Second-Round Effects from Food and Energy Prices: a SBVAR approach

Franz Ruch* Stan du Plessis†

August 18, 2015

Abstract

Relative food and energy price shocks are important in South Africa and have contributed an average of 2.4 percentage points (or 38 per cent) to an average 6.1 per cent headline consumer price inflation from 2000 to 2014. In general, monetary policy can look-through these shocks as long as there are no second-round effects raising inflation expectations and salaries (expectations channel), and core inflation (cost channel through marginal cost) in the economy. To measure the importance of second-round effects this paper estimates a Structural Bayesian VAR with short- and long-run as well as sign restrictions in South Africa since 1994. The results show that there are second-round effects in SA with a one per cent shock to relative food, petrol and energy prices leading to a 0.4 per cent increase in unit labour cost after four quarters and 0.2 per cent increase in core inflation after three quarters. Higher core inflation is mainly due to households and businesses bidding-up inflation expectations and wages (i.e. the expectations channel).

JEL Classification: C11; E31.

Keywords: Second-round effects, Inflation, relative price shocks, Bayesian estimation

Preliminary and incomplete. Please do not quote.

* *Corresponding author*. South African Reserve Bank, PO Box 427, Pretoria, South Africa, 0001. Email: franz.ruch@resbank.co.za. The author would like to thank Byron Botha for help with Matlab code. Matlab code available upon request.

† Department of Economics, University of Stellenbosch

Contents

List of Tables

List of Figures

1 Introduction

Wage negotiations in South Africa always start the same - workers demand double-digit wage increases while employers offer below-inflation increases. Then the rhetoric builds and in the worse case these negotiations falter to strikes. At the beginning of 2015 as part of negotiations for municipal workers wages, Independent Municipal and Allied Trade Union (Imatu) general secretary Johan Koen said "[o]ur members, like the majority of South Africans, are really feeling the pinch of unprecedented increases in the costs of electricity, fuel, food and public transport." This is why second-round effects from food, petrol and electricity matter in South Africa. These price increases are entrenched in the language of wage-setters.

Relative food and energy price shocks are important in South Africa and have contributed an average of 2.4 percentage points (or 38 per cent) to the average 6.1 per cent headline Consumer Price Index (CPI) from 2000 to 2014. In general, monetary policy can look-through these shocks as long as there are no second-round effects through rising inflation expectations and wages, and core inflation in the economy. Second-round effects emanate from the ability of price-setting firms and wage-setting labour to increase prices (through increasing mark-ups or marginal cost) and wages and therefore prices of other goods and services in response to a relative price shock (Baumeister et al., 2010). It is the response of inflation expectations and wages to relative price shocks conditional on the supply and demand conditions in the economy that determine the magnitude of second-round effects.

The impact of second-round effects occurs through two channels, costs and expectations. The cost channel refers to the direct impact of changes to a firms marginal cost, for example when energy is used in the production process of other goods and services in the economy. The cost channel can be measured through changes in core inflation.

The expectations channel refers to the response of wage-setting labour to a relative price shock. If labour perceives this shock to be permanent, or has the bargaining power to raise wages, then labour's higher inflation expectations will fuel demand for higher nominal wages.

The ability to measure second-round effects adequately relies on proper indicators of relative price shocks, core inflation, wages and inflation expectations.[1] Of these the most difficult to define is core inflation given the broad range of theoretical and practical definitions (see for example Roger, 1998, for a discussion on thoeretical definitions of core inflation) and properties required. In South Africa, Blignaut et al. (2009), Rangasamy (2009), Ruch and Bester (2013) and Du Plessis et al. (2015) all provide alternative measures of core inflation. Ultimately, however, for the purpose of this paper the core measure used has to adequately capture underlying prices and the impact of second-round effects. Another complicating factor is the practicality of implementing monetary policy. Roger (1998) highlights that from a internal forecasting process as well as for the ability of the policymaker to explain policy choices to the public, it is usually necessary for a "central bank to 'tie its colours' to one mast."[2] Given that a general consensus around core inflation, being defined as headline CPI less food and energy, has emerged as an appropriate measure for policymakers and analysts around the world, and the use of this

[1] In South Africa, measures of inflation expectations are sparse and from a time series perspective short. This makes the use of these measures in estimating the impact of relative price shocks difficult and hence are not included in this analysis.

[2] This is equally true for a relative price measure.

type of core measure to explain policy choices in South Africa, this is the core measure of choice in this paper. This choice also simplifies the issue of the right relative price measure to use; in this case food and energy prices.

Despite anecdotal evidence and analyst rhetoric that second-round effects represent a fundamental driver of the inflation process in South Africa, there is relatively little work that quantifies second-round effects (Rangasamy and Nel, 2014, are notable exceptions). This paper estimates both the cost and expectations channel of second-round effects using a seven variable structural Bayesian vector-autoregression (VAR) model. The results show that both channels are important and policy relevant in South Africa.

2 Theory of second round effects

Second-round effects emanate from the ability of price-setting firms and wage-setting labour to increase prices (through increasing mark-ups or marginal cost) and wages and therefore prices of other goods and services in response to a relative price shock (Baumeister et al., 2010).

The impact of second-round effects occurs through two channels, costs and expectations. The cost channel refers to the direct impact of changes to a firms marginal cost due to an increase in input costs. This assumes that the relative price shock is larger than the menu cost. A familiar example of this is energy prices. Recent increases in electricity prices following the 2008 energy crisis in SA increased the cost of production by raising the price of intermediate inputs. These increases were then passed on to the consumer.

The expectations channel refers to the response of wage-setting labour to a relative price shock in, for example, food and energy. If labour perceives the relative price shock to be permanent, or has the bargaining power to raise wages, it will raise its inflation expectations and demand higher nominal wages. This would increase the price of other goods and services either through the price adjustment by firms as their marginal cost increases or through increasing consumption. If wages increase the marginal cost of firms then this would increase the cost channel of second-round effects.

Second-round effects have been formalised in Aoki (2001), Hlédik and Banka (2003), Bodenstein et al. (2008), Blanchard and Gali (2007) and Anand and Prasad (2010). Aoki (2001) builds a two-sector dynamic stochastic general equilibrium (DSGE) model, with a flexible- and sticky-price sector. Flexible-price goods are standardised, traded in an almost competitive market and used as both an input in production as well as consumed by households. This is analogous to goods such as food and energy. Sticky-price goods are differentiated and traded in a monopolistically competitive environment. This is analogous to all other goods in the economy and can be conveniently thought of as core inflation. His model can be used as a basis from which to understand the transmission of relative price shocks on inflation and modifies the New Keynesian Phillips curve for the sticky-price good to include impacts from the relative price of the flexible-price good. The mechanism through which this occurs is the substitution effect between flexible-price goods and sticky-price goods. The relative price shock raises demand for sticky-price goods as consumers substitute away from flexible-price goods. With the increase in demand of sticky-price goods sellers raise the price. As a consequence the relationship between core inflation (sticky-price goods) and relative price shocks (changes in the prices of flexible-price goods) is always positive, due to a relatively elastic substitution between these two goods.

An important outcome from formalising the role of relative prices in DSGE modeling is that optimal monetary policy requires the central bank to target core inflation instead of headline inflation. Aoki (2001) finds that targeting core maximises welfare and is sufficient to stablise relative prices around their efficient level. He finds that this also applies for a small open economy. This outcome is echoed in Bodenstein et al. (2008) who uses a stylised DSGE model including a separate energy sector in order to study the impact of an adverse energy supply shock on optimal monetary policy in the context of alternative policy rules. Policy rules that focus on headline inflation in the presence of an adverse energy shock imply significantly different responses to those that focus on core inflation with headline inflation introducing significantly larger volatility. The optimality of targeting core inflation in emerging market economies is questioned, however, in Anand and Prasad (2010) who expand the DSGE model of Aoki (2001) to include financial frictions that limit credit-constrained consumers' access to financial markets. They argue that targeting core inflation (in the sense of CPI less food and energy) in emerging market economies would not be optimal as these economies generally face higher food consumption to total consumption as well as low price and income elasticity's of food. Therefore, economic agents are likely to factor in food price changes with wage negotiations affecting inflation expectations and the presence of second-round effects.

Much of the focus of Aoki (2001), Bodenstein et al. (2008), and Anand and Prasad (2010) is on optimal monetary policy in the context of relative price movements; an important topic but one which does not provide estimates of the size and importance of second-round effects in an economy. Hlédik and Banka (2003) take the first step in answering these questions by modeling second-round effects of supply shocks on inflation using a small dynamic rational expectations open economy model. The paper finds that second-round effects from import prices and the nominal exchange rate have a material impact on inflation but their size is dependent on the reaction function of the central bank. Cecchetti and Moessner (2008) and Baumeister et al. (2010) go a step further by identifying and quantifying second-round effects. Cecchetti and Moessner (2008) directly analyses the impact of second-round effects (including from both food and energy prices) on headline inflation in a group of advanced and emerging market economies. They find that recent higher commodity prices have generally not led to strong second-round effects on inflation. Baumeister et al. (2010) also analyse second-round effects, but look only at the oil market (through analysing the impact of an oil supply shock) on total labour costs per employee, real consumer wages and the producer price-wage ratio. Results show that second-round effects are present in some economies (such as Switzerland and the euro area) and not in others (US) and that these effects are the key determinant of cross-country differences in the ultimate impact of relative price shocks on inflation.

