Essays on Inflation Forecasts and Bayesian Estimation of Central Bank Policy Preferences

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Abstract

This thesis consists of three essays which address important topics on inflation forecasts and central bank policy preferences in Ghana and South Africa. The second Chapter evaluates the Bank of Ghana's (BoG) inflation forecasts. First, it investigates whether the BoG's inflation forecast is efficient. It also assesses how its inflation forecast performs when compared to other benchmark forecasts. Finally, this Chapter assesses the effectiveness of an intervention technique, the Step Indicator Saturation (SIS) method in explaining forecast performance when there are structural shifts in the data. The third Chapter investigates whether New Keynesian Philips Curve (NKPC)-based forecasts that incorporates a time-varying-trend (TVT) improves on forecasts when compared to institutional and other empirical-based benchmark forecasts. The Chapter also investigates whether the incorporation of indicator variables improves on the performance of NKPC forecasts. The fourth Chapter investigates whether African Inflation Targeting (AFIT) central banks are committed to price stability as mandated. The Chapter also examines whether there are alternative policy objectives that distract from the commitment of AFITs to price stability. Finally, I address the question of whether there are significant differences in the level of commitment to inflation stabilisation among AFITs, Latin American Inflation targeters (LAIT) and advanced small open economy inflation targeters (ASOE).

Inflation Forecasts Evaluation - The Case of Ghana.

The main contribution of Chapter 2 is its use of a combination of Mincer-Zarnowitz regressions and step indicator saturation (SIS) variables to evaluate inflation forecasts of a developing economy central bank. Using a Mincer-Zarnowitz regression, I conclude that the one-quarter ahead BoG inflation forecast with SIS variables provides the strongest evidence in support of forecast efficiency. The BoG's one-quarter ahead inflation forecast is efficient with or without the incorporation of SIS variables, however, a stronger efficiency is exhibited when SIS variables are incorporated in the forecast. The BoG's two-quarters ahead inflation forecast is inefficient even with the inclusion SIS variables.

Inflation Forecasting using the New Keynesian Philips Curve with a Time-Varying Trend and Structural Breaks.

Chapter 3 evaluates the performance of a time-varying trend New Keynesian Phillips Curve (TVT-NKPC) inflation forecast versus other time series-based benchmark forecasts in a developing economy. This Chapter's contribution is its focus on a developing economy as previous research have focused on developed economies and the use of saturation variables to analyse the effect of structural shifts in the data on inflation forecasts. For the immediate forecast horizon (one quarter ahead), the Atkeson and Ohanian (2001) (AO) GDP deflator inflation forecast is the most accurate forecast, when compared to the random walk forecast and the four variants of the TVT-NKPC forecasts. In the medium to long-term forecast horizon, even though the random walk (RW) forecast consistently outperforms the AO and TVT-NKPC inflation forecasts, it is not statistically significantly different from the TVT-NKPC inflation forecast.

Bayesian Estimation of Policy Preferences of African Inflation Targeters.

This Chapter is the first known research on African Inflation Targeting (AFIT) Central Banks' policy preferences. It also compares results with those of Latin American (LAIT) and some Advanced Small Open-Economies (ASOE) inflation targeting central banks. The results confirmed that Ghana and South Africa are committed to their price stability mandates with the estimated price stability weights for both countries well within those recorded in Latin America and other ASOE. Output stabilisation is the next policy preference for Ghana, the policy weight is the highest among inflation targeting (IT) central banks. Aside inflation stabilisation, interest rate smoothing is the next important policy consideration for South Africa. As expected of IT central banks, Ghana and South Africa placed the least weight on exchange rate stability.

Declaration

I hereby declare that this thesis has not been and will not be submitted in whole or in part to another University for the award of any other degree.

Signature:

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Stephen Kwame Opata, Doctor of Philosophy

Essays on Inflation Forecasts and Bayesian Estimation of Central Bank Policy Preferences

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Contents

List of Tables

List of Figures

Chapter 1

Introduction

A growing number of developing economy central banks have adopted Inflation Targeting (IT) as their key monetary policy framework in the past two decades. A key component of an IT framework is the generation of forecasts which represent the outlook of future inflation and other important macroeconomic variables such as real output growth (GDP growth). Inflation forecasts are necessary in an IT regime to formulate forward-looking monetary policy. A number of studies have evaluated forecasts typically for advanced economy central banks as in Gavin (2003), Clements (2004) and Stockton (2013) but no significant research has been done to evaluate such forecasts for developing economy central banks. Since policy-making depends on these forecasts they need to be accurate and reliable hence the drive to conduct this research. In Chapter 2, I undertook a purely empirical exercise in which I compared the BoG's forecasts to the actual out-turn to assess forecast accuracy. Chapter 3 also evaluated the forecast accuracy of the BoG in an empirical and theoretical context based on the New Keynesian Philips curve (NKPC). Given previously identified limitations of NKPC-based forecasts in the literature (see Duncan and Martínez-García (2019)), this Chapter followed McKnight et al. (2020) by using a time-varying trend (TVT) framework in deriving forecasts and assessing the forecasts thereof. In Chapter 4, I go further in estimating the preferences of African Inflation Targeters (AFIT) to assess whether they are indeed committed to their price stability mandates.

The second Chapter evaluates the BoG's inflation forecasts. It answers three research questions. First, it investigates whether the BoG's inflation forecast is efficient. It also assesses how the BoG's forecast performs when compared to other benchmark forecasts. Finally, this Chapter assesses the effectiveness of an intervention technique, the Step Indicator Saturation (SIS) method in explaining forecast performance evaluation when there are structural shifts in the data.

In Chapter 2, the question of inflation forecast performance of the BoG is assessed by evaluating how closely the forecasts have been, compared to actual inflation using Mincer-Zarnowitz regressions. The relative performance of the BoG's forecast versus other competing forecasts is assessed using the Theil-U statistic. I also deploy the Diebold and Lopez (1996) test to assess the statistical significance of the differences in performance between the BoG's forecast and the benchmark random walk forecasts.

I use the General-to-Specific (GETS) module in RStudio as prescribed in Pretis et al. (2018) to determine significant shifts in the data identified by step indicator variables (SIS). The SIS variables are then incorporated in the forecasting framework and using an F-test I assess whether the inclusion of the SIS variables improves forecast efficiency.

Using a Mincer-Zarnowitz regression, I conclude that the one-quarter ahead BoG inflation forecast with SIS variables provides the strongest evidence in support of forecast efficiency. The BoG's one-quarter ahead inflation forecast is efficient with or without the incorporation of SIS variables, however a stronger efficiency is exhibited when SIS variables are incorporated in the forecast. The stronger efficiency exhibited by the forecast that incorporates the SIS variables points to the importance of addressing outliers and structural breaks in evaluating inflation forecasts framework, especially in developing economies such as Ghana. The central bank's one-step-ahead forecast is superior with a statistically significant difference in its accuracy compared to the random walk forecast, it outperforms the random walk and the International Monetary Fund (IMF)'s WEO forecasts. The central bank's two-steps-ahead inflation forecast for the naive and SIS incorporated models are inefficient.

The main contribution of Chapter 2 is its use of a combination of Mincer-Zarnowitz regressions and step indicator saturation (SIS) variables to evaluate inflation forecasts of a developing economy central bank.

In Chapter 3, I examine inflation forecasts for Ghana using a NKPC by incorporating time varying trend and address structural breaks in the data using indicator saturator variables. Two research questions are investigated. Firstly, does NKPC-based forecasts, which incorporate TVT, improve on forecasts when compared to institutional and other empirical-based benchmark forecasts. The Chapter also investigates whether the incorporation of indicator variables improves the performance of NKPC forecasts.

I assess the performance of the TVT-NKPC forecast by comparing it with a random walk forecast (RW) and a pseudo random walk forecast as in Atkeson and Ohanian (2001), hereafter, AO forecast, using these as benchmarks, in line with previous forecast evaluation literature (see, Duncan and Martínez-García (2019), Clements and Reade (2020)). The pseudo-out-of-sample forecast is assessed using the root mean square forecast error (RMSFE) and the ratio of the TVT-NKPC RMSFE and the benchmark RMSFEs, the Thiel-U statistic, and its statistical significance is evaluated using the original and modified versions of the Diebold and Lopez (1996) tests. This Chapter provides for a robust forecast which can deal with structural breaks by incorporating indicator saturation variables.

For the immediate policy relevant forecast horizon (one quarter ahead), the AO GDP deflator inflation forecast is the most accurate forecast, it outperforms the random walk forecast and the four variants of the TVT-NKPC forecasts. It is statistically significantly more accurate than the three variants of the TVT-NKPC inflation forecasts, but I do not observe a statistically significant difference in forecast accuracy between this forecast and the RULC RMC (rec) forecast. This result for the one-quarter ahead forecast is like Duncan and Martínez-García (2019) who concluded that in emerging market economies, it was difficult to add-value beyond AO forecasts without adding subjective judgement to account for structural shifts in the data.

The RULC-REC TVT-NKPC forecast is not statistically significantly different from the AO forecast for the immediate forecast horizon. So, for the policy relevant forecast horizon, the RULC-REC TVT-NKPC forecast provides a theoretical and empirical basis for its use for inflation forecasting. The results show a more accurate RW inflation forecast, but there is not a statistically significant difference in forecast accuracy among the TVT-NKPC and the two benchmark inflation forecasts for the medium to long term forecast horizons.

The inclusion of a statistically significant indicator saturation variable improves the model fit but does not lead to an improvement of forecast performance. Rather it leads to a rejection of a null hypothesis of an unbiased and efficient forecast according to the joint test of the null hypothesis using Mincer-Zarnowitz regressions.

Chapter 3, which deploys a time-varying trend NKPC inflation forecast and indicator saturation variables to evaluate inflation forecasts, is the first such study in an emerging-market economy as previous studies had focused on developed economies.

In chapter 4, I address the following research questions. I am interested in knowing whether AFITs are committed to price stability as mandated. Secondly, I would like to find out whether are there alternative policy objectives that distract from the commitment of AFITs to price stability. Finally, I address the question of whether there are significant differences in the level of commitment to inflation stabilisation among AFITs, Latin

American Inflation targeters (LAIT) and advanced small open economy inflation targeters (ASOE).

The marginal likelihoods for complete asset markets (CAM) and incomplete asset markets (IAM) for Ghana and South Africa under restricted and unrestricted log-linearised models are estimated. The models with the highest marginal likelihoods are the preferred ones. The structural parameters of the preferred log-linearised model are estimated using Bayesian estimation. I follow McKnight et al. (2020) by assessing the importance attached by the central bank to exchange rate stability by estimating two versions of the model, one in which the weight attached to real exchange rate stability is positive ($\mu_q > 0$) and the other in which this weight is zero ($\mu_q = 0$) in both complete and incomplete asset markets. The estimated weight of inflation stabilisation is compared to the weights of alternative policy choices to infer on how focused the central bank is on its price stability mandate. Using the estimated weights on central bank policy choices I draw conclusions on the order of importance of policy choices. The Chapter also estimates policy weights from other LAITs and ASOEs that have also been published in earlier research and compares results among these groups of inflation targeting central banks.

The key findings of Chapter 4 are as follows. Ghana and South Africa are committed to their price stability mandates. Ghana's parameter weight on inflation stabilisation of 42% is lower than South Africa's weight of 59% but both countries recorded weights within the range recorded in previous literature. Results from previous literature have the weights for the inflation stabilisation parameter between 38% and 63% in McKnight et al. (2020).

Other policy options are considered by AFITs after prioritising inflation stabilisation. Output stabilisation with a policy weight of 38% is second to inflation stabilisation as a policy preference for Ghana. This policy weight is the highest among IT central banks according to results from previous literature. Interest rate smoothing is not as important for Ghana but is of significant consideration. Aside inflation stabilisation, interest rate smoothing is the next most important policy consideration for South Africa, this is followed by output stabilisation. As expected of IT central banks, Ghana and South Africa place the least weight on exchange rate stability.

AFITs second preferred policy option after inflation stabilisation is output stabilisation, followed by interest rate stabilisation. The least policy preference for AFITs is exchange rate stabilisation, recording an average policy weight of 3%, the lowest among the IT central bank groupings relative to LAIT and ASOEs.

ASOEs most preferred policy objective is price stability, followed by interest rate smoothing and then output stabilisation. Unlike results in Kam et al. (2009) where ASOEs did not care at all about exchange rate stabilisation, the results in this study show a significant weight for this policy choice, this is a clear departure from results in earlier research.

LAIT central banks second policy preference after inflation stabilisation is output stabilisation followed by interest rate smoothing, the least preferred policy choice is exchange rate stabilisation. Compared with previous results in McKnight et al. (2020) I observe a drop in preference for interest rate smoothing and an increase in preference for exchange rate stabilisation.

The order of policy preferences was the same for AFITs and LAITs; with inflation stabilisation, output stabilisation, interest rate stabilisation, and then exchange rate stabilisation in descending order of preference. ASOES order of policy preference was slightly different, after inflation stabilisation, interest rate stabilisation was the next preferred policy choice followed by output stabilisation and exchange rate stabilisation in descending order of preference.

Chapter four is of policy relevance for the evaluation of central bank monetary policies. It enables the assessment of the level of commitment of inflation targeting central banks towards their price stability mandates and also provides a framework to assess their alternative policy preferences. Since the data and computational power requirements to conduct this type of research could be high, it is important to gauge the cost of implementing this framework in comparison to its benefits especially since central bank policy preferences can also shift over time.

To the best of my knowledge, Chapter 4 is the first study of central bank policy preferences in Africa. Previous research had focused on advanced IT economies and LAIT. This Chapter bridges this research gap by conducting a cross-country study of monetary policy preferences in Ghana and South Africa, using Bayesian estimation methods. Furthermore, there is no published research on Ghana that makes use of Bayesian estimation techniques. Another contribution of this chapter is its use of results from similar previous literature in addition to results from this chapter to make conclusions on inflation targeting central banks' policy preferences in advanced small open economies, Latin America and in Africa.

The concluding remarks are in chapter 5 on page 110.

Chapter 2

Inflation Forecasts Evaluation-The Case of Ghana

2.1 Introduction

Many advanced economy central banks have price stability as their key mandate, which they pursue by running an inflation targeting (IT) macroeconomic framework. A growing number of developing economy central banks have also adopted an IT regime in the past two decades. A critical component of an IT framework is having an outlook of future inflation and other important macroeconomic variables such as real output growth (GDP growth), which is implemented through the generation of forecasts. Fawcett et al. (2015) has noted that the publication of macroeconomic forecasts in inflation reports forms a key component of policy-making of the Bank of England (BOE)'s Monetary Policy Committee (MPC).

The Chapter seeks to answer three research questions. I investigate whether the Bank of Ghana's inflation forecast is efficient and assess how the BoG's forecast performs when compared to other benchmark forecasts. I also assess the effectiveness of an intervention technique, the SIS method in explaining forecast performance evaluation.

Svensson (1997) explained the importance of an inflation forecast for an inflation targeting central bank as it becomes the key "quantitative target" for setting the policy interest rate. Due to "policy lags" associated with "monetary policy", it is more effective if policy making is forward looking by relying on inflation forecasts (see Mandalinci (2017)). Sinclair et al. (2009) found out that forecast errors in growth and inflation on average would lead to a one percentage point deviation from the intended target for a Fed policy that is based on the Taylor rule. These examples illustrate the importance of macroeconomic forecasts in monetary policy formulation and the need to evaluate macroeconomic forecasts.

Castle et al. (2016) and Romer and Romer (2008) have suggested that policy decisions can be influenced by forecasts and vice-versa. For example, the Bank of Ghana's inflation reports, which are published after every MPC round, contain inflation fan charts which reflect multiple-quarters ahead inflation forecasts of the MPC. The ultimate objective of the forecasting framework is to support the MPC discussions and decision-making. It is important to evaluate these forecasts and investigate how they can be improved as their accuracy or otherwise can impact the interest rate decisions taken by the MPCs. While inflation forecasts are important, as Skrove Falch and Nymoen (2011) put it, the occasional failure in their forecast does not automatically undermine an inflation targeting regime.

A number of studies have evaluated these forecasts typically for advanced economy central banks as in Gavin (2003), Clements and Hendry (2008), Stockton (2013) and Hackworth et al. (2013) but little research has been done to evaluate such forecasts for developing economy central banks. Many of the studies conducted on emerging market economies (EMEs) have focused on evaluating the forecasting ability of alternative models rather than assessing the forecast efficiency in a Zarnowitz and Mincer (1969) sense. Mandalinci (2017) for example conducted a forecast evaluation across selected EMEs using point and density forecasts from different models. Gupta and Kabundi (2011) compared the forecasting ability of alternative models based on Root Mean Square Errors (RMSEs) using South African data. Duncan and Martínez-García (2019) used data from fourteen (14) EMEs, a simple univariate random walk forecast and nine (9) competing inflation forecast models to assess the effectiveness of the forecasts.

This Chapter fills gaps in research by using Bank of Ghana data to assess the efficiency of its inflation forecast and also examines whether the one-quarter-ahead forecasts performed better than two-quarters ahead forecast. The Chapter addresses the problem of structural breaks and outliers in the data which can sometimes be significant in developing economies due to the structure of their economies by the inclusion of step indicator saturation (SIS) variables, deploying the general-to-specific (GETS) model selection method as in Pretis et al. (2018). The Chapter goes further to compare the forecast accuracy of the BoG with a random walk forecast and the IMF's WEO forecast and uses the concept of forecast encompassing to assess the robustness of the BoG's forecast relative to the benchmark random walk forecast. The Chapter's contribution to research is through the combination of Mincer-Zarnowitz regressions and SIS variables to evaluate inflation forecasts of a developing country central bank and the application of forecast encompassing method to assess the robustness of a developing economy central bank inflation forecast.

The rest of the Chapter is organised as follows. Section 2.2 reviews the macroeconomic forecast evaluation literature. Section 2.3 describes the data and Section 2.4 presents the forecasting evaluation methodology and diagnostic testing of the regression models. The estimation results are presented in Section 2.5 with the conclusions of the Chapter in Section 2.6.

2.2 Review of Macroeconomic Forecast Evaluation

The macroeconomic forecasts evaluation literature distinguishes between "strong" rationality or efficiency as in Stock (2007) and "weak" rationality (see, Nordhaus (1987) and Clements and Harvey (2009)). Weak rationality requires that the forecast contains all information available when the forecast was made and therefore does not deviate systematically from outcomes without additional information. A requirement for strong rationality or efficiency is that forecast errors must be uncorrelated with any other information available at the time of forecast. This Chapter uses the concept of weak rationality in evaluating inflation forecasts of the BoG's MPC by comparing actual outcome of inflation versus forecasts, a framework first used in Zarnowitz and Mincer (1969).

The rationality test proposed by Zarnowitz and Mincer (1969) is based on the idea that an efficient forecast must have an error that is unbiased and uncorrelated with the forecast itself (See Carstensen et al. (2011)). This forms the basis of the standard Mincer-Zarnowitz regression. In this Chapter I am interested in assessing the accuracy of the central bank's inflation forecasts. A review of the literature including Croushore (2012), Romer and Romer (2002) and Franses (2021) point to the widely accepted use of the Mincer-Zarnowitz (MZ) regressions as the standard test for forecast bias. For example, Romer and Romer (2002) use a MZ regression to evaluate inflation forecasts of the US Federal Reserve Bank and conclude that its forecast is rational and outperforms commercial forecasts. Sucarrat (2009) argue that MZ regressions are useful in the forecast evaluation of a range of different economic variables. This analysis does not compare the central bank's forecasts to survey or private forecasts as not enough historical data is available for these types of forecasts.

Researchers of macroeconomic forecasting including Meese and Rogoff (1983), Duffee (2013) and Croushore (2010) support the view that subjective forecasts are superior and simple forecasts performed better than sophisticated models. Ang et al. (2007) and Faust and Wright (2013) have documented that survey or institutional forecasts are more accurate than model-based forecasts because the former tends to incorporate many approaches. Wright (2019) however found out that survey/institutional forecasts still do not clearly outperform simple benchmarks except at noticeably short horizons. Faust and Wright (2013) have argued that a good inflation forecast must consider the time-varying trend in inflation.

In selecting a benchmark inflation forecast to compare with the BoG's inflation forecast, this chapter relied on Duncan and Martínez-García (2019) who found out that in almost all instances, a simple uni-variate random walk forecast as in Atkeson and Ohanian (2001), hereafter, RW-AO outperformed conventional model-based forecasts.

According to Faust and Wright (2013), inflation forecasts that capture low frequency shifts due to structural changes or changes in the policy environment have tended to perform better. Duncan and Martínez-García (2019) supported this finding, noting that model-based forecasts were only able to outperform the RW-AO forecasts when subjective judgment is incorporated to capture structural shifts in the data. They noted further that certain variables that were influenced mainly by external developments, including the exchange rate and commodity prices were not significant in forecasting inflation in small open economies. Significant research has been conducted on the evaluation of macroeconomic forecasts. The notable ones which have focused on advanced economy central banks include, Clements (2004), Wallis (2004), Ashley et al. (2016) and Clements and Reade (2020).

Clements (2004) and Wallis (2004) concluded that the BoE's short horizon point forecasts (less than one year) were unbiased, but Wallis (2004) found evidence that the density forecasts overstated uncertainty. Clements (2004) also concluded that for the short horizon forecasts, the BOE forecasts outperformed naive statistical benchmarks. Skrove Falch and Nymoen (2011) found out that the Norges Bank's inflation forecast were preferable to external one-step model forecasts.

The conclusions on longer term forecasts (one year or more) were rather mixed. Ericsson (2017a) concluded "significantly biased" one-year forecast of US Federal debt by US agencies that changed with time. Fawcett et al. (2015) found out that the one year ahead forecasts were biased at the ten(10) percent significance level.

On the other hand, Gamber and Liebner (2017) did not find statistically significant bias at any forecast horizon. Wallis (2004) also reached a similar conclusion that one-year point forecasts were biased though their density forecasts were found to have too wide bands. Groen et al. (2009) and Fawcett et al. (2015) concluded that naive benchmarks or pure statistical models tended to outperform MPC point estimates with Clements (2004) noting that the MPC fan charts overstated the upside risks to inflation.

Clements (2004) and Groen et al. (2009) concluded superior performance of pure statistical models over the BOE's forecasts at longer horizons. Skrove Falch and Nymoen (2011) also concluded that the Norge's Bank forecast cannot be said to be superior to ex-ante independent econometric models which were based on real time data. Clements (2004) and Wallis (2004) found the BOE's inflation fan charts had a history of wide bands even before the global financial crisis, but Stockton (2013) found out that the BOE's forecast errors have become bigger since the global financial crisis under-performing external forecasters.

Ericsson and Reisman (2012) considered the use of impulse indicator saturation (IIS) variables for "detecting crises, jumps and changes in regime". Ericsson (2017a), using standard methods and IIS detected "time-varying" highly significant errors in the one-year forecast at turning points of the USA business cycles. He noted that standard tests including Mincer-Zarnowitz tests failed to detect these errors. In this chapter I use SIS as described in Castle et al. (2016) and Pretis et al. (2018) to account for outliers and structural change in the data, this is especially important for emerging and frontier economies which are susceptible to sudden parameter shifts.

I examine scholarly peer-reviewed literature in economics and business discipline on forecasting inflation in developing economies in the past ten years. This research has been tilted towards structural models largely based on the new Keynesian Phillips Curve (NKPC) in South Africa and to a lesser extent, China.

Given that Chapter 2 is on empirical inflation forecasting, some of the appropriate references include Botha et al. (2023), Ruch et al. (2020), Heaton et al. (2020), Gupta et al. (2015) and Ahmed and Abdelsalam (2017). Ahmed and Abdelsalam (2017) and Heaton et al. (2020) are based on the Egyptian and Chinese economies respectively but the remainder of published research on the topic are based on South Africa.

Botha et al. (2023) combine the use of large macroeconomic data set, statistical learning, and traditional times series to assess inflation forecasts for South Africa and conclude that statistical learning models compete with most benchmark models over the medium to longer horizons. Over the shorter-term horizons, they find, the traditional benchmarks are superior to their statistical learning models. Their result over the short-term horizon differs from my results in Chapter 2 in which I conclude that the central bank's one-quarter ahead forecast is superior to the benchmark forecasts. Ruch et al. (2020), focus on core inflation in South Africa and address changing dynamics by using time-varying parameter vector autoregressive (TVP-VAR), factor-augmented VARs and structural break models and conclude that small TVP-VARs forecast outperform all other forecasts. They also note that allowing for discrete structural breaks does not improve the forecasts of core inflation. Their results differ from my results in Chapter 2; first they focus on core inflation as opposed to headline inflation. Their conclusion on the use of discrete structural breaks differs from my results in which I conclude that the inclusion of step indicator saturation variables to cater for structural shifts in the data improves on the immediate horizon forecast.

Heaton et al. (2020) considered 19 time series-based forecasting models of inflation and GDP growth for China. They find evidence that the one-month ahead producer-price based inflation forecasts using AR, ARMA, VAR, and Bayesian VAR models performed better when compared to simple benchmarks but were not superior to simple benchmarks at longer horizons. Their research differs from Chapter 2 in the sense they were comparing several statistical models including benchmark forecasts. In Chapter 2, I conclude that the central bank's one-quarter ahead forecast outperforms the random walk forecast but the two-quarters-ahead forecast underperforms the random walk forecast.

Gupta et al. (2015) forecast core and non-core inflation based on a DSGE model and conclude that the RMSE statistics for 1, 2, 4 and 12 quarters-ahead forecasts of the GDP deflator are lower than the corresponding RMSEs of forecasts associated with the AR(1) model. They conclude that the forecast accuracy for the estimated DSGE models improves at longer horizons and compared to the AR(1) model, the DSGE model performs better in forecasting the GDP deflator inflation. They show that forecasts of various measures of inflation based on the DSGE-based procedure are superior to those obtained from statistical benchmark models. Their result is different from my conclusion in Chapter 3 where I find that for the immediate policy relevant forecast horizon (one quarter ahead), the Atkeson and Ohanian (2001) (AO), a pseudo random walk GDP deflator inflation forecast is the most accurate forecast, outperforming the random walk forecast and the four variants of the TVT-NKPC forecasts.

For the medium to long term forecast horizons, my results in Chapter 3 point to a more accurate random walk inflation forecast, but there is not a statistically significant difference in forecast accuracy among the TVT-NKPC and the two benchmark inflation forecasts. So, my results in Chapter 3 for the medium to long term forecast horizons also differ from Gupta et al. (2015).

Mandalinci (2017) conducted a forecast evaluation across selected emerging market economies (EMEs) using point and density forecasts from different models and Gupta and Kabundi (2011) compared the forecasting ability of alternative models based on Root Mean Square Errors (RMSEs) using South African data. However, as far as I am aware this chapter is one of the few if not the first which deploys Mincer-Zarnowitz regressions and SIS to evaluate inflation forecasts in a developing country.

2.3 Data

2.3.1 Data Source

The end-of-quarter year-on-year headline inflation rates were obtained from the Ghana Statistical Service and the one-quarter ahead and two-quarters-ahead inflation forecasts from the first quarter of 2006 to the first quarter of 2020 were obtained from the Bank of Ghana. The Bank of Ghana's MPC has produced inflation forecasts since 2004 having adopted an inflation targeting monetary policy framework in 2002. Since March of 2008, the Bank of Ghana has included a fan chat of its inflation forecast in inflation reports that are published after each MPC round. For each quarter of the study period, I obtained the one-quarter ahead and two-quarters ahead inflation forecasts from the inflation fan charts reported in the Bank of Ghana inflation reports. The data for the IMF inflation forecast analysis was obtained from the fall forecasts picked from the IMF' World Economic Outlook (WEO) database for Ghana since 1990. The benchmark inflation forecast derived for the RW-AO forecast is measured as the simple arithmetic average of the current inflation and the inflation recorded in the past three quarters.

2.3.2 Forecasting Framework at the Bank of Ghana

Inflation forecasting has played an integral role in Ghana's monetary policy formulation since BoG started implementing the inflation targeting framework. Prior to the use of more sophisticated models, single equations and auto-regressive (AR) process frameworks were employed. As a forward-looking approach to monetary policy, inflation targeting requires that the central bank forecasts inflation over the policy horizon (six to eight quarters ahead) with reasonable accuracy. To achieve this, inflation forecasts are conducted at each MPC round to determine the most likely path for inflation over the policy horizon. Such inflation forecasts provide useful information for the MPC in setting the appropriate monetary policy stance.

The near-term (one or two quarters ahead) forecasting tools deployed by the BoG include the auto-regressive moving average (ARMA) model, vector error correction model, calibration of CPI path using the profile from previous years and an event study method.

Mkhatrishvili et al. (2022) described the quarterly projection model (QPM) of the Bank of Ghana. In this model, the medium-term forecast represents the baseline forecast or the most probable outcome. The QPM, similar to what is used in many central banks, is a semi-structured New Keynesian model also known as the 'gap' model because the key endogenous variables are measured in gaps. The model consists of four main blocks including behavioural equations and several identities. The blocks are the aggregate demand, the Phillips curve, uncovered interest parity condition, and the monetary policy block, which closes the model. The interaction among the key macro-variables provides a coherent macroeconomic analysis and ensures that a consistent story about the economy is told. This model which is more of a policy analysis tool rather than a pure forecasting model, obtains its parameters through calibration as opposed to estimation.

The inflation fan chart published by the central bank after each MPC round reflects the relative likelihood of possible outcomes for headline inflation at thirty, sixty and ninety percent confidence intervals. The width of the fan chart represents the degree of uncertainty surrounding the baseline inflation forecast, hence, the wider the fan chart, the greater the uncertainty of the forecast. Inflation forecasts were produced by the Bank of Ghana's staff but were signed off and extensively discussed by the MPC.

The central bank has also produced real output growth forecasts based on growth projections in the national budget of the fiscal authority since 2007. The growth projections only change when the Ministry of Finance presents its mid-year budget reviews.

2.3.3 Descriptive Statistics

Table 2.1 shows summary descriptive statistics of the actual inflation series, one-quarter ahead and two-quarters ahead forecasts, and the respective inflation forecast errors. I note that the average actual inflation is higher than the averages for the one-quarter and two quarters ahead forecast, with the average forecast error for the one-quarter ahead smaller than the average two-quarters ahead forecast error.

The standard deviation for the actual inflation series is bigger than the forecast standard deviations but the standard deviations of the forecast errors were smaller with the one-quarter ahead error lower than the two-quarter ahead forecast error. All the variables are positively skewed or skewed to the right. The right tail of the distribution is longer than the left, therefore more observations were to the right and the distribution of the variables was not symmetric. The excess kurtosis of the actual inflation series is negative, meaning that the inflation series has lighter or flat tails with small outliers and a flatter peak than the normal distribution. The forecast inflation series and inflation error series have positive excess kurtosis, meaning the series have heavy tails on either side with large outliers.

Indicator	Actual Inflation rate(%)	1Q-ahead forecast(%)	2Q-ahead forecast(%)	1Q-ahead forecast bias(%)	2Q-ahead forecast bias(%)
Mean	12.72	12.05	11.31	0.67	1.41
Median	10.81	10.50	10.40	0.40	1.10
Standard Deviation (sd)	3.75	3.17	2.82	1.45	2.14
Skewness	0.52	0.68	0.85	1.38	1.38
Excess Kurtosis	-1.05	0.89	0.24	3.04	2.46
Minimum	7.60	7.80	7.10	-1.66	-1.72
Maximum	20.74	19.30	18.50	6.23	8.83
No. of observations	57	57	57	57	57

Table 2.1: Summary of Descriptive Statistics of BoG Forecasts

2.3.4 Data Plots

Figure 2.1 shows one-quarter-ahead, and two-quarters ahead forecasts since the first quarter of 2006, alongside outcomes of inflation. There were sharp increases in inflation from the fourth quarter of 2007 due to a surge in crude oil prices and the corresponding increase in domestic prices of petroleum products, the increase in electricity tariffs and the fiscal impulse associated with the execution of the 2007 fiscal budget. The increasing trend in inflation continued throughout 2008 and peaked in the second quarter of 2009, after which it declined sharply between the third quarter of 2009 and the fourth quarter of 2012, staying within a band of 8.4% to 9.5%. The main factors accounting for the dis-inflationary path were a general decline in the fiscal deficit, a decrease in the rate of growth of money supply and a more stable local currency. This dis-inflationary path continued till the fourth quarter of 2012.

