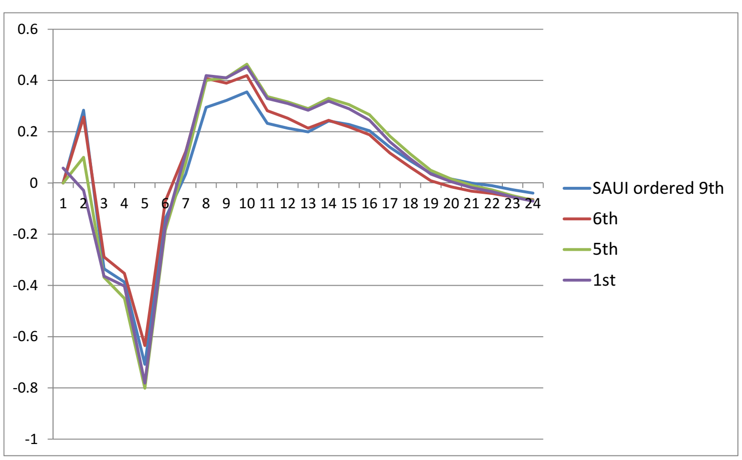
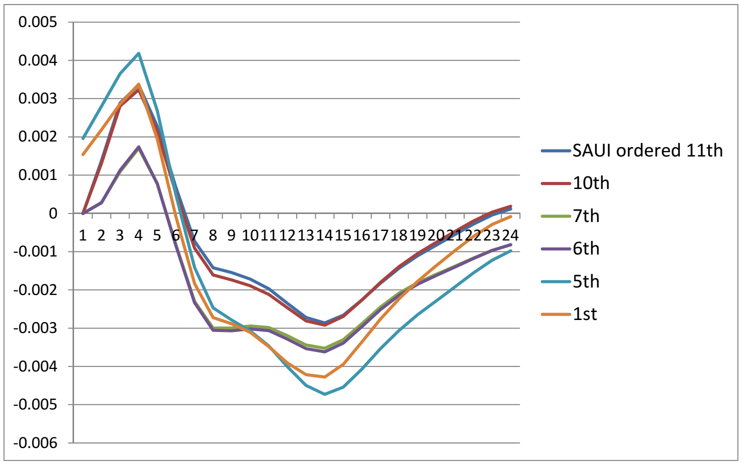


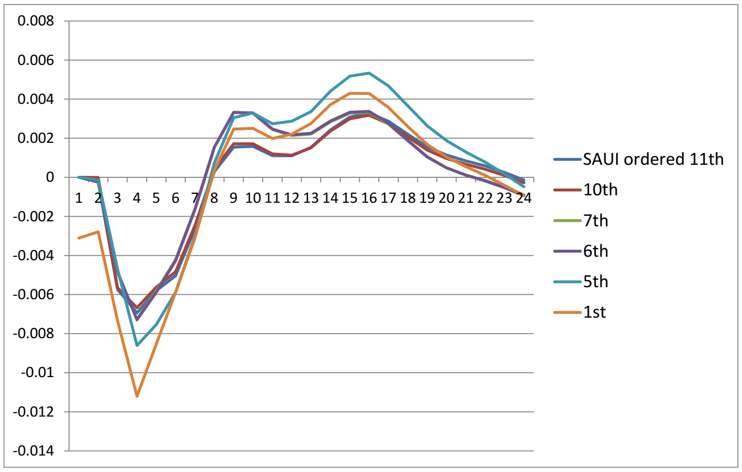
Figure 18: Alternative Cholesky Orderings with Consumer Confidence and Credit Spreads

Baseline: (1) Private Employment Rate (2) log(Industrial Production) (3) log(Investment) (4) log(GDP) (5) log(CPI) (6) Credit Spread (7) log(All Share Index) (8) 10 Year Government Bond Yield (9) Repo Rate (10) Confidence Index (11) Uncertainty Index SAUI

(a) CPI Inflation



(b) Industrial Production



(c) Private Sector Employment Rate

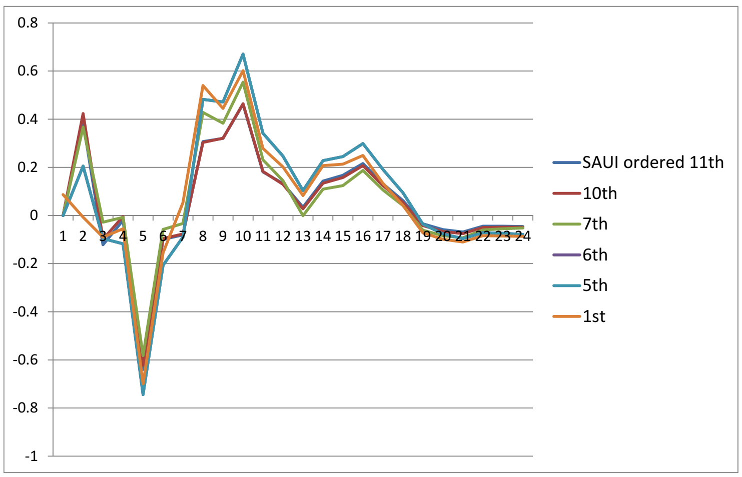


Figure 19: Generalised Impulse Responses to SAUI

Response to Generalized One S.D. Innovations ± 2 S.E.