In South Africa, Rangasamy (2011) and Rangasamy and Nel (2014) provide evidence that second-round effects, or at least the cost channel, are significant. Chisadza et al. (2013) in contradiction suggest that second-round effects from oil shocks are not important. Rangasamy and Nel (2014) show that a shock to food prices leads to a significant positive increase in core inflation with a peak effect after five months. Rangasamy (2011) finds that food prices play a significant role in inflationary episodes in

South Africa, that these prices are driven mainly by domestic factors and that there exists "strong second-round impacts" that require attention from policymakers. Rangasamy (2011) argues that "core measures of inflation that exclude food price movements may not accurately reflect the underlying inflationary pressures in the economy and could compromise the attainment of the goal of price stability." This is due to the likelihood that core will no longer be an unbiased estimator of headline inflation. This point is repeated in Walsh (2011) who finds that a core inflation measure that excludes food can misspecify inflation prompting higher inflation expectations and slow policy responses. Chisadza et al. (2013), on the other hand, find that an oil supply shock increases consumer prices in the short-run with no positive persistence on inflation. This implies that there are no/little second-round effects. They estimate a sign restriction VAR of the impact of differentiated oil price shocks on the South African macroeconomy.

3 The (generalised) Phillips curve and VAR model

Theoretical models that have entrenched the role of relative price shocks, such as those of food and energy prices, into the inflation process include Aoki (2001) and Blanchard and Gali (2007) and form a useful starting point for this analysis. Assume an economy has a continuum of households who consume two types of goods; a flexible-price good and a sticky-price good. The flexible-price good is standardised, traded in an almost competitive market and used as both an input in production as well as consumed by households. This is analogous to goods such as food and energy. The sticky-price good is differentiated and traded in a monopolistically competitive environment. This is analogous to all other goods in the economy and the change in sticky prices can be conveniently thought of as core inflation; in the context of this paper, headline CPI less food, petrol and energy.

Assume also that there is a continuum of monopolistically competitive firms who produce differentiated domestic goods (sticky-price good) using labour and the flexible-price good.

Prices for the sticky-price good are set according to Calvo's (1983) scheme such that a fraction $1-\theta$ of firms can reset prices each period with the remaining fraction of firms, θ, leaving prices unchanged. Following Smets and Wouters (2002), price inertia is introduced by assuming that domestic firms partially index prices to the previous period's domestic inflation rate. This yields the following log-linearised sticky-price Phillips curve:

$$\pi_{S,t} = \frac{\beta}{1+\delta\beta} E_t \pi_{S,t+1} + \frac{\delta}{1+\delta\beta} \pi_{S,t-1} + \kappa y_t + \lambda_p \Gamma_x x_{F,t} \tag{1}$$

where $\pi_{S,t} = \ln \frac{P_{S,t}}{P_{S,t-1}}$ is sticky-price inflation with $P_{S,t}$ the price index, y_t is output and $X_{F,t} = ln \frac{P_{F,t}}{P_{S,t}}$ is the relative price of flexible-price good to the sticky-price good.

This can be specified in a more general form as:

$$\pi_{S,t} = C_t + \sum_{i=1}^{k} \theta_i \pi_{S,t-i} + x'_{t-1}\beta + \mu_t \tag{2}$$

where x_t' is a vector of variables including output, the exchange rate, wages, relative price of food and energy, imported prices, and the interest rate, and μ_t is an identically and independently distributed (i.i.d.) error.

In order to estimate the Phillips curve specified in equation 2 as well as introduce a more general dynamic structure we specify a VAR(p) model as:

$$y_t = c + \sum_{j=1}^{p} \beta_j y_{t-j} + \mu_t \tag{3}$$

where y_t is an $M \times 1$ vector of endogenous variables for $t = 1, ..., T$, p is the lag length, μ_t is an $M \times 1$ vector of reduced-form errors assumed to be i.i.d. $N(0, \Sigma)$, and c is an $M \times 1$ vector of intercepts. Note that equation 2 is the single-equation form of the core inflation Phillips curve that is estimated in equation 3.

In matrix form this would be:

$$y = (I_M \otimes X)\beta + \mu \tag{4}$$

where $X = [x_1, x_2 ..., x_T]'$ is a $T \times K$ matrix with $x_t = (1, y_{t-1}', ..., y_{t-p}')$ and $K = Mp + 1$. $\beta = vec(B)$ is a $KM \times 1$ vector with $B = (cB_1 ... B_2)'$ and $\mu \sim N(0, \Sigma \otimes I_M)$.

Since we are estimating a seven variable model with a relatively short sample period it is useful to frame the estimation in the context of a likelihood function where we can introduce priors to shrink the parameter space. Following Koop and Korobilis (2010) it can be shown that the likelihood function can be written in two parts:

$$\beta | \Sigma, y \sim N(\hat{\beta}, \Sigma \otimes (X'X)^{-1}) \tag{5}$$

which is the distribution of β given Σ, and

$$\Sigma | y \sim W(S^{-1}, T - K - M - 1) \tag{6}$$

is the Wishart distribution of Σ^{-1} with $\hat{B} = (X'X)^{-1}X'Y$ the OLS estimate of B and $S = (Y - X\hat{B})'(Y - X\hat{B})$.

4 Data

In order to determine the cost and expectations effect of relative price shocks we estimate a seven variable VAR. Table one describes the variables used in the VAR model, their transformations and sources.

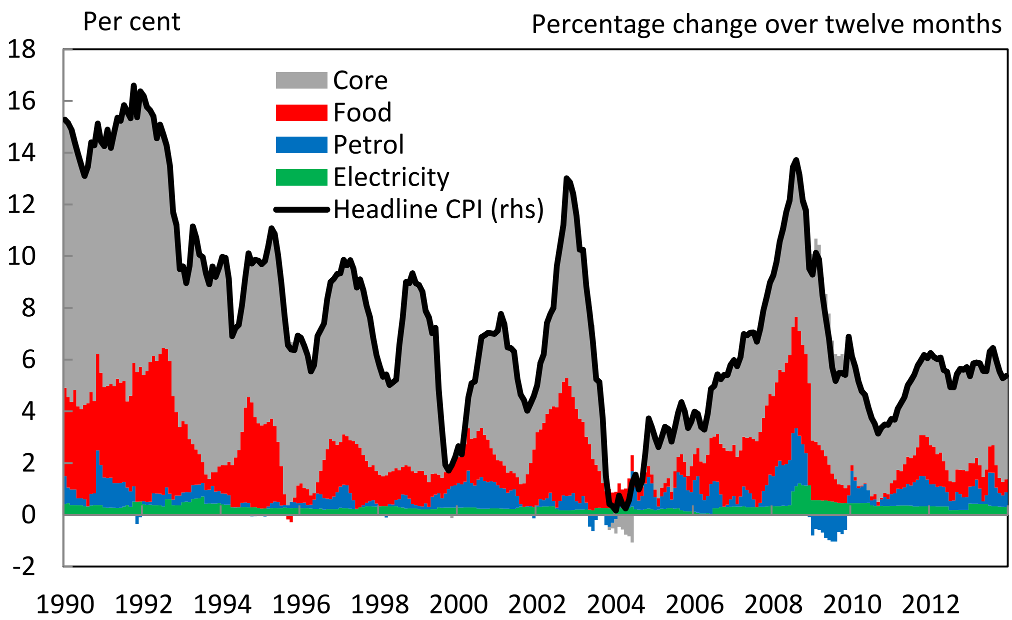
The VAR includes the relative price of food, petrol and energy to core inflation (relative food and energy); imported inflation; real GDP; Unit Labour Cost (ULC); CPI less food, petrol and energy (or core inflation); the repurchase rate; and the nominal effective exchange rate.

Table 1: Variables included in the VAR

Variable	Transformation	Source
Headline CPI less food, petrol and energy (core CPI)	Percentage change over four quarters	StatsSA
Headline CPI less food, petrol and energy as a ratio to core CPI (Relative food and energy)	Percentage change over four quarters	StatsSA
Import prices (trade weighted)	Percentage change over four quarters	SARB & own calc.
Real GDP (Seasonally adjusted annualise rate)	Percentage change over previous quarter	SARB
Unit labour cost (ULC) defined as salaries and wages in the non-agricultural sector as a ratio to real GDP	Percentage change over four quarters	SARB & own calc.
Repurchase rate	Per cent	SARB
Nominal effective exchange rate	Percentage change over previous quarter	SARB

Food, petrol and energy (electricity) prices play a significant role in the evolution and dynamics of headline inflation in South Africa. These components also help consumers form inflation expectations since these items are bought regularly and are a significant part of their budget. Figure 1 plots the contribution of food, petrol and energy to headline inflation since 1990. Food inflation is by far the biggest contributor to inflation averaging 1.5 percentage points of the 5.9 per cent headline inflation average figure. Petrol is next with an average contribution of 0.6 percentage points and electricity only contributes 0.3 percentage points to headline consumer inflation over this period. Combined these prices explain over 40 per cent of inflation during this period.