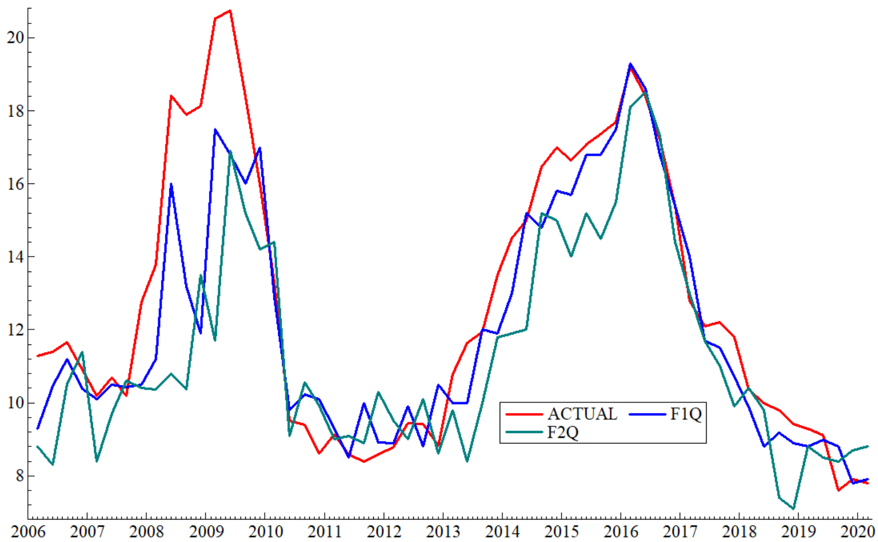

Figure 2.1: Trends in one-quarter ahead and two-quarters ahead forecast and actual inflation

These episodes of significant increases and decreases in inflation are associated with bigger inflation forecast errors, a result similar to findings of Engle (1982). Between the second quarter of 2010 to the second quarter of 2012 when inflation is below 10%, the inflation forecast error is generally low and does not exceed +/-2% as shown in Figure 2.3. Figure 2.3 also shows that inflation forecast errors tend to decrease with the passage of time as forecast errors trended downwards for both one-quarter-ahead and two-quarters-ahead inflation forecasts.

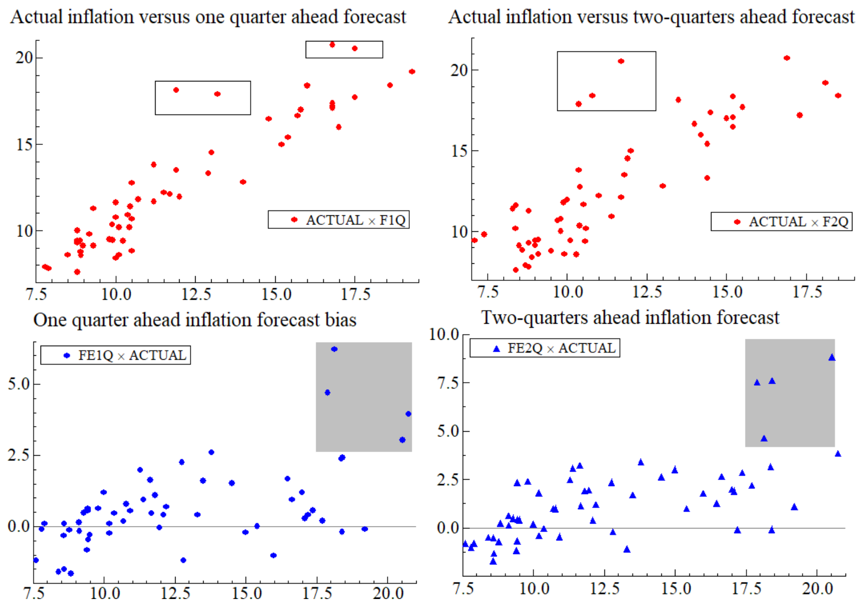

Figure 2.2: Scatter plots of inflation forecast error versus actual inflation

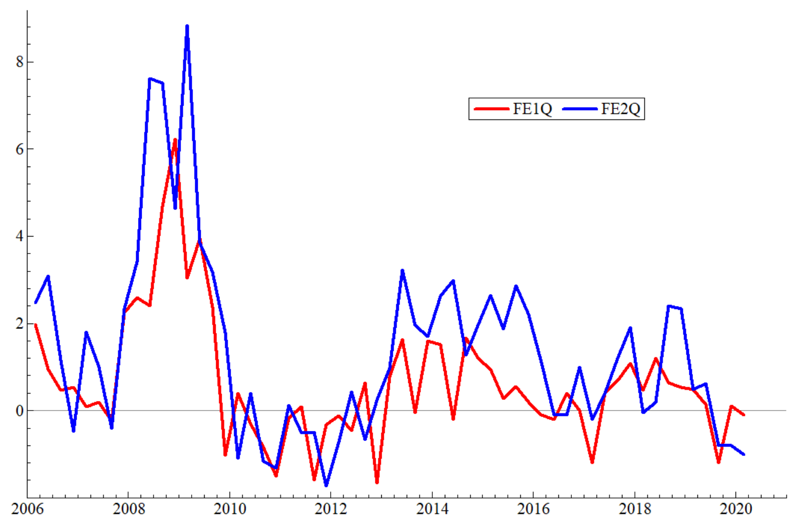

Figure 2.3: Trends in inflation forecast errors

2.3.5 Explaining Data Shifts and Outliers

The scatter plot of actual inflation (Actual) against one-quarter-ahead forecast (F1Q) and two-quarters ahead inflation forecast (F2Q) respectively are shown in the top panel of Figure 2.2. This plot shows that an upward sloping straight line can be fitted in the two scatter plots but for four outliers in the top left panel (actual versus F1Q) and three outliers in the top right panel (actual versus F2Q).

The four outliers for the scatter plot of actual versus one-quarter ahead forecast occurred between the third quarter of 2008 and the second quarter of 2009, a period of relatively high inflation outcomes (between 17.9% to 20.7%) but the forecast for these quarters underestimated these inflation outcomes. One reason for a higher than forecast inflation is the implementation of a combination of expansionary domestic fiscal policies to address the possible impact of a slowdown in global growth caused by the global financial crisis. There are three outliers in the scatter plot of actual inflation versus two-quarters ahead forecast (top right panel of Figure 2.2.) which occur between the second quarter of 2008 and the first quarter of 2009, a period when inflation outcomes were between 17.9% and 20.5% but the two quarters ahead forecast were much lower, between 10.4% and 11.7%. These outliers are also associated with higher inflation forecast errors shown in the shaded portions of the lower panels in Figure 2.2.

The MPC press releases in the second and third quarters of 2008 attributed the sharp rise in inflation to the increase in global crude oil prices which fed into ex-pump prices and resulted in utility price and food price increases. However, both the one-quarter and two-quarters ahead forecasts did not adequately reflect these shifts in inflation hence the outliers recorded during these periods as shown in the scatter plots.

Figure 2.1 shows some periods of notable shifts in inflation outcomes, one of such shifts in inflation occurred between the second quarter of 2008 and the first quarter of 2009. The second and third quarters of 2009 are characterised by falling domestic inflation due to a falling global inflation resulting from a significant aggregate demand contraction associated with the global financial crises, easing food inflation pressures and signs of stabilisation due to supportive fiscal and monetary policy measures. To help detect outliers and breaks in inflation forecasts and inflation outcomes, this chapter makes use of SIS variables using the GETS library in R studio[1].

[1] Pretis et al. (2018) provide an overview of the R package "gets". This package has a toolkit for the automated general-to-specific (GETS) modeling of the mean and variance of a regression. It also has a feature that can perform indicator saturation (IS) methods for the detection and modeling of outliers and structural breaks using impulses (IIS), step (SIS) as in Castle et al. (2015), and trend indicators (TIS).

2.3.6 Unit Root/Stationarity Tests

The variables that make up the model estimations in equations 2.6 and 2.7 needed to be stationary or transformed to be covariance stationary with a stable mean, variance, and auto covariance (See Yaffee et al. (2010)).

Unit root tests were conducted using the Augmented Dickey Fuller (ADF) see Fuller and A. (1979)), the Phillips and Pierrre (1988),(PP) and the KPSS (see Kwiatkowski et al. (1992)) stationarity tests for the actual inflation series, the one quarter ahead, two quarters ahead forecasts series as well as their respective forecast errors.

The detailed results of unit root/stationarity tests for one-quarter ahead inflation forecast error as well as the summarised results of unit root/stationary tests for all the other variables of interest in this chapter are presented in Tables 2.2 and 2.3 respectively.

Test	**Null Hypothesis**	**Test Statistic**	**Critical Value at 5% sig level**	**Decision**	**Conclusion**
ADF	1-quarter ahead inflation forecast error has a unit root	-3.08	-2.89	Reject null hyp	Process is stationary
PP	1-quarter ahead inflation forecast error has a unit root	-3.45	-2.91	Reject null hyp	Process is stationary
KPSS	1-quarter ahead inflation forecast error is stationary	0.22	0.46	Do not reject null hyp	Process is stationary

Table 2.2: Unit Root/ Stationarity Tests for One- Quarter Ahead Inflation Forecast error.

Indicator	**Tests**	**Conclusion**
One quarter ahead inflation forecast bias	ADF, PP, KPSS	Process is stationary
Two quarters ahead inflation forecast bias	ADF, PP, KPSS	Process is stationary by KPSS test only at 1% signficance level
One quarter ahead inflation forecast	ADF, PP, KPSS	Process is stationary by KPSS test only at 1% signficance level
Two quarters ahead inflation forecast	ADF, PP, KPSS	Process is stationary by KPSS test only at 2.5% signficance level
Annual IMF inflation forecast	ADF, PP, KPSS	Process is stationary by ADF and KPSS tests only

Table 2.3: Unit Root/ Stationarity Tests for Actual Inflation and Inflation Forecast Variables.

Results of unit root and stationarity tests led to the conclusion that the one-quarter-ahead inflation forecast, two-quarters-ahead inflation forecast, and the two-quarters-ahead inflation forecast error were stationary series according to the KPSS test. The actual inflation series is also stationary according to the ADF and KPSS tests and the one-quarter-ahead inflation forecast error series is stationary using all ADF, PP and KPSS tests.

2.4 Forecast Evaluation

2.4.1 Evaluation Methodology

The Chapter takes a cue from Ericsson (2017a) who followed three approaches in evaluating U.S.A government forecasts of the federal debt. First, I tested for forecast unbiasedness and efficiency using Mincer-Zarnowitz regressions as in Zarnowitz and Mincer (1969), Holden and Peel (2008), Sinclair et al. (2012) and more recently, papers by Ericsson (2016) and Clements and Reade (2020). These papers evaluated macroeconomic forecasts by regressing actual (realised) values on forecasts to determine the quality of forecasts. I then proceed with the Chong and Hendry (1986) forecast encompassing test for time-varying forecast bias and included step indicator saturation (SIS) variables in the Mincer Zarnowitz regression model to test for arbitrarily time-varying forecast bias.

To evaluate the relative performance of the BoG's forecast versus other competing forecasts, I calculate the Theil-U statistic, which is the ratio of the root mean square forecast error (RMSFE) of the BoG's forecast to the RMSFE of each of the competitor forecasts. Finally, I deploy the Diebold and Lopez (1996) test to assess the statistical significance of the differences in performance between the BoG forecast and the benchmark random walk forecasts.

2.4.2 Mincer-Zarnowitz Regressions

This chapter assesses the inflation forecasting performance of the BoG by evaluating how closely the forecasts have been, compared to actual inflation.

Let $\hat{\pi}_{t/t-h}$ represent the h-step ahead forecast of inflation, π_t, made at time t; h is fixed but t varies. Zarnowitz and Mincer (1969) showed that the test of forecast unbiasedness involves running a regression of equation 2.1:

$$\pi_t = \alpha + \beta \hat{\pi}_{t/t-h} + u_t \tag{2.1}$$

where u_t is the error term at time, t. The test of forecast unbiasedness is a joint test of the null hypothesis; H_0: $\alpha = 0$, $\beta = 1$. Equation 2.1 can be rewritten as:

$$\pi_t - \hat{\pi}_{t/t-h} = \alpha + (\beta - 1)\hat{\pi}_{t/t-h} + u_t \tag{2.2}$$

.

The joint test of the null hypothesis; H_0: $\alpha = 0$, $\beta = 1$ (H_0: Forecast is unbiased and efficient. H_1: Forecast is biased and/or inefficient.) then amounts to jointly testing that the regression coefficients in equation 2.2 above are equal to zero; H_0: $\alpha = 0$, $\beta^* = 0$, where $\beta^* = \beta - 1$. We test this joint hypothesis involving q restrictions, a sample size of n and k parameters in the regression model using an F-test calculated as follows:

$$F_{q,n-k} = \frac{(SSR_R - SSR_U)/q}{SSR_U/(n-k)} \tag{2.3}$$

.

The F-test arises because we are comparing the estimated residual error variances between the original model and the restricted model. Ericsson (2017b) noted that the F-statistic may be appropriate for one-step ahead forecasts as the error term u_t may be serially uncorrelated, this test may however be inappropriate for multi-step ahead forecasts without examining the presence of auto-correlation.

Let $e_{t/t-1}$ and $e_{t/t-2}$ represent the one-quarter-ahead and two-quarters-ahead forecast errors respectively. Where

$$e_{t/t-1} = \pi_t - \hat{\pi}_{t/t-1} \tag{2.4}$$

and

$$e_{t/t-2} = \pi_t - \hat{\pi}_{t/t-2} \tag{2.5}$$

Then using equation 2.2 I estimate the forecast errors for one-quarter and two-quarters ahead using the following equations:

$$e_{t/t-1} = \alpha + \beta^* \hat{\pi}_{t/t-1} + u_t \tag{2.6}$$

$$e_{t/t-2} = \alpha + \beta^* \hat{\pi}_{t/t-2} + u_t \tag{2.7}$$

The results of these regressions including the residual diagnostics tests statistics are reported are reported in Table 2.5.

2.4.3 Mincer-Zarnowitz Regression-Based Test with Step Indicator Saturation Variables

Ericsson (2016) considered extensions to the Mincer Zarnowitz regressions to deal with data truncations, distortions and forecast bias due to time variations and in (Ericsson (2017b) presented "saturation-based tests" as generalizations of the Mincer-Zarnowitz tests which incorporated forecast biases that change with time. He noted some limitations with Mincer-Zarnowitz regression-based tests. The tests may not accurately detect forecast errors if these errors are heteroscedastic. The tests do not "improve the efficiency of parameter estimates" that could be gained with SIS estimation method. To address the problem of outliers and structural breaks in the data I deployed the SIS method as in Castle et al. (2015) and Pretis et al. (2018), by adding step-indicator saturation variables in addition to the inflation forecast as explanatory variables in the estimation of our mean regression.

When there are significant shifts in the policy and the macroeconomic environment over the sampled period, it is possible that at some points during that period there will be large forecast errors which might lead to the rejection of the null hypothesis of unbiased or efficient forecast and the conclusion of unsatisfactory forecast.

The incorporation of SIS variables in such a case is appropriate as the model then allows for large forecast errors that could have been associated with an otherwise satisfactory forecasting procedure. Some large forecast errors are due to exogenous shocks. The incorporation of SIS terms allows the evaluation to proceed without a severe penalty for such errors and avoid misclassification of what might otherwise be a satisfactory forecasting procedure. If the naive model rejects the null hypothesis but the SIS model does not reject, then we could argue that the forecast is efficient/unbiased under normal circumstances and only fail under exceptional circumstances when a within-sample forecast failure could lead to a rejection of the null hypothesis if the outliers are not accounted for.

A better fit would be associated with less estimation errors and provide a higher probability of rejecting the null hypothesis, all other things being equal, but other things are not necessarily equal and, the coefficient estimates might change not only the residual variance.

The failure of the naive model to reject the null hypothesis when the SIS model rejects the null hypothesis could be attributed to a large residual variance of the naive model. The removal of the noise in the SIS regressions helps detects the inefficiency of the forecast, with the conclusion that the forecasts are biased/inefficient even in periods of relative calm or predictability. The failure of both the naive and SIS models to reject the null hypothesis could be attributed to the presence of large residual variances in both models with neither able to provide a good fit in the presence of distortions in the data nor the absence in distortions. Finally, the rejection of the null hypothesis in both models could be due to small residual variances in both cases even in the presence of distortions or shifts in the data. The 2x2 contingency table (Table 2.4) summarises the possible outcomes of the hypothesis tests involving the naive model and the SIS-based tests.

Test type	**Naive Test**		
	Decision	Do not reject null	Reject null
SIS Test	Do not reject null	Large residual variances for both models	Efficient forecast under normal circumstances, fails under exceptional circumstances
	Reject null	Large residual variance for the naïve model	Small residual variance in both models, even in the presence of distortions

Table 2.4: Hypothesis Testing - Naive Versus SIS model.

The inflation forecast error equation set out in equation 2.8 below was estimated using an approach in Ericsson (2016) who accounted for periods of distortions by including dummies in a Mincer-Zarnowitz regression. In our case we used step indicator saturator variables, S_{it}, defined as $S_{it} = 1$ for $t \geq i$, and zero otherwise. and c_i is the corresponding coefficient for S_{it}. We tested the null hypothesis that there are no outliers or structural breaks and used a chi-square (χ^2) distribution setting linear restrictions of $\alpha = 0$, $\beta^* = \beta - 1 = 0$ and $c_i = 0$, equation 2.8 is a test of forecast unbiasedness:

$$\pi_t - \hat{\pi}_{t/t-h} = (\beta - 1)\hat{\pi}_{t/t-h} + \sum c_i S_{it} + u_t \tag{2.8}$$

$for\ t = 1, ..., T$ and where $\alpha_t = \sum c_i S_{it}$ The χ^2 test like the F-test described above is a one-tailed test with the degrees of freedom equal to the number of linear restrictions. The step indicator weighted by the estimated coefficients marks shifts in the intercept over time. The SIS variables were detected using the R package "gets" which is available through the general-to-specific (GETS) modelling of the mean and variance of a regression.

2.4.4 Forecast Encompassing

Clements and Harvey (2009) explained the concept of forecast encompassing as to whether one forecast incorporates all the significant information embedded in another forecast and described a test of forecast encompassing as one of the most useful ways of assessing forecasts and their predictive ability. While the Mincer-Zarnowitz test can be used in assessing for unbiasedness or efficiency, forecasts can be assessed more effectively by testing whether a set of forecasts uses all information embedded in another set of forecasts at the time of making the forecast. Ericsson (2016) established that if in the Mincer-Zarnowitz framework discussed above, if we consider an alternative forecast of inflation, $\tilde{\pi}_t$, we have new forecast error $\pi_t - \tilde{\pi}_{t/t-h}$ which is equivalent to $\sum(\pi_t - \tilde{\pi}_{t/t-h})I_{it}$, where I_{it} is an impulse indicator, then the forecast error is a weighted sum of impulse indicators and we have the Chong and Hendry (1986) forecast encompassing test. The forecast encompassing test checks for time-varying forecast bias and investigates whether one model's forecast provides more information about another model's forecast errors. If so, then those forecast errors are partly predictable, if not then the latter model "forecast-encompasses" the former model.

The forecast encompassing test is related to the Diebold and Lopez (1996) test as illustrated in Ericsson (1992) who stated a necessary condition for forecast encompassing was having the smallest MSFE. I conducted this test to compare the BoG's forecast with another benchmark forecast.

2.4.5 Diagnostic Testing

I investigate whether the econometric model is properly specified by ensuring that there is no significant "autocorrelation or ARCH effects, no structural breaks, we have a linear functional form, there is residual homoscedasticity, residual normality, and constant parameters".

The AR(1) serial correlation test leads to a strong evidence of first order serial correlation for the naive models of one-step-ahead inflation forecast error and two-steps-ahead inflation forecast error with p-values of 0. I conduct the Ljung Box test of auto-correlation for the SIS mean estimations in which the null hypothesis is that there is no auto-correlation against the alternative hypothesis of the existence of auto-correlation. For the one-quarter ahead SIS inflation forecast error mean regression, with a p-value of 0.192, I fail to reject the null hypothesis and conclude that there is no auto-correlation of the residual terms. For the two-steps-ahead-ahead SIS inflation forecast error mean regression, the p-value of 0.018 leads to a rejection of the null hypothesis and a conclusion of the existence of auto-correlation in the model.

The normality test of the residuals in the model estimations is conducted under a null hypothesis of normality using a χ^2 distribution. The Normality test statistics reported in Table 2.5 leads to the rejection of normality for the naive models, but normality is not rejected for the one-step ahead and two-steps-ahead SIS inflation forecast error mean regressions. I test for heteroscedasticity in which the null hypothesis is that the error terms in the model estimations have a constant variance. This test is based on White (1980) and follows an F-distribution. For both naive models of the one-step-ahead and two-steps-ahead inflation forecast error, I fail to reject the null hypothesis due to large p-values and conclude that the error terms are homoscedastic.

The ARCH test of no conditional heteroskedasticity auto-correlation is rejected for both naive models but I do not reject the null hypothesis for the SIS mean regression models and conclude that there is no conditional heteroskedasticity auto-correlation for the models estimated by including the SIS variables. Woodbridge (2010) noted that OLS estimates are still consistent even in the presence of ARCH and HAC standard errors and test statistics are valid.

The RESET test is meant to detect functional form misspecification and has a null hypothesis that the model is correctly specified. With the large p-values of 0.137 and 0.241

for the naive one-ahead- step ahead and two-step-ahead inflation forecast error estimation respectively, I fail to reject the null hypothesis and conclude that the models are correctly specified.

The regression model fails the autocorrelation and normality tests but the incorporation of the step indicator saturation variables helps to cope with this situation even though strictly speaking hypothesis and other statistical tests are based on the assumption that all residuals in the model are well specified.

2.5 Results

The results of the one-quarter ahead and two-quarters ahead naive Mincer-Zarnowitz regressions are labelled "(1)" and "(3)" in Table 2.5. The columns labelled "1Q-ahead (1)" and "2Q-ahead (3)" refer to equation (2.6) and equation (2.7) respectively. The "naive model" is described in equation (2.2). From the results in Model (1), the estimates of α and β^* in equation (2.6) are -0.457 and 0.093 respectively, which are individually statistically insignificant with large p-values of 0.566 and 0.218, respectively. These coefficients are also jointly statistically insignificant with the calculated F-statistic of 2.437 and a p-value of 0.097 meaning the smallest significance level at which can reject the null hypothesis of an efficient forecast is 9.7%, this is not a strong rejection of the null hypothesis of forecast accuracy.

For the Model 3, the coefficients of α and β^* in equation (2.7) (two-quarters ahead naive model) are 0.353 and 0.093 respectively, these coefficients are individually statistically insignificant but the calculated F-statistic of 4.829 and a p-value of 0.012 signifies a strong rejection of the null hypothesis of an efficient forecast. So, for the naive models, the one-quarter-head is an efficient forecast, but the two-quarters-ahead forecast is inefficient.

2.5.1 SIS Model Results

The model estimations for the one-quarter-ahead inflation forecast error and two-quarters-ahead inflation forecast error with SIS variables included are reported in Table 2.5 as "(2)" and "(4)" respectively.

From 1Q-ahead with SIS Model, the estimates of α and β^* in equation 2.8 are 0.931 and -0.035 respectively, which are individually statistically insignificant with p-values of 0.080 and 0.378, respectively. The SIS estimation results for the one-quarter ahead forecast error mean regression reveals three step-shifts, in the fourth quarter of 2007 (labelled as SISQ4-2007), the fourth quarter of 2009 (labelled as SISQ4-2009) and the first quarter of

Parameter	1Q-ahead (1)	1Q -ahead with SIS (2)	2Q-ahead (3)	2Q- ahead with SIS (4)
Constant	-0.457	0.931	0.353	1.898
	[0.566]	[0.080]*	[0.778]	[0.016]**
Forecast	0.093	-0.035	0.093	-0.030
	[0.218]	[0.378]	[0.374]	[0.643]
SISQ4-2007		3.005		
		[0.004]**		
SISQ2-2008				5.602
				[0.000]***
SISQ2-2009				-4.101
				[0.000]***
SISQ4-2009		-4.100		
		[0.000]***		
SISQ1-2010				-3.641
				[0.000]***
SISQ1-2013		1.072		1.807
		[0.001]**		[0.000]***
σ	1.448	0.859	2.165	1.217
Observations	57	57	57	57
Adj. R2	0.024	0.681	0.015	0.711
Test of Efficiency	2.437	3.843	4.829	15.758
	[0.097]*	0.146	[0.012]**	[0.000]***
	F(2,55)	Chi-sq(2)	F(2,55)	Chi-sq(2)
AR test	15.529	1.701	27.258	5.565
	[0.000]***	[0.192]	[0.000]***	[0.018]**
	F(2,53)	Chi-sq(1)	F(2,53)	Chi-sq(1)
ARCH test	10.484	0.030	6.964	0.289
	[0.002]**	[0.862]	[0.011]**	[0.591]
	F(1,55)	Chi-sq(1)	F(1,55)	Chi-sq(1)
Normality test	14.444	3.393	20.009	2.267
	[0.001]**	[0.1834]	[0.000]***	[0.322]
	$\chi^2(2)$	$\chi^2(2)$	$\chi^2(2)$	$\chi^2(2)$
Hetero test	1.707		1.0062	
	[0.191]		[0.372]	
	F(2,54)		F(2,54)	
Reset test	2.0618		1.4607	
	[0.137]		[0.241]	
	F(2,53)		F(2,53)	
p-values are in square brackets	*p<0.1	**p<0.05	***p<0.01	

Table 2.5: Mincer-Zarnowitz Regression Results of Inflation Forecast Error for Naive and Step Indicator(SIS) Models.

2013 (labelled as SISQ1-2013). The coefficients for SISQ4-2007, SISQ4-2009 and SISQ1-2013 were individually highly statistically significant with p-values of 0.004, 0.000 and 0.001, respectively.

In the 2Q-ahead with SIS Model, the estimates of α and β^* in equation 2.8 are 1.898 and -0.030 respectively, the constant term is statistically significant with a p-value of 0.016 but the coefficient for the two-quarters ahead forecast was statistically insignificant with a p-value and 0.643, respectively. The two-quarters ahead inflation forecast error mean regression also revealed four step-shifts, in the second quarters of 2008 and 2009, labelled SISQ2-2008 and SISQ2-2009 respectively and the first quarters of 2010 and 2013 (labelled SISQ1-2010 and SISQ1-2013 respectively). The coefficients of the SIS variables are relatively big and are all statistically significant indicating that these step shift variables are important in explaining inflation forecast error.

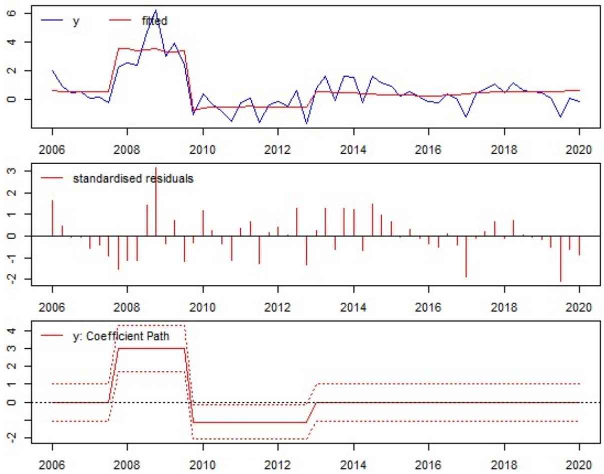

Figure 2.4: One-Quarter Ahead Inflation Forecast Error: SIS Model Results.

Figure 2.4 and Figure 2.5 show SIS models results for the one-quarter ahead inflation forecast error and two quarters ahead inflation forecast error mean estimations. In the top panel of Figure 2.4, the observed one-quarter ahead inflation forecast error in shown in blue and the fitted shown in red. The standardised residuals are shown in the middle panel and the coefficient path compared to the intercept with 95% confidence interval is shown in the bottom panel.

In the one-quarter ahead inflation forecast error mean regression I observe an upward step-shift in the fourth quarter of 2007 with a large coefficient of 3.005%, a downward step-shift in the last quarter of 2009 (-4.1% coefficient) and another upward step-shift in the first quarter of 2013 (coefficient of 1.072%). The two-quarters ahead inflation forecast error records an upward step-shift in the second quarter of 2008 (5.602% coefficient step shift), a downward step-shift in the second quarter of 2009 (a step shift coefficient of -4.101%) a downward step shift in the first quarter of 2010 (a step shift coefficient of -3.641%) and an upward step shift in the first quarter of 2013 (a step shift coefficient of 1.807%). The one-quarter ahead inflation forecast error's upward step shift spanned a longer period than the two-quarters ahead inflation forecast error upward step shift.

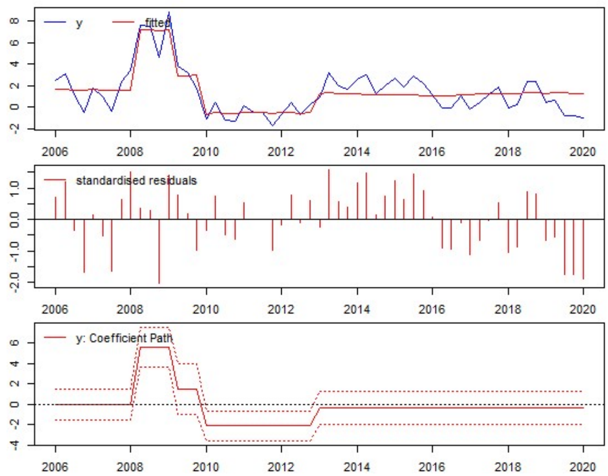

Figure 2.5: Two-Quarters Ahead Inflation Forecast Error: SIS Model Results.

The χ^2 test statistic led to the strong rejection of the null hypothesis with a p-value less than 1% for the two-quarters-ahead inflation forecast error estimation that incorporates detected SIS variables. The χ^2 test however fails to reject the null hypothesis with a p-value of 0.146 and led to the conclusion of an efficient forecast for the one-quarter-ahead inflation forecast when SIS variables were included.

The SIS method deployed in the mean regression estimations makes use of an ordinary variance covariance matrix, however I also examine the robust estimation using White (1980) or Newey and Kenneth (2019) variance-covariance matrix, but this results in too many SIS variables (twenty-eight) given that my sample size of 57 may not lend itself to the asymptotic properties that these variance-covariance estimations require.

2.6 IMF Forecast and Other Benchmark Forecasts

2.6.1 IMF WEO Forecast

The IMF's inflation forecast is the projected year-on-year percentage change in the end-of-period consumer price index (CPI). This forecast is based on "projections made by IMF staff relying on information gathered by its country desk officers during their missions and through their ongoing analysis of a country's economy". Splicing and other techniques are

Statistic	Actual Inflation rate	One-year-ahead forecast	One-year-ahead forecast bias
Mean	19.72	19.74	-0.01
Median	15.58	16.84	-0.48
Standard Deviation (sd)	12.99	11.62	15.16
Skewness	2.20	1.72	0.67
Excess Kurtosis	5.54	2.95	1.40
Minimum	7.90	7.21	-26.94
Maximum	70.82	59.50	45.92
No. of observations	30	30	30

Table 2.6: Descriptive Statistics of Annual IMF Inflation Forecast for Ghana, 1990-2019

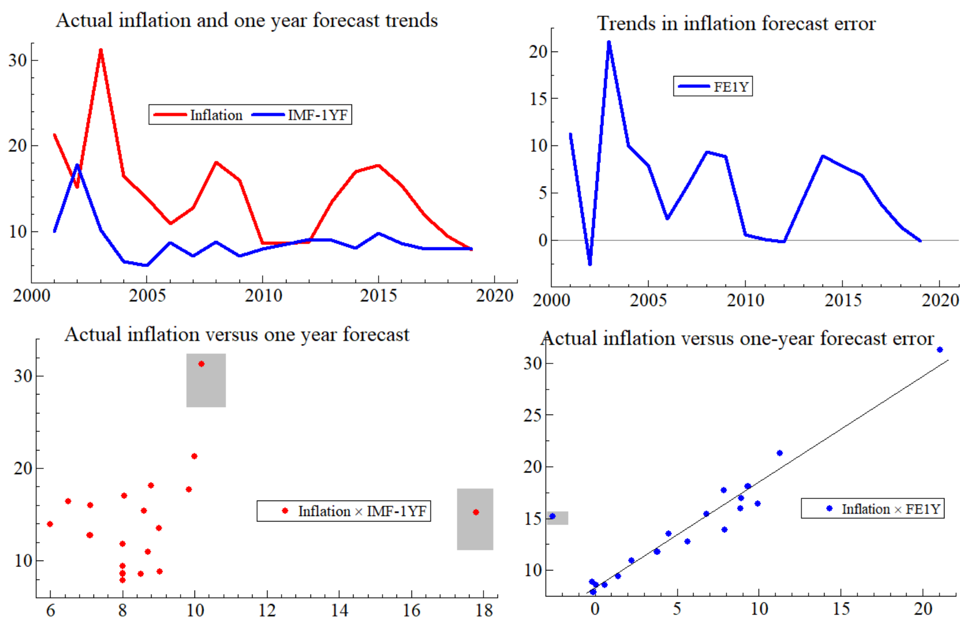

Figure 2.6: Trends in IMF Inflation Forecasts

used to deal with structural breaks in the data to produce a smooth series. This historical data is updated on a continual basis, as more information becomes available.

The inflation measure that the IMF forecast is the same as the BoG's measure of inflation, both forecast headline inflation. Every year the IMF publishes two forecasts, in spring and fall and provides the historical forecasts' data in its World Economic Outlook (WEO) database in a bid to "promote transparency". The data for the IMF inflation forecast analysis is taken from the fall forecasts picked from the WEO database for Ghana since 1990.

I note that the IMF's inflation forecast follows a similar pattern as the actual inflation rate. From inspection of the top left plot in Figure 2.6, it is clear that the deviations of the IMF forecasts from the actual inflation rates are much bigger when compared to the BoG's one-quarter ahead and two-quarters ahead forecasts shown in Figure 2.1 and the AO-Random Walk forecasts shown in Figure 2.7. From the top right plot in Figure 2.6, the IMF's inflation forecast error trended downwards with the passage of time, showing an improvement with this forecast. The scatter plot of the actual inflation rate against the IMF inflation forecast did not show any discernible relationship but I note that the IMF forecast error increases with the rise in inflation rates as shown in the bottom right plot in Figure 2.6.

The summary of descriptive statistics for the IMF WEO forecast is shown in Table 2.6. This data is of annual frequency over a 30-year period (1990-2019). Compared to the BoG forecasts, the average actual inflation rate and average inflation forecast are bigger, but the average inflation forecast error is smaller and the standard deviations for the actual inflation, inflation forecast, and inflation forecast error are bigger.

2.6.2 Random Walk Benchmark Model

The selected benchmark model is the random walk model used in Atkeson and Ohanian (2001) (referred to hereafter as RW-AO). The RW-AO model has also been used in other empirical work by Stock (2007), Faust and Wright (2013) and Clements and Reade (2020). The choice of the RW-AO model is further supported by Duncan and Martínez-García (2019) who showed in their cross-section study of 14 EMEs that the RW-AO forecast is the most empirically relevant benchmark for EMEs because it outperforms more complex models of forecasting inflation including factor-augmented models. The RW-AO forecast in derived as the simple arithmetic mean of the current and three previous observations.

The random walk inflation forecast trends in a similar pattern as actual inflation rate, but I note that the forecast is lower when actual inflation is rising but is higher when actual inflation is declining. Even though the forecast error also improves with the passage of time, the improvement is not as strong and clear as is the case with the Bank of Ghana's inflation forecasts. The scatter plots of actual inflation versus forecasts does not show a strong linear relationship and there is not a discernible relationship between the random work inflation forecast and the forecast error.

These trends are shown in Figure 2.7. The summary of descriptive statistics for the RW-AO forecast is shown in Table 2.7.

Compared to the one-quarter-ahead BoG inflation forecasts, the average inflation forecast obtained from the random walk method was bigger, less volatile and exhibited a lower dispersion.

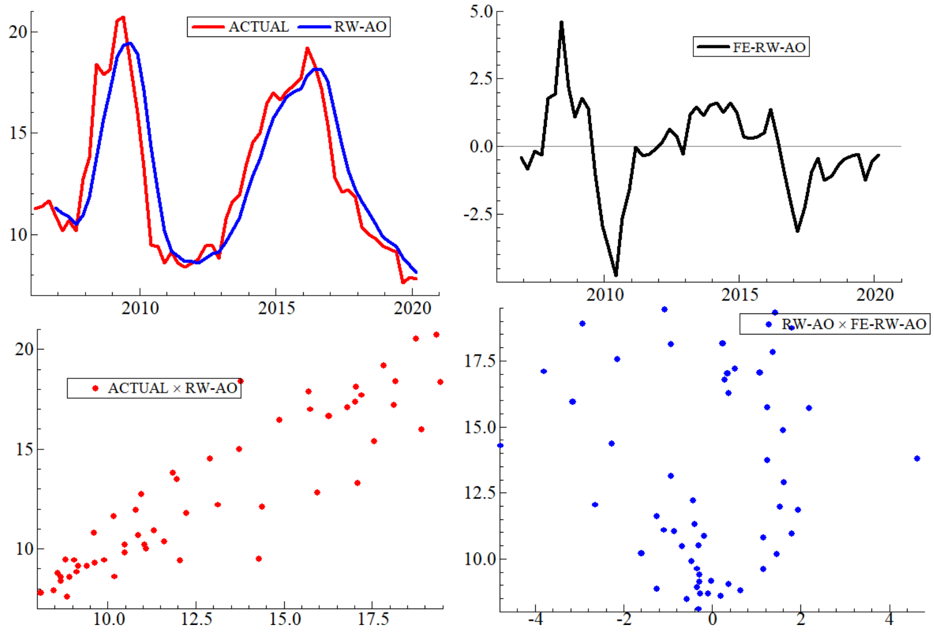

Figure 2.7: Trends in AW-RW Inflation forecasts

Statistic	Actual Inflation rate	RW-AO	RW-AO forecast error
Mean	12.82	12.98	-0.16
Median	11.95	11.97	-0.35
Standard Deviation (sd)	3.86	3.50	2.57
Skewness	0.43	0.38	-0.35
Excess Kurtosis	-1.20	-1.28	0.66
Minimum	7.60	8.48	-7.60
Maximum	20.74	19.44	6.56
No. of observations	53	53	53

Table 2.7: Descriptive Statistics of AO-RW Inflation Forecast for Ghana, Q1-2007 to Q1-2020.

1Q Forc/RW Forc	1Q Forc/IMF WEO Forc	2Q Forc/ RW Forc	2Q Forc/IMF WEO Forc
0.622	0.105	0.997	0.169

Table 2.8: Comparing Root Mean Square Forecast Errors.

2.6.3 Relative Performance- Comparing Forecast Errors

To evaluate the relative performance of the BoG's forecast versus the IMF's WEO forecast and the RW-AO forecast, I calculated the Theil-U statistic, which is the ratio of the Root Mean Square Forecast Error (RMSFE) of the BoG's forecast to the RMSFE of each of the competitor forecasts as in Timmermann (2007) and Duncan and Martínez-García (2019).

The benchmark forecast is in the denominator so that if this ratio is less than one, then the BoG forecast is deemed to have performed better. The results of this analysis in shown in Table 2.8, a ratio below one indicates that the BoG forecast is superior to the random walk forecast or the IBM WEO forecast depending on the ratio being examined. So, the one-quarter ahead BOG inflation forecast outperforms the random walk forecast as well as the IMF WEO forecast. Similarly, the two-quarters-ahead BoG forecast outperforms the random walk and the IBM WEO forecasts. A ratio of almost close to one can be interpreted that the two-quarters-ahead BoG inflation forecast, and the random walk forecast performed almost the same with a slight superiority seen in the former. According to this measure, of the four inflation forecasts, the BOG's one-quarter ahead forecast performed the best while the least performing forecast was the IMF WEO forecast.

2.6.4 Assessing the Differences in Forecast Performance - Diebold Mariano Test

The Diebold and Lopez (1996) test (See Clements and Reade (2020), Timmermann (2007)) is used to assess the statistical significance of the differences in performance between the BoG forecasts and the RW-AO forecast. The IMF WEO forecast is not included in this test because of a mismatch in the frequency of the forecast data. While the BoG had quarterly forecast, the IMF WEO forecast was an annual forecast. The Diebold Mariano (DM) test compares forecasts by evaluating whether the differences in RMSFEs reflect statistically significant differences between the forecasts. The DM test can be used to compare the accuracy of two different forecasts. Here, the difference between the squared forecast errors for each forecast was treated as the dependent variable and the regressor was a constant. I define the following regression functions:

$$e_{t/t-1}^{BOGF1Q} = \alpha + \beta\hat{\pi}_{t/t-1}^{RW-AO} + u_t \tag{2.9}$$

$$e_{t/t-1}^{BOGF2Q} = \alpha + \beta\hat{\pi}_{t/t-1}^{RW-AO} + u_t \tag{2.10}$$

$$e_{t/t-1}^{RW-AO} = \alpha + \beta\hat{\pi}_{t/t-1}^{BOGF1Q} + u_t \tag{2.11}$$

$$e_{t/t-1}^{RW-AO} = \alpha + \beta\hat{\pi}_{t/t-1}^{BOGF2Q} + u_t \tag{2.12}$$

where $e_{t/t-1}^{RW-AO}$, $e_{t/t-1}^{BOGF1Q}$ and $e_{t/t-1}^{BOGF2Q}Q$ are the forecast errors of the RW-AO, BoG one-quarter ahead and BoG two-quarters ahead forecasts, respectively. The loss function L, is the cost of making an error in forecasting the variable of interest and assume L is purely a quadratic loss function of the form:

$$L(e) = e^2 \tag{2.13}$$

In the case where the RW-AO forecast serves as a benchmark forecast, I defined

$$e_{t/t-1}^{DM-F1Q} = ({e_{t/t-1}}^{BOGF1Q})^2 - ({e_{t/t-1}}^{RW-AO})^2 \tag{2.14}$$

$$e_{t/t-1}^{DM-F2Q} = ({e_{t/t-1}}^{BOGF2Q})^2 - ({e_{t/t-1}}^{RW-AO})^2 \tag{2.15}$$

If the forecast performance of the BoG and the RW-AO are equal then $E(e_{t/t-1}^{DM-F1Q}) = 0$ and $E(e_{t/t-1}^{DM-F2Q}) = 0$ and the null hypothesis of no difference in forecast accuracy equals to testing that the intercept term, $\alpha = 0$ and can be tested by running regressions of $e_{t/t-1}^{DM-F1Q}$ and $e_{t/t-1}^{DM-F2Q}$ separately on an intercept as follows:

$$e_{t/t-1}^{DM-F1Q} = \alpha + u_t \tag{2.16}$$

$$e_{t/t-1}^{DM-F2Q} = \alpha + u_t \tag{2.17}$$

where u_t is the disturbance term.

A rejection of the null hypothesis will lead to the conclusion that there is a statistically significant difference in forecast performance between the two forecasts. A positive α implies the benchmark RW-AO forecast performed better whereas a negative α can be interpreted that the BoG forecast performed better. The results of my regression lead to the conclusion that we can only reject the null hypothesis at a p-value of 7.34% and

	Bank of Ghana forecasts versus AO Random Walk forecast	
Statistic	**One-quarter-ahead forecast**	**Two-quarters-ahead forecast**
Constant	-0.396	0.127
	[0.073]*	[0.969]
No. of Observations	53	53
*p<0.1; **p<0.05; ***p<0.01		height

Table 2.9: Diebold-Mariano Test of Equal Forecast Accuracy Between the BoG's Forecasts and the Random Walk (RW-AO) Forecasts.

conclude that the BoG one-quarter-ahead forecast is more accurate. At smaller significance levels of 5% and below, I fail to reject the null hypothesis and conclude that there is not a statistically significant difference between the BoG one-quarter-ahead forecast and our benchmark random walk forecast. Our results also point to a stronger non-rejection of the null hypothesis and the conclusion that there is no statistically significant difference between the forecast accuracy of the BoG's two-quarters-ahead forecast and the RW-AO forecast, supporting the results obtained by comparing the RMSFE between these two forecasts that is almost close to 1. The results of the DM test are presented in Table 2.9.

2.6.5 Forecast Encompassing Test

For robustness check, I follow the concept of forecast encompassing used by Clements and Harvey (2009) by investigating whether the BoG forecasts incorporates all predictive information contained in the benchmark random walk forecast and vice versa. Clements (2004) noted that while forecast encompassing is one of many tests that could be used to evaluate the predictive ability of a forecast, in terms of practicality, testing "whether one set of forecast encompasses the rival set" is the most useful way of evaluating a forecast.

To conduct the forecast encompassing test, I examine whether the RW-AO forecast adds more to the BoG forecasts or vice versa using an approach in Chong and Hendry (1986) by regressing the BoG inflation forecast errors on the RW-AO inflation forecast as follows:

$$e_{t/t-1}^{BOGF1Q} = \alpha + \beta\hat{\pi}_{t/t-1}^{RW-AO} + u_t \tag{2.18}$$

$$e_{t/t-1}^{BOGF2Q} = \alpha + \beta\hat{\pi}_{t/t-1}^{RW-AO} + u_t \tag{2.19}$$

If $\beta = 0$ then the BoG forecast encompasses the information embedded in the RW-AO forecast. The results of these regressions shown in Table 2.10, pointed to statistically insignificant parameter estimates for the random walk inflation forecasts for both the one-quarter-ahead and two-quarters-ahead BoG inflation forecast error regressions. I therefore

Statistic	BoG forecasts error 1-quarter-ahead inflation forecast	2-quarters-ahead inflation forecast
Constant	-0.529	-0.822
	[0.551]	[0.544]
AO-RW forecast	0.090	0.171
	[0.261]	[0.136]
No. of Observations	53	53

*p<0.1; **p<0.05; ***p<0.01

Table 2.10: Encompassing Regression for each Forecast Horizon of BoG Inflation Forecasts.

	AO-RW forecast error		AO-RW forecast error
Constant	-2.980	Constant	-1.544
	[0.0133]**		[0.2181]
1Q-ahead forecast	0.232	2Q-ahead forecast	0.121
	[0.0209]**		[0.2204]
No. of Observations	53	No. of Observations	53

*p<0.1; **p<0.05; ***p<0.01

Table 2.11: Encompassing Regression for RW-AO inflation forecasts.

concluded that the BoG forecasts encompassed information embedded in the random walk forecast.

I also run the reverse order of the above regressions where the inflation forecast errors of RW-AO are regressed against the BoG inflation forecasts as per the following equations:

$$e_{t/t-1}^{RW-AO} = \alpha + \beta \hat{\pi}_{t/t-1}^{BOGF1Q} + u_t \tag{2.20}$$

$$e_{t/t-1}^{RW-AO} = \alpha + \beta \hat{\pi}_{t/t-1}^{BOGF2Q} + u_t \tag{2.21}$$

The results, shown in Table 2.11 of the Appendix lead to the conclusion that the one-step-ahead forecast is important in explaining the random walk forecast error and therefore the random walk forecast does not encompass information embedded in the BoG's one-step inflation forecast. However, I conclude that the two-quarters-ahead BoG inflation forecast does not significantly explain the random walk forecast error and therefore the random walk forecast encompasses all information embedded in the BoG's two-quarters-ahead inflation forecast. I summarise the findings of the encompassing test in Table 2.12 with the detailed results of the regressions shown in Table 2.10 and 2.11.

2.7 Conclusion

This Chapter examines the efficiency of the Bank of Ghana's inflation forecasts. I also compare these forecasts versus a benchmark forecast and an institutional forecast.

Using a Mincer-Zarnowitz regression, I conclude that the one-quarter ahead BoG in-

Forecast	**Forecast encompassing result**
BoG 1Q-ahead forecast	Forecast encompasses all information embedded in the random walk forecast
BoG 2Q-ahead forecast	Forecast encompasses all information embedded in the random walk forecast
Random walk forecast	Forecast does not encompass all information embedded in the BoG's 1Q-ahead forecast
Random walk forecast	Forecast encompasses all information embedded in the BoG's 2Q-ahead forecast

Table 2.12: Summary of Results of Encompassing Tests

flation forecast with SIS variables provides the strongest evidence in support of forecast efficiency. The Bank of Ghana's one-quarter ahead inflation forecast is efficient with or without the incorporation of SIS variables, however a stronger efficiency is exhibited when SIS variables are incorporated in the forecast. The stronger efficiency exhibited by the forecast that incorporates the SIS variables points to the importance of addressing outliers and structural breaks in evaluating inflation forecasts framework especially in developing economies such as Ghana.

Even though the constant term and the coefficient of the forecast term are individually statistically insignificant for the naive model of two-steps-ahead inflation forecast error, the forecast is inefficient both for the naive and SIS incorporated models.

The central bank's forecast outperforms the random walk and the IMF WEO forecasts. The central bank's one-step-ahead forecast was superior with a statistically significant difference in its accuracy compared to the random walk forecast.

Using the concept of encompassing, I conclude that the central bank's forecasts is robust and reflects all information embedded in the random walk forecast at the time of forecast but the same cannot be said of random walk benchmark forecast.

There is evidence that the Bank of Ghana's forecasting performance as measured by the inflation forecast error improves with time. Finally, I also note by the inspection of the scatter plots of the inflation forecast errors against actual inflation that outliers tend to occur at higher levels of inflation; as inflation increases the forecast error increases through the tendency of the forecasting framework to underestimate the inflation forecast. This finding supports earlier results of Zarnowitz and Mincer (1969) who concluded that "there is also evidence that increases in the series with strong upward trends are likely to be under-predicted".

Chapter 3

Inflation forecasting Using The New Keynesian Philips Curve With a Time-Varying Trend and Structural Breaks

3.1 Introduction

In Chapter 2, a Mincer Zarnowitz (MZ) regression is used to assess the CPI-based inflation forecast accuracy of the Bank of Ghana. Whereas Chapter 2 is a purely empirical analysis, Chapter 3, which also deploys the MZ regression relies on a GDP deflator-based TVT-NKPC inflation forecast to assess the unbiasedness and efficiency of the forecasts. The results of these two Chapters lead to the conclusion that the central bank's immediate-term forecast produces the least forecast error. Chapter 2 does not analyse the central bank's medium to long term forecasts due to data constraints, however, the medium to long-term inflation forecasts in Chapter 3 reveal that the random walk inflation forecast is the most accurate but there is not a statistically significant difference in forecast accuracy between this forecast and the AO-RW forecast and TVT-NKPC inflation forecasts.

This Chapter generates new Keynesian Philips curve (NKPC)-based forecasts using an approach in McKnight et al. (2020) and compares this forecast with a random walk forecast (RW) and a pseudo-random-walk forecast as in Atkeson and Ohanian (2001), hereafter, AO forecast. To address structural shifts in the data, we introduced indicator saturation variables, see Castle et al. (2015), Pretis et al. (2018) and Castle et al. (2018).

Two research questions are investigated. Firstly, do the NKPC-based forecasts improve on forecasts when compared to institutional and other empirical-based benchmark forecasts? Secondly, I investigate whether the incorporation of indicator variables improves and addresses the episodic performance of NKPC forecasts. To the best of my knowledge no such study has been conducted in Ghana or other emerging or frontier market economies as most of the forecast evaluation literature has focused on developed economies.

McKnight et al. (2020) showed that it was possible to outperform the random walk and AO-based forecasts at policy relevant horizons using their time-varying trend (TVT) NKPC-based inflation forecast. They showed that a theory-based approach that incorporated time-varying trend information could outperform what until right now had been believed to be hard to out-perform AO-based forecasts. (See, Duncan and Martínez-García (2019)).

There have been two strands of approach in the inflation dynamics and forecasting literature; times series techniques and structural approach. The former approach, such as the RW and AO-based forecasts, made minimal use of theoretical input, while the structural approach used micro-economic foundations to macroeconomic modeling such as the NKPC-based approach. So far, the literature has pointed to the simple time-series based inflation forecasting models as in Duncan and Martínez-García (2019) outperforming the structural NKPC-based approach. McKnight et al. (2020) used TVT inflation to incorporate changes in central bank preferences and policy frameworks. The key difference between their approach and previous NKPC-based inflation forecasts was that the latter assumed a constant or zero inflation at steady state and ignored TVT inflation. McKnight et al. (2020) is the first study to analyse the implication of TVT inflation on NKPC-based inflation forecasts.

This Chapter uses McKnight et al. (2020)'s approach, which separated the trend from the cyclical component of inflation. These two components were then summed to generate inflation forecasts. To estimate the marginal cost component required to forecast the generalised TVT-NKPC, two proxies are deployed. First, real marginal cost is approximated by real unit labor cost (RULC) as in McKnight et al. (2020) and Galí and Gertler (1999). Real marginal cost is also proxied as in the monetary open economy (MOE) model in Mcknight and Mihailov (2015). The inflation forecasts are modelled using recursively estimated samples based on fixed rolling samples(ROLL) and augmented length(REC) samples.

Hendry and Mizon (2011) and Hendry and Mizon (2014) pointed out how unanticipated shifts in the data can impede forecasting ability if not correctly handled. This chapter provides for a robust forecast which can deal with structural breaks by incorporating indicator saturation variables.

To assess the performance of the TVT-NKPC forecast, the AO inflation forecast and the RW forecast without drift are used as benchmarks, in line with previous forecast evaluation literature (see, Duncan and Martínez-García (2019), Clements and Reade (2020)). The pseudo-out-of-sample forecast is assessed using the root mean square forecast error (RMSFE) and the ratio of the TVT-NKPC RMSFE and the benchmark RMSFEs, the Thiel-U statistic, and its statistical significance is evaluated using the original and modified versions of the Diebold and Lopez (1996) tests.

The AO inflation forecast delivers the smallest forecast error for the one-quarter ahead horizon. It outperforms the best TVT-NKPC forecast and the RW forecasts by 0.6% and 33.9% respectively. All the variants of the TVT-NKPC inflation forecasts are more accurate than the RW inflation forecast.

The result for the one-quarter ahead forecast is like Duncan and Martínez-García (2019) who concluded that in emerging market economies, it was difficult to add-value beyond AO-RW forecasts without adding subjective judgement to account for structural shifts in the data but also supportive of the TVT-NKPC forecasts which were more accurate than the RW forecast. In fact, the RULC RMC(REC) forecast is not statistically significantly different from the AW forecast for the more policy relevant one-quarter ahead horizon.

In the medium to long-term forecast horizons, the random walk (RW) forecast consistently outperforms both the AO forecast and the TVT-NKPC inflation forecasts. While the results show a more accurate RW inflation forecast, using the Theil U statistic and the one-sided modified Diebold and Lopez (1996) (MDM) test, I did not find a statistically significant difference in forecast accuracy among the TVT NKPC and the two benchmark inflation forecasts for the 4, 8, 12, 16 and 20-quarters ahead forecast horizons.

For the one-quarter ahead forecast horizon, the TVT-NKPC forecasts using the RULC RMC (ROLL) and the RULC RMC (REC) forecasts are statistically significantly more accurate than the RW forecasts at the 1% significance level. The MOE RMC (ROLL), MOE RMC (REC) and RULC RMC (ROLL) inflation forecasts statistically significantly under-performed the AO forecast at the 1%, 10% and 1% respectively. Even though the AO inflation forecast is more accurate than the RULC RMC (REC) inflation forecast, there is not a statistically significant difference in forecast accuracy.

The original Diebold Mariano (DM) test which ignores the small sample size correction that the MDM test provides, also concludes that there is not a statistically significant difference between the TVT-NKPC and the RW forecasts for the medium- and long-term forecast horizons (4, 12, 16, 20 quarters ahead), like the conclusions obtained from the MDM test. The only exception is for the 8 quarter-ahead forecast horizon where the RW forecast is statistically significantly more accurate than the RULC RMC (ROLL) forecast. Using the DM test, the one-quarter-ahead AO inflation forecast is more accurate than all the four variants of the TVT-NKPC inflation forecasts and is statistically significantly more accurate than the MOE RMC (ROLL), MOE RMC (REC) and RULC (ROLL) forecasts at 1%, 10% and 1% significance levels respectively.

The results show that in the medium to long-term forecast horizons, there is not a statistically significant difference in forecast accuracy between the NKPC-based forecast (TVT-NKPC forecast) and time series-based forecasts using data from Ghana. This result contrasts earlier empirical research findings in advanced economies by Duncan and Jel (2015) and Kabukcuoglu and Martinez-Garcia (2018) who concluded that Philips curve-based forecast models performed better. The Bank of Ghana forecasts performed better than the benchmark forecasts in the immediate forecast horizon.

To assess the usefulness of addressing structural shifts in the data in the TVT NKPC inflation modelling framework, this chapter introduces indicator saturation variables in a Mincer-Zarnowitz regression setting to assess whether this addition improved ex post diagnostic analysis of points in the data when shifts occur or outliers are observed and whether this improves model performance.

3.2 Theoretical Framework

Research on NKPC-based estimation has been dominated by studies on developed economies. A few studies have been based on developing open economies similar in characteristics to Ghana. Maichal (2012) used the generalised moments method(GMM) method and concluded that the hybrid NKPC was appropriate for the Indonesian economy. Ooft et al. (2021) also forecast inflation in Suriname using a hybrid NKPC and a MIDAS regression model. Piao and Joo (2014) estimated an open economy NKPC for Korea and used this to explain inflation dynamics, concluding that external factors were more important drivers of inflation relative to domestic factors.

Behera and Patra (2022) deployed a regime switching model and a NKPC to model trend inflation in India. Finally, Yılmaz and Tunc (2022) incorporated a positive trend inflation in a NKPC framework to explain inflation dynamics in Turkey. These studies point to the relevance of NKPC estimation even for developing open economies and justifies NKPC estimation for forecasting inflation in Ghana.

Given the important role export commodities play in the Ghanaian economy, I consider other approaches that might stress the role of commodity prices. The impact of export commodity prices on inflation is evaluated by the introduction of an instrumental variable in the estimation model. The instrumental variable is the simple average of the commodity price indices of the three major export commodities of Ghana with 2015 serving as the base year. Adding this commodity price instrument rather reduced the forecast performance and therefore was not pursued further in the analysis.

3.2.1 Time-varying Trend New Keynesian Philips Curve (TVT-NKPC) Framework

The theoretical framework is based on a two-country extension of the Neo-Wicksellian model (see Woodford (2003)). Each country has a representative infinitely lived household, a representative final-goods producer, a monetary authority and a continuum of intermediate-goods producers. The representative final-good producer is a competitive firm and puts together domestic and imported intermediate goods into non-tradeble final goods. The intermediate goods producers are monopolistically competitive and set prices in a staggered Calvo (1983) fashion. The central bank, using the Taylor rule, sets nominal interest rates based on expected future inflation. The theoretical framework of the TVT-NKPC follows previous research by Mcknight and Mihailov (2015), McKnight et al. (2020) and the indicator saturation methodology presented in Ericsson (2017a). This framework assumes the full indexation of non-optimized prices for any firm to be a combination of the last period actual inflation and the current period time-varying trend inflation, with the time varying trend inflation following an AR(1) process. In this framework, ρ $(0 < \rho < 1)$ represents the weight on the last period actual inflation and is set to a value of 0.2 following Cogley and Sbordone (2008). The generalized NKPC is then specified using the Calvo (1983) price setting specification and transformed to make it more suitable to forecast inflation.

I adopt the quasi first difference generalized TVT-NKPC equation as follows:

$$\widehat{\pi}_t - \rho\widehat{\pi}_{t-1} = \gamma[\mathrm{E}_t\widehat{\pi}_{t+1} - \rho\widehat{\pi}_t] + \kappa\widehat{mc}_t + \rho(\theta\gamma - 1)\widehat{g}_t^{\overline{\pi}} \tag{3.1}$$

where $\widehat{\pi}_t$ is current inflation, $\widehat{mc}_t$ is the cyclical component of real marginal cost (RMC) and $\widehat{g}_t^{\overline{\pi}}$ is the time varying trend inflation. In equation 3.1, ρ is the coefficient associated with the backward-looking component of inflation. κ is the real marginal cost elasticity of inflation, γ is the coefficient associated with the forward-looking component of inflation and θ is the coefficient associated with is the Dixit-Stiglitz elasticity of substitution among differentiated goods. The standard real unit labour cost (RULC) in Galí and Gertler (1999) and the open economy monetary model in Mcknight and Mihailov (2015) are used as proxies for real marginal cost for the evaluation of the efficiency of the TVT-NKPC forecasts. $\widehat{mc}_t$ is a log linear approximation around a time varying trend which is a function of domestic output, $\widehat{Y}_t$, consumption, $\widehat{C}_t$, real money balances, $\widehat{m}_t$, and the home economy terms of trade, $\widehat{S}_t$. The real marginal cost is stated as follows:

$$\widehat{mc}_t = \overline{\omega}\widehat{Y}_t + \sigma\widehat{C}_t - \chi\widehat{m}_t + (1-\alpha)\widehat{S}_t \tag{3.2}$$

Using the calibrated values for the structural parameters of McKnight et al. (2020) where $\overline{\omega} = 0.47$ is the output elasticity of RMC and represents the inverse of the Frisch labor supply elasticity, $\sigma = 0.16$ is the coefficient of relative risk aversion (CRRA) $=$ 1/EIS, implying elasticity of intertemporal substitution in consumption EIS=6.4, $\chi = 0.02$ is the degree of non-separability of real money balances from real consumption in the utility function and $\alpha = 0.85$ is the degree of trade openness, corresponding to home bias in (intermediate goods) production. The four observable variables are used with the calibrated parameters to estimate the unobservable real marginal cost, $\widehat{mc}_t$.

If the trend component of inflation follows an AR(1) process with a drift, McKnight et al. (2020) showed that a one-step ahead forecast can be formulated and used iteratively to generate forecasts for future horizons. The h-step ahead forecast assuming a trend component inflation which followed an AR(1) process could be represented as follows:

$$\widehat{\Pi}_{t+h/t} = ({g_t}^{\overline{\Pi}})^h \overline{\Pi}_t \tag{3.3}$$

$for\ h \geq 1$

where ${g_t}^{\overline{\Pi}}$ is the growth rate of time-varying trend inflation in period t relative to period t-1. They also showed that the h-horizon forecast of the cyclical component of inflation can be written as:

$$\widehat{\pi}_{t+h/t} = \rho^h\widehat{\pi}_t + \kappa {e'}_1(\mathbf{I}-\gamma\mathbf{A})^{-1}h\sum\rho^{(i-1)}\mathbf{A}^i\widehat{Z}_t + \rho(\theta\gamma-1)e'_2(\mathbf{I}-\gamma\mathbf{A})^{-1}h\sum\rho^{(i-1)}\mathbf{A}^i\widehat{Z}_t \tag{3.4}$$

In this equation, e'_1 is the selection vector which extracts the forecast of the cyclical component of marginal cost and e'_2 is the selection vector that extracts the forecast of time varying trend inflation and $\widehat{Z}_t$ is the vector entering the companion form matrix $\mathbf{A}$ of the nVAR(p) system, where p is the number of lags in the VAR system and $\mathbf{I}$ is an identity matrix.

The forecasts of the trend component of inflation and the cyclical component of inflation are combined to obtain the TVT-NKPC inflation forecast.

I compare the trend specification adopted in this chapter versus that used in Stock and Watson (2007). Stock and Watson (2007) decomposed inflation into two components; a permanent stochastic trend and a serially uncorrelated transitory component. Where the time-varying trend inflation was modeled as a first order integrated moving average IMA(1,1). In this Chapter, I combine forecasts of trend and cyclical components of inflation to generate the TVT-NKPC inflation forecast and specify the time-varying trend inflation as an AR(1) rather than the IMA(1,1) process used in Stock and Watson (2007).

This Chapter shared some similarities with Stock and Watson (2007) in the sense that both were based on quarterly GDP-deflator inflation using recursive and rolling window samples to generate a pseudo out-of-sample forecast. Stock and Watson (2007) also used other measures of inflation including CPI and Personal Consumption Expenditure deflator for core items.

3.2.2 Saturation Estimation Techniques

The use of IIS for capturing in-sample features of the data which are hard to model is easily justifiable. Its use out-of-sample however requires careful justification. Shifts in the macroeconomic environment and policy responses over the sample period could lead to periods of large forecast errors in-sample leading to a rejection of the null hypothesis of efficient forecasts. In such an instance the incorporation of saturation indicator variables would allow for large forecast errors in what would otherwise be a satisfactory forecasting framework. By incorporating indicator saturation variables, the forecast evaluation could be carried out without necessarily penalizing the existence of large forecast errors.