Figure 1: Contribution of food and energy prices to headline consumer inflation



Conventionally inflation targeting central banks use headline or overall consumer prices as an operational target but use a core or underlying inflation measure to look through relative price shocks. In

South Africa, the monetary policy committee also looks at a number of core measures, however, generally refers to headline CPI less food, petrol and energy in its deliberations on the direction that policy should take. Therefore, this paper focuses on defining the second-round effects that precipitate from food, petrol and energy (or electricity) price movements.

4.1 Stationarity

The seven variables are tested using a union of rejections testing strategy as proposed in Harvey et al. (2009). The strategy states that the null hypothesis of a unit root be rejected if "either $DF-QD_{\mu}$ or $DF-QD_{\tau}$ rejects", i.e. if the quasi-differenced demeaned or detrended Dickey-Fuller test rejects the null hypothesis. The lag length used in the Dickey-Fuller tests are automatically selected based on the Bayesian Information Criterion (BIC) with a maximum lag length of 11.

Table 2: Elliott-Rothenberg-Stock DF-GLS test (P-values)

	$DF-QD_{\mu}$ intercept	$DF-QD_{\tau}$ intercept and trend
Relative food and energy	0.1877	0.0014
Imported inflation	0.0191	0.0192
Real GDP	0.0132	0.0001
Unit labour cost (ULC)	0.0110	0.0103
Core inflation	0.6256	0.0128
Repo rate	0.1189	0.0037
Nominal effective exchange rate	0.0000	0.0000

Table 2 shows the $p-values$ for the quasi-differenced demeaned , which includes only an intercept term (labeled $\mathbf{DF-QD_{\mu}}$ **intercept** in table 2), and the quasi-differenced detrended, which includes both an intercept and trend term (labeled $\mathbf{DF-QD_{\tau}}$ **intercept and trend** in table 2), Dickey-Fuller tests. Based on the union of rejections rule, all variables are stationary.

5 Priors

In the case of a seven variable VAR with two lags, over 100 coefficients need to be estimated. Due to the likelihood of overfitting it is necessary to use priors to shrink the parameter space and ensure precise estimates. There are a number of prior types available to estimate this model. The main results presented below are based on the Minnesota prior from work by Doan et al. (1984) and Litterman (1986). This prior is used since it leads to simple posterior inference. We show in the robustness section that the results presented are generally robust to the choice of prior.

The Minnesota prior assumes that the coefficients of longer lag lengths are likely to have a mean of zero with the first lag having a mean of unity. We fit a prior to the β matrix such that:

$$\beta \sim N(\underline{\beta}_{min}, \underline{V}_{min}) \tag{7}$$

with the elements of $\underline{\beta}_{min}$ set to zero except for the first own lag which is set to 0.9 assuming that the data is fairly persistent but not a random walk. Empirical evidence in South Africa shows that inflation is a highly persistent series with inflation expectations sufficiently backward-looking.

The prior covariance matrix, $\underline{V}_{min}$, is a diagonal matrix such that the diagonals elements $\underline{V}_{i,jj}$ for equation i is:

$$\underline{V}_{i,jj} = \begin{cases} \frac{\underline{a}_1}{p^2} & \text{for coefficients on own lags} \\ \frac{\underline{a}_2 \sigma_{ii}}{p^2 \sigma_{jj}} & \text{for coefficients on lags of variables i} \neq \text{j} \\ \underline{a}_3 \sigma_{ii} & \text{for all coefficients on exogenous vriables} \end{cases} \tag{8}$$

where $\bar{a}_1$, $\bar{a}_2$, and $\bar{a}_3$ are hyperparameters set to 0.5, 0.5, and 10^2 respectively; p is the lag length, and $\sigma_{ii} = S_i^2$ are the OLS estimates of the variance from an AR(p) model. This prior has the property that as the lag length increases, the variance tends to zero. In the robustness section we show that the results of this paper are robust to a variety of hyperparameter choices.

Alternate priors including a Diffuse, Normal-Wishart, Independent Normal-Wishart, and two versions of Stochastic Search Variable Selection (SSVS) are used in the robustness section to assess the impact of prior choices. Monte Carlo integration is used to estimate the posterior distribution of β when using the diffuse, Minnesota and Normal-Wishart priors. The Gibbs sampler is used to estimate models with the Independent Normal-Wishart and SSVS priors. An initial burn-in phase is implemented to ensure convergence. For more details on each prior see Koop and Korobilis (2010).

6 Identification

Identifying the structural shocks from the reduced-form shocks estimated in equation (3) requires assumptions about the relationship between these shocks. We can use a short-run impact matrix such that:

$$\mu_t = Z\varepsilon_t, \quad E\varepsilon_t\varepsilon_t' = I, \quad ZZ' = \Sigma \tag{9}$$

where Z is a short-run impact matrix and ε_t are the structural shocks. The information used to determine Z can come from short- and long-run zero restrictions as well as sign restrictions. Short-run zero restrictions force the impact of a shock at time t to be zero. However, from t+1 the impact of the shock on the model's variables is driven by the dynamics of the model. Long-run zero restrictions ensure that there is no long-run ($t = \infty$) impact of the shock on a particular variable. Since the infinite duration is not observable in practice we confirm long-run restrictions by looking at impulse response functions 100-quarters ahead. Combining zero restrictions in both the short- and long-run initially required numerical optimization to solve due to the highly non-linear nature of the problem (see Gali, 1992). Rubio-Ramirez et al. (2010) solved this technical problem with an algorithm that finds the correct rotation matrix that satisfies these restrictions. Sign restrictions were introduced to solve under-identified VAR models by sampling iteratively solutions to the sign restrictions that are consistent with the reduced-form VAR. This generated a distribution of impulse response functions that can be restricted based on the sign-restrictions imposed. In Rubio-Ramirez et al. (2010) and Binning (2013) the imposition of sign restrictions is done using a QR decomposition.

An exactly-identified model requires $n(n-1)/2$ restrictions on the impact matrix where n is the number of endogenous variables (in the case of a seven variable VAR this equates to 21 restrictions). However, exactly-identified models using zero restrictions generally require "incredible" identifying assumptions which can be entirely ad hoc. This problem is particularly acute in larger VARs as is the case here.

We follow an agnostic approach in this paper specifying an under-identified system with 14 zero restrictions on the short- and long-run impact matrix as well as 11 contemporaneous sign restrictions derived from economic theory and following work of Sims (1980), Blanchard and Quah (1988), Gali (1992), Baumeister et al. (2010), Rubio-Ramirez et al. (2010) and Binning (2013). We use the algorithm of Binning (2013) which further enhances the Rubio-Ramirez et al. (2010) algorithm to handle short- and long-run zero restrictions, sign restrictions or a combination of the three. Since this model is under-identified there are numerous Z matrices that are consistent with the reduced-form model.

The zero restrictions on the short- and long-run impact matrices are specified as:

$$f(Z,B)=\begin{bmatrix} L_0 \\ L_\infty \end{bmatrix} = \begin{array}{ll} & \begin{array}{ccccccc} \textit{Relative price} & \textit{Imported inflation} & \textit{Aggregate supply} & \textit{Wage} & \textit{Aggregate demand} & \textit{Monetary policy} & \textit{Exchange rate} \end{array} \\ \begin{array}{l} \textit{Relative Price} \\ \textit{Imported inflation} \\ \textit{Real GDP} \\ \textit{ULC} \\ \textit{Core inflation} \\ \textit{Repo rate} \\ \textit{Exchange rate} \\ \hline \textit{Relative Price} \\ \textit{Imported inflation} \\ \textit{Real GDP} \\ \textit{ULC} \\ \textit{Core inflation} \\ \textit{Repo rate} \\ \textit{Exchange rate} \end{array} & \begin{bmatrix} \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & 0 & \times \\ 0 & \times & \times & \times & \times & 0 & \times \\ 0 & \times & \times & \times & \times & 0 & \times \\ \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \\ - & - & - & - & - & - & - \\ \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \\ 0 & 0 & \times & 0 & 0 & 0 & 0 \\ \times & \times & \times & \times & \times & \times & 0 \\ 0 & \times & \times & \times & \times & \times & 0 \\ \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \end{bmatrix} \end{array} \quad (10)$$

Where L_0 is an $m \times m$ short-run impact matrix, with $L_0 = Z$ and $L_0 L_0' = \Sigma$, and L_∞ is an $m \times m$ long-run impact matrix, $L_\infty = (I-B)^{-1} L_0$ where $B = \sum_{j=1}^{p} B_j$.