Marczak and Proietti (2016) point out that the detection of structural change is important when analyzing forecasts of economic time series. Shifts in the level of inflation and the time varying trend inflation can reflect in the form of outliers and mean shifts respectively. Structural shifts and outliers can cause forecast failure and distort inferences. Since the length and the impact of these shifts on economies are unknown, time series research should analyse these shifts and possibly neutralize their impact on parameter estimates. I used a technique which is an extension of least squares regression for testing for outliers and structural breaks in a regression analysis known as saturation estimation techniques. Saturation estimation uses indicator variables for every observation in the regression to detect dates when location shifts, or trend breaks occur [1].

The GDP deflator series as shown in Figure 3.1 exhibits significant volatility with a wide dispersion from -50% and 60% and notable periods of shifts in the level of inflation. One such period is the first quarter of 2021. During this period the economy experienced significant increases in prices emanating from local and imported non-food sources.

I follow Zarnowitz and Mincer (1969), Sinclair et al. (2012) and Clements and Reade (2020) in assessing the unbiasedness and efficiency in the TVT-NKPC inflation forecasts using Mincer-Zarnowitz regressions by regressing actual GDP deflator inflation on the TVT-NKPC inflation forecasts over the out-of-sample forecast period of 2015Q1 to 2021Q3. It can be shown that this regression is equivalent to running a regression of the inflation forecast error, actual inflation minus inflation forecast, on the inflation forecast and the test of unbiasedness amounts to jointly testing the null hypothesis; $H_0 : \alpha = 0, \beta = 0$. In this estimation, α is the constant term and β and is the estimated coefficient of the TVT-NKPC inflation forecast variable. This joint null hypothesis test is conducted on the Mincer-Zarnowitz regression model to assess the forecast unbiasedness using an F-statistic[2].

The introduction of indicator saturation variables can control for non-fundamental omitted variables which impact inflation, such as policy changes, non-economic news, micro-structural changes, or changes in forecasting due to learning or imperfect knowledge. This Chapter considered the use of impulse-indicator saturation (IIS) and step-indicator saturation (SIS) because they are simple and flexible to use for modeling structural changes but also explored the data for the possible use any of trend saturation indicator (TIS) variables (see Pretis et al. (2015)).

IIS is designed to detect outliers rather than location shifts and can detect economically large and highly significant time-varying biases, particularly at turning points in the business cycle. IIS defines a generic procedure for examining forecast properties; it

[1]The inclusion of indicator variables for each observation would ordinarily not be appropriate because of the singularity of the regressor matrix but the use of block estimation through GETS modelling makes this procedure possible.

[2]The F-test arises because we compared the estimated residual variances between the original model and a restricted model in which two parameter estimates were set to zero. Ericsson (2017b) indicated that this test may be inappropriate for multi-step ahead forecasts without examining the error terms for the presence of auto-correlation.

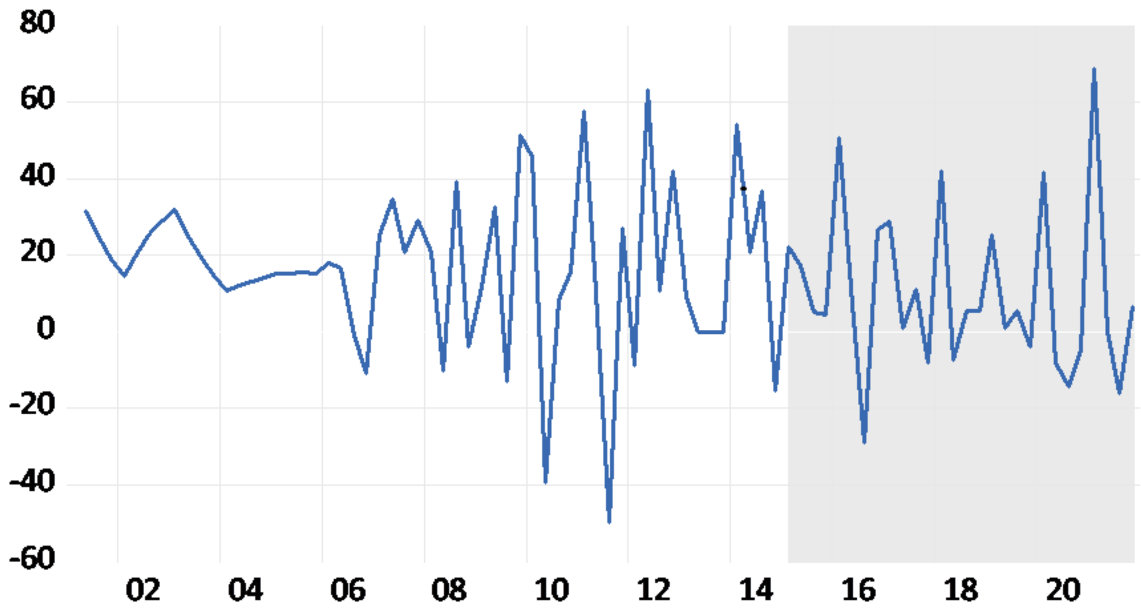

Figure 3.1: GDP-deflator at Annualised Rate, Percent, on a RULC proxy for Marginal Cost and a REC Sample Window

explains why standard tests fail to detect bias; and it provides a mechanism for potentially improving forecasts. Castle et al. (2015) note that when features of multiple shifts are unknown, the use of SIS can be beneficial as standard tests typically fail to detect biases in these forecasts.

The definitions of Castle and Hendry (2019) for these three saturation indicators are used. First, the IIS is defined as $1_{j=t}$, where $1_{j=t}$ is equal to one when j=t and equal to zero otherwise for j= 1,………,T. The IIS is useful in detecting outliers whereas the SIS variable is used to analyse step shifts. A step shift is a block of adjoining impulses of the same magnitude and sign. The step indicator is defined as $1_{t<=j}$, j= 1,………, T where $1_{t<=j} = 1$ for observations up to j, and zero otherwise for a sample of T observations.

When the growth rate of a variable shifts, this may often require a change in the trend of that variable. One way to capture the change in trend of a variable is by incorporating a trend indicator in the analysis. A trend indicator generates a trend up to a given observation and takes a value of zero thereafter for every observation. A break in trend is difficult to identify as this may involve small changes which build up over time to significant movements. The TIS is defined as $T_{jt} = t - j + 1$ for $t \geq j$, j=1, ……..,T and zero otherwise.

3.3 Empirical Strategy

3.3.1 Data

Quarterly Ghana data spanning the first quarter of 2001 to the fourth quarter of 2021 is used, with the pseudo out-of-sample forecast evaluation period covering the first quarter of 2015 to the fourth quarter of 2021. The forecasting evaluation period is determined using a third of the sample data. The real GDP denominated in millions of Ghana cedis, is obtained from the Ghana Statistical Service and the seasonally adjusted GDP deflator is derived using 2015 as the base year. Imports and exports of goods and services deflators are derived using a base year of 2015. Services are priced using the United States of America consumer price index (CPI) and export goods are priced using the prices of Ghana's main exports of gold, crude oil and cocoa, while prices for imports for goods are proxied using bent crude oil prices. All the prices of goods that constitute exports and imports are obtained from Bloomberg and the Ghana CPI is obtained from the Ghana Statistical Service. The money supply data is obtained from the Bank of Ghana. The compensation data used to compute the real unit labor cost is obtained from the Ghana Statistical Service.

The quarterly GDP deflator is the inflation measure used in this chapter and is calculated in percentage terms as the annualized log difference of the quarterly GDP deflator series, where $\pi_t = 400 \ln P_t/P_{t-1}$. P_t is the quarterly GDP deflator price index which is used to represent the aggregate price level in Ghana. The literature on inflation in Ghana has largely used the CPI to measure the aggregate price level, this chapter differs in that respect by following Stock (2007) and Faust and Wright (2013) whose preference was to use the GDP deflator to measure the aggregate price level because it was a broader measure of the aggregate price level.

The Chapter forecast single quarter inflation to enable the assessment of how the forecast horizon may impact the predictability of inflation.

Figure 3.1 depicts the quarterly series of annualized GDP-deflator inflation for Ghana for the period; 2001:1 to 2021:4 using the series obtained from the recursive sample windows and the cyclical component of the standard real marginal cost proxy.

The area shaded in grey is the forecasting evaluation period which covers the period 2015:1 to 2021:4. This series rose between 2007:2 and 2012:2, due to rising domestic fuel prices fueled by increases in international crude prices in 2007/2008, in 2009 food prices dropped but petrol prices rose by 45%. Consumer inflation was stable in 2010 up to February 2012 due to a decline in food inflation, the impact of the decline in food inflation

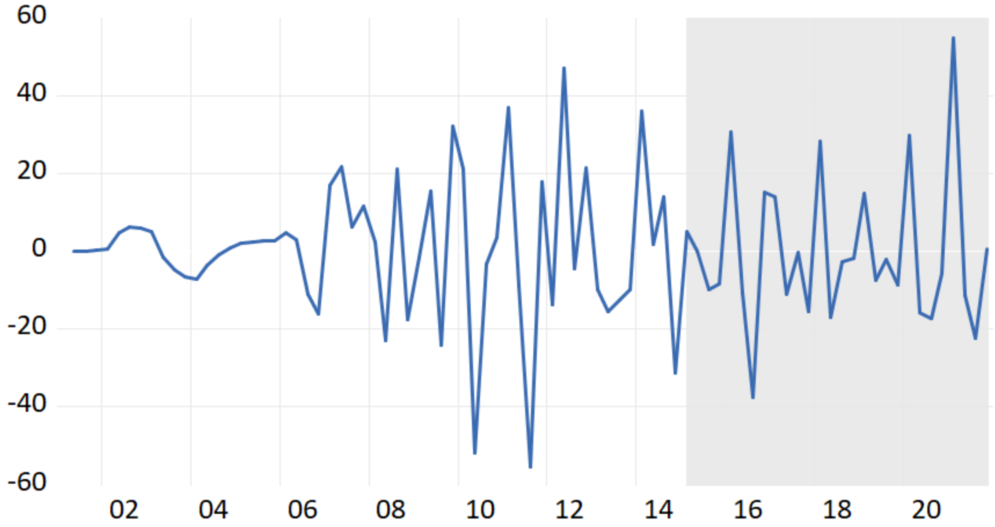

Figure 3.2: GDP-deflator Cyclical Inflation at Annualized Rate, percent per Annum Based on a RULC Proxy and a REC Sample Window.

was however negated by an increase in non-food inflation.

Inflation trended downwards between 2012:2 and 2020:3 and was largely due to a reduction in non-food inflation between 2012-2014, a fall in crude oil prices in 2015, a tighter fiscal policy stance and a stable local currency in 2016, dampening inflation expectations driven by non-food inflation in 2017, and a lower non-food inflation in 2018 followed by a moderate pick-up in inflationary expectations in 2019[3]. The general trend of a reduction of GDP deflator inflation was characterized with spikes in the GDP deflator series in 2014:1, 2016:1, 2018:1, 20201:1, which also were periods with spikes in cyclical inflation. The GDP-deflator inflation series has been more volatile when compared to the CPI inflation series.

Figure 3.2 shows the quarterly GDP deflator cyclical inflation for the sample period for Ghana and Figure 3.3 shows that the quarterly GDP-deflator trend inflation for Ghana has been declining since 2014:3 but for a spike in 2021:1. In Figure 3.4, I show the quarterly GDP deflator and CPI inflation for Ghana noting that the GDP deflator inflation series has been more volatile.

3.3.2 Stationarity Tests

The results of the stationarity tests of the GDP-deflator inflation and its components are shown in Table 3.1. The stationarity tests using Augmented Dickey Fuller (ADF) and

[3]See various Inflation Outlook and Monetary Policy reports on the Bank of Ghana's web site, see

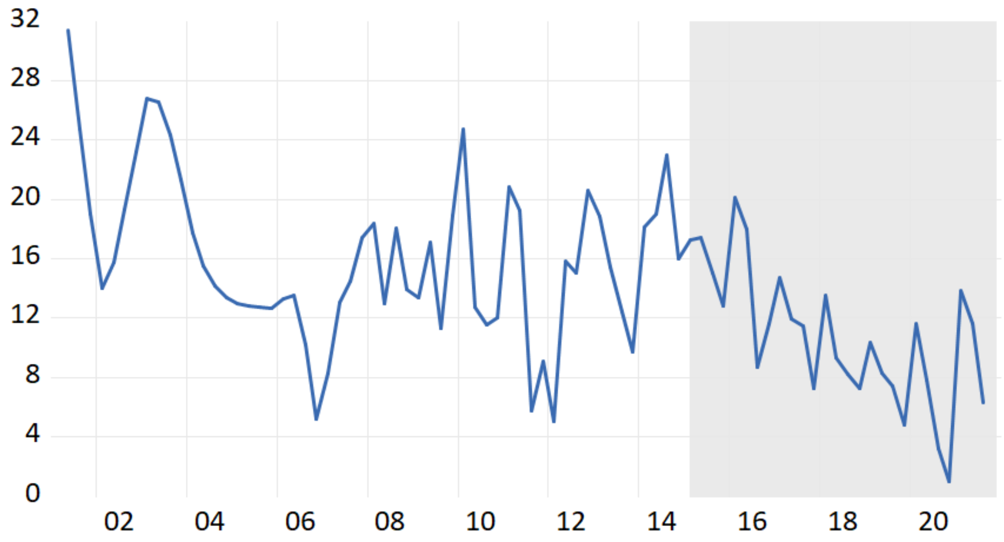

Figure 3.3: GDP-deflator Trend Inflation at Annualized Rate, % Per Annum based on a RULC proxy and a REC Sample Window.

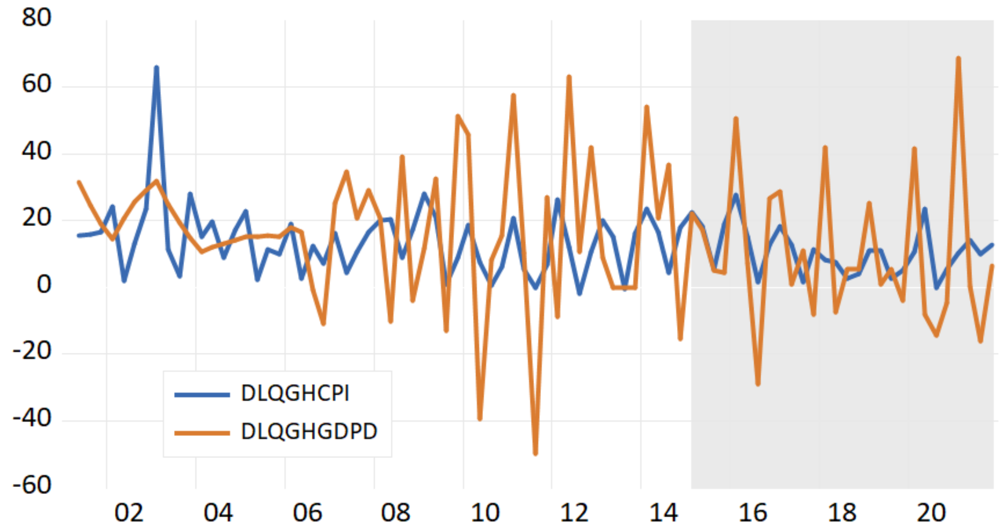

Figure 3.4: GDP-deflator/CPI Inflation at Annualized Rate, percent per Annum Based on a RULC Proxy for Marginal Cost and a REC Sample Window where DLQGHCPI = CPI Inflation and DLQGHGDPD = GDP-deflator Inflation.

Kwiatkowski-Phillips-Schmidt-Shin (KPSS) for both cyclical and trend inflation indicate that these components of inflation are stationary.

			Critical Values					
Null Hypothesis	**Test type**	**Test Statistic**	**1% Level**	**5% Level**	**10% Level**	**P-value**	**Decision**	**Conclusion**
Ghana GDP-deflator inflation has a unit root	ADF Test	-1.3835	-2.5962	-1.9452	-1.6139	0.1535	Do not reject null hyp	Process is not stationary
Ghana GDP-deflator inflation is stationary	KPSS Test	0.4252	0.739	0.463	0.347		Do not reject null hyp at 1% S.L	Process is stationary
Ghana GDP-deflator trend inflation has a unit root	ADF Test	-5.3607	-4.0753	-3.4662	-3.1598	0.0002	Reject null hyp	Process is stationary
Ghana GDP-deflator trend inflation is stationary	KPSS Test	0.1301	0.216	0.146	0.119		Do not reject null hyp at 1% S.L	Process is stationary
Ghana GDP-deflator cyclical inflation has a unit root	ADF Test	-9.0819	-2.5942	-1.9449	-1.6141	0.0000	Reject null hyp	Process is stationary
Ghana GDP-deflator cyclical inflation is stationary	KPSS Test	0.2074	0.739	0.463	0.347		Do not reject null hyp at 1% S.L	Process is stationary

Table 3.1: Stationary Test

The GDP-deflator inflation series is however not conclusively stationary as the Augmented Dickey Fuller (ADF) test concludes that the variable was non-stationary, but the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test concludes stationarity. The GDP-deflator trend and cyclical inflations are conclusively stationary at the smallest traditional significance level of 1%.

3.3.3 Empirical Methodology

As in Stock (2007), inflation forecasts are obtained using two types of recursively estimated samples. The first sample is a fixed length rolling (ROLL) sample and the second sample is based on an augmented length (REC). Two different proxies for the unobservable real marginal cost (RMC) are used to check for robustness of the TVT-NKPC forecast. The first proxy uses the monetary open economy (MOE) RMC proxy computed from four observable variables (output, consumption, real money balances and terms of trade) and structural parameters used in Mcknight and Mihailov (2015). The second RMC proxy is derived using the standard real unit labour cost (RULC) as originally specified Galí and Gertler (1999).

Following McKnight et al. (2020), I compare the TVC-NKPC forecasts with three univariate benchmark inflation forecasts; the random walk without drift forecast, originally formulated in Meese and Rogoff (1983), the AO random walk forecast and the Bank of Ghana's institutional forecasts with a caveat that the latter is based on forecasts of CPI inflation. The AO inflation forecast has been among the most successful inflation forecasts especially in emerging market economies (See, Duncan and Martínez-García (2019)). The drift-less random walk forecast views the inflation forecast for any future horizon, h, as equal to the observed inflation in the most recent quarter, $\pi_{t+h/t} = \pi_t$. The AO random walk forecast, is based on a forecast of inflation computed as the average inflation over four quarters, consisting of the current quarter inflation and the past three quarters' inflation. The trend component of inflation is forecast based on an AR(1) process, while the cyclical component of inflation was forecast using an auxiliary tri-variate vector autoregressive (VAR) process with four lags (3VAR(4)) based on a multi-period forecast of the generalised NKPC equation.

The Theil U statistic, defined as the ratio of the RMSFE of the theory-based forecast relative to the univariate benchmarks, RW and AO, over 1, 4, 8,12, 16 and 20-quarters ahead is used to assess the forecast accuracy of the theory-based forecast. The modified (Diebold and Lopez, 1996) test (MDM), proposed by (Harvey et al., 1997) is used to correct for small-sample bias and test whether the theory-based forecast is an improvement of the univariate benchmarks. The null hypothesis for this test, is that there no statistically significant difference in the forecast accuracy of the two compared forecasts.

3.3.4 Saturation Estimation Using Indicator Variables

Hendry and Mizon (2011) and Hendry and Mizon (2014) noted that unanticipated shifts in the data can impede forecasting ability if not correctly handled and showed that robust economic theory-based econometric models were capable of forecasting efficiently for long periods of time even in the presence of structural changes.

One effective way to address the challenges that outliers and shifts in the data pose to forecasting is by reducing or removing their "contaminating effects" as shown in Castle et al. (2015) using the indicator saturation techniques. Ericsson (2016) noted that indicator saturation techniques could be used as a generic diagnostic tool for detecting model specification errors and has also been used to detect time-varying biases in forecasts.

Ericsson (2017a) argues that when relevant indicator saturation variables were omitted from a model, the estimated residual variance was larger than the residual variance of the data generating process(DGP) and the estimated standard errors of the coefficients of the included variables in the model were bigger than the corresponding coefficient's estimated standard errors in the DGP. The bigger standard errors reduces the coefficient's t-ratios in the model with the omitted variables leading to false conclusions on hypothesis tests. Indicator saturation techniques could be a very useful tool for identifying times in the data when the model does not capture data movements particularly well and can serve as an ex-post diagnostic tool for detecting points in the data when the model is biased, the real challenge is in using the technique as a tool to improve model performance.

This Chapter explores the use of the indicator saturation techniques in conducting an ex-post diagnostic analysis and examines its use as a tool to improve model performance. Using the General-to-specific (GETS) modelling technique as detailed in Pretis et al. (2018), I look for outliers and structural breaks in the data. This technique is implemented using the PcGive Professional™[4] module for time series data in the Oxmetrics™[5] software and applying the functionality that allows for the outlier and break detection.

[4]This is a user-friendly software that provides an operational and structured way to econometric modelling.

[5]This is a menu-driven desktop for econometric and statistical modelling.

3.3.5 Evaluation of Inflation forecasts

The forecast accuracy of the TVT-NKPC inflation forecasts against the RW and the AO RW forecasts is evaluated by first comparing their root-mean forecast errors (RMSFE) as shown in Panel A of Table 3.2.

If inflation fluctuates widely, then AO/RW forecasts might perform poorly. To address this concern, the analysis also estimates a univariate AR(1) process and compares this with the other benchmark forecasts. The AR(1) forecast does not show superior performance relative to these benchmark forecasts and therefore is not given further consideration in this chapter. The Diebold Mariano, modified Diebold Mariano and Thiel statistics are used to assess the TVT inflation forecast relative to the benchmark forecasts.

The AO inflation forecast as shown in Table 3.2, delivers the smallest forecast error for the one-quarter ahead horizon. It outperforms the RULC RMC (REC) and RW forecasts by 0.6% and 33.9% respectively. In the medium to long-term forecast horizons, the random walk (RW) forecast consistently outperforms both the AO forecast and the TVT-NKPC inflation forecasts. In the 4-quarters-ahead, the RW inflation forecast outperforms the AO and MOE RMC (ROLL) forecasts by 13.9% and 14.2% respectively. In the 8, 12 and 16 quarters-ahead, the RW forecast outperforms the most accurate TVT-NKPC forecast, the MOE RMC (ROLL) by 16.6%, 19.6% and 20.5% respectively. For these forecast horizons, the RW inflation forecasts also outperforms the AO inflation forecast by 10.7%, 19.7% and 20.4% respectively. In the 20-quarter ahead forecast horizon, the RW forecast outperforms the AO forecast and MOE RMC (REC) forecasts by 35.5% and 40% respectively.

The results for the one-quarter ahead forecast is like Duncan and Martínez-García (2019) who concluded that in emerging market economies, it was difficult to add-value beyond AO-RW forecasts without adding subjective judgement to account for structural shifts in the data. For the one-quarter ahead forecast horizon, the TVT-NKPC forecasts using the RULC RMC (ROLL) and the RULC RMC (REC) forecasts are statistically significantly more accurate than the RW forecasts at the 1% significance level. I also use the one-sided MDM test to test whether there is a statistically significant difference in forecast accuracy between the TVT-NKPC and AO forecasts.

For the one-quarter ahead forecast horizon, the MOE RMC (ROLL), MOE RMC (REC) and RULC RMC (ROLL) forecasts statistically significantly underperforms the AO forecast at the 1%, 10% and 1% respectively when the original DM test is applied. Even though the AO forecast is more accurate than the RULC RMC (REC) forecast, there is not a statistically significant difference in forecast accuracy between these forecasts.

Using the Theil U statistic in Panel B of Table 3.2. and the one-sided modified Diebold-Mariano (MDM) test, there is not a statistically significant difference between the forecast accuracy of the TVT-NKPC and the benchmark forecasts for the 4, 8, 12, 16 and 20-quarters ahead forecast horizons. So, for medium to long-term horizons, the results show no empirical evidence of a significant difference in forecast performance between the TVT-NKPC-based forecasts and the statistical time series-based approaches. McKnight et al. (2020) found out that the TVT-NKPC forecasts were superior to RW forecasts in the medium (8 and 12-quarters ahead) to longer-term horizons (16 and 20-quarters ahead) using USA and Euro area data.

I also conduct the one-sided original Diebold and Lopez (1996) (DM) test with a null hypothesis of equal forecast accuracy between the TVT-NKPC and the benchmark forecast using a forecast evaluation period of 28 quarters. The original DM test which ignores the small sample size correction that the MDM test provides are shown in Table 3.2. The results for forecast horizon for 12,16, 20 quarters ahead are like the MDM test results with the conclusion that there is no statistically significant difference between the TVT-NKPC and the benchmark forecasts. For the 8 quarter-ahead, the RW forecast is found to be more accurate and statistically significantly different from the RULC RMC (ROLL) but the other three variants of the TVT-NKPC forecasts are not statistically significantly different from the RW forecast.

For the 4-quarters ahead forecast horizon, using the original DM test, the AO forecast is found to be superior and statistically significantly different from the RULC RMC (REC) forecast. All the remaining variants of the TVT-NKPC forecasts are not statistically different in terms of forecast accuracy from the AO forecast. The one-quarter-ahead AO inflation forecasts is superior to all the four variants of the TVT-NKPC inflation forecasts but is statistically significantly different in forecast accuracy to the MOE RMC (ROLL), MOE RMC (REC) and RULC (ROLL) forecasts at 1%, 10% and 1% respectively.

In Table 3.4 I show the results of the original DM test for evaluating the BoG's CPI inflation forecast versus the AO inflation forecast and note that the former was statistically significantly more accurate that the AO forecast. I do not compare the BoG inflation forecast with the TVT-NKPC forecasts as the data is available for different time periods and the BoG inflation forecasts are based on the CPI, whereas the TVT-NKPC forecasts are based on the GDP deflator inflation series.

Shown in Figure 3.5 is the one-quarter-ahead TVT-NKPC forecast using the real unit labour cost proxy for real marginal cost and a recursive window sample versus the actual

Forecast evaluation period	2015:1 to 2021:4					
Forecast horizon, quarters	1	4	8	12	16	20
Panel A: Root MSFE						
Theory-based TVT-NKPC Inflation forecasts						
MOE RMC (roll)	33.9746	21.9215	22.2120	23.3411	24.2170	27.8824
MOE RMC (rec)	30.5462	22.6781	22.5996	23.4192	23.8166	27.8813
RULC RMC (roll)	27.5988	23.1669	23.9035	23.9730	24.4955	27.9652
RULC RMC (rec)	22.7777	23.7623	23.1537	23.8142	24.3952	27.9940
Univariate benchmarks of inflation forecasts						
RW Forecast	34.2840	**18.8127**	**18.5208**	**18.7749**	**19.2577**	**16.7370**
AO Forecast	**22.6495**	21.8416	20.7346	23.3763	24.2073	25.9601
CPI-Based Forecasts						
Bank of Ghana	1.5987					
RW-AO (Chapter2)	2.5716					
IMF Forecast	15.1633					
Panel B: Theil U-stat; Ratio of RMSFEs of TVT-NKPV and RW Forecasts						
MOE RMC (roll)	0.9910	1.1653	1.1993	1.2432	1.2575	1.6659
MOE RMC (rec)	0.8910	1.2055	1.2202	1.2474	1.2367	1.6658
RULC RMC (roll)	**0.8050*****	1.2315	1.2906	1.2769	1.2720	1.6709
RULC RMC (rec)	**0.6644*****	1.2631	1.2501	1.2684	1.2668	1.6726
Panel C: Theil U-stat; Ratio of RMSFEs of TVT-NKPV and AO Forecasts						
MOE RMC (roll)	**1.5000*****	1.0037	1.0713	0.9985	1.0004	1.0740
MOE RMC (rec)	**1.3487***	1.0383	1.0899	1.0018	0.9839	1.0740
RULC RMC (roll)	**1.2185*****	1.0607	1.1528	1.0255	1.0119	1.0772
RULC RMC (rec)	1.0057	1.0879	1.1167	1.0187	1.0078	1.0783
Bank of Ghana	**0.622****					

MOE RMC =monetary open economy real marginal cost proxy
RULC RMC = real unit labor cost real marginal cost proxy
Roll =fixed length rolling window
Rec = augmenting length recursive window
***,**,* = statistical significance of the one-sided MDM test at the 1%, 5% and 10% respectively

Table 3.2: Forecasting Performance of TVT-NKPC, Random Walk(RW) and AO-RW and MDM test of statistical significance

forecast horizon, quarters	1	4	8	12	16	20
Panel B: Theil U-stat; RMSFE of TVT-NKPV relative to RMSFE of RW forecast						
MOE RMC (ROLL)	0.9910	1.1653	1.1993	1.2432	1.2575	1.6659
MOE RMC (REC)	0.8910	1.2055	1.2202	1.2474	1.2367	1.6658
RULC RMC (ROLL)	0.8050***	1.2315	1.2906*	1.2769	1.2720	1.6709
RULC RMC (REC)	0.6644***	1.2631	1.2501	1.2684	1.2668	1.6726
Panel C: Theil U-stat; RMSFE of TVT-NKPV relative to RMSFE of AO forecast						
MOE RMC (ROLL)	1.5000***	1.0037	1.0713	0.9985	1.0004	1.0740
MOE RMC (REC)	1.3487*	1.0383	1.0899	1.0018	0.9839	1.0740
RULC RMC (ROLL)	1.2185***	1.0607	1.1528*	1.0255	1.0119	1.0772
RULC RMC (REC)	1.0057	1.0879*	1.1167*	1.0187	1.0078	1.0783

MOE RMC =monetary open economy real marginal cost proxy

RULC RMC = real unit labor cost real marginal cost proxy
ROLL =fixed length ROLLing window
REC = augmenting length RECursive window
***,**,* = statistical significance of the one-sided MDM test at the 1%, 5% and 10% respectively

Table 3.3: Forecasting performance of TVT-NKPC forecasts, original DM test of statistical significance

forecast evaluation period	**2006:1 to 2020:1**
forecast horizon, quarters	1
Panel A: Root MSFE	
BoG CPI Inflation forecast	1.5986
Panel B: Theil U-stat; RMSFE of BoG forecast relative to RMSFE of AO forecast	
	0.6216*
***,**,* = statistical significance of the one-sided DM test at the 1%, 5% and 10% respectively	

Table 3.4: Forecasting performance of BoG CPI forecast Versus AO-RW forecasts, original DM test of statistical significance.

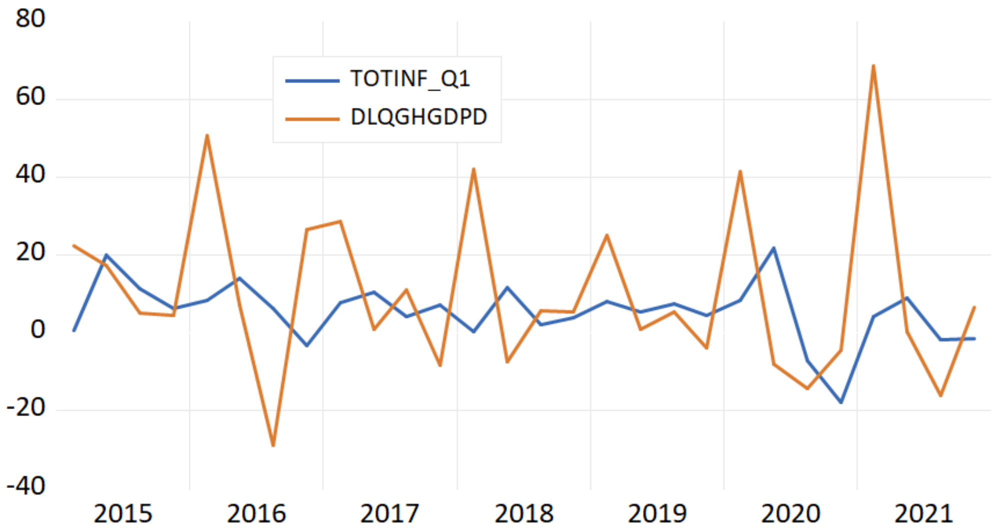

Figure 3.5: One-quarter-ahead TVT-NKPC Inflation forecast versus Actual inflation-based on real unit labour cost (RULC) proxy and Recursive(REC) window samples, where TOTINF_Q1 = One-quarter-ahead TVT-NKPC Inflation Forecast and DLQGHGDPD = GDP-deflator Inflation.