First, based on Blanchard and Quah (1988), we assume that only real (aggregate supply) shocks have a long-run impact on real GDP growth. This assumption has been used in papers such as Gali (1992) and Christiano et al. (2006). This implies that monetary policy is neutral in the long-run. Second, we assume that relative food and energy price shocks have no long-run impact on core inflation. This assumption is based on the idea that only the expectations channel (i.e. the impact of food and energy prices on wages) can lead to a self-sustaining price spiral with higher wages leading to higher prices. Third, since prices are sticky in the short-run we assume that a relative food and energy price shock has no contemporaneous impact on core inflation and wages. We do not place a contemporaneous zero restriction on real GDP as demand effects from commodity price moves are generally instantaneous. Fourth, we assume that exchange rate shocks have no long-run impact on real GDP, unit labour cost and core inflation. Fifth, we assume that a monetary policy shock has no contemporaneous impact on real GDP growth, ULC and core inflation. This is a common assumption in short-run restricted VAR models starting with the work of Sims (1980).

The following contemporaneous sign restrictions are also imposed in order to identify the model:

$$S = \begin{array}{l c}
 & \begin{array}{ccccccc} \rotatebox{90}{\textit{Relative price}} & \rotatebox{90}{\textit{Imported inflation}} & \rotatebox{90}{\textit{Aggregate supply}} & \rotatebox{90}{\textit{Wage}} & \rotatebox{90}{\textit{Aggregate demand}} & \rotatebox{90}{\textit{Monetary policy}} & \rotatebox{90}{\textit{Exchange rate}} \end{array} \\
\begin{array}{l} \textit{Relative Price} \\ \textit{Imported inflation} \\ \textit{Real GDP} \\ \textit{ULC} \\ \pi_s \\ \textit{Repo rate} \\ \textit{Exchange rate} \end{array} &
\begin{bmatrix}
+ & \times & \times & \times & \times & \times & \times \\
\times & \times & \times & \times & \times & \times & \times \\
- & \times & \times & + & + & \times & \times \\
\times & \times & \times & + & \times & \times & \times \\
\times & + & \times & + & + & \times & \times \\
+ & \times & \times & \times & + & + & \times \\
\times & \times & \times & \times & \times & \times & \times
\end{bmatrix}
\end{array} \tag{11}$$

Due to contemporaneous zero restrictions there is no need to place sign restrictions at corresponding points. We impose the following sign restrictions. First, we assume that a shock to relative food and energy prices would decrease real GDP due to initially higher imports as well as negative income effects on consumers. The policy rate will increase as monetary policy reacts to anticipated second-round effects. The relative price shock is assumed to be positive. Baumeister et al. (2010) provide empirical evidence for these sign restrictions. Second, a wage inflation shock is expected to increase real GDP, as consumers are able to increase spending; and core inflation, as inflation expectations rise. The wage shock is assumed to be positive. Third, an aggregate demand shock is assumed to increase real GDP, core inflation and the repo rate. Fourth, a monetary policy shock is expected to increase the repo rate.

7 Estimation methodology

The estimation and identification steps are both iterative. In the estimation step, impulse response functions are calculated from the posterior distribution taking into account parameter uncertainty. This involves taking draws of Σ^{-1} from equation 6 and finding β from equation 5 conditional on this draw. In the identification step, since the VAR is under-identified, there are many possible models or Zs that satisfies the zero- and sign-restrictions. This introduces some degree of model uncertainty. To minimise this model uncertainty, an adequate number of zero and sign restrictions are imposed. In this paper, we combine the estimation and identification steps into an iterative process with each draw providing an estimate of β conditional on Σ^{-1} and a Z matrix that satisfies the zero- and sign-restrictions. The advantage of this approach is that both model and parameter uncertainty is taken into account in the impulse response functions. In the robustness section, results are generated using the posterior mean estimates of the parameters to highlight the role of model versus parameter uncertainty.

7.1 Bayesian estimation step

The Minnesota prior ensures that posterior inference has an analytical solution involving only the normal distribution such that:

$$\beta|y \sim N(\bar{\beta}_{min}, \bar{V}_{min}) \tag{12}$$

where

$$\bar{V}_{min} = [\underline{V}_{min}^{-1} + (\hat{\Sigma}^{-1} \otimes (X'X))]^{-1} \tag{13}$$

and

$$\bar{\beta}_{min} = V_{min}[\underline{V}_{min}^{-1}\underline{\beta}_{min} + (\hat{\Sigma}^{-1} \otimes X)'y] \tag{14}$$

The iteration step is augmented with a rule that discards any draws that produces an unstable VAR, i.e. the eigenvalues of the companion form of the parameter matrix are greater than 1. The discard rate is in the region of 2 per cent, i.e. we discard 2 draws in 100. See appendix A for more details.

7.2 Identification step

Following Binning (2013), the zero restrictions imposed in $f(Z,B)$ can be written as an $m \times 2m$ matrix Q_j such that:

$$Q_j f(Z,B) e_j = 0 \tag{15}$$

Where e_j is the j^{th} column of the $m \times m$ identity matrix. The VAR model will be exactly-identified if $q_j = rank(Q_j) = m - j$ for $1 \leq j \leq m$. In order to solve for Z in an under-identified model an orthogonal rotation matrix, P^*, is found that will rotate an initial impact matrix until the zero restrictions imposed in L_0 and L_∞ are solved. The Cholesky decomposition of the covariance matrix ($C = chol(\Sigma)$) post-multiplied by a randomly drawn orthogonal matrix, Q^*, is used for the initial short-run impact matrix ($L_0^* = CQ^*$). The j^{th} column of P^* is equal to the m^{th} column of the Q matrix from a QR decomposition of $\tilde{Q}_j = Q_j F$. The solution is $Z = CQ^* P^*$. For full details of the algorithm see Binning (2013).

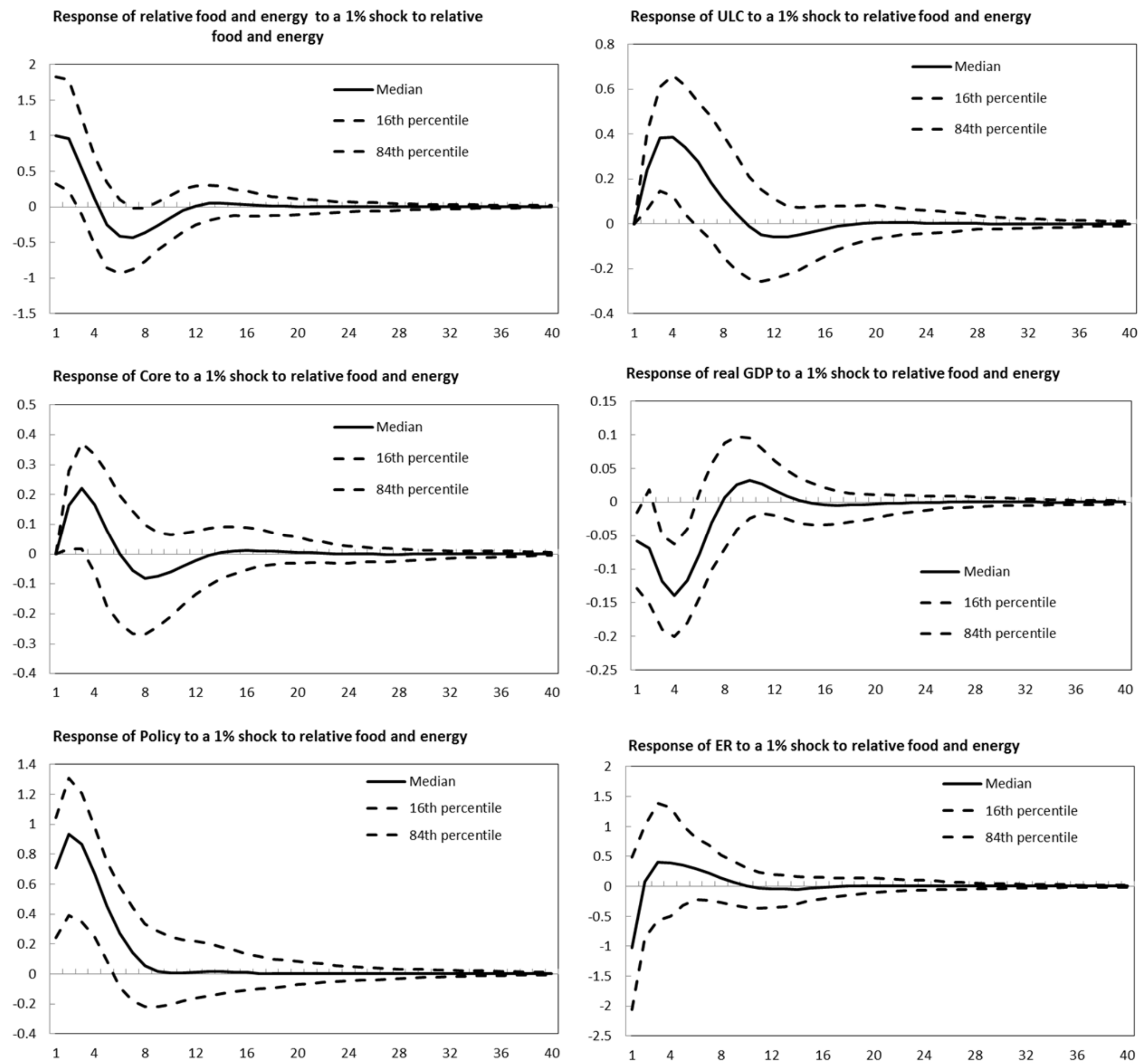
8 Results

The VAR model is estimated using the Minnesota prior on data from 1994Q1 to 2014Q2. We iterate over 1000 draws with burn-in of 1000 for priors requiring the Gibbs sampler. We include a trend variable to take into account the disinflation that took place over the 1990s to the introduction of inflation targeting in 2000 as well as the concomitant decline seen in interest rates. Although Bayesian estimation mitigates the over-fitting problem, we use 2 lags in the estimation step due to the relatively short time period. The Bayesian Information Criterion (BIC) suggests a lag length of one, the Likelihood Ratio test suggests a lag length of four while the Akiake Information Criterion (AIC) suggest a lag length of 6. In the robustness section we test the sensitivity of results to lag length.