GDP-deflator. It is noted that the actual inflation was much more volatile than the forecast suggested and in majority of the time periods, actual inflation was higher than the forecast. A similar pattern is noted for the RULC ROLL forecast, but with increased volatility in 2020 and 2021 (See Appendix, Figure A.1). The trend of the MOE REC (See Appendix, Figure A.3) one quarter-ahead forecast is like the RULC REC forecast but for sharp drops in the former's forecast in early 2019. The MOE ROLL forecast is very volatile in the 2019, 2020 and 2021(See Appendix, A.2)

3.3.6 Incorporating Location Shifts

To assess the usefulness of incorporating location shifts in the TVT-NKPC inflation forecasts, I introduce IIS, SIS and TIS indicators that searched for seventy-eight indicators in two blocks. The detected indicator saturator variable is then used as an additional explanatory variable in a Mincer Zarnowitz regression. The estimation results reveal a statistically significant impulse indicator saturation variable in the first quarter of 2021 with a coefficient value of 60.82 and a p-value of 0.0044, revealing a rejection of the null hypothesis and leads to the conclusion that the impulse indicator variable is important in explaining the forecast error. Figure A.4 in the Appendix illustrates the indicator trajectory showing the impulse indicator with a 95% confidence interval for the first quarter of 2021 and then reverts to the trajectory after this quarter.

I analyse the results of the Mincer Zarnowitz regressions with and without the incorporation of saturation variables. The results of the one-quarter ahead Mincer-Zarnowitz regressions (with inflation forecast error as the dependent variable) with or without the IIS variable as a regressor is shown in Table 3.5 in the Appendix. The constant term as well as the parameter estimate for the inflation forecast variable are individually statistically insignificant with large p-values of 0.294 and 0.680 respectively for the regression model without the IIS variable. The coefficients are also jointly statistically insignificant with the p-value for the restricted F statistic of 1.0, which led to the conclusion the TVT-NKPC forecast was efficient and unbiased using the Mincer-Zarnowitz approach. The model estimation which incorporates an IIS variable conclude that the parameter estimates for the constant and inflation forecast are individually insignificant with p-values of 0.447 and 0.655 respectively, the null hypothesis that these parameter estimates were zero is therefore not rejected. For the IIS:Q1-2021 variable, we observed a relatively large and statistically significant regressor with a p-value of 0.0036, leading to the conclusion that this IIS variable is statistically significant. The restricted F-statistic is used to jointly test

	1Q-ahead Forecast error	1Q -ahead with IIS Forecast error	
Constant	6.092	3.806	
	[0.294]	[0.447]	
Forecast	-0.286	-0.266	
	[0.680]	[0.655]	
IIS:Q1-2021		60.836	
		[0.0036]**	
	21.668	18.589	
Observations	28	28	
Adj. R2	-0.032	0.241	
Test of Efficiency	**0.000**	**9.265**	
	[1.000]	**[0.0004]****	
	F(1,26)	F(3,22)	
	Chi-sq(2)	Chi-sq(2)	
p-values are in square brackets	*p<0.1	**p<0.05	***p<0.01

Table 3.5: Mincer-Zarnowitz Regression Results

the null hypothesis test that the constant and the coefficient for inflation forecast are zero is rejected with a p-value of 0.0004, leading to the conclusion that even though the IIS is individually statistically significant, a model which included this indicator saturation variable produces a biased and inefficient TVT-inflation forecast.

Figure 3.6 illustrates the trajectory of TVC-NKPC inflation forecast error and shows that the fitted model which includes the IIS indicator for 2021Q1 very well aligns with the actual inflation forecast error.

Figure 3.7 and Figure 3.8 show model results for the one quarter-ahead inflation forecast error mean estimations with and without IIS variable incorporated respectively. In Figure 3.8 we observe that the incorporation of the $\text{IIS}_{Q1-2021}$ variable helps to provide a perfect fit for the model in the first quarter of 2021 unlike Figure 3.7 where the model does not fit well with the actual inflation forecast error resulting in a relatively large, scaled residual of the inflation forecast error.

3.4 Conclusion

For the immediate forecast horizon (one quarter ahead), the AO-RW GDP deflator inflation forecast is the most accurate forecast when compared to the random walk forecast and the four variants of the TVT-NKPC forecasts. It is statistically significantly more accurate than the three variants of the TVT-NKPC inflation forecasts, but there is not a statistically significant difference in forecast accuracy between this forecast and the RULC RMC (REC) forecast. This result for the one-quarter ahead forecast is like Duncan and Martínez-García (2019) who concluded that in emerging market economies, it was difficult to add-value beyond AO forecasts without adding subjective judgement to account

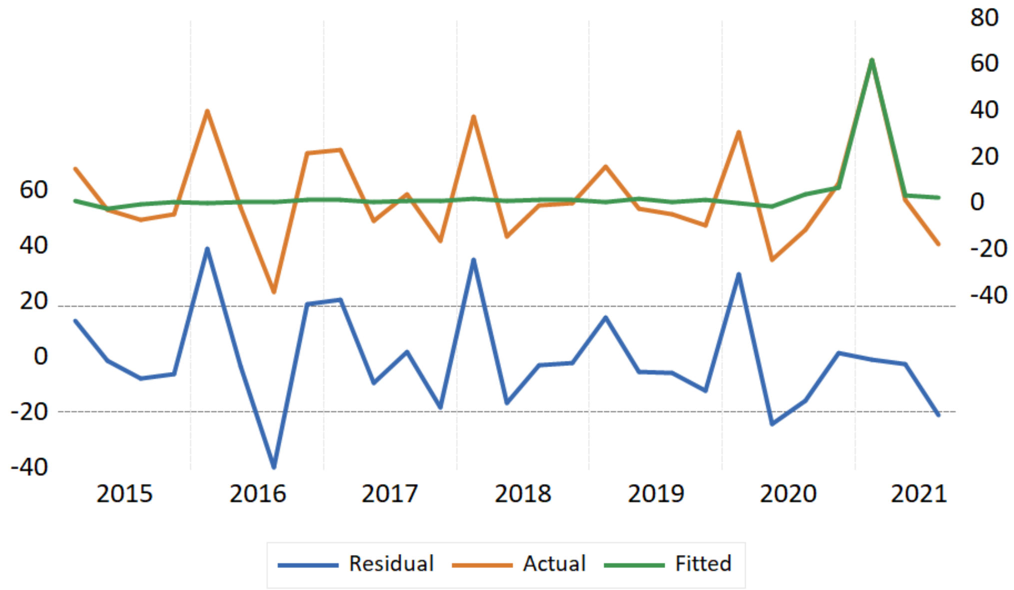

Figure 3.6: Actual, Fitted, and Residual Graphs for the TVT Inflation forecast Error with IIS Indicator.

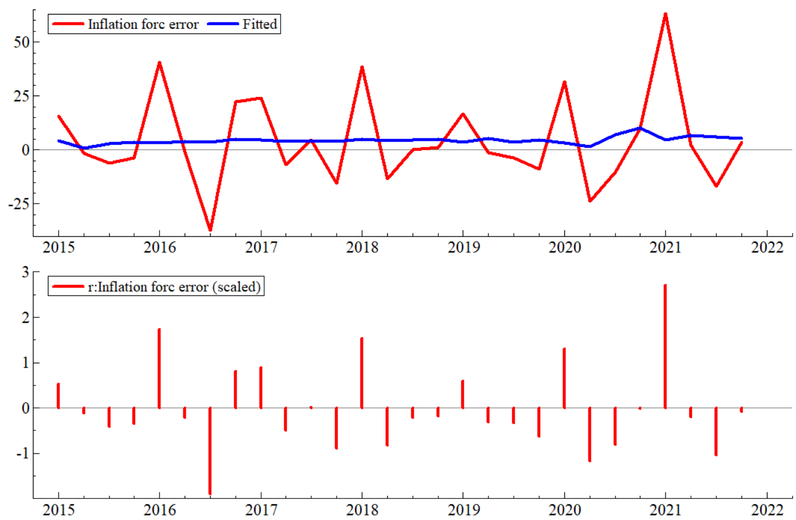

Figure 3.7: Inflation Forecast Error Model Fit With no Indicator Saturation.

for structural shifts in the data.

The RULC-REC TVT-NKPC forecast is statistically significantly not different from the AO forecast for the immediate forecast horizon. So, for the policy relevant one-quarter ahead forecast, the RULC-REC TVT-NKPC forecast provides a theoretical and empirical basis for its use for inflation forecasting.

The results show a more accurate RW inflation forecast, but there is not a statistically significant difference in forecast accuracy among the TVT NKPC and the two benchmark

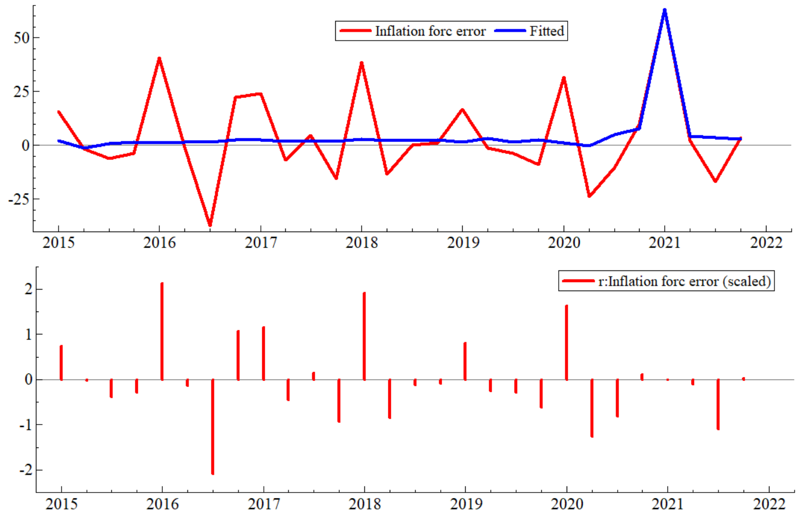

Figure 3.8: Inflation Forecast Error Model Fit With Indicator Saturation.

inflation forecasts for the 4, 8, 12, 16 and 20-quarters ahead forecast horizons.

This Chapter detects a statistically significant impulse indicator saturation variable in the first quarter of 2021, pointing to an outlier observation for that quarter. While the inclusion of this indicator saturation variable improves the model fit, it does not lead to an improvement of forecast performance but rather leads to a rejection of a null hypothesis of an unbiased and efficient forecast according to the joint test of the null hypothesis using Mincer-Zarnowitz regressions.

An area for further research will be to investigate whether the findings here apply to other inflation targeting emerging or frontier open economies such as South Africa. The use of indicator saturation variables to address shifts in the data within the context of a time-varying trend and a new Keynesian Philips curve framework is an area that will require further research.

Chapter 4

Bayesian Estimation of Policy Preferences of African Inflation Targeters

4.1 Introduction

The number of central banks that have adopted inflation targeting (IT) as the main monetary policy framework has grown since 1990[1]. Zhang and Wang (2022) used a panel data of 69 countries compiled between 1990-2021 and noted that 32 were inflation targeters making 47% of their sampled data. IT central banks state their primary mandate as price stability, it is therefore expected that their policy preferences will be dominated by this objective over other central bank policy objectives such as economic growth, exchange rate stability and interest rate smoothing. The policy preferences of advanced small open economies (ASOEs) and Latin American Inflation Targeters (LAITs) has been been studied (Kam et al. (2009) (KLL), Palma and Portugal (2014) and McKnight et al. (2020) (MMP)). However no similar published research exists for African Inflation Targeters (AFIT). This Chapter bridges this research gap by studying policy preferences of two AFITs, namely Ghana and South Africa who have more matured IT regimes.

Many inflation-targeting central banks can be described as ”flexible” inflation targeters in the sense that their objectives go beyond inflation. No matter the level of transparency about the macroeconomic variables they are most concerned about, the trade-offs across these macroeconomic objectives are less clear. Flexible inflation targeting central banks, such as the Reserve Bank of New Zealand, are more explicit that achieving their price

[1]When the first IT framework was launched in New Zealand, see, Buckle (2019)

stability objective is also dependent on a more stable financial system, and output, interest rate and exchange rate stability. In this context, I believe transparency is improved by providing more clarity on the weights these central banks place on alternative stabilization objectives (see Svensson (2007)), which is what this Chapter seeks to do.

The goals of these flexible inflation targeting central banks are their macroeconomic objectives, which they reveal as positive weights of all the variables other than inflation in their loss functions (See Caputo and Pedersen (2020)). In this framework, shifts in the central bank's preferences are interpreted as changes in the monetary policy regime because monetary policy objectives and targets are not necessarily constant over time. Previous research such as Clarida et al. (2000), Caputo and Pedersen (2020) and Arestis et al. (2016) show that central bank preferences have changed as monetary authorities have migrated to full-fledged IT regimes. For example, since the introduction of the IT regimes in the UK and Chile, these countries have increased their focus on price stability and placed less emphasis on real exchange rate stability and output stability. So even though flexible inflation targeting central banks mainly focus on price stability, it is not necessarily the sole policy objective as they may also tolerate some trade offs with other policy objectives depending on the macroeconomic dynamics of the economy. The estimated weights provide a framework for central bank boards in assessing central bank performance.

The key research question is whether AFITs are committed to price stability as mandated. A second but related research question is whether other alternative policy objectives distract their commitment to price stability. Finally, using results from previous studies and this Chapter, I compare policy preferences of AFITs with LAIT and ASOEs to assess whether there are significant differences in their level of commitment to inflation stabilisation.

Using Bayesian methods, I select the version of the model with a higher marginal likelihood function from two versions and estimate the central bank parameters, private sector deep parameters and parameters for the exogenous processes from the posterior density function. One model assumes that the central bank does not attach any importance to exchange rate stability ($\mu_q = 0$) and the other version assumes the central bank places a positive weight on exchange rate stability ($\mu_q > 0$). The models are estimated for complete asset markets (CAM) and incomplete asset markets (IAM) allowing for incomplete exchange pass through with international asset market structures.

The Bayesian estimation methodology is used to assess the monetary policy preferences of the BoG, the South African Reserve Bank (SARB) and also update estimates for the sampled countries in Latin America and three advanced small open economies. These countries have set inflation targeting as their key monetary policy objective and operate flexible exchange rate regimes. They are assumed to select the appropriate interest rate (policy rate) that minimises their quadratic loss functions which are a combination of deviations of real output, inflation and real exchange rate from their respective optimum or equilibrium levels. The importance or the weight placed on these policy objectives is then dependent on the central bank's monetary policy focus. My approach is similar to McKnight et al. (2020) [2], Kam et al. (2009) and Palma and Portugal (2014).

I adopt the dynamic medium-scale small open economy (SOE) New Keynesian structural model that was used in McKnight et al. (2020) for Latin American Inflation targeting (LAIT) economies as the structure of these economies are very similar to those of the countries studied in this Chapter. The Random-Walk Metropolis-Hastings Markov Chain Monte Carlo algorithm is used to estimate the posterior and convergence diagnostics for these two economies.

The key findings of this Chapter are outlined below. First, the empirical results confirm that Ghana and South Africa are committed to their price stability mandates. Ghana's parameter weight to inflation stabilisation is 42% compared to South Africa's weight of 59%. According to results from previous literature the weights for the inflation stabilisation parameter is in the range between 38% for Chile and 63% for Mexico in McKnight et al. (2020). The estimated weights for Ghana and South Africa are within those recorded from the previous literature.

The Chapter also concludes that other policy options are considered by AFITs after prioritising inflation stabilisation. Output stabilisation with a policy weight of 38% is second to inflation stabilisation as a policy preference for Ghana. This policy weight is the highest among IT central banks according to results from previous literature. Interest rate smoothing is not as important for Ghana but is of significant consideration. Aside inflation stabilisation, interest rate smoothing was the next important policy consideration for South Africa, this was followed by output stabilisation. As expected of IT central banks, Ghana and South Africa placed the least weight on exchange rate stability.

The results show that AFIT average weight for the inflation stabilisation parameter is higher than the average weights for ASOEs and LAIT countries, albeit heavily influenced by the high weight of South Africa. On the whole, individually, ASOEs all showed high commitments towards their price stability mandates, this was followed by their preference

[2] I am grateful to Prof Mihailov for enabling public assess to their Mathlab code used in this Chapter.

for interest rate smoothing and then output stabilisation. ASOEs were the not concerned about exchange rate stabilisation with no weight placed on this objective.

AFIT's second preferred policy choice after inflation stabilisation is output stabilisation (heavily influenced by Ghana's weight), the third policy preference for AFITs is interest rate smoothing. The least policy preference for AFITs is exchange rate stabilisation, as was the case of ASOEs, even though the average policy weight of 3% is lower compared to the average policy weights for exchange rate stabilisation of 14% in ASOEs and LAITs.

LAIT central banks second policy preference after inflation stabilisation is output stabilisation, this preference is followed by interest rate smoothing with the least preferred policy choice being exchange rate stabilisation. Compared to previous results in the literature, I observe a drop in preference for interest rate smoothing and an increase in preference for exchange rate stabilisation.

The order of policy preferences was the same for AFITs and LAITs; with inflation stabilisation, output stabilisation, interest rate stabilisation, and then exchange rate stabilisation in descending order of preference. ASOES order of policy preference was slightly different, after inflation stabilisation, interest rate stabilisation was the next preferred policy choice followed by output stabilisation and exchange rate stabilisation in descending order of preference.

Studies on the Ghanaian economy that make use of calibrated Bayesian estimation methods is limited. Dagher et al. (2012) used a calibrated DSGE approach to assess the impact of oil windfall on monetary and fiscal policy responses in Ghana. The Bank of Ghana's Forecasting and Policy Analysis System (FPAS) as in Mkhatrishvili et al. (2022) also deployed a calibrated DSGE approach. Houssa et al. (2010) estimated a SOE DSGE model for Ghana using Bayesian estimation methods using quarterly data between 1981-2007. Di Bartolomeo et al. (2014) also deployed a calibrated DSGE model to assess the impact of oil price volatility on economic growth in Ghana.

Central bank policy preferences have been well studied in advanced IT economies and LAIT. However, to the best of my knowledge, research in this area in the past decade in Africa has only been limited to the South Africa Reserve Bank's (SARB) changing monetary policy reaction function using regime switching techniques [3]. This Chapter breaks this research gap by conducting a cross country study of monetary policy preferences in Ghana and South Africa using Bayesian estimation methods. Furthermore there is no published research on Ghana that makes use of Bayesian estimation techniques. The only research

[3] Balcilar et al. (2017), Naraidoo and Paya (2012) and Kasaï and Naraidoo (2013) have studied the shifts in the preferences of the SARB's monetary policy using regime switching techniques.

that used Bayesian estimation methods for Ghana has been in a recent PhD thesis in Akosah (2020), this chapter fills this research gap.

Another contribution of this Chapter is that it makes use of methodology from similar previous literature and same countries but updated sampled data for all the countries to make conclusions on inflation targeting central bank policy preferences in advanced small open economies, Latin America and in Africa.

This Chapter is of policy relevance for the evaluation of central bank monetary policies as it enables the assessment of the level of commitment of inflation targeting central banks towards their price stability mandates and also provides a framework in assessing their alternative policy preferences. The main limitation of the Chapter is its use of results from different countries over different time periods. In future research this limitation can be addressed by combining the data from the various studies across the different countries using panel data.

The rest of the Chapter is organised as follows. Section 2 sets up the theoretical framework of the model DSGE economy. Section 3 describes the data and sets up the empirical strategy. Section 4 discusses the Bayesian estimation results and Section 5 presents the conclusions of the Chapter.

4.2 The Model Economy

The model used in this section is based on the framework developed in prior research on a small open economy (SOE) by Schmitt-Grohé and Uribe (2003), Smets and Wouters (2003), Galí and Monacelli (2005) and Justiniano (2010). This economy is an infinitesimally small part of the world economy because its output does not have a significant impact on the rest of the world economy. In this framework, Ghana and South Africa are the representative domestic economies and the United States of America (USA) serves as the foreign economy. Since the representative domestic economies are small in size relative to the USA, the latter's economic actions is assumed to have an exogenous effect on the domestic economies.

The domestic representative economy is inhabited by infinitely-lived households, domestic-goods producers, foreign-goods importing retail firms and a central bank. The retail firms are assumed to import goods at competitive world prices and they, as well as the domestic-goods producers, operate under monopolistic competition and set prices in a Calvo (1983) staggered-fashion.

It is assumed that the law of one price does not hold due to market power in the retail sector which results in incomplete exchange rate pass through. Thus international financial markets can be complete (CAM) or incomplete (IAM). The domestic inflation targeting central bank is treated as an optimising agent who uses its discretion to minimise a quadratic loss function by placing the preferred weights on inflation stabilisation, output stabilisation, real exchange rate stability and interest rate smoothing.

The domestic and foreign economies consist of economic agents who are assumed to be rational and forward-looking. These agents are households or firms. Households seek to maximise their lifetime expected utility by consuming and supplying labour and capital to firms, while firms produce goods and aim to maximise expected profit through their pricing decisions. Before I describe in detail the two main economic agents in the model, I introduce some simplifying notations. Variables without an i-index refer to the SOE being modelled and variables with an $i \in [0, 1]$ subscript is used to refer to economy i, which is one of the economies among a continuum of economies that make up the world economy. Variables with a star superscript refer to the world economy as a whole, and subscripts H and F denote variables of home and foreign origin respectively.

4.2.1 Households

The SOE is inhabited by a representative household that seeks to maximize the following expected discounted utility function.

$$E_0 \sum_{t=0}^{\infty} \beta^t U(C_t, H_t, N_t) \tag{4.1}$$

where $\beta \in [0, 1]$ is the discount factor, N_t represents hours of labour in period t and receives income in the form of wages, W_t, $H_t = hC_{t-1}$ is an external habit stock, with $h \in [0, 1]$ representing the *degree of habit persistence.* The household also receives profits, Π_t from ownership of domestic and retail firms. C_t is a composite consumption index defined by:

$$C_t = \left[(1-\alpha)^{1/\eta} (C_{H,t})^{\frac{\eta-1}{\eta}} + \alpha^{1/\eta} (C_{F,t})^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta-1}{\eta}} \tag{4.2}$$

In the above equation, $C_{H,t}$ represents the index of the consumption of domestic goods, $C_{F,t}$ is an index of imported goods and $\eta > 0$ is the *elasticity of substitution between domestic and foreign goods*, and finally $\alpha \in [0, 1]$ defines the *weight of foreign goods in the composite consumption index.*

The utility function is assumed to have the following functional form:

$$U(C_t, H_t, N_t) = \frac{(C_t - H_t)^{1-\sigma}}{1-\sigma} - \frac{N_t^{1+\phi}}{1+\phi} \tag{4.3}$$

where $\sigma, \phi > 0$ are *the inverse elasticities of inter-temporal substitution of consumption* and *labour supply respectively.* Next we define $C_{H,t}$ and $C_{F,t}$ as follows:

$$C_{H,t} = \left[\int_0^1 C_{H,t}(i)^{\frac{\epsilon-1}{\epsilon}} di\right]^{\frac{\epsilon-1}{\epsilon}}, \quad C_{F,t} = \left[\int_0^1 C_{F,t}(j)^{\frac{\epsilon-1}{\epsilon}} dj\right]^{\frac{\epsilon-1}{\epsilon}} \tag{4.4}$$

where $i, j \in [0, 1]$ define differentiated domestic and foreign goods respectively and $\varepsilon > 1$ defines the elasticity of substitution between the varieties of goods produced domestically and abroad.

It can be shown that the optimal consumption demand of domestic and foreign goods can be derived respectively as follows:

$$C_{H,t} = (1-\alpha)\left(\frac{P_{H,t}}{P_t}\right)^{-\eta} C_t, \quad C_{F,t} = \alpha\left(\frac{P_{F,t}}{P_t}\right)^{-\eta} C_t \tag{4.5}$$

where $P_{H,t}$ and $P_{F,t}$ represent the domestic price index and imported goods price index respectively and are defined as follows:

$$P_{H,t} = \left[\int_0^1 P_{H,t}(i)^{1-\epsilon} di\right]^{\frac{1}{1-\epsilon}}, \quad P_{F,t} = \left[\int_0^1 P_{F,t}(j)^{1-\epsilon} dj\right]^{\frac{1}{1-\epsilon}} \tag{4.6}$$

The optimal allocation of household expenditure across each good type produces the following demand functions:

$$C_{H,t}(i) = \left(\frac{P_{H,t}(i)}{P_{H,t}}\right)^{-\varepsilon} C_{H,t}, \quad C_{F,t}(j) = \left(\frac{P_{F,t}(j)}{P_{F,t}}\right)^{-\varepsilon} C_{F,t}, \tag{4.7}$$

Substituting these price indices into the composite consumption index (C_t) yields the consumer price index (P_t) as follows:

$$P_t = \left[(1-\alpha)P_{H,t}^{1-\eta} + \alpha P_{F,t}^{1-\eta}\right]^{\frac{1}{1-\eta}} \tag{4.8}$$

If we let P_t^* denote the rest of the world consumer price index and $\tilde{e}_t$ is the home nominal exchange rate, we can the define the conventional real exchange rate for the domestic economy, $\tilde{q}_t$ as:

$$\tilde{q}_t = \tilde{e}_t \frac{P_t^*}{P_t} \tag{4.9}$$

and the home terms of trade then becomes:

$$S_t = \frac{P_{F,t}}{P_{H,t}} \tag{4.10}$$

Complete versus Incomplete Asset Markets

I incorporate the presence of international financial markets distinguishing between complete asset markets (CAM)[4] versus incomplete asset markets (IAM). Let B_{t-1} and B^*_{t-1} represent the level of bond holdings of domestic and foreign risk free bonds respectively that mature in period t with nominal interest rates of $\tilde{r_t}$ and $\tilde{r_t^*}$ respectively.

I assume the only assets available to households were one-period domestic and foreign bonds. Therefore household optimisation occurs subject to the following budget constraint:

$$P_tC_t + B_t + \tilde{e_t}B^*_t = B_{t-1}(1 + \tilde{r}_{t-1}) + \tilde{e_t}B^*_{t-1}(1 + \tilde{r^*}_{t-1})\phi_t(A_t) + W_tN_t + \Pi_t \tag{4.11}$$

Where $\tilde{e_t}$ is the nominal exchange rate, π_t is the profit a household earns from ownership of domestic and imported goods firms and $\phi_t(.)$ is a function that represents a debt elastic interest rate premium defined as follows:

$$\phi_t = exp[-\chi(A_t + \tilde{\phi_t}] \tag{4.12}$$

where $\tilde{\phi_t}$ is the risk premium shock and

$$A_t = \frac{\tilde{e}_{t-1}B_{t-1}}{Y_{ss}P_{t-1}} \tag{4.13}$$

represents the ratio of the real quantity of foreign bond holdings to steady state output, Y_{ss} expressed in local currency. The functional form of the debt elastic interest rate premium is such that stationarity of the foreign debt level is ensured in the log-linear approximation to the model.

The household optimisation problem under IAM requires that three first order conditions be satisfied. First, the intratemporal condition that relates labour supply to the real wage requires that the marginal rate of substitution between consumption and leisure must equal the marginal product of labour. This intratemporal labour supply condition is expressed as follows:

[4]Following Benigno (2009), this market is one in which domestic and foreign households can trade in a set of risk-free securities that deliver one unit of the home and/or foreign currency in each state of nature.

$$(C_t - H_t)^{\sigma} N_t^{\phi} = \frac{W_t}{P_t} \tag{4.14}$$

The the optimal household decision making yields the familiar stochastic intertemporal consumption Euler equation:

$$\beta(1+\tilde{r}_t)\mathbb{E}_t\left\{\left(\frac{C_{t+1}-H_{t+1}}{C_t-H_t}\right)^{-\sigma}\left(\frac{P_t}{P_{t+1}}\right)\right\} = 1 \tag{4.15}$$

Thirdly, the interest rate parity condition yields:

$$\mathbb{E}_t\left\{\frac{(C_{t+1}-H_{t+1})^{-}\sigma}{P_{t+1}}\left[(1+\tilde{r}_t)-(1+\tilde{r}_t^*)\left(\frac{\tilde{e}_{t+1}}{\tilde{e}_t}\right)\phi_t(A_t,\tilde{\phi}_t)\right]\right\} = 0 \tag{4.16}$$

Assuming identical global preferences and CAM, the interest rate parity condition yields a perfect risk sharing condition for all dates and states of:

$$\left(\frac{C_{t+1}-H_{t+1}}{C_t-H_t}\right)^{-\sigma}\left(\frac{P_t}{P_{t+1}}\right) = \left(\frac{C_{t+1}^*-H_{t+1}^*}{C_t^*-H_t^*}\right)^{-\sigma}\left(\frac{P_t^*}{P_{t+1}^*}\right)\left(\frac{\tilde{e}_{t+1}}{\tilde{e}_t}\right) \tag{4.17}$$

With some rearranging the above equation becomes:

$$\frac{\left(\frac{C_{t+1}^*-H_{t+1}^*}{C_t^*-H_t^*}\right)^{-\sigma}}{\left(\frac{C_{t+1}-H_{t+1}}{C_t-H_t}\right)^{-\sigma}} = \frac{\frac{P_{t+1}^*\tilde{e}_{t+1}}{P_{t+1}}}{\frac{P_t^*\tilde{e}_t}{P_t}} = \frac{\tilde{q}_{t+1}}{\tilde{q}_t} \tag{4.18}$$

Where $\tilde{q}_t$ is the real exchange rate at time t, we can interpret the above equation which is derived from the perfect risk sharing condition in CAM as such that the real exchange rate growth equates to the marginal rate of substitution in consumption growth across countries. So CAM incorporates perfect risk sharing whereas in an IAM there is a higher domestic-inflation to output-gap trade-off.

Alonso-Carrera and Kam (2016) show that the equilibrium policy trade-off between domestic inflation and the output gap can be steeper in an IAM than in CAM. The resulting endogenous cost-push can increase this trade-off when agents are sufficiently risk averse. This is because openness under international capital markets allows the SOE to have access to perfect cross-country insurance of its domestic fluctuations. The real exchange rate then acts as a complete shock absorber for the economy by allowing consumption to be smootened across countries. Therefore, in an IAM although domestic agents attempt to smoothen domestic fluctuations in consumption by borrowing or lending internationally, they do not have the perfect international risk sharing observed in CAMs.

They point out further that in IAMs, policies that respond directly to expectations may turn out to increase the cost-push trade-off further and more likely fuel self-fulfilling multiple or unstable equilibria.