8.1 Cost and expectations channel

We highlight two specific channels through which relative food, petrol and energy prices feed through to overall inflation: the cost and expectations channel. The expectations channel refers to the response of wage-setting labour to a relative price shock. If labour can successfully increase nominal wages or price-setters their mark-up in response to a relative food and energy price shock then there will be second-round effects. This is compounded by cost effects as the prices of other goods and services in the economy increase due to the role of food and energy in the production process. If firms pass on the higher production costs to consumers than the cost effect can be large. Figure 2 plots the 40-quarter impulse response functions of the variables of interest in the VAR to a one per cent shock to relative food, petrol and energy prices including the median, 16^{th} and 84^{th} percentile bands. These bands include both parameter and model uncertainty.

Figure 2: The impact of food, petrol and electricity prices



In order to measure second-round effects we look at the impact of a relative food and energy price shock on ULC. Figure 2 indicates a strong second-round effect in post-Apartheid South Africa. A one per cent shock to relative food and energy increases unit labour costs by 0.39 per cent after four quarters. The shock only dissipates after ten quarters. This is only part of understanding second-round effects. It is necessary to understand how higher labour costs feed into core inflation. Figure 3 shows the impact of a 1 per cent shock to ULC. Core inflation rises by 0.47 per cent two quarters after the shock.

Figure 3: The impact of ULC on Core inflation

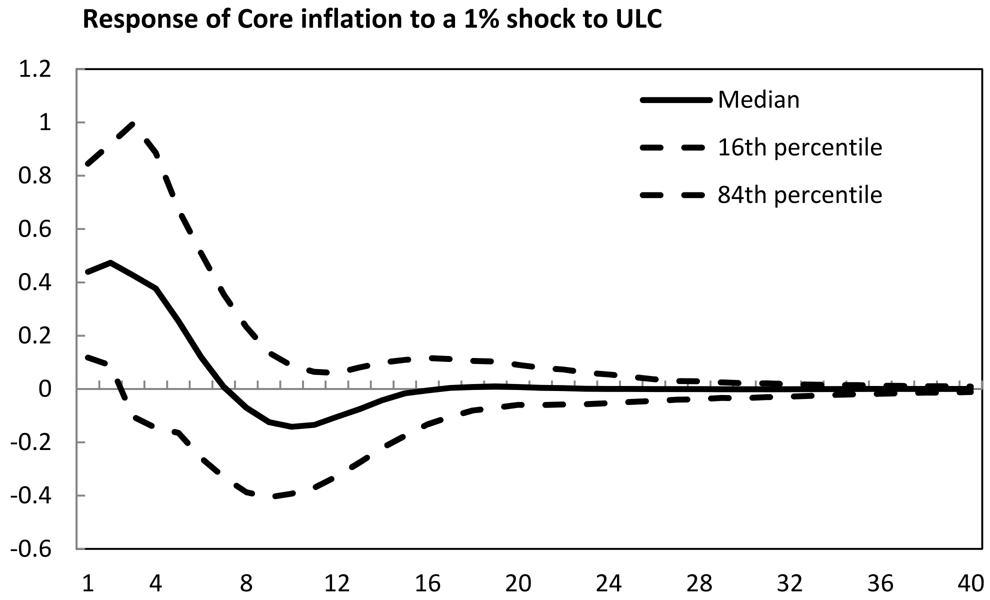


Figure 2 also shows the impact of a relative price shock on core inflation. A one per cent shock to relative food and energy prices has a significant impact on core inflation, with a maximum impact of 0.22 per cent three quarters after the shock. This is due to both the cost and expectations channel. The restrictions imposed ensure that only the expectations channel leads to a permanent increase in core inflation and hence accounts for the majority of the shocks impact.

A relative food and energy shock also leads to an approximately one per cent depreciation in the nominal effective exchange rate which puts further pressure on prices. The endogenous policy response mutes the overall impact of the relative price shock on core inflation.

There is limited literature to compare these results to. From a cross-country perspective, Cecchetti and Moessner (2008) shows that in the majority of emerging market economies there is no evidence of second-round effects. The study includes South Africa, however, it is not possibly to determine whether or not South Africa is an economy where second-round effects occur. Baumeister et al. (2010) provides some context to the impact of second-round effects, but this is only for oil. They find that second-round effects is the key determinant to cross-country differences on inflation in advanced economies. Countries, like Switzerland and the euro area, experience second-round effects and hence higher inflation outcomes, requiring an immediate policy response. The US and Japan, on the other hand, experience no second-round effects.

There is mixed evidence of the existence of second-round effects in the South African literature. Our results are supported by Rangasamy and Nel (2014) who show that second-round effects from food and energy prices matter with impacts on core inflation similar to our estimates. The transmission of the peak impact of the relative price shock to core inflation is, however, five months in Rangasamy and Nel (2014), compared to something closer to 9-12 months in this analysis. They also find that energy prices lead to cost effects on core inflation but are short-lived. Rangasamy (2011) using a single equation estimate of the impact of food on non-food prices finds for every one per cent increase in food inflation, non-food inflation increases 0.5 per cent 12-months after the shock. He also finds that the impact is greatest 12- to 18-months after the shock. Chisadza et al. (2013) estimate a sign-restriction VAR of the impact of differentiated oil price shocks on SA and find that an oil supply shock only has a transitory impact on headline inflation suggesting no cost or expectation effects. This is in contrast to the finding in this paper.

8.2 Demand effects

For an oil-importing country such as SA, theory states that increases in food and energy prices erode disposable income, increase risk leading to higher precautionary savings, decrease business and consumer confidence, and postpone investment and durable consumption expenditure. The presence of strong second-round effects limit the ability of firms to react to the fall in production through cost containment forcing firms to adjust profit margins. This is compounded by the need for the central bank to react to higher inflation by raising interest rates. These downward factors are somewhat mitigated by the immediate depreciation of the exchange rate by one per cent in response to the relative price shock.

Figure 2 shows that in response to a one per cent relative price shock, real GDP growth declines peaking at 0.14 per cent after four quarters. In comparison, the domestic literature only addresses the impact of oil price shocks and is inconclusive. Chisadza et al. (2013) find that an oil supply shock has no significant impact on domestic output. In contrast, Nkomo (2006) highlights that oil price shocks have important negative consequences for domestic output. Wakeford (2006) using a case study approach finds that during episodes of rising oil prices such as in 1979-80, 1990 and 2003-06, there are significant price pressures and negative output impacts. Finally, Fofana et al. (2009) using a macro-meso-micro analysis find that although there is a negative and significant impact from an oil price shock, the impact is smaller-than-expected. The impact is also smaller-than-expected in this analysis. The reason that this is surprising is that the negative relative price shock is amplified by contractionary monetary policy.

8.3 Monetary policy response

The strong cost and second-round effects from food and energy mean that monetary policy needs to react by increasing interest rates. A one per cent increase in relative prices leads to an immediate response of interest rates of 71 basis points. This is equivalent to about a 1.8 inflation coefficient in a conventional Taylor type rule if the central bank was targeting headline inflation and 1.9 coefficient if the bank was targeting core inflation.[3]

Chisadza et al. (2013) find that monetary policy does not react to an oil supply shock due to the fact that they find only a transitory small impact on headline inflation. Part of the reason they do not find a significant policy response may be the sample chosen. The VAR is estimated on data from 1975, two decades before the interest rate in used as an instrument of monetary policy.

[3]The inflation coefficient is the ratio of the peak policy response to the two-year cumulative inflation response.

9 Robustness

In this section we look at an alternative estimation methodology, separating out the parameter and model estimation step, as well as the sensitivity of the results to changes to the priors, hyperparameters and changes to the lag length.

9.1 Estimation methodology

The estimation methodology followed introduces both model and parameter uncertainty to the estimate of the impact of a relative food and energy price shock. However, since each parameter draw of the Monte Carlo integration step includes a model draw that satisfies the identification restrictions, it is not possible to distinguish between what is model uncertainty and what is parameter uncertainty. Therefore, an alternative strategy is followed in order to distinguish the two impacts. This involves changing the algorithm to first solve the parameter estimation step and then use the mean parameter estimates to draw models that satisfy the identification restrictions, i.e. shifting from one-step to two-step estimation. This is analogous to assuming that there is no parameter uncertainty and the mean estimate is the true value of this parameter and then iterating over a number of models that solve the identification restrictions. We use 1000 iterations in each step of the two-step process.