4.2.2 Domestic Goods Producers

The domestic goods market is made up of a continuum of monopolistically competitive firms $i \in [0,1]$ that produce differentiated goods. These firms hire labour, N, to produce output using a linear production technology:

$$Y_{H,t}(i) = \epsilon_{a,t} N_t(i) \tag{4.19}$$

where $\epsilon_{a,t}$ is an exogenous *domestic technology shock*. Domestic firms are assumed to set prices optimally using Calvo (1983) in each period, t, with probability $1 - \theta_H$. The remaining fraction $\theta_H \in [0,1]$ of firms partially adjust their prices following the domestic price index:

$$P_{H,t}(i) = P_{H,t-1}(i) \left(\frac{P_{H,t-1}}{P_{H,t-2}} \right)^{\delta_H} \tag{4.20}$$

All firms receive the same signal to reset prices or do not receive any signal and therefore pursue the same pricing strategies. The evolution of the aggregate price index of domestic goods assumes a Calvo price setting as follows:

$$P_{H,t} = \left\{ (1-\theta_H)(\tilde{P}_{H,t})^{1-\varepsilon} + \theta_H \left[P_{H,t-1} \left(\frac{P_{H,t-1}}{P_{H,t-2}} \right)^{\delta_H} \right]^{1-\varepsilon} \right\} \tag{4.21}$$

where $\delta_H \in [0,1]$ measures the *degree of inflation indexation*. Let firm i set its price at time t, optimally as $P_{H,t}(i)$. At time t+s, for $s \geq 0$ if the price $P_{H,t}(i)$ still prevails, then the firm will face market demand for its product which takes into account the inflation indexation between time t and t+s based on the following constraint:

$$Y_{H,t+s}(i) = \left[\frac{P_{H,t}(i)}{P_{H,t+s}} \left(\frac{P_{H,t+s-1}}{P_{H,t-1}} \right)^{\delta_H} \right]^{-\varepsilon} (C_{H,t+s} + C^*_{H,t+s}) \tag{4.22}$$

A domestic firm i that is faced with changing its price at time t, chooses $P_{H,t}(i)$ to maximise the present value of the stochastic stream of profits as follows:

$$\max_{P_{H,t}(i)} \mathbb{E}_t \sum_{n=0}^{\infty} Q_{t,t+s}\theta_H^s Y_{H,t+s}(i)\left[P_{H,t}(i)\left(\frac{P_{H,t+s-1}}{P_{H,t-1}}\right)^{\delta_H} - P_{H,t+s}MC_{H,t+s}exp(\epsilon_{H,t+s})\right] \tag{4.23}$$

where $\epsilon_{H,t} \sim i.i.d(0, \sigma_H)$ is the *independent cost-push shock to domestic goods producers* and represents the structural shock to real marginal cost, with the real marginal cost defined as:

$$MC_{H,t+s} = \frac{W_{t+s}}{\epsilon_{a,t+s}P_{H,t+s}}. \tag{4.24}$$

Finally, the first order necessary condition for domestic firms' optimal pricing is given as:

$$\max_{P_{H,t}(i)} \mathbb{E}_t \sum_{n=0}^{\infty} Q_{t,t+s}\theta_H^s Y_{H,t+s}(i)\left[\tilde{P}_{H,t}(i)\left(\frac{P_{H,t+s-1}}{P_{H,t-1}}\right)^{\delta_H} - \left(\frac{\varepsilon}{\varepsilon-1}\right)P_{H,t+s}(i)MC_{H,t+s}exp(\epsilon_{H,t+s})\right] = 0 \tag{4.25}$$

4.2.3 Import Retail Firms

Assuming a continuum of monopolistically competitive import retailers $j \in [0,1]$ who add markups to differentiated goods imported at competitive world market prices. These retail firms price similarly to domestic goods producers following Calvo optimal pricing methods and partial inflation indexation for firms that do not set their prices optimally. The pricing behaviour of import retailing firms is similar to domestic goods producing firms with the imports price index as follows:

$$P_{F,t} = \left\{(1-\theta_F)(\tilde{P}_{F,t})^{1-\varepsilon} + \theta_F\left[P_{F,t-1}\left(\frac{P_{F,t-1}}{P_{F,t-2}}\right)^{\delta_H}\right]^{1-\varepsilon}\right\}^{1-\varepsilon} \tag{4.26}$$

The import retail firm j at time t+s, for $s \geq 0$ faces a product demand as follows:

$$Y_{F,t+s}(j) = \left[\frac{P_{F,t}(j)}{P_{F,t+s}}\left(\frac{P_{F,t+s-1}}{P_{F,t-1}}\right)^{\delta_H}\right]^{-\varepsilon} C_{F,t+s}. \tag{4.27}$$

An import retail firm j, faced with changing its price at time t for a good imported at a cost of $\tilde{e}_t P^*_{F,t}(j)$ would maximise its expected discounted value of profits as follows:

$$\max_{P_{F,t}(j)} \mathbb{E}_t \sum_{n=0}^{\infty} Q_{t,t+s}\theta_F^s Y_{F,t+s}(j)\left[P_{F,t}(j)\left(\frac{P_{F,t+s-1}}{P_{F,t-1}}\right)^{\delta_H} - \tilde{e}_{t+s}P^*_{F,t+s}(j)exp(\epsilon_{F,t+s})\right] \tag{4.28}$$

subject to the product demand constraint, $Y_{F,t+s}(j)$ where $\epsilon_{F,t} \sim i.i.d(0, \sigma_H)$ is the *cost-push shock* that import retail firms face.

Finally the first order necessary condition that characterised import retail firms pricing behaviour is specified as:

$$\max_{P_{H,t}(j)} \mathbb{E}_t \sum_{n=0}^{\infty} Q_{t,t+s}\theta_F^s Y_{F,t+s}(j) \left[\tilde{P}_{F,t}(j) \left(\frac{P_{F,t+s-1}}{P_{F,t-1}} \right)^{-\delta_H} - \left(\frac{\varepsilon}{\varepsilon - 1} \right) \tilde{e}_{t+s} P_{F,t+s}(j) exp(\epsilon_{F,t+s}) \right] = 0 \tag{4.29}$$

4.2.4 Market Clearing

The market clearing condition in the goods market in the small open economy requires that domestic output must equal total domestic and foreign demand for home produced goods. This is expressed as follows:

$$Y_{H,t}(i) = C_{H,t}(i) + C^*_{H,t}(i) \tag{4.30}$$

Substituting demand functions for the households from 4.4 yields the goods market clearing condition for domestic firms as:

$$Y_{H,t}(i) = \left(\frac{P_{H,t}(i)}{P_{H,t}} \right)^{-\varepsilon} [C_{H,t} + C^*_{H,t}] \tag{4.31}$$

$$Y_t \equiv \int_0^1 Y_{H,t}(i)di = C_{H,t} + C^*_{H,t} \tag{4.32}$$

where $C^*_{H,t} = \alpha \left(\frac{P^*_{H,t}}{P^*_t} \right)^{-\eta} C^*_t$ and $Y^*_t = C^*_t$

Finally, the domestic bond market is cleared by assuming that the net supply of domestic debt is zero so that:

$$B_t = 0 \tag{4.33}$$

for all t.

4.2.5 Log-linear Approximation of the Model

The log-linearised equilibrium conditions are summarised in this section. I log-linearised around a deterministic zero-inflation steady-state with zero bond holdings and a steady-state terms of trade of one. Variables in lower case are used to denote the log-deviations of the respective variables from their steady-state levels.

Log-linearising the consumption Euler equation in equation 4.15 and taking expectations conditional on time, yields:

$$c_t - hc_{t-1} = \mathbb{E}_t(c_{t+1} - hc_t) - \frac{1-h}{\sigma}(r_t - \mathbb{E}_t\pi_{t+1}) \tag{4.34}$$

The log-linear approximation of the optimal pricing decision rule can be expressed as a Phillips curve for domestic goods inflation as follows:

$$\pi_{H,t} - \delta_H\pi_{H,t-1} = \beta(\mathbb{E}_t\pi_{H,t+1} - \delta_H\pi_{H,t}) + \lambda_H(mc_{H,t} + \epsilon_{H,t}), \tag{4.35}$$

where $\lambda_H = \frac{(1-\beta\theta_H)(1-\theta_H)}{\theta_H}$, $\pi_{H,t} = ln(\frac{P_{H,t}}{P_{H,t-1}})$, $y_t = ln(\frac{Y_t}{Y_{ss}})$ is the percentage deviation of home output from steady state and $mc_t = \varphi y_t - (1+\varphi)\epsilon_{a,t} + \alpha s_t + \frac{\sigma}{1-h}(c_t - hc_{t-1})$. Log linearising the equation for the first order condition for import retail firms 4.29 and the aggregate price index for imports equation 4.26 produces the aggregate supply condition for imported retail goods as follows:

$$\pi_{F,t} - \delta_F\pi_{F,t-1} = \beta(\mathbb{E}_t\pi_{F,t+1} - \delta_F\pi_{F,t}) + \lambda_F(\psi_{F,t} + \epsilon_{F,t}), \tag{4.36}$$

where $\psi_{F,t}$ is the law of one price (LOP) gap and is defined as: $\psi_{F,t} = e_t + p_t^* - p_t$. Log-linearising the real exchange rate equation 4.9 and the home terms of trade equation 4.10 and using the definition of the one price gap yields the relationship between the real exchange rate and the terms of trade as follows:

$$q_t = e_t + p_t^* - p_t = \psi_t + (1-\alpha)S_t. \tag{4.37}$$

If we first-difference the log-linearised version of the terms of trade equation 4.10 we obtain the following:

$$s_t - s_{t-1} = \pi_{F,t} - \pi_{H,t} + \epsilon_{s,t}, \tag{4.38}$$

where $\epsilon_{s,t}$ is an exogenous *terms of trade shock*. Now if we first difference the log-linearised version of the CPI index 4.8 we obtain the following:

$$\pi_t = (1-\alpha)\pi_{H,t} + \alpha\pi_{F,t}, \tag{4.39}$$

The real interest rate parity condition under IAM is obtained by first differencing equation (4.37) and applying the log-linearised version of the interest rate parity condition in equation (4.16) as follows:

$$(r_t - \mathbb{E}_t\pi_{t+1}) - (r_t^* - \mathbb{E}_t\pi_{t+1}^*) = \mathbb{E}_t(q_{t+1} - q_t) - \chi(d_t + \epsilon_{q,t}), \tag{4.40}$$

where $\epsilon_{q,t}$ measures the time varying deviations from real interest parity and $d_t = log(D_t) = log(\frac{\tilde{e}_t B^*}{Y_{ss}P_t})$ is real foreign bond holdings in domestic currency. Under CAM the real interest parity condition is characterised as follows:

$$(r_t - \mathbb{E}_t\pi_{t+1}) - (r_t^* - \mathbb{E}_t\pi_{t+1}^*) + \epsilon_{q,t} = \mathbb{E}_t(q_{t+1} - q_t), \tag{4.41}$$

The goods market clearing condition in equation (4.31) implies:

$$y_t = (1-\alpha)c_t + \alpha\eta q_t + \alpha\eta s_t + \alpha y_t^*. \tag{4.42}$$

Assuming the exogenous stochastic shocks follow independent AR(1) processes for the terms of trade, technology and real-interest-parity shocks as follows:

$$\epsilon_{k,t} = \rho_k \epsilon_{k,t-1} + \nu_{k,t}; \quad \rho_k \in (0,1), \quad \nu_k \sim i.i.d(0, \sigma_k^2) \tag{4.43}$$

for k=s,a,q and noting that the cost-push shocks in the domestic and retail sectors follow an i.i.d process, in particular, the marginal shocks in the home goods and import retail firms profit functions are $\epsilon_H \sim i.i.d(0, \sigma_H)$ and $\epsilon_F \sim i.i.d(0, \sigma_F)$, respectively. For simplicity we assume that the foreign country variables $\{\pi^*, y^*, r^*\}$ follow uncorrelated AR(1) processes as follows:

$$\begin{bmatrix} \pi_t^* \\ y_t^* \\ r_t^* \end{bmatrix} = \begin{bmatrix} a_1 & 0 & 0 \\ 0 & b_2 & 0 \\ 0 & 0 & c_3 \end{bmatrix} \times \begin{bmatrix} \pi_{t-1}^* \\ y_{t-1}^* \\ r_{t-1}^* \end{bmatrix} + \begin{bmatrix} \sigma_{\pi^*} & 0 & 0 \\ 0 & \sigma_{y^*} & 0 \\ 0 & 0 & \sigma_{r^*} \end{bmatrix} \times \begin{bmatrix} \nu_{\pi^*,t} \\ \nu_{y^*,t} \\ \nu_{r^*,t} \end{bmatrix} \tag{4.44}$$

where $\nu_{\pi^*,t}, \quad \nu_{y^*,t} \quad \nu_{r^*,t} \sim N(0, I_3)$.

Within an IAM and a given monetary policy context, if we set up the domestic technology, interest parity and terms of trade shocks denoted by $\{\epsilon_{a,t}, \epsilon_{q,t}, \epsilon_{s,t}\}$, the foreign processes $\{\pi^*, y^*, r^*\}$, the cost-push shocks $\{\epsilon_{H,t}, \epsilon_{F,t}\}$, we can determine ten endogenous variables as $\{c_t, y_t, d_t, q_t, s_t, r_t, \psi_t, \pi_t, \pi_{H,t}, \pi_{F,t}\}$. Similarly we can determine nine endogenous variable in a CAM that excludes, d_t , real foreign bond holdings in domestic currency. So this forms the basis of the data I collected as part of the empirical strategy.

4.2.6 Central Bank Preferences

Each central bank is assumed to optimally set the nominal interest rate by minimizing a quadratic loss function that includes four specific policy objectives: price stability, output gap stabilisation, reducing real exchange rate variability, and nominal interest rate smoothing.

Accordingly, the one-period central bank quadratic loss function, L is defined as:

$$L(\widehat{\pi}_t, y_t, q_t, r_t - r_{t-1}) = \frac{1}{2}[\widehat{\pi}_t{}^2 + \mu_y y_t^2 + \mu_q q_t^2 + \mu_r (r_t - r_{t-1})^2] \tag{4.45}$$

where $\widehat{\pi}_t$, y_t and q_t are the log-linear deviations of the average annual inflation rate, real GDP and real exchange rate from their respective steady state levels. $\mu_y, \mu_q, \mu_r \in [0, \infty)$ represent the weights placed on output stabilisation, real exchange rate stabilisation and targeted interest rate smoothing respectively, and the weight attached to inflation stabilisation, $\widehat{\pi}_t$ is normalised to one.

The loss function specified here is a flexible inflation targeting regime as described in Svensson (1999). The weight on the change in the interest rate is to reflect monetary policy inertia. Obstfeld and Rogoff (1998) and Svensson (2000) also point out the importance of the real exchange rate in the monetary policy transmission mechanism especially in small open economies.

4.3 Empirical Strategy

4.3.1 Data

This chapter followed KLL and MMP in assuming a dynamic medium-scale SOE New Keynesian(NK) model, incomplete international asset markets (IAM) versus complete international asset markets (CAM) and incomplete exchange rate pass through (ERPT). The model is estimated using quarterly data for nine observable variables and nine shock processes for Ghana and South Africa. In this set up, the foreign economy, the United States of America (USA) is assumed to follow a reduced-form 3VAR(1) in CPI inflation, the output gap and the nominal interest rate (policy rate).

Quarterly data is used for this analysis, even though Ghana and South Africa began the implementation of inflation targeting at different time periods, for the purposes of this analysis I used data from 2009:Q1 to 2021:Q4. I also use data over the same period for the sampled countries in LAIT and ASOE to make comparison of results meaningful.

To be able to compare my results with previous related literature, I used the same nine variables and exogenous shocks used in McKnight et al. (2020) and Kam et al. (2009). The data set for the the analysis is summarised in Table 4.1.

Variable	**Unit**	**Notation**	**Source**
Imported goods inflation	(%) Local currency	$\pi_{F,t}$	Bank of Ghana/South Africa Reserve Bank/International Financial Statistics, IMF
Terms of trade	Price of imports to exports	s_t	World Bank/International Financial Statistics, IMF
Real exchange rate	Local currency per 1 USD	q_t	Bank of Ghana/South Africa Reserve Bank/International Financial Statistics, IMF
Domestic Real GDP	Millions of Ghana Cedis/ Rands	y_t	Ghana Statistical Service/International Financial Statistics, IMF
Domestic CPI inflation	Percent	π_t	Ghana Statistical Service/International Financial Statistics, IMF
Nominal interest rate	Percent	r_t	Bank of Ghana/South Africa Reserve Bank/International Financial Statistics, IMF
US CPI inflation	Percent	π_t^*	International Financial Statistics, IMF
US real output	Percent	y_t^*	International Financial Statistics, IMF
US federal funds rate	Percent	r_t^*	International Financial Statistics, IMF

Table 4.1: Data Description

All the variables are transformed by detrending them using the Hodrick-Prescot (HP) filter and were expressed in logs with the exception of interest rate and inflation. Interest rates are expressed as quarterly percentage changes. The output gap is constructed as the deviation of actual output from the HP filter trend. Following DSGE model estimation methods, all the variables are demeaned to their theoretical deviations from their steady state.

Figure 4.1 and Figure 4.2 show trends in the raw data for Ghana and South Africa respectively. The data trends for the remaining countries analysed in this Chapter can be found in the Appendix from Figure A.5 to Figure A.12. Real GDP was growing steadily in both countries but dropped sharply in South Africa and the USA in 2020 due to the impact of the Covid-19 pandemic. Read GDP did not drop in Ghana during the pandemic but grew at a slower pace. CPI inflation showed similar trends for Ghana and South Africa but the latter's was more volatile. Both the nominal and the real exchange rate for the Ghana cedi and the South African rand showed similar trends with the nominal rates depreciating over the sample period. Both currencies experienced real appreciation between 2016 and 2018 and after 2020. Money market rates for both Ghana and South Africa have declined since 2016, similarly US money market rates have declined since 2019. Ghana's terms of trade declined between 2017 and 2020 but rose after that. South Africa's terms of trade has generally declined between 2014 and 2020 but started increasing afterwards.

Figure 4.1: Raw Data for Ghana

Figure 4.2: Raw Data for South Africa

4.3.2 Methodology and Estimation Strategy

The estimation strategy is similar to earlier research by McKnight et al. (2020) and Kam et al. (2009). The log-linearised model, denoted here as M, was estimated using Bayesian methods [5]. I begin by defining some notations that would be used going forward in this Chapter. First let Y be a vector or matrix of data and θ a vector of parameters to the model, M, which sought to explain Y. I was interested in knowing more about the parameters of the model θ given the data set, Y.

The structural parameters of the model, M, and variations of it were estimated using Bayesian estimation. I assess the importance attached by the central bank to exchange rate stability by estimating two versions of the model, one in which the weight attached to real exchange rate stability is positive ($\mu_q > 0$) and the other in which this weight is zero ($\mu_q = 0$) in both complete and incomplete asset markets. This assessment is done using Bayesian marginal likelihood functions.

This Chapter models the deeper central bank objectives to empirically infer the importance a central bank places on defined monetary policy objectives such as inflation stabilisation and output stabilisation. The central bank is treated as an optimising agent like the other optimising agents in the model economy. The weight attributed to each policy objective will depend on the institutional preferences of each central bank, which we can make inferences about using estimates of the respective Bayesian posterior distributions. Three sets of parameters were estimated; central bank parameters, $\{\mu_y, \mu_q, \mu_r\}$, the private sector deep parameters, $\{h, \sigma, \phi, \eta, \delta_H, \delta_F, \theta_H, \theta_F\}$ and the parameters for the exogenous processes $\{a_1, b_2, c_3, \rho_a, \rho_q, \rho_s, \sigma_H, \sigma_F, \sigma_a, \sigma_q, \sigma_s, \sigma_{\pi^*}, \sigma_{y^*}, \sigma_{r^*}, \sigma_r\}$.

This Chapter is based on Bayesian econometrics[6] which made use of Bayes' rule stated below as:

$$p(\theta/Y, M) = \frac{p(Y/\theta, M)p(\theta/M)}{p(Y/M)} \tag{4.46}$$

My main interest is in calculating, $p(\theta/Y, M)$ (referred to as *posterior density*), that is, for our given data and model, what do we know about θ. The posterior summarises all we know about the parameters of the model examining the data, it combines data and non-data information. The probability density function (p.d.f) for the data given the parameters for the model, M, $p(Y/\theta, M)$ is often referred to as the *likelihood function*

[5]For a detailed overview of Bayesian methods, see, Koop and Potter (2003) and Gelman et al. (2013)

[6]DeJong et al. (2000) first applied Bayesian Maximum Likelihood Estimation (MLE) to Dynamic Stochastic General Equilibrium (DSGE) models, since then this method has been applied by other researchers notable among them include An and Schorfheide (2007) and Almeida (2011).

or data generating process (DGP). Finally, $p(\theta/M)$ is referred to as the *prior density*, is independent of the data set and may contain non-data information or our beliefs about our parameters before examining the data set.

Koop and Potter (2003) showed that if both sides of the posterior density equation above were integrated with respect to θ and noting that $\int p(\theta/Y,M)d\theta{=}1$, then

$$p(Y/M) = \int p(Y/\theta, M)p(\theta/M)d\theta$$

and the posterior density then becomes:

$$p(\theta/Y, M) = \frac{p(Y/\theta, M)p(\theta/M)}{\int p(Y/\theta, M)p(\theta/M)d\theta} \tag{4.47}$$

The denominator on the right hand side of the posterior density equation above is referred to as the *marginal likelihood*, it depends on only the prior and likelihood function.

A characterisation of the properties of the posterior distribution is required in order to make Bayesian inferences. A posterior simulator is required to characterise the posterior since analytical results of the posterior density are usually not available. I follow what is commonly deployed in the literature by using a class of the Metropolis-Hastings algorithm. Since the mid 1990s, statisticians have been increasingly drawn to Markov chain Monte Carlo (MCMC) methods to simulate complex, nonstandard multivariate distributions. The Metropolis-Hastings (M-H) algorithm belongs to the class of MCMC algorithms used to simulate multivariate distributions. The M-H algorithm constructs a Markov chain such that the stationary distribution associated with this Markov chain is unique and equals the posterior distribution of interest[7]. A type of the M-H algorithm, known as the Random Walk Chain Metropolis (RWMH) algorithm has been used when it is difficult to find a good approximation for the posterior density. I use the RWMH Markov Chain Monte Carlo (MCMC) algorithm to simulate draws for the posterior density function.

For both Ghana and South Africa I simulate 2,000,000 RWMH-MCMC draws and apply 2,500 Kalman filter iterations discarding the first half of the draws to reduce any initial condition biases.

4.4 Results

The interpretation of the results in this Chapter requires a careful context. Firstly, many of the inflation-targeting central banks discussed in this Chapter consider themselves as

[7]For a good introduction to this algorithm, see, Chib and Greenberg (1995)

"flexible" inflation targeters in the sense that their objectives go beyond simply inflation. Even though inflation targeting central banks are often explicit about the importance of inflation, the trade-offs across inflation and other macroeconomic objectives have been rarely discussed. The approach in Chapter 4 is consistent with Svensson (2007) in which transparency is enhanced by providing a clearer view on the weights a central bank attaches to alternative stabilisation objectives.

Secondly, for central bank boards seeking to assess central bank performance, historical estimates of stabilisation objectives which are subject to an explicit structural and micro-founded model as presented here can provide a framework to do so. As an example, the Bank of Ghana (Amendment) Act, 2016 (Act 918) in Section 3 states the objects of the central bank as "(1) The primary objective of the Bank is to maintain stability in the general level of prices. (2) Without limiting subsection (1), the Bank shall (a) support the general economic policy of the Government; (b) promote economic growth and development, and effective and efficient operation of the banking and credit system; and (c) Contribute to the promotion and maintenance of financial stability in the country." If one simply observes the unconditional volatilities of the goal variables in this Act, it may be inadequate for the assessment of monetary policy, as these volatilities also depend on non-policy structural features of the economy.

I replicate the analysis of prior research in Latin America and advanced small open economies and also estimate the macroeconomic policy objectives of the central banks of Ghana and South Africa over the same time period within the context of an optimizing DSGE model. The parameter estimates reflect the objectives of these small open economy inflation targeters and has important implications for assessing the accountability and transparency of monetary policy.

Finally, since the parameters are jointly estimated based on the same DSGE model, inferences can made about policy objectives conditional on the environment in which each central bank operates under. The joint estimates result in different conclusions when compared to inferences based on the unconditional distributions of goal variables such as annual inflation, the output gap, interest rates and the exchange rate.

4.4.1 Prior Distribution

As the formulation of the posterior density is achieved by combining the prior density and the likelihood functions, I needed to specify the priors used for the parameters and this is stated in the table below. I follow the literature as in Güngör and Güloğlu (2019), and

Sobieraj and Metelski (2021) in using distributions for the required prior density functions. A Beta distribution was used for the persistence parameters, the feedback parameter for the degree of indexations and for parameters that were expected to take the value of between 0 and 1. I assume that the standard error of the shocks also follows an inverse gamma distribution in order for the parameters could be forced to take on a value greater than zero. All other parameters for the prior density function are assumed to follow a gamma distribution process.

For each country, α, which represents the share of imports in domestic consumption is calibrated to values corresponding to the sample average share of imports of goods and services in consumption. I follow common practice in the literature by fixing the discount factor, β, at 0.99 for all countries. The debt-elastic interest rate parameter (χ), which is applicable only in the case of IAM is fixed at 0.05 consistent with the estimates of Jorge (2003). I follow Kam et al. (2009) and assume that the prior distributions for the central bank preference parameters μ_y, μ_q, and μ_r are the same. For the structural parameters which could not be estimated with precision due to limited information in the data set, these parameters are assumed to be the same values used in Kam et al. (2009) or McKnight et al. (2020) prior to estimation of the posterior values. Therefore, any resulting differences in the posterior distributions of these parameters will be due to the data itself.

I use the approach of Kam et al. (2009) and McKnight et al. (2020) who make use of Bayesian methods to estimate the model applying an identical prior to Ghana, South Africa, Brazil, Chile, Columbia, Mexico, Peru, Australia, Canada and New Zealand under assumptions of complete asset market and incomplete asset markets based on quarterly data. Thus, I make use of the same priors used in their research and apply it to Ghana and South Africa and make inferences regarding central bank preferences using Bayesian posterior distributions on the model parameters. The structure of the Latin American economies in the sample is like those of South Africa and Ghana so the use of the priors can be justified. Even though I tried using different priors for Ghana as used in Akosah (2020) and shown in Table A.1 in the Appendix, the acceptance rate was very low and therefore could not be relied upon. All cases in the sampled countries where the simulated acceptance rates are very low aree dropped and therefore not reported. The priors as well posterior parameter estimates in the case of Ghana for CAM in an unrestricted model is summarised in Table 4.2.

Parameter	**Description**	**Prior Distribution**			**Posterior Distribution**						
		Type	Mean	S.D	Mean	S.D	2.50%	97.50%	NSE (8%)	p-value	B-GF
h	habit persistence	Beta	0.60	0.20	0.86	0.06	0.19	0.93	0.01	0.00	1.18
σ	inverse elasticity of intertemporal substitution of consumption	Gamma	1.00	0.50	0.48	0.16	0.27	2.19	0.03	0.02	1.08
ϕ	inverse of Frisch elasticity of intertemporal labour supply	Gamma	1.50	0.25	1.30	0.24	1.05	2.03	0.02	0.00	1.10
η	elasticity of substitution between home made and foreign goods	Gamma	1.00	0.50	0.59	0.15	0.27	2.19	0.01	0.01	1.03
δ_H	degree of indexation in domestic-output markets	Beta	0.70	0.20	0.19	0.10	0.25	0.98	0.01	0.00	1.11
δ_F	degree of indexation in imported-goods markets	Beta	0.70	0.20	0.59	0.23	0.25	0.98	0.05	0.00	1.31
θ_H	degree of inflation persistence in domestic-output markets	Beta	0.50	0.20	0.48	0.06	0.13	0.87	0.01	0.39	1.01
θ_F	degree of inflation persistence in imported-goods markets	Beta	0.50	0.20	0.11	0.03	0.13	0.87	0.01	0.00	1.09
a_1	degree of persistence in foreign inflation	Beta	0.50	0.20	0.93	0.02	0.19	0.96	0.00	0.00	1.20
b_2	degree of persistence in foreign output	Beta	0.50	0.20	0.41	0.11	0.19	0.96	0.00	0.01	1.00
c_3	degree of persistence in foreign interest rate	Beta	0.50	0.20	0.72	0.08	0.19	0.96	0.00	0.00	1.02
ρ_a	degree of persistence in technology shock	Beta	0.50	0.20	0.92	0.03	0.13	0.87	0.00	0.05	1.01
ρ_q,	degree of persistence in risk premium	Beta	0.90	0.20	0.86	0.17	0.23	1.00	0.03	0.54	1.01
ρ_s	degree of persistence in terms of trade	Beta	0.25	0.20	0.36	0.09	0.01	0.72	0.01	0.00	1.11
	Relative Policy Target Weights										
μ_q	real exchange rate stabilisation	Gamma	0.50	0.30	0.14	0.09	0.09	1.24	0.02	0.00	1.43
μ_y	output gap stabilisation	Gamma	0.50	0.30	0.91	0.27	0.09	1.23	0.06	0.00	1.59
μ_r	interest rate smoothing	Gamma	0.50	0.30	0.34	0.16	0.09	1.24	0.03	0.00	1.70
	Standard Deviation of Shock Innovations										
σ_H	domestic-output cost-push shock	Inverse Gamma	0.50	0.25	0.74	0.20	0.91	7.37	0.02	0.50	1.00
σ_F	imported-goods cost-push shock	Inverse Gamma	0.50	0.25	9.01	5.93	0.91	7.35	1.59	0.00	2.27
σ_a	technology shock	Inverse Gamma	1.00	0.40	8.83	1.05	0.52	2.66	0.20	0.07	1.05
σ_q	risk premium shock	Inverse Gamma	2.00	0.50	1.08	0.55	0.32	0.87	0.13	0.00	1.71
σ_s	terms of trade shock	Inverse Gamma	1.00	0.40	24.51	0.50	0.52	2.66	0.05	0.41	1.01
$\sigma_{\pi *}$	foreign inflation shock	Inverse Gamma	1.00	0.40	0.44	0.08	0.52	2.66	0.00	0.00	1.01
$\sigma_{y *}$	foreign output shock	Inverse Gamma	1.00	0.40	1.25	0.14	0.52	2.66	0.01	0.00	1.02
$\sigma_{r *}$	foreign interest rate shock	Inverse Gamma	1.00	0.40	0.40	0.06	0.52	2.66	0.00	0.00	1.00
σ_r	interest rate shock	Inverse Gamma	1.00	0.40	0.28	0.05	0.52	2.65	0.00	0.02	1.00

Table 4.2: **Prior and Posterior Parameter estimates for Ghana under CAM and an unrestricted Model($\mu_q > 0$)**, $\alpha = 0.29$.

Using the RWMH-MCMC method based on two million MCMC draws and 2500 Kalman filter iterations, I simulate posterior densities of the parameter vector. Posterior MCMC chains are plotted for the estimated parameters along the computed convergence statistics for the estimated parameters in tables of posterior estimator statistics. The distribution of the deep and exogenous parameters with over one million MCMC draws are shown in Figure A.20 in the Appendix.

The Chapter set up the structural parameters for the domestic (Ghana, South Africa) and foreign economies (USA). The exogenous AR(1) processes as well as central bank preferences and standard deviation of shocks are presented as well as the set-up of the equilibrium conditions.

The consumption Euler function, domestic goods inflation NKPC, imports inflation NKPC, real uncovered interest parity (RUIP) condition, terms of trade growth and the market clearing condition (using the law of one price gap definition) were specified.

In the next section, I evaluate the results for CAM and IAM under restricted and unrestricted models for both Ghana and South Africa.

4.4.2 Bayesian Model Comparison

I define a complete asset market (CAM) as one involving complete international risk sharing as opposed to an incomplete asset market (IAM) which breaks this link (see, Chari et al. (2002), Benigno (2009), Rabanal and Tuesta (2010) and Alonso-Carrera and Kam (2016)). In CAMs, economic agents have access to a complete array of state-contingent claims through which domestic and foreign households can trade in a set of government securities that deliver one unit of the home and/or foreign currency in each state of nature. The expected nominal return from these risk-free bonds in the domestic economy would equal the expected nominal return of a similar bond in the foreign economy, when expressed in domestic currency. The assumption of CAMs implies that the level of the real exchange rate equals the marginal rate of substitution of consumption across countries.

Although domestic agents in IAMs can borrow or lend internationally to smooth out domestic fluctuations in consumption, they do not have the perfect international risk sharing present in CAMs. In IAMs, agents have access to a single financial asset that pays a risk-free real rate of return but there are transaction costs in trading in the international markets. The positive trade-off between domestic inflation and output gap, is much larger with IAMs. In short, in the absence of complete international risk sharing, a given external shock to the small open economy cannot be fully insured against by a single incomplete market claim. Hence the effect of the shock gets amplified or transmitted more to domestic allocations via the inflation process.

Adolfson et al. (2007) list reasons why asset markets may be incomplete, these include asymmetric information, moral hazard, and transaction costs. This incompleteness implies that perfect competition need not necessarily lead to market efficiency, and nominal assets differ significantly from real assets in terms of their impact on the existence of equilibrium.

In this section, I analyse the performance of the Bayesian models under complete and incomplete markets using the restricted ($\mu_q = 0$) and unrestricted ($\mu_q > 0$) scenarios. The marginal likelihoods for complete asset markets (CAM) and incomplete asset markets (IAM) for the two countries under restricted and unrestricted models are reported in Table 4.3. The models with the highest marginal likelihoods are the preferred ones. So using Table 4.3, the preferred model according to the Ghanaian data is the unrestricted CAM model version. Similarly the preferred model based on the South African data is the restricted IAM model version.

Other results of the Bayesian RWMH-MCMC estimation for the unrestricted and restricted model versions are also presented in Table 4.4 and Table 4.5 for CAM and IAM respectively. Among the key statistics reported here is the acceptance rate. Herbst and Schorfheide (2015) stated that most practitioners target an acceptance rate of between 0.20 and 0.40.

The summary statistics of the Bayesian estimation is generally satisfactory; the acceptance rates are not too low (below 5%) and the indeterminacy rates are not too high (above 40%). The acceptance rates for the CAM scenario are much higher for Ghana than for South Africa. The indeterminacy rates for Ghana are also much lower than for South Africa.

	CAM		**IAM**	
	$\mu_q > 0$	$\mu_q = 0$	$\mu_q > 0$	$\mu_q = 0$
Ghana	**-1.7666**	-1.7696	-1.8316	-1.8103
South Africa	-1.9157	-1.9087	-1.8306	**-1.8119**

Table 4.3: Bayesian Model Comparison- Complete versus Incomplete Asset Markets, the numbers are the marginal likelihood for each model version with the preferred model version in bold.

In the next section I focus on the posterior estimates of the model parameters for the preferred model versions based on the marginal likelihood functions and conduct the model diagnostics with respect to the inherit shocks and impulse response functions to

Bayesian Model Comparison - Complete Asset Market.

Ghana(2009-2021)

Parameters	$\mu_q > 0$	$\mu_q = 0$
Acceptance Rate	43.98	47.43
Indeterminacy Rate (%)	0.078	0.044
Invalid Likelihood Rate(%)	2.44	1.74
μ_q	0.14(0.09)	0
μ_y	0.91(0.27)	1.14(0.61)
μ_r	0.34(0.16)	0.31(0.16)

South Africa(2009-2021)

Parameters	$\mu_q > 0$	$\mu_q = 0$
Acceptance Rate	15.27	14.8049
Indeterminacy Rate (%)	5.28	6.34
Invalid Likelihood Rate(%)	6.01	5.49
μ_q	0.06(0.24)	0
μ_y	0.41(0.24)	0.51(0.31)
μ_r	0.64(0.24)	0.31(0.15)

Table 4.4: Bayesian Model Comparison- Complete Asset markets. Reported Posterior Means, with the Posterior Standard Deviations in Parentheses, Marginal Likelihoods, Ghana:-1.7666 ($\mu_q > 0$); -1.7696 ($\mu_q = 0$); Marginal Likelihoods, South Africa:-1.9157 ($\mu_q > 0$); -1.9087 ($\mu_q = 0$).

assess whether the estimation results are satisfactory for the two countries under study.

4.4.3 Posterior Parameter Estimates

The key structural parameter estimates for the prior and posterior density functions for Ghana under the CAM scenario, are shown in Figure 4.3 and Figure A.13 (in the Appendix) for the unrestricted and restricted models respectively. The prior and posterior density functions for Ghana assuming IAM under unrestricted and restricted models are shown in the Appendix as Figure A.14 and A.15 respectively. The posterior parameter estimates as well as the prior and posterior density functions for Australia, Brazil, Canada, Chile, Columbia, Mexico, New Zealand and Peru are all shown in the Appendix.

I note that the posterior distributions for the preferred model in the case of Ghana, that is CAM and the unrestricted model are uni-modal and well shaped for most of the key parameters with a few exceptions (μ_y, μ_r, σ and θ_H). The posterior distributions for Ghana under CAM and $\mu_q = 0$ is not as well behaved and has more parameters that have multi-modal points (σ_q, σ_a, σ_F, ρ_q and ρ_s). The posterior distributions for Ghana, under IAM for both unrestricted and restrictive models are shown in the Appendix in Figure

Bayesian Model Comparison - Incomplete Asset Market.
Ghana(2009-2021)

Parameters	$\mu_q > 0$	$\mu_q = 0$
Acceptance Rate(%)	10.42	23.29
Indeterminacy Rate (%)	18.81	3.66
Invalid Likelihood Rate(%)	0	0
μ_q	0.02(0.015)	0
μ_y	0.056(0.03)	0.178(0.103)
μ_r	0.3(0.164)	0.168(0.135)

South Africa(2009-2021)

Parameters	$\mu_q > 0$	$\mu_q = 0$
Acceptance Rate(%)	0.89	9.24
Indeterminacy Rate (%)	41.66	7.89
Invalid Likelihood Rate(%)	0.00	0.00
μ_q	0.038(0.017)	0
μ_y	0.037(0.017)	0.26(0.135)
μ_r	0.173(0.096)	0.44(0.271)

Table 4.5: Bayesian model comparison- Incomplete Asset markets. Reported posterior means, with the posterior standard deviations in parentheses, Marginal likelihoods, Ghana:-1.8316 ($\mu_q > 0$); -1.8103 ($\mu_q = 0$); Marginal likelihoods, South Africa:-1.8306 ($\mu_q > 0$); -1.8119 ($\mu_q = 0$).

A.14 and Figure A.15 respectively.

The prior and posterior density functions for the key parameters for South Africa assuming IAM under the restricted and unrestricted models are shown in Figure 4.4 and Figure A.18 (in the Appendix) respectively. The distributions for the restricted model and unrestricted versions for the key parameters are mostly uni-modal and well shaped (excerpt h and μ_r in the restricted model). The posterior distributions for South Africa under the assumption of CAM for the restricted and unrestricted models are shown in the Appendix in Figure A.16 and Figure A.17 respectively.

In this Chapter, the mean of the posterior density is used as the point estimate for the key parameters of interest. As it is typical in the literature, it is also desirable to present a measure of the extent of uncertainty associated with the point estimate, here I used the posterior standard deviation.

The mean, standard deviation, the corresponding 5 percent and 95 percent credible intervals for the posterior estimates and selected diagnostic tests[8] for MCMC convergence to check for the reliability of the estimated results under the assumption of CAM for

[8]For a detailed discussion of MCMC diagnostics, see, Gelman (1996), and Geweke (1999)

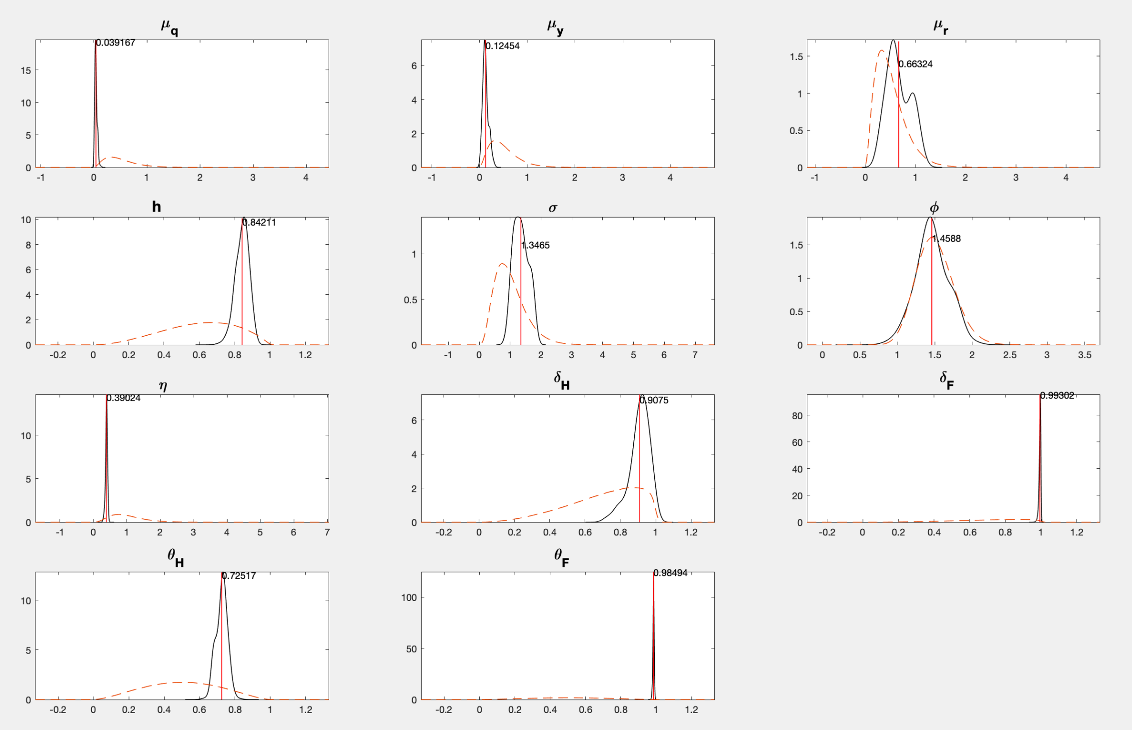

Figure 4.3: Posterior Distributions of Key Parameters: Ghana, CAM and $\mu_q > 0$. Posterior (solid) and Prior (dashed).

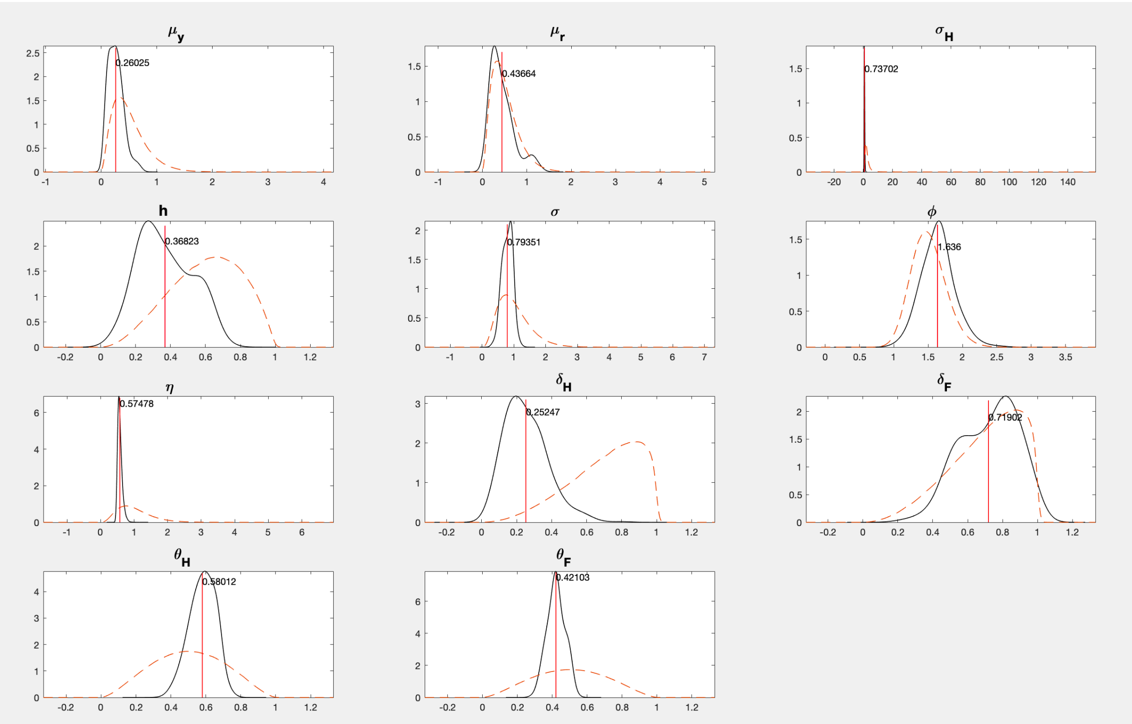

Figure 4.4: Posterior Distributions of Key Parameters for South Africa, assuming IAM and Restricted Model($\mu_q = 0$). Posterior (solid) and Prior (dashed)

Ghana and IAM for South Africa are reported.

The posterior parameters and convergence diagnostics under the assumption of CAM using an unrestricted model for Ghana is reported in Table 4.2. The posterior parameters and convergence diagnostics under the assumption of CAM using a restricted model for Ghana is reported in Table A.3 in the Appendix. The posterior parameters and convergence diagnostics under the assumption of IAM using a restricted model for South Africa is reported in Table 4.6. The posterior parameters and convergence diagnostics under the assumption of IAM using an unrestricted model for South Africa is reported in Table A.6 in the Appendix.

The posterior estimate results for Ghana assuming IAM (Figure A.14 and Figure A.15) and for South Africa assuming CAM (Figure A.16 and Figure A.17) are presented in the Appendix. The numerical standard error (NSE), which is a measure of the approximation error is reported as well as the G p-values[9] and the Brooks-Gelman univariate shrink factor (B-GF) were reported[10]. For both Ghana and South Africa, most of the shrink factors were less than 1.1, suggesting convergence to a stationary distribution. The parameters which had shrink factors greater than 1.1 were those that failed to satisfy the 5% equality test, so on the whole, I concluded that the Markov chains converged to stationary distributions.

The tables are made up of three types of parameter estimates; the structural parameters, the relative policy target weights and their corresponding statistics and the estimated posterior distribution of the shock innovations and their corresponding statistics.

Generally I observe different posterior estimates of the means and standard deviations from those assumed by the priors for the behavioural parameters. On the whole, I observe lower variances of the posterior distribution estimates relative to the prior distributions, thus the posterior estimates contained important information derived from the actual data. The prior means and standard deviations of the parameters for the policy weights are also quite different from the observed posterior means and standard deviations. Finally the observed posterior means of the shock processes are generally higher than the assumed priors. A few exceptions to this pattern are the technology, risk premium, the terms of trade and foreign inflation shock processes. The observed standard deviation of the posterior estimates of the shock processes are generally lower than the priors.

[9] Represents the p-value of the Geweke (1992) chi-squared test. It is expected that the means from the two halves of the generated sample to be statistically indifferent if the Markov chains of draws has converged to a stable distribution. A low p-value may be evidence of problems of convergence.

[10] A shrink factor close to 1 is indicative of convergence to a stationary distribution. For a good exposition on MCMC convergence statistics, see Brooks and Gelman (1998).

Parameter	Description	Prior Distribution			Posterior Distribution						
		Type	Mean	S.D	Mean	S.D	2.50%	97.50%	NSE (8%)	p-value	B-GF
h	habit persistence	Beta	0.60	0.20	0.37	0.15	0.20	0.93	0.03	0.55	1.01
σ	inverse elasticity of intertemporal substitution of consumption	Gamma	1.00	0.50	0.79	0.16	0.27	2.19	0.03	0.22	1.02
ϕ	inverse of Frisch elasticity of intertemporal labour supply	Gamma	1.50	0.25	1.64	0.24	1.05	2.03	0.01	0.93	1.00
η	elasticity of substitution between home made and foreign goods	Gamma	1.00	0.50	0.58	0.07	0.27	2.19	0.01	0.96	1.00
δ_H	degree of indexation in domestic-output markets	Beta	0.70	0.20	0.25	0.12	0.25	0.98	0.02	0.00	1.14
δ_F	degree of indexation in imported-goods markets	Beta	0.70	0.20	0.72	0.16	0.25	0.98	0.03	0.00	1.16
θ_H	degree of inflation persistence in domestic-output markets	Beta	0.50	0.20	0.58	0.07	0.13	0.87	0.01	0.72	1.00
θ_F	degree of inflation persistence in imported-goods markets	Beta	0.50	0.20	0.42	0.05	0.13	0.87	0.01	0.00	1.46
a_1	degree of persistence in foreign inflation	Beta	0.50	0.20	0.79	0.12	0.19	0.96	0.02	0.38	1.01
b_2	degree of persistence in foreign output	Beta	0.50	0.20	0.39	0.10	0.19	0.96	0.00	0.32	1.00
c_3	degree of persistence in foreign interest rate	Beta	0.50	0.20	0.65	0.13	0.19	0.96	0.01	0.37	1.00
ρ_a	degree of persistence in technology shock	Beta	0.50	0.20	0.88	0.04	0.13	0.87	0.01	0.91	1.00
ρ_q,	degree of persistence in risk premium	Beta	0.90	0.20	1.00	0.07	0.24	1.00	0.00	0.74	1.00
ρ_s	degree of persistence in terms of trade	Beta	0.25	0.20	0.27	0.16	0.01	0.73	0.03	0.01	1.09
	Relative Policy Target Weights										
μ_y	output gap stabilisation	Gamma	0.50	0.30	0.26	0.14	0.09	1.24	0.03	0.00	1.17
μ_r	interest rate smoothing	Gamma	0.50	0.30	0.44	0.27	0.10	1.24	0.07	0.00	1.25
	Standard Deviation of Shock Innovations										
σ_H	domestic-output cost-push shock	Inverse Gamma	0.50	0.25	0.74	0.20	0.91	7.34	0.03	0.90	1.00
σ_F	imported-goods cost-push shock	Inverse Gamma	0.50	0.25	1.38	1.24	0.91	7.34	0.24	0.05	1.06
σ_a	technology shock	Inverse Gamma	1.00	0.40	14.74	2.07	0.52	2.66	0.52	0.00	1.76
σ_q	risk premium shock	Inverse Gamma	2.00	0.50	4.17	0.87	0.32	0.88	0.16	0.83	1.00
σ_s	terms of trade shock	Inverse Gamma	1.00	0.40	10.93	1.30	0.52	2.66	0.29	0.75	1.00
$\sigma_{\pi*}$	foreign inflation shock	Inverse Gamma	1.00	0.40	0.26	0.03	0.52	2.67	0.00	0.30	1.00
σ_{y*}	foreign output shock	Inverse Gamma	1.00	0.40	1.19	0.11	0.52	2.67	0.00	0.40	1.00
σ_{r*}	foreign interest rate shock	Inverse Gamma	1.00	0.40	0.20	0.02	0.52	2.66	0.00	0.56	1.00
σ_r	interest rate shock	Inverse Gamma	1.00	0.40	0.29	0.05	0.52	2.66	0.00	0.33	1.00

Table 4.6: **Prior and Posterior Parameter estimates for South Africa under IAM and a restricted Model**($\mu_q = 0$). α is calibrated as the average share of imports of goods and services in consumption over the sample period for each country, it is .20 for South Africa.

Estimated Key Structural Parameters- Ghana

Table 4.2 shows the model estimates for the unrestricted model ($\mu_q > 0$) for Ghana and assuming CAM. Table A.3 shows the the restricted model estimates ($\mu_q = 0$). The posterior mean estimate for the degree of inflation persistence in the home goods sector, $\theta_H = 0.48$ for the unrestricted model and $\theta_H = 0.43$ for the restricted model. These estimates are 0.11 for both models for the imported goods market. Indicating the prices stay unchanged for a longer period of time for the homes goods sector relative to the imported goods sector for both models in Ghana. The degree of indexation or "backward lookingness" denoted by δ_H and δ_F is quite low compared to the prior and especially for the domestic goods sector (0.22 and 0.19 for the restricted and unrestricted models respectively) compared to the imported goods sector (0.65 and 0.59 for the restricted and unrestricted models respectively).

Judging from the low values of σ, the coefficient of relative risk aversion, of 0.48 and 0.56 for unrestricted and restricted models respectively, I conclude that consumption is not very sensitive to real interest rate changes. The habit parameter, h, is higher than the assumed prior mean of 0.6, the obtained estimates of 0.8 for restricted model and 0.86 for the unrestricted model showing high persistence of Ghanaian households' consumption between periods.

The elasticity of substitution between home-made and foreign goods, η, for the restricted and unrestricted models of 0.71 and 0.59 respectively are considered somewhat low compared to the prior of 1.0 and falls outside the 1-2 range that is generally found in the literature (See Corsetti et al. (2008)).[11]

The inverse of the Frisch elasticity of intertemporal labour supply are 1.4 and 1.3 respectively for the restricted and unrestricted models versus a prior of 1.5.

Estimated Key Structural Parameters- South Africa

The marginal posterior density estimates for the key parameters for the South African Reserve Bank assuming IAM, are shown in Tables 4.6 and Table A.6 for the restricted and unrestricted models respectively. The model estimates for the SARB assuming CAM for the restricted and unrestricted models are shown in Appendix.

The notable differences between Ghana and South Africa are in terms of the coefficients of relative risk aversion, σ, also referred to as the inverse elasticity of inter-temporal substitution (EIS) of consumption, the degree of habit persistence (h), the inverse of

[11] Obstfeld and Rogoff (2000) proposed that fairly large elasticity of substitution in combination with transaction costs could help explain a number of important questions in international economics.

Frisch elasticity of intertemporal labour supply (ϕ), the degree of indexation in imported goods markets, δ_F and the degree of inflation persistence in imported goods markets, θ_F.

South Africa has a lower degree of habit persistence (0.37 versus 0.86). The coefficient of relative risk aversion is much higher in South Africa than in Ghana (0.79 versus 0.48). The inverse of Frisch elasticity of intertemporal labour supply is higher in South Africa (1.64 versus 1.30). The degree of indexation in imported goods markets is higher in South Africa (0.72 versus 0.59). The degree of inflation persistence in imported goods markets is also higher in South Africa (0.42 versus 0.11).

Estimated Key Structural Parameters- Comparison with Previous Studies

The degree of habit persistence for Ghana and South Africa is 0.86 and 0.37 respectively. The range of this parameter, combining results of prior research and estimates based on the revised sample period is between 0.30 and 0.97. Ghana and South Africa's parameter estimates are within this range but South Africa is significantly lower indicating that habit formation is less important for the South African household consumer behaviour. The average habit persistence parameter for AFIT of 0.62 is lower than the averages of 0.81 and 0.74 for ASOE and LAIT countries respectively showing that habit formation is less important in AFIT countries.

The inverse of the elasticity of intertemporal substitution of consumption, σ (Coefficient of relative risk aversion) of Ghana and South Africa are 0.48 (versus a prior of 1) and 0.79 respectively. The range for this parameter from the previous literature of 0.01 and 2.54 respectively. The results reveal that Peru, Chile, and Ghana have high elasticity of intertemporal substitution of consumption [12] relative to other countries.

The parameter estimate of the inverse of the Frisch elasticity of intertemporal labour supply [13], ϕ, in previous literature has ranged between 1.30 and 2.22. Ghana and South Africa's parameter estimates are 1.3 and 1.64 respectively. Ghana recorded the lowest value for this parameter estimate for the countries surveyed in this chapter. In complete asset markets, purely transitory wage rate changes should have no impact on the marginal utility of wealth. The Frisch elasticity of labour supply is important in explaining the impact of transitory tax or productivity shocks and predictable life-cycle patterns on wage

[12] The elasticity of inter-temporal substitution of consumption measures the sensitivity of consumption to a change in real interest rate expectations. The literature on the probable values of EIS is conflicting. Guvenen (2006) indicated that whilst the growth literature suggests an EIS value close to 1, the empirical consumption literature pointed to a value close to zero.

[13] Following Bredemeier et al. (2019), the Frisch elasticity of intertemporal labour supply measures the percentage change in labour hours worked due to a one percentage change in the net wage rate holding the marginal utility of wealth constant. This measure reflects changes in labour supply emanating from wage rate changes that lead to pure intertemporal substitution effects but no income effects.

Country	h	σ	ϕ	η	δ_H	δ_F	θ_H	θ_F	a_1	b_2	c_3	ρ_a	ρ_q	ρ_s
Australia	0.69	1.41	1.49	0.55	0.93	0.66	0.92	0.53	0.77	0.45	0.61	0.76	0.69	0.49
Canada	0.83	1.31	1.50	0.85	0.38	0.63	0.90	0.49	0.88	0.44	0.70	0.36	0.92	0.18
New Zealand	0.90	2.54	1.51	2.07	0.81	0.50	0.91	0.38	0.81	0.41	0.83	0.62	0.92	0.39
Brazil	0.97	1.33	1.52	0.23	0.33	0.79	0.87	0.97	0.91	0.45	0.48	0.70	0.35	0.98
Chile	0.66	0.93	1.47	1.19	0.93	0.64	0.91	0.63	0.92	0.41	0.12	0.28	0.89	0.22
Columbia	0.72	0.57	1.34	0.25	0.67	0.57	0.66	0.96	0.93	0.40	0.74	0.32	0.88	0.96
Mexico	0.68	2.54	1.50	0.84	0.86	0.72	0.89	0.42	0.72	0.41	0.70	0.66	0.84	0.25
Peru	0.66	1.00	1.47	0.85	0.84	0.66	0.89	0.24	0.73	0.43	0.65	0.50	0.90	0.30
Ghana	0.86	0.48	1.30	0.59	0.19	0.59	0.48	0.11	0.93	0.41	0.72	0.92	0.86	0.36
South Africa	0.36	0.79	1.64	0.58	0.25	0.72	0.58	0.421	0.79	0.39	0.65	0.88	1.00	0.27

Table 4.7: Posterior Parameter Estimates for Previous Studies and Current Study

rates. There is no consensus in the literature on the size of the Frisch elasticity of labour supply. Quantitative macroeconomic models tend to require relatively large values for the Frisch elasticity of labour supply but the micro-economic literature typically estimates smaller values for this parameter. The relatively lower value for the inverse of the Frisch elasticity of intertemporal labour supply of Ghana compared to the other countries, point to a larger reaction of changes in the labour supply in Ghana due to changes in net real wages.

Another important structural parameter estimated is the elasticity of substitution between home and foreign goods, η. The elasticity of substitution between home and foreign goods links the times series variation in exports and imports to movements in the terms of trade [14]. The range of estimates for this parameter from previous studies and computations in this Chapter is between 0.11 and 1.51, Ghana and South Africa's parameter estimates are 0.59 and 0.58 respectively and are within this range.

The inflation persistence parameter estimates for both domestic output markets, θ_H, and imported-goods markets, θ_F, (Calvo parameters) in previous studies and in this Chapter range between 0.18 and 0.93 for θ_H and 0.07 and 0.96 for θ_F. The parameter estimates of θ_H for Ghana and South Africa are 0.48 and 0.58 respectively and are consistent with the referenced literature. The parameter estimates of θ_F for Ghana and South Africa

[14]The international macroeconomics literature has used this parameter to determine the business cycle effects of certain macroeconomics shocks in which a low elasticity between home and foreign goods explained short-term fluctuations in international relative prices such as terms of trade and real exchange rates, see Crucini and Davis (2016).

of 0.11 and 0.42 respectively though comparatively lower, are also in line with results from previous studies and in this Chapter.

The backward-looking components of the Philips curve, that is the degree of indexation of the domestic-output markets(δ_H) and the degree of indexation of the imported-goods markets markets(δ_F) were also estimated. δ_H was 0.190 and 0.25 for Ghana and South Africa respectively, the range of estimates from previous studies and this Chapter is between 0.18 and 0.87. δ_F is 0.59 and 0.72 for Ghana and South Africa respectively, the range of this parameter estimate from previous studies and this Chapter is between 0.14 and 0.80. The estimates of the backward looking parameters of the Philips curve are within the ranges obtained from previous studies.

4.4.4 Estimated Persistence and Volatility of Shock Processes

The persistence and shock innovations parameters are closely examined. For Ghana, the auto-regressive persistent parameters were in the range of 0.36 and 0.93 (for the unrestricted CAM model) and in the range of 0.26 and 1.0 (for the unrestricted IAM model). The parameters are not excessively persistent except the degree of persistence in risk premium in the case of South Africa whose 97.5% percentile was 1.

The parameters for the standard deviation of the shock processes are particularly high for the imported goods cost-push, technology shock and the terms of trade shock when compared with their priors for Ghana.

For South Africa, I also observe very high mean estimates of the standard deviation of shock processes for technology shock and the terms of trade shock when compared to other shocks and their respective priors.

The parameter estimates of the shock processes for Ghana and South Africa are comparable with those obtained from previous studies, in fact all the persistence parameter estimates were between 0 and 1 as expected.

4.4.5 Comparing Results with Related Studies

In this section, I compare results for Ghana and South Africa with those of countries studied in previous DSGE studies in Kam et al. (2009) and McKnight et al. (2020) but using data over the same sample period across all the countries.

I use loss function estimates for central bank policy weights which are reported for Australia, Brazil, Canada, Chile, Columbia, Mexico, New Zealand and Peru, Ghana and South Africa reported in Table 4.8, Table 4.9, Table 4.10, Table 4.11, Table 4.12, Table

4.13, 4.14, Table 4.15, Table 4.2 and 4.6 respectively to assess the preference that these inflation targeting central banks attach to inflation stabilisation (μ_π), output stabilisation (μ_y), interest rate smoothing (μ_r) and exchange rate stabilisation (μ_q). These results are shown in Table 4.16 [15].

[15] In the one-period central bank quadratic loss function, L, if the weight attached to the annual inflation rate, $\tilde{\pi}_t$ is normalised to one and the estimated weights placed on output stabilisation (μ_y), real exchange rate stabilisation (μ_q) and targeted interest rate smoothing (μ_r) are used, then the weights placed on all the four policy preferences can be summed up to 100% to determine the relative importance of each policy choice. This method was also used in Palma and Portugal (2014).