Figure 4: Model versus parameter uncertainty

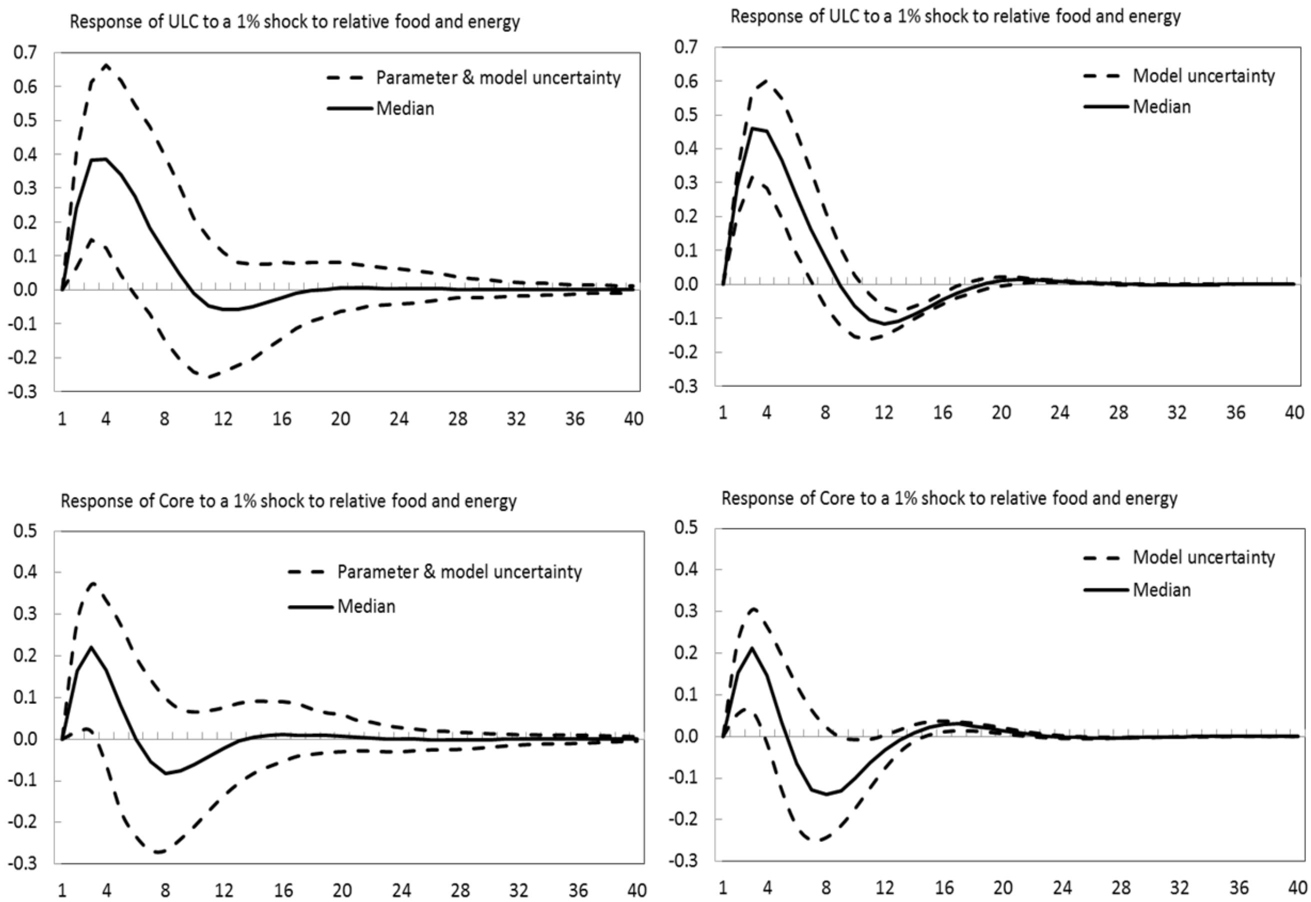


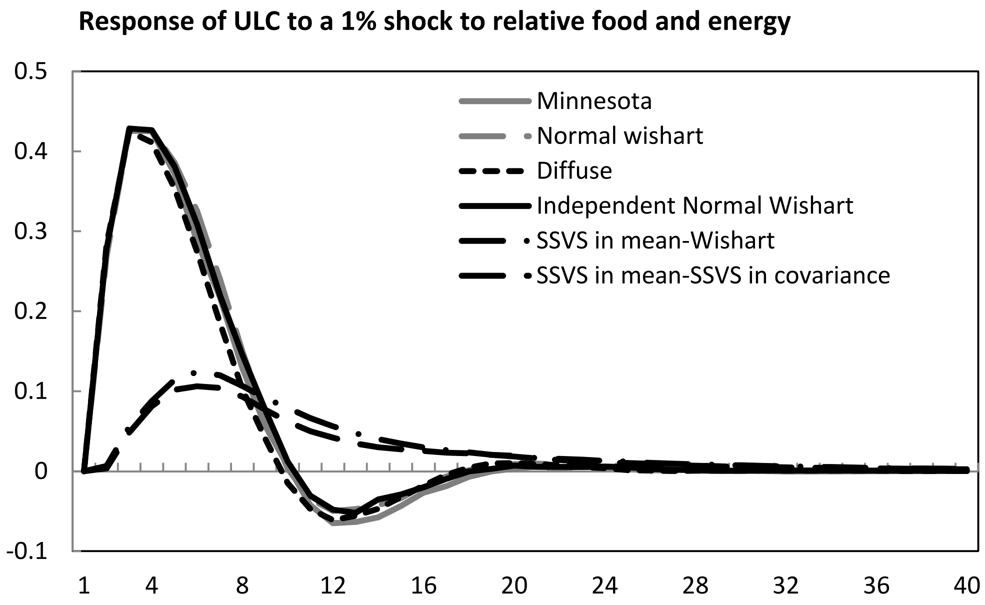
Figure 4 plots the median impulse response of core inflation and ULC to a one per cent shock to relative food and energy prices with the left panels showing the initial results (which includes both parameter and model uncertainty) and the right panels showing only model uncertainty from the two-step process. The results show that both parameter and model uncertainty contribute significantly to the variance of the coefficient estimates. Model uncertainty effectively doubles the degree of uncertainty around ULC at the peak impact while increasing uncertainty by 1.4 times at the peak impact of core. Model uncertainty has little impact on the median response. Model uncertainty also does not materially change the results of the IRFs which continue to have the same overall trend and magnitude negating the need for “incredible” restrictions from an exactly identified VAR model.

9.2 Sensitivity to priors

Prior selection requires a number of choices regarding the treatment of the covariance matrix as well as the size of hyperparameters. For example the drawback of the Minnesota prior used in this paper is that although it simplifies estimation, it treats the covariance matrix as known. To address this shortcoming we look at priors that treat the covariance matrix as unknown and introduce uncertainty in its estimation.

These priors include the Independent Normal-Wishart (where the coefficients and error covariance are independent of one another) as well as the two SSVS priors. The SSVS priors implemented in this paper are different from George et al. (2008) and follow the work of Koop and Korobilis (2010).