Parameter	Description	Prior Distribution			Posterior Distribution						
		Type	Mean	S.D	Mean	S.D	2.50%	97.50%	NSE (8%)	p-value	B-GF
h	habit persistence	Beta	0.60	0.20	0.69	0.19	0.19	0.93	0.04	0.43	1.01
σ	inverse elasticity of intertemporal substitution of consumption	Gamma	1.00	0.50	1.41	0.41	0.27	2.19	0.10	0.29	1.01
ϕ	inverse of Frisch elasticity of intertemporal labour supply	Gamma	1.50	0.25	1.49	0.24	1.05	2.03	0.01	0.85	1.00
η	elasticity of substitution between home made and foreign goods	Gamma	1.00	0.50	0.55	0.28	0.27	2.20	0.04	0.88	1.00
δ_H	degree of indexation in domestic-output markets	Beta	0.70	0.20	0.93	0.07	0.25	0.98	0.01	0.41	1.01
δ_F	degree of indexation in imported-goods markets	Beta	0.70	0.20	0.66	0.20	0.25	0.98	0.04	0.24	1.02
θ_H	degree of inflation persistence in domestic-output markets	Beta	0.50	0.20	0.92	0.02	0.13	0.87	0.00	0.10	1.01
θ_F	degree of inflation persistence in imported-goods markets	Beta	0.50	0.20	0.53	0.14	0.13	0.87	0.02	0.51	1.01
a_1	degree of persistence in foreign inflation	Beta	0.50	0.20	0.77	0.05	0.19	0.96	0.01	0.93	1.00
b_2	degree of persistence in foreign output	Beta	0.50	0.20	0.45	0.11	0.19	0.96	0.00	0.90	1.00
c_3	degree of persistence in foreign interest rate	Beta	0.50	0.20	0.61	0.12	0.19	0.96	0.01	0.90	1.00
ρ_a	degree of persistence in technology shock	Beta	0.50	0.20	0.76	0.09	0.13	0.87	0.01	0.49	1.00
ρ_q,	degree of persistence in risk premium	Beta	0.90	0.20	0.69	0.31	0.24	1.00	0.08	0.00	1.74
ρ_s	degree of persistence in terms of trade	Beta	0.25	0.20	0.49	0.21	0.01	0.72	0.05	0.00	1.13
	Relative Policy Target Weights										
μ_q	real exchange rate stabilisation	Gamma	0.50	0.30	0.17	0.09	0.09	1.24	0.01	0.63	1.00
μ_y	output gap stabilisation	Gamma	0.50	0.30	0.44	0.21	0.09	1.24	0.04	0.03	1.07
μ_r	interest rate smoothing	Gamma	0.50	0.30	0.58	0.30	0.09	1.23	0.07	0.00	1.46
	Standard Deviation of Shock Innovations										
σ_H	domestic-output cost-push shock	Inverse Gamma	0.50	0.25	2.36	0.56	0.91	7.33	0.08	0.16	1.02
σ_F	imported-goods cost-push shock	Inverse Gamma	0.50	0.25	22.76	1.43	0.91	7.37	0.30	0.05	1.07
σ_a	technology shock	Inverse Gamma	1.00	0.40	0.89	0.09	0.52	0.87	2.66	0.17	1.00
σ_q	risk premium shock	Inverse Gamma	2.00	0.50	1.55	0.33	0.32	0.87	0.02	0.69	1.00
σ_s	terms of trade shock	Inverse Gamma	1.00	0.40	0.71	0.19	0.52	2.66	0.03	0.30	1.01
$\sigma_{\pi*}$	foreign inflation shock	Inverse Gamma	1.00	0.40	0.52	0.12	0.52	2.66	0.01	0.92	1.00
σ_{y*}	foreign output shock	Inverse Gamma	1.00	0.40	0.98	0.14	0.52	2.66	0.01	0.80	1.00
σ_{r*}	foreign interest rate shock	Inverse Gamma	1.00	0.40	0.45	0.08	0.52	2.65	0.00	0.06	1.00
σ_r	interest rate shock	Inverse Gamma	1.00	0.40	0.35	0.09	0.52	2.66	0.01	0.02	1.01

Table 4.8: **Prior and Posterior Parameter estimates for Australia under CAM and an unrestricted Model($\mu_q > 0$).**

Parameter	Description	Prior Distribution			Posterior Distribution						
		Type	Mean	S.D	Mean	S.D	2.50%	97.50%	NSE (8%)	p-value	B-GF
h	habit persistence	Beta	0.60	0.20	0.97	0.01	0.19	0.93	0.00	0.90	1.00
σ	inverse elasticity of intertemporal substitution of consumption	Gamma	1.00	0.50	1.33	0.12	0.27	2.19	0.03	0.00	1.18
ϕ	inverse of Frisch elasticity of intertemporal labour supply	Gamma	1.50	0.25	1.52	0.26	1.05	2.03	0.02	0.52	1.00
η	elasticity of substitution between home made and foreign goods	Gamma	1.00	0.50	0.23	0.11	0.27	2.20	0.01	0.00	1.15
δ_H	degree of indexation in domestic-output markets	Beta	0.70	0.20	0.33	0.09	0.25	0.98	0.02	0.00	1.23
δ_F	degree of indexation in imported-goods markets	Beta	0.70	0.20	0.79	0.11	0.25	0.98	0.02	0.00	1.14
θ_H	degree of inflation persistence in domestic-output markets	Beta	0.50	0.20	0.87	0.02	0.13	0.87	0.00	0.00	1.09
θ_F	degree of inflation persistence in imported-goods markets	Beta	0.50	0.20	0.97	0.01	0.13	0.87	0.00	0.04	1.03
a_1	degree of persistence in foreign inflation	Beta	0.50	0.20	0.91	0.02	0.19	0.96	0.00	0.01	1.04
b_2	degree of persistence in foreign output	Beta	0.50	0.20	0.45	0.12	0.19	0.96	0.01	0.27	1.00
c_3	degree of persistence in foreign interest rate	Beta	0.50	0.20	0.48	0.15	0.19	0.96	0.02	0.02	1.03
ρ_a	degree of persistence in technology shock	Beta	0.50	0.20	0.70	0.08	0.13	0.87	0.02	0.00	1.12
ρ_q,	degree of persistence in risk premium	Beta	0.90	0.20	0.35	0.24	0.24	1.00	0.06	0.46	1.01
ρ_s	degree of persistence in terms of trade	Beta	0.25	0.20	0.98	0.01	0.01	0.72	0.00	0.00	1.16
	Relative Policy Target Weights										
μ_y	output gap stabilisation	Gamma	0.50	0.30	0.62	0.26	0.09	1.24	0.07	0.00	1.78
μ_r	interest rate smoothing	Gamma	0.50	0.30	0.69	0.14	0.09	1.24	0.03	0.00	1.20
	Standard Deviation of Shock Innovations										
σ_H	domestic-output cost-push shock	Inverse Gamma	0.50	0.25	1.03	0.22	0.91	7.34	0.03	0.00	1.09
σ_F	imported-goods cost-push shock	Inverse Gamma	0.50	0.25	4.35	1.95	0.91	7.35	0.52	0.00	1.83
σ_a	technology shock	Inverse Gamma	1.00	0.40	0.30	0.06	0.52	2.65	0.00	0.02	1.01
σ_q	risk premium shock	Inverse Gamma	2.00	0.50	6.09	1.49	0.32	0.88	0.39	0.00	1.91
σ_s	terms of trade shock	Inverse Gamma	1.00	0.40	0.98	0.14	0.52	2.65	0.01	0.89	1.00
$\sigma_{\pi*}$	foreign inflation shock	Inverse Gamma	1.00	0.40	0.66	0.12	0.52	2.66	0.01	0.49	1.00
σ_{y*}	foreign output shock	Inverse Gamma	1.00	0.40	1.01	0.13	0.52	2.66	0.01	0.49	1.00
σ_{r*}	foreign interest rate shock	Inverse Gamma	1.00	0.40	0.49	0.11	0.52	2.66	0.01	0.55	1.00
σ_r	interest rate shock	Inverse Gamma	1.00	0.40	1.28	0.14	0.52	2.66	0.02	0.00	1.08

Table 4.9: **Prior and Posterior Parameter estimates for Brazil under CAM and a restricted Model($\mu_q = 0$).**

Parameter	Description	Prior Distribution			Posterior Distribution						
		Type	Mean	S.D	Mean	S.D	2.50%	97.50%	NSE (8%)	p-value	B-GF
h	habit persistence	Beta	0.60	0.20	0.83	0.08	0.19	0.93	0.01	0.06	1.03
σ	inverse elasticity of intertemporal substitution of consumption	Gamma	1.00	0.50	1.31	0.27	0.27	2.20	0.06	0.00	1.22
ϕ	inverse of Frisch elasticity of intertemporal labour supply	Gamma	1.50	0.25	1.50	0.24	1.05	2.03	0.01	0.66	1.00
η	elasticity of substitution between home made and foreign goods	Gamma	1.00	0.50	0.85	0.43	0.27	2.19	0.04	0.60	1.00
δ_H	degree of indexation in domestic-output markets	Beta	0.70	0.20	0.38	0.14	0.25	0.98	0.02	0.58	1.00
δ_F	degree of indexation in imported-goods markets	Beta	0.70	0.20	0.63	0.17	0.25	0.98	0.03	0.43	1.01
θ_H	degree of inflation persistence in domestic-output markets	Beta	0.50	0.20	0.90	0.02	0.13	0.87	0.00	0.87	1.00
θ_F	degree of inflation persistence in imported-goods markets	Beta	0.50	0.20	0.49	0.13	0.13	0.87	0.02	0.70	1.00
a_1	degree of persistence in foreign inflation	Beta	0.50	0.20	0.88	0.03	0.19	0.96	0.00	0.22	1.01
b_2	degree of persistence in foreign output	Beta	0.50	0.20	0.44	0.12	0.19	0.96	0.00	0.60	1.00
c_3	degree of persistence in foreign interest rate	Beta	0.50	0.79	0.70	0.10	0.19	0.96	0.00	0.76	1.00
ρ_a	degree of persistence in technology shock	Beta	0.50	0.20	0.36	0.14	0.13	0.87	0.02	0.41	1.01
ρ_q,	degree of persistence in risk premium	Beta	0.90	0.20	0.92	0.09	0.23	1.00	0.01	0.10	1.03
ρ_s	degree of persistence in terms of trade	Beta	0.25	0.20	0.18	0.13	0.01	0.72	0.02	0.00	1.13
	Relative Policy Target Weights										
μ_q	real exchange rate stabilisation	Gamma	0.50	0.30	0.53	0.22	0.09	1.24	0.05	0.00	1.21
μ_y	output gap stabilisation	Gamma	0.50	0.30	0.34	0.19	0.09	1.24	0.04	0.10	1.04
μ_r	interest rate smoothing	Gamma	0.50	0.30	0.47	0.25	0.09	1.24	0.06	0.72	1.00
	Standard Deviation of Shock Innovations										
σ_H	domestic-output cost-push shock	Inverse Gamma	0.50	0.25	3.25	0.64	0.91	7.34	0.11	0.05	1.05
σ_F	imported-goods cost-push shock	Inverse Gamma	0.50	0.25	12.58	2.07	0.91	7.36	0.53	0.00	1.22
σ_a	technology shock	Inverse Gamma	1.00	0.40	0.34	0.07	0.52	2.66	0.00	0.21	1.00
σ_q	risk premium shock	Inverse Gamma	2.00	0.50	3.40	0.64	0.32	0.87	0.11	0.19	1.02
σ_s	terms of trade shock	Inverse Gamma	1.00	0.40	0.41	0.08	0.52	2.66	0.00	0.14	1.00
$\sigma_{\pi*}$	foreign inflation shock	Inverse Gamma	1.00	0.40	0.37	0.06	0.52	2.66	0.00	0.80	1.00
σ_{y*}	foreign output shock	Inverse Gamma	1.00	0.40	1.02	0.12	0.52	2.66	0.00	0.82	1.00
σ_{r*}	foreign interest rate shock	Inverse Gamma	1.00	0.40	0.40	0.07	0.52	2.65	0.00	0.83	1.00
σ_r	interest rate shock	Inverse Gamma	1.00	0.40	0.29	0.06	0.52	2.66	0.00	0.31	1.00

Table 4.10: **Prior and Posterior Parameter estimates for Canada under CAM and an unrestricted Model($\mu_q > 0$).**

Parameter	Description	Prior Distribution			Posterior Distribution						
		Type	Mean	S.D	Mean	S.D	2.50%	97.50%	NSE (8%)	p-value	B-GF
h	habit persistence	Beta	0.60	0.20	0.66	0.13	0.19	0.93	0.02	0.27	1.02
σ	inverse elasticity of intertemporal substitution of consumption	Gamma	1.00	0.50	0.93	0.32	0.27	2.19	0.08	0.00	1.28
ϕ	inverse of Frisch elasticity of intertemporal labour supply	Gamma	1.50	0.25	1.47	0.24	1.05	2.03	0.01	0.00	1.02
η	elasticity of substitution between home made and foreign goods	Gamma	1.00	0.50	1.19	0.49	0.27	2.20	0.08	0.01	1.06
δ_H	degree of indexation in domestic-output markets	Beta	0.70	0.20	0.93	0.04	0.25	0.98	0.00	0.05	1.02
δ_F	degree of indexation in imported-goods markets	Beta	0.70	0.20	0.64	0.23	0.25	0.98	0.05	0.91	1.00
θ_H	degree of inflation persistence in domestic-output markets	Beta	0.50	0.20	0.91	0.02	0.13	0.87	0.00	0.41	1.01
θ_F	degree of inflation persistence in imported-goods markets	Beta	0.50	0.20	0.63	0.09	0.13	0.87	0.01	0.06	1.04
a_1	degree of persistence in foreign inflation	Beta	0.50	0.20	0.92	0.02	0.19	0.96	0.00	0.24	1.01
b_2	degree of persistence in foreign output	Beta	0.50	0.20	0.41	0.11	0.19	0.96	0.00	0.01	1.01
c_3	degree of persistence in foreign interest rate	Beta	0.50	0.79	0.12	0.19	0.96	0.01	0.00	1.04	
ρ_a	degree of persistence in technology shock	Beta	0.50	0.20	0.28	0.15	0.13	0.87	0.02	0.12	1.03
ρ_q,	degree of persistence in risk premium	Beta	0.90	0.20	0.89	0.14	0.24	1.00	0.03	0.09	1.04
ρ_s	degree of persistence in terms of trade	Beta	0.25	0.20	0.22	0.15	0.01	0.72	0.03	0.23	1.02
	Relative Policy Target Weights										
μ_q	real exchange rate stabilisation	Gamma	0.50	0.30	0.37	0.16	0.09	1.24	0.03	0.30	1.02
μ_y	output gap stabilisation	Gamma	0.50	0.30	0.43	0.33	0.09	1.24	0.08	0.00	1.51
μ_r	interest rate smoothing	Gamma	0.50	0.30	0.32	0.17	0.09	1.23	0.03	0.00	1.19
	Standard Deviation of Shock Innovations										
σ_H	domestic-output cost-push shock	Inverse Gamma	0.50	0.25	14.02	1.82	0.91	7.33	0.44	0.33	1.02
σ_F	imported-goods cost-push shock	Inverse Gamma	0.50	0.25	23.35	1.15	0.91	7.37	0.25	0.00	1.13
σ_a	technology shock	Inverse Gamma	1.00	0.40	1.30	0.79	0.52	2.66	0.15	0.15	1.03
σ_q	risk premium shock	Inverse Gamma	2.00	0.50	6.78	2.23	0.32	0.87	0.59	0.00	1.56
σ_s	terms of trade shock	Inverse Gamma	1.00	0.40	2.22	0.30	0.52	2.66	0.03	0.02	1.03
$\sigma_{\pi*}$	foreign inflation shock	Inverse Gamma	1.00	0.40	0.39	0.08	0.52	2.66	0.00	0.19	1.00
σ_{y*}	foreign output shock	Inverse Gamma	1.00	0.40	1.07	0.13	0.52	2.66	0.01	0.18	1.00
σ_{r*}	foreign interest rate shock	Inverse Gamma	1.00	0.40	0.38	0.07	0.52	2.65	0.00	0.00	1.01
σ_r	interest rate shock	Inverse Gamma	1.00	0.40	0.29	0.06	0.52	2.66	0.00	0.00	1.01

Table 4.11: **Prior and Posterior Parameter estimates for Chile under CAM and an unrestricted Model($\mu_q > 0$).**

Parameter	Description	**Prior Distribution**			**Posterior Distribution**						
		Type	Mean	S.D	Mean	S.D	2.50%	97.50%	NSE (8%)	p-value	B-GF
h	habit persistence	Beta	0.60	0.20	0.72	0.21	0.19	0.93	0.05	0.00	1.19
σ	inverse elasticity of intertemporal substitution of consumption	Gamma	1.00	0.50	0.57	0.16	0.27	2.20	0.03	0.00	1.27
ϕ	inverse of Frisch elasticity of intertemporal labour supply	Gamma	1.50	0.25	1.34	0.23	1.05	2.03	0.01	0.17	1.01
η	elasticity of substitution between home made and foreign goods	Gamma	1.00	0.50	0.25	0.11	0.27	2.19	0.01	0.00	1.10
δ_H	degree of indexation in domestic-output markets	Beta	0.70	0.20	0.67	0.19	0.25	0.98	0.04	0.03	1.08
δ_F	degree of indexation in imported-goods markets	Beta	0.70	0.20	0.57	0.19	0.25	0.98	0.04	0.01	1.12
θ_H	degree of inflation persistence in domestic-output markets	Beta	0.50	0.20	0.66	0.06	0.13	0.87	0.01	0.00	1.12
θ_F	degree of inflation persistence in imported-goods markets	Beta	0.50	0.20	0.96	0.01	0.13	0.87	0.00	0.01	1.04
a_1	degree of persistence in foreign inflation	Beta	0.50	0.20	0.93	0.01	0.19	0.96	0.00	0.98	1.00
b_2	degree of persistence in foreign output	Beta	0.50	0.20	0.40	0.11	0.19	0.96	0.00	0.63	1.00
c_3	degree of persistence in foreign interest rate	Beta	0.50	0.20	0.74	0.09	0.19	0.96	0.00	0.04	1.00
ρ_a	degree of persistence in technology shock	Beta	0.50	0.20	0.32	0.16	0.13	0.87	0.03	0.00	1.27
ρ_q,	degree of persistence in risk premium	Beta	0.90	0.20	0.88	0.13	0.23	1.00	0.02	0.76	1.00
ρ_s	degree of persistence in terms of trade	Beta	0.25	0.20	0.96	0.02	0.01	0.72	0.00	0.49	1.00
	Relative Policy Target Weights										
μ_y	output gap stabilisation	Gamma	0.50	0.30	0.49	0.30	0.09	1.24	0.07	0.00	1.21
μ_r	interest rate smoothing	Gamma	0.50	0.30	0.22	0.14	0.09	1.24	0.03	0.18	1.03
	Standard Deviation of Shock Innovations										
σ_H	domestic-output cost-push shock	Inverse Gamma	0.50	0.25	1.14	0.20	0.91	7.35	0.02	0.03	1.02
σ_F	imported-goods cost-push shock	Inverse Gamma	0.50	0.25	1.31	0.75	0.91	7.33	0.14	0.09	1.04
σ_a	technology shock	Inverse Gamma	1.00	0.40	0.42	0.10	0.52	2.66	0.00	0.14	1.00
σ_q	risk premium shock	Inverse Gamma	2.00	0.50	7.32	1.77	0.32	0.88	0.43	0.00	1.20
σ_s	terms of trade shock	Inverse Gamma	1.00	0.40	1.04	0.17	0.52	2.65	0.01	0.05	1.01
$\sigma_{\pi*}$	foreign inflation shock	Inverse Gamma	1.00	0.40	0.46	0.09	0.52	2.66	0.00	0.57	1.00
σ_{y*}	foreign output shock	Inverse Gamma	1.00	0.40	1.19	0.13	0.52	2.66	0.01	0.26	1.00
σ_{r*}	foreign interest rate shock	Inverse Gamma	1.00	0.40	0.39	0.06	0.52	2.66	0.00	0.51	1.00
σ_r	interest rate shock	Inverse Gamma	1.00	0.40	0.29	0.06	0.52	2.65	0.00	0.35	1.00

Table 4.12: **Prior and Posterior Parameter estimates for Columbia under CAM and a restricted Model($\mu_q = 0$).**

Parameter	Description	Prior Distribution			Posterior Distribution						
		Type	Mean	S.D	Mean	S.D	2.50%	97.50%	NSE (8%)	p-value	B-GF
h	habit persistence	Beta	0.60	0.20	0.68	0.20	0.19	0.93	0.04	0.02	1.08
σ	inverse elasticity of intertemporal substitution of consumption	Gamma	1.00	0.50	2.54	0.59	0.27	2.20	0.15	0.54	1.01
ϕ	inverse of Frisch elasticity of intertemporal labour supply	Gamma	1.50	0.25	1.50	0.25	1.05	2.03	0.01	0.45	1.00
η	elasticity of substitution between home made and foreign goods	Gamma	1.00	0.50	0.84	0.46	0.27	2.19	0.03	0.51	1.00
δ_H	degree of indexation in domestic-output markets	Beta	0.70	0.20	0.86	0.08	0.25	0.98	0.01	0.67	1.00
δ_F	degree of indexation in imported-goods markets	Beta	0.70	0.20	0.72	0.14	0.25	0.98	0.02	0.98	1.00
θ_H	degree of inflation persistence in domestic-output markets	Beta	0.50	0.20	0.89	0.02	0.13	0.87	0.00	0.71	1.00
θ_F	degree of inflation persistence in imported-goods markets	Beta	0.50	0.20	0.42	0.08	0.13	0.87	0.01	0.55	1.00
a_1	degree of persistence in foreign inflation	Beta	0.50	0.20	0.72	0.14	0.19	0.96	0.01	0.27	1.00
b_2	degree of persistence in foreign output	Beta	0.50	0.20	0.41	0.11	0.19	0.96	0.00	0.61	1.00
c_3	degree of persistence in foreign interest rate	Beta	0.50	0.20	0.70	0.11	0.19	0.96	0.01	0.29	1.00
ρ_a	degree of persistence in technology shock	Beta	0.50	0.20	0.66	0.12	0.13	0.87	0.02	0.40	1.01
ρ_q,	degree of persistence in risk premium	Beta	0.90	0.20	0.84	0.17	0.24	1.00	0.03	0.48	1.01
ρ_s	degree of persistence in terms of trade	Beta	0.25	0.20	0.25	0.19	0.01	0.72	0.04	0.01	1.09
	Relative Policy Target Weights										
μ_q	real exchange rate stabilisation	Gamma	0.50	0.30	0.85	0.27	0.09	1.24	0.06	0.01	1.11
μ_y	output gap stabilisation	Gamma	0.50	0.30	0.26	0.14	0.09	1.24	0.02	0.33	1.01
μ_r	interest rate smoothing	Gamma	0.50	0.30	0.18	0.11	0.09	1.24	0.02	0.03	1.05
	Standard Deviation of Shock Innovations										
σ_H	domestic-output cost-push shock	Inverse Gamma	0.50	0.25	3.28	0.64	0.91	7.33	0.08	0.00	1.08
σ_F	imported-goods cost-push shock	Inverse Gamma	0.50	0.25	21.76	2.01	0.91	7.36	0.51	0.20	1.03
σ_a	technology shock	Inverse Gamma	1.00	0.40	0.27	0.05	0.52	2.66	0.00	0.52	1.00
σ_q	risk premium shock	Inverse Gamma	2.00	0.50	9.67	2.20	0.32	0.87	0.56	0.00	1.29
σ_s	terms of trade shock	Inverse Gamma	1.00	0.40	0.30	0.05	0.52	2.66	0.00	0.47	1.00
$\sigma_{\pi*}$	foreign inflation shock	Inverse Gamma	1.00	0.40	0.36	0.07	0.52	2.66	0.00	0.84	1.00
σ_{y*}	foreign output shock	Inverse Gamma	1.00	0.40	1.11	0.14	0.52	2.66	0.00	0.91	1.00
σ_{r*}	foreign interest rate shock	Inverse Gamma	1.00	0.40	0.38	0.06	0.52	2.65	0.00	0.48	1.00
σ_r	interest rate shock	Inverse Gamma	1.00	0.40	0.29	0.06	0.52	2.65	0.00	0.77	1.00

Table 4.13: **Prior and Posterior Parameter estimates for Mexico under CAM and an unrestricted Model($\mu_q > 0$).**

Parameter	Description	Prior Distribution			Posterior Distribution						
		Type	Mean	S.D	Mean	S.D	2.50%	97.50%	NSE (8%)	p-value	B-GF
h	habit persistence	Beta	0.60	0.20	0.90	0.05	0.19	0.93	0.01	0.70	1.00
σ	inverse elasticity of intertemporal substitution of consumption	Gamma	1.00	0.50	2.54	1.27	0.26	0.27	2.20	0.06	0.35
1.02											
ϕ	inverse of Frisch elasticity of intertemporal labour supply	Gamma	1.50	0.25	1.51	0.25	1.05	2.03	0.01	0.90	1.00
η	elasticity of substitution between home made and foreign goods	Gamma	1.00	0.50	2.07	0.72	0.27	2.19	0.07	0.61	1.00
δ_H	degree of indexation in domestic-output markets	Beta	0.70	0.20	0.81	0.15	0.25	0.98	0.03	0.76	1.00
δ_F	degree of indexation in imported-goods markets	Beta	0.70	0.20	0.50	0.20	0.25	0.98	0.04	0.92	1.00
θ_H	degree of inflation persistence in domestic-output markets	Beta	0.50	0.20	0.91	0.02	0.13	0.87	0.00	0.37	1.00
θ_F	degree of inflation persistence in imported-goods markets	Beta	0.50	0.20	0.38	0.08	0.13	0.87	0.01	0.10	1.03
a_1	degree of persistence in foreign inflation	Beta	0.50	0.20	0.81	0.05	0.19	0.96	0.00	0.42	1.00
b_2	degree of persistence in foreign output	Beta	0.50	0.20	0.41	0.11	0.19	0.96	0.00	0.81	1.00
c_3	degree of persistence in foreign interest rate	Beta	0.50	0.20	0.83	0.07	0.19	0.96	0.01	0.20	1.01
ρ_a	degree of persistence in technology shock	Beta	0.50	0.20	0.62	0.21	0.13	0.87	0.04	0.17	1.03
ρ_q,	degree of persistence in risk premium	Beta	0.90	0.20	0.92	0.08	0.24	1.00	0.01	0.77	1.00
ρ_s	degree of persistence in terms of trade	Beta	0.25	0.20	0.39	0.13	0.01	0.72	0.02	0.43	1.01
	Relative Policy Target Weights										
μ_q	real exchange rate stabilisation	Gamma	0.50	0.30	0.35	0.15	0.09	1.24	0.02	0.49	1.01
μ_y	output gap stabilisation	Gamma	0.50	0.30	0.73	0.35	0.09	1.24	0.09	0.00	1.37
μ_r	interest rate smoothing	Gamma	0.50	0.30	0.44	0.23	0.09	1.24	0.05	0.00	1.26
	Standard Deviation of Shock Innovations										
σ_H	domestic-output cost-push shock	Inverse Gamma	0.50	0.25	0.86	0.32	0.91	7.33	0.04	0.68	1.00
σ_F	imported-goods cost-push shock	Inverse Gamma	0.50	0.25	18.17	2.12	0.91	7.36	0.54	0.00	1.58
σ_a	technology shock	Inverse Gamma	1.00	0.40	0.34	0.07	0.52	2.66	0.00	0.01	1.01
σ_q	risk premium shock	Inverse Gamma	2.00	0.50	3.60	0.92	0.32	0.87	0.18	0.00	1.16
σ_s	terms of trade shock	Inverse Gamma	1.00	0.40	1.29	0.23	0.52	2.66	0.02	0.98	1.00
$\sigma_{\pi*}$	foreign inflation shock	Inverse Gamma	1.00	0.40	0.43	0.09	0.52	2.66	0.00	0.35	1.00
σ_{y*}	foreign output shock	Inverse Gamma	1.00	0.40	1.04	0.13	0.52	2.66	0.00	0.08	1.00
σ_{r*}	foreign interest rate shock	Inverse Gamma	1.00	0.40	0.37	0.06	0.52	2.65	0.00	0.89	1.00
σ_r	interest rate shock	Inverse Gamma	1.00	0.40	0.29	0.06	0.52	2.65	0.00	0.97	1.00

Table 4.14: **Prior and Posterior Parameter estimates for New Zealand under CAM and an unrestricted Model($\mu_q > 0$).**

Parameter	Description	Prior Distribution			Posterior Distribution						
		Type	Mean	S.D	Mean	S.D	2.50%	97.50%	NSE (8%)	p-value	B-GF
h	habit persistence	Beta	0.60	0.20	0.66	0.21	0.19	0.93	0.04	0.37	1.01
σ	inverse elasticity of intertemporal substitution of consumption	Gamma	1.00	0.50	1.00	0.26	0.27	2.20	0.05	0.04	1.07
ϕ	inverse of Frisch elasticity of intertemporal labour supply	Gamma	1.50	0.25	1.47	0.24	1.05	2.03	0.01	0.23	1.00
η	elasticity of substitution between home made and foreign goods	Gamma	1.00	0.50	0.85	0.46	0.27	2.19	0.04	0.68	1.00
δ_H	degree of indexation in domestic-output markets	Beta	0.70	0.20	0.84	0.11	0.25	0.98	0.02	0.79	1.00
δ_F	degree of indexation in imported-goods markets	Beta	0.70	0.20	0.66	0.18	0.25	0.98	0.03	0.23	1.02
θ_H	degree of inflation persistence in domestic-output markets	Beta	0.50	0.20	0.89	0.02	0.13	0.87	0.00	0.11	1.02
θ_F	degree of inflation persistence in imported-goods markets	Beta	0.50	0.20	0.24	0.08	0.13	0.87	0.01	0.33	1.01
a_1	degree of persistence in foreign inflation	Beta	0.50	0.20	0.73	0.06	0.19	0.96	0.00	0.91	1.00
b_2	degree of persistence in foreign output	Beta	0.50	0.20	0.43	0.11	0.19	0.96	0.00	0.88	1.00
c_3	degree of persistence in foreign interest rate	Beta	0.50	0.79	0.65	0.09	0.19	0.96	0.01	0.65	1.00
ρ_a	degree of persistence in technology shock	Beta	0.50	0.20	0.50	0.16	0.13	0.87	0.03	0.10	1.04
ρ_q,	degree of persistence in risk premium	Beta	0.90	0.20	0.90	0.16	0.23	1.00	0.03	0.03	1.07
ρ_s	degree of persistence in terms of trade	Beta	0.25	0.20	0.30	0.23	0.01	0.72	0.05	0.08	1.05
	Relative Policy Target Weights										
μ_q	real exchange rate stabilisation	Gamma	0.50	0.30	0.50	0.30	0.09	1.24	0.08	0.00	1.26
μ_y	output gap stabilisation	Gamma	0.50	0.30	0.35	0.19	0.09	1.24	0.03	0.00	1.11
μ_r	interest rate smoothing	Gamma	0.50	0.30	0.23	0.11	0.09	1.24	0.01	0.45	1.01
	Standard Deviation of Shock Innovations										
σ_H	domestic-output cost-push shock	Inverse Gamma	0.50	0.25	4.89	1.02	0.91	7.33	0.19	0.55	1.01
σ_F	imported-goods cost-push shock	Inverse Gamma	0.50	0.25	12.44	2.06	0.91	7.36	0.50	0.50	1.01
σ_a	technology shock	Inverse Gamma	1.00	0.40	0.72	0.23	0.52	2.66	0.03	0.00	1.07
σ_q	risk premium shock	Inverse Gamma	2.00	0.50	22.64	1.45	0.32	0.87	0.29	0.17	1.03
σ_s	terms of trade shock	Inverse Gamma	1.00	0.40	0.58	0.22	0.52	2.66	0.02	0.24	1.01
$\sigma_{\pi*}$	foreign inflation shock	Inverse Gamma	1.00	0.40	0.69	0.13	0.52	2.66	0.01	0.25	1.00
σ_{y*}	foreign output shock	Inverse Gamma	1.00	0.40	1.00	0.14	0.52	2.66	0.01	0.70	1.00
σ_{r*}	foreign interest rate shock	Inverse Gamma	1.00	0.40	0.44	0.08	0.52	2.65	0.00	0.70	1.00
σ_r	interest rate shock	Inverse Gamma	1.00	0.40	0.33	0.08	0.52	2.65	0.00	0.01	1.01

Table 4.15: **Prior and Posterior Parameter estimates for Peru under CAM and an unrestricted Model($\mu_q > 0$).**

First, I note that for African Inflation targeters (AFITs), Ghana's preference for inflation stabilisation of 42% is lower than South Africa's weight of 59%. Ghana places a higher weight on exchange rate stabilisation compared to South Africa (6% versus 0%). Ghana is more concerned about output stabilisation than South Africa (38% versus 15%). South Africa places more weight on interest rate smoothing relative to Ghana (30% versus 14%).

In terms of countries' preference for inflation stabilisation, South Africa placed the highest weight (59%) followed by Columbia (58%). Ghana revealed the lowest preference to inflation stabilisation (42%) and followed closely by Brazil (43%). Examining inflation stabilisation preferences in terms of regional/category averages, AFITs recorded the highest average weight of 50% followed by LAITs with an average weight of 46% and then ASOEs with an average policy weight of 43%. AFIT's average inflation stabilisation weight is heavily influenced by South Africa's high weight, the average for LAIT is also driven much higher by the relatively higher weights of Columbia (58%) and Chile (47%). Inflation stabilisation is the most preferred policy choice in all the ten countries with no country recording a policy weight less than 40%.

After inflation stabilisation which has an average policy weight of 50%, the next policy preference for the countries surveyed here is output stabilisation with an average policy weight of 22% followed by interest rate smoothing (18%) and exchange rate stabilisation (13%). Output stabilisation is second to inflation stabilisation in four out of the ten countries. The highest weight for output stabilisation is estimated for Ghana at 38% and the lowest is 11% for Mexico. In terms of groupings, the AFITs average policy weight of 27% is the highest, whilst LAITs and ASOEs average weights are equal at 21%.

After inflation stabilisation and output stabilisation, interest rate smoothing is the next policy choice popular with IT central banks studied here. The weights placed on this policy varied from the highest of 30% for Brazil, Mexico placed the least weight on this policy choice with a weight of 8%. Among the three groupings, ASOEs placed the highest average weight of 22% as all three ASOEs placed quite high weights on this policy objective.

Finally, I reviewed the preference of the IT central banks studied here on the use of exchange rate stabilisation as a policy objective. This policy choice is now most popular with ASOEs with an average policy weight of 16%, followed by LAITs (14%). This result marks a significant shift from results obtained in Kam et al. (2009) in which this policy objective was not considered at all by ASOEs (See Table A.8 in the Appendix). Exchange

Category	Country	Period	μ_π	μ_y	μ_r	μ_q
Advance SOE	Australia	2009Q1-2021Q4	46%	20%	36%	8%
Advance SOE	Canada	2009Q1-2021Q4	44%	15%	21%	21%
Advance SOE	New Zealand	2009Q1-2021Q4	40%	29%	17%	14%
LAIT	Brazil	2009Q1-2021Q4	43%	27%	30%	0%
LAIT	Chile	2009Q1-2021Q4	47%	20%	15%	17%
LAIT	Columbia	2009Q1-2021Q4	58%	29%	13%	0%
LAIT	Mexico	2009Q1-2021Q4	44%	11%	8%	37%
LAIT	Peru	2009Q1-2021Q4	48%	17%	11%	24%
AFIT	Ghana	2009Q1-2021Q4	42%	38%	14%	6%
AFIT	South Africa	2009Q1-2021Q4	59%	15%	26%	0%

Table 4.16: Comparison of Policy weights of various IT countries studied in (Kam et al., 2009), (McKnight et al., 2020), Ghana and South Africa based a revised sample data over the period 2009Q1-2021Q4

rate stabilisation is the least popular policy objective among AFITs with an average policy weight of 3%.

4.5 Conclusion

With regard to the first research question, the empirical results confirm that Ghana and South Africa are committed to their price stability mandates. Ghana's weight to inflation stabilisation is 42% compared to South Africa's weight of 59%. Results from previous literature had