Figure 5: Sensitivity to prior selection



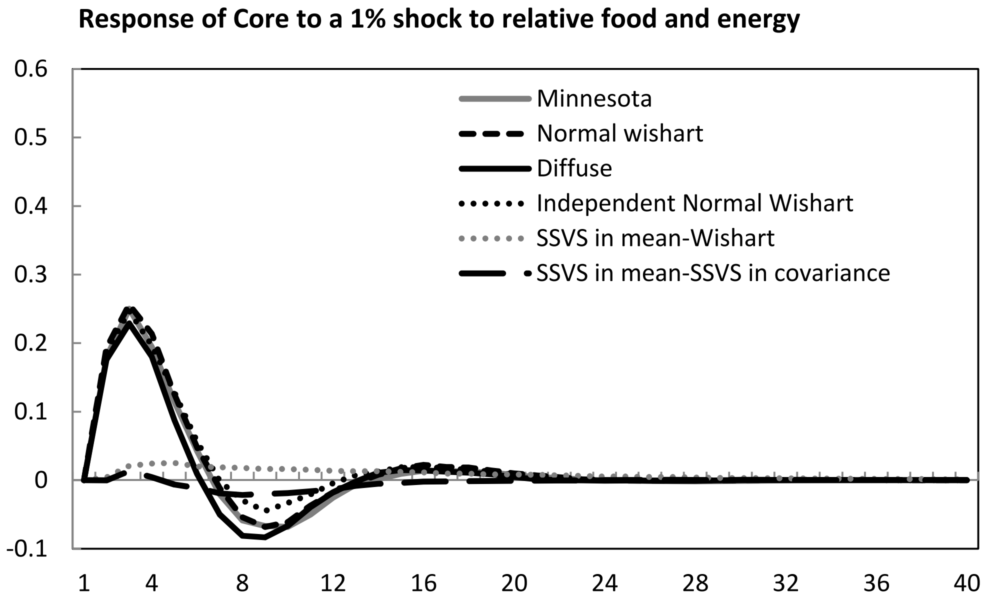


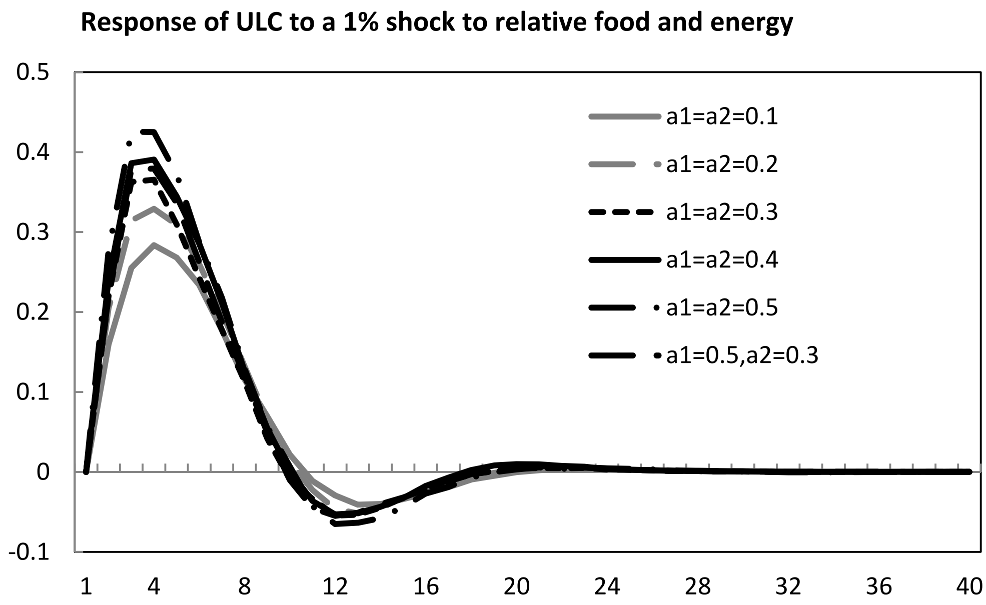
Figure 5 shows the impact of alternative prior choices on the response of core inflation and unit labour cost to a one per cent shock to relative food and energy prices. All priors, except the two SSVS priors, provide analytically similar results. In the case of the response of unit labour cost the impacts are around the 0.4 per cent estimate of the Minnesota prior and follow a similar path. The SSVS priors flatten the impact, suggesting that a one per cent shock to food and energy prices lead to a 0.12 per cent impact on ULC with the maximum impact only six to seven quarters after the shock. In the case of the response of core inflation, a similar pattern emerges with all the priors, except the SSVS priors, indicating a just above 0.2 per cent impact. The SSVS priors suggest no impact from a shock to relative food and energy.

The results of the Independent Normal-Wishart prior show that the IRFs are robust to the treatment of the covariance matrix. In both the core inflation and ULC response the Independent Normal-Wishart prior has effectively the same response to that of the Minnesota prior.

9.3 Sensitivity to prior hyperparameters

Hyperparameters control the shrinkage on the parameter estimates by increasing or decreasing the size of the variance. In order to determine the sensitivity of the results to the hyperparameters we re-estimate the model with combinations of $(\underline{a}_1, \underline{a}_2) = [(0.1, 0.1); (0.2, 0.2); (0.3, 0.3); (0.4, 0.4); (0.5, 0.5); (0.5, 0.3)]$. The last combination, $(0.5, 0.3)$, highlights the impact of the assumption "that own lags are more likely to be important predictors than lags of other variables" (Koop and Korobilis, 2010). We do not test the sensitivity of hyperparameter $\underline{a}_3$ as in practice it is diffuse, i.e. set to 10^2.

Figure 6: Sensitivity to prior hyperparameters



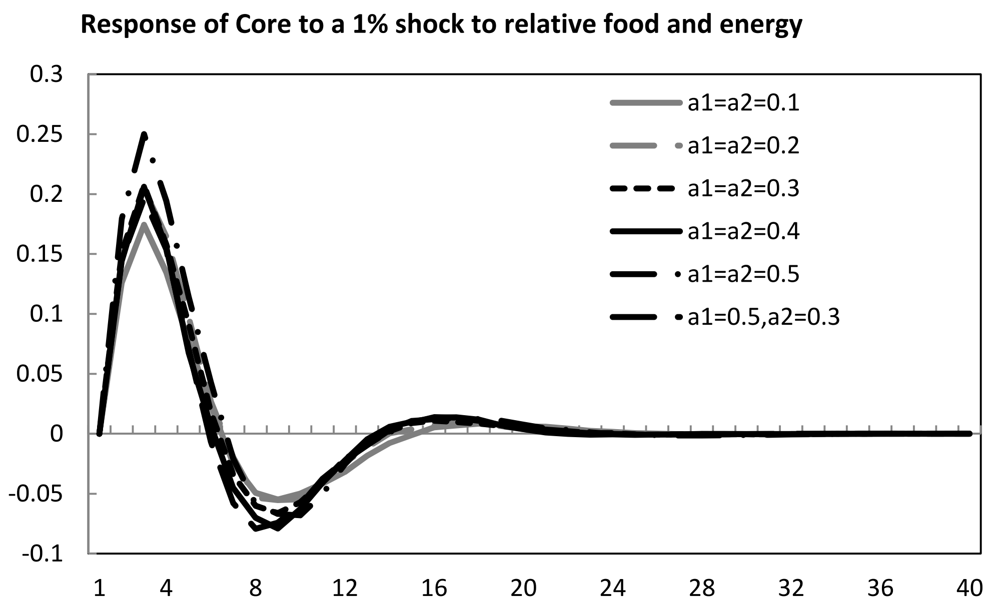
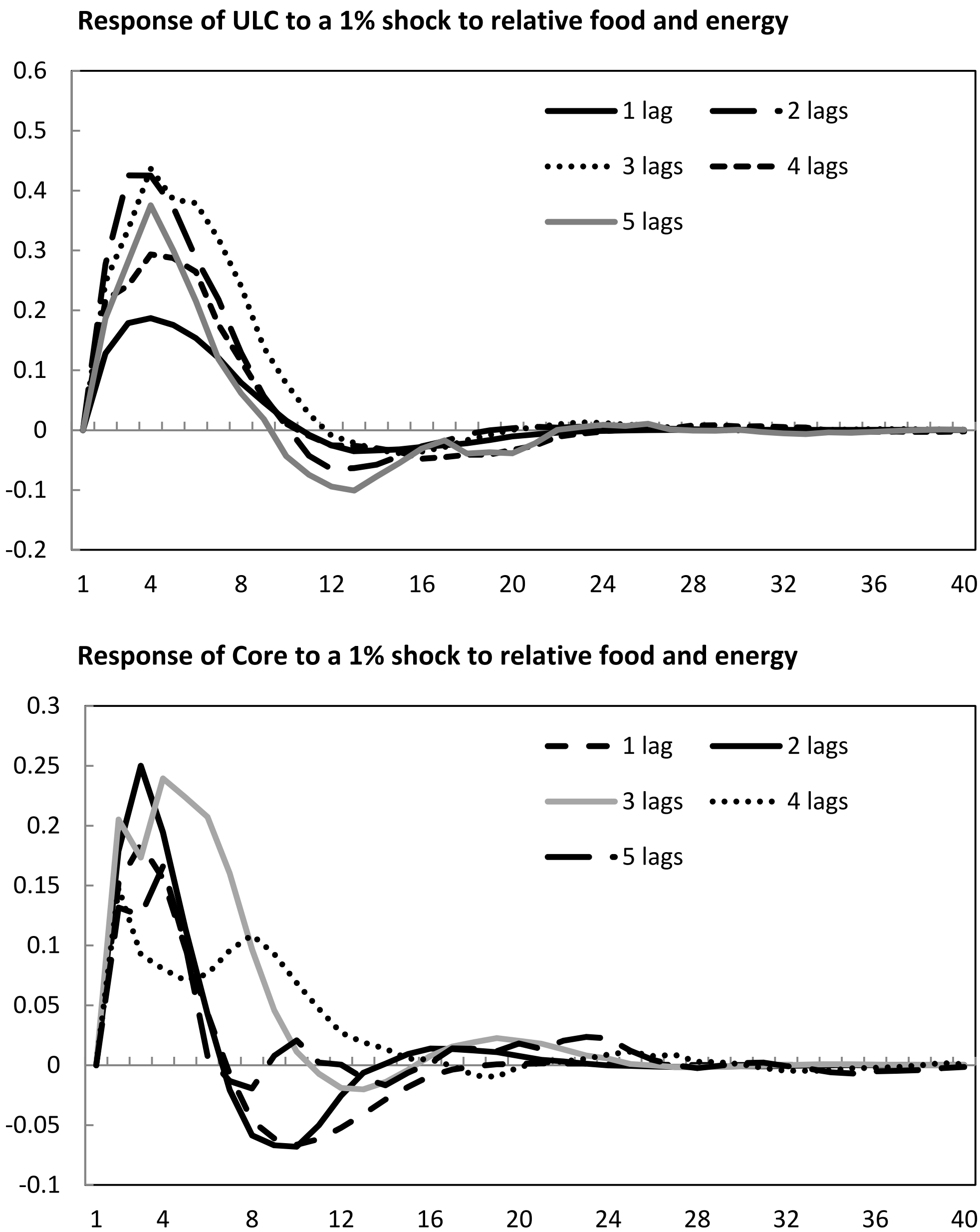


Figure 6 plots the IRFs of core inflation and ULC to different combinations of hyperparameters. The results suggest that outcomes are robust to the choice of hyperparameters. The impact on core inflation follows the same trajectory and peaks in the same quarter for all combinations. The amplitude, however, does differ but marginally in the range of [0.17:0.25]. The outcomes for ULC are similar. The amplitude for ULC is in the range of [0.28:0.42].

9.4 Sensitivity to lag length

Figure 7 plots the IRFs of core inflation and ULC for lag lengths from one to five. In the case of the response of core inflation, alternate lag lengths confirm that there remains a cost effect from a relative food and energy price shock. The maximum response however varies from 0.14 (for a lag length of four) to 0.25 (for a lag length of two). The maximum response also shifts from peaking one quarter after the response (for four lags) to four quarters after (in the case of three and five lags). In the case of the response of ULC, there is slightly more variation in the magnitude of the response but not in its timing. The peak response varies from 0.19 per cent (for one lag) to 0.44 per cent (for three lags). The peak response however is four quarters after the shock for all lag lengths.

Figure 7: Sensitivity to lag length



10 Policy implications

The results of this paper have a number of important implications for the conduct of monetary policy. First, relative price shocks lead to large cost and expectations effects requiring an immediate monetary policy response to stabilise core inflation. A lack of this response can lead to persistent inflationary impacts and a wage-price spiral. Second, the peak impact of second-round effects occur three-to-four quarters after the shock suggesting that impacts take time to feed into underlying inflation and wage-setters adjust wage demands for the next wage cycle. Third, the presence of strong second-round effects amplifies the decline on output since it requires an aggressive monetary response.

11 Conclusion

The ability of monetary policy to respond to second-round effects requires that policymakers know about the existence and magnitude of these effects. In South Africa, relative price shocks to food and energy prices are entrenched in the language and responses of wage-setters. However, much of the evidence of this remains anecdotal. In order to measure these effects we build a structural Bayesian VAR with plausible zero and sign restrictions based on economic theory which highlight the role of both cost and expectations channel of second-round effects.

The results of this paper confirm the impact of wage-setters in South Africa; that changes in the price of food, petrol and energy are accommodated and lead to strong second-round effects. According to the structural Bayesian VAR model, shocks to relative food and energy prices increase the price of other goods and services with a maximum impact of 0.2 per cent, three quarters after the shock. Most of this impact is due to higher wages bidding up the cost of goods and services. These shocks also have a significant impact on wages increasing nominal unit labour cost by 0.4 per cent four quarters after the shock.

The presence of second-round effects change how a central bank needs to respond to relative price shocks. Generally, when these do not occur a central bank can look through shocks to food and energy prices as they will be temporary in nature. However, when second-round effects are present, the central bank has to respond aggressively to ensure that inflation expectations remain anchored around the target.

References

Anand, R. and E. S. Prasad (2010). Optimal price indices for targeting inflation under incomplete markets. Technical report, National Bureau of Economic Research.

Aoki, K. (2001). Optimal monetary policy responses to relative-price changes. *Journal of Monetary Economics 48*(1), 55–80.

Baumeister, C., G. Peersman, I. Van Robays, et al. (2010). The economic consequences of oil shocks: differences across countries and time. *Inflation in an era of relative price shocks, Reserve Bank of Australia*, 91–128.

Binning, A. (2013). Underidentified svar models: A framework for combining short and long-run restrictions with sign-restrictions. *Available at SSRN 2350094*.

Blanchard, O. J. and J. Gali (2007). The macroeconomic effects of oil shocks: Why are the 2000s so different from the 1970s? Technical report, National Bureau of Economic Research.

Blanchard, O. J. and D. Quah (1988). The dynamic effects of aggregate demand and supply disturbances.

Blignaut, Z., G. Farrell, V. Munyama, and L. Rangasamy (2009). A note on the trimmed mean measure of core inflation in south africa. *South African Journal of Economics 77*(4), 538–552.

Bodenstein, M., C. J. Erceg, and L. Guerrieri (2008). Optimal monetary policy with distinct core and headline inflation rates. *Journal of Monetary Economics 55*, S18–S33.

Calvo, G. A. (1983). Staggered prices in a utility-maximizing framework. *Journal of monetary Economics 12*(3), 383–398.

Cecchetti, S. G. and R. Moessner (2008). Commodity prices and inflation dynamics. *BIS Quarterly Review*, 55–66.

Chisadza, C., J. Dlamini, R. Gupta, and M. Modise (2013). The impact of oil shocks on the south african economy. Technical report, University of Pretoria, Department of Economics.

Christiano, L. J., M. Eichenbaum, and R. Vigfusson (2006). Alternative procedures for estimating vector autoregressions identified with long-run restrictions. *Journal of the European Economic Association 4*(2-3), 475–483.

Doan, T., R. Litterman, and C. Sims (1984). Forecasting and conditional projection using realistic prior distributions. *Econometric reviews 3*(1), 1–100.

Du Plessis, S., G. Du Rand, and K. Kotzé (2015). Measuring core inflation in south africa. *South African Journal of Economics*, n/a–n/a.

Fofana, I., M. Chitiga, and R. Mabugu (2009). Oil prices and the south african economy: A macro–meso–micro analysis. *Energy Policy 37*(12), 5509–5518.

Gali, J. (1992). How well does the is-lm model fit postwar us data? *The Quarterly Journal of Economics*, 709–738.

George, E. I., D. Sun, and S. Ni (2008). Bayesian stochastic search for var model restrictions. *Journal of Econometrics 142*(1), 553–580.

Harvey, D. I., S. J. Leybourne, and A. Taylor (2009). Unit root testing in practice: dealing with uncertainty over the trend and initial condition. *Econometric Theory 25*(03), 587–636.

Hlédik, T. and Č. N. Banka (2003). *Modelling the Second-Round Effects of Supply-Side Shocks on Inflation*. Czech National Bank.

Koop, G. and D. Korobilis (2010). *Bayesian multivariate time series methods for empirical macroeconomics*. Now Publishers Inc.

Litterman, R. B. (1986). Forecasting with bayesian vector autoregressionsâĂŤfive years of experience. *Journal of Business & Economic Statistics 4*(1), 25–38.

Nkomo, J. (2006). Crude oil price movements and their impact on south africa. *Journal of Energy in Southern Africa 17*(4), 25.

Rangasamy, L. (2009). Inflation persistence and core inflation: The case of south africa. *South African Journal of Economics 77*(3), 430–444.

Rangasamy, L. (2011). Food inflation in south africa: Some implications for economic policy. *South African Journal of Economics 79*(2), 184–201.

Rangasamy, L. and E. Nel (2014). Reconsidering the role of food prices in south african headline inflation. *Agrekon 53*(4), 16–37.

Roger, S. (1998). Core inflation: concepts, uses and measurement. *Reserve Bank of New Zealand Discussion Paper* (G98/9).

Rubio-Ramirez, J. F., D. F. Waggoner, and T. Zha (2010). Structural vector autoregressions: Theory of identification and algorithms for inference. *The Review of Economic Studies 77*(2), 665–696.

Ruch, F. and D. Bester (2013). Towards a measure of core inflation using singular spectrum analysis. *South African Journal of Economics 81*(3), 307–329.

Sims, C. A. (1980). Macroeconomics and reality. *Econometrica: Journal of the Econometric Society*, 1–48.

Smets, F. and R. Wouters (2002). Openness, imperfect exchange rate pass-through and monetary policy. *Journal of monetary Economics 49*(5), 947–981.

Wakeford, J. (2006). The impact of oil price shocks on the south african macroeconomy: History and prospects. In *Accelerated and Shared Growth in South Africa: Determinants, Constraints and Opportunities,(18-20 October 2006). The Birchwood Hotel and Conference Centre, Johannesburg, South Africa*.

Walsh, J. P. (2011). *Reconsidering the role of food prices in inflation*. International Monetary Fund.

Appendices

A Stability of the VAR model

The estimation methodology involves iteratively solving the model to determine the posterior distributions of the parameters as well as satisfy the under-indentifying restrictions (Zs). To ensure that we do not draw results from an unstable VAR, on each iteration the algorithm checks the maximum eigenvalue of the companion form of the parameter matrix. If this eigenvalue is greater than or equal to one then the draw is discarded. Figure 8 shows a histogram of the maximum eigenvalue of the 1000 draws, with a vertical line indicating the cut-off. About 2 per cent of draws are discarded in the main results of this paper. The discard rate remains relatively constant to the number of iterations run. The mean posterior estimate of the parameter matrix has a maximum eigenvalue of 0.8082. Hence our VAR is stable.

Figure 8: Maximum eigenvalue of the parameter matrix on each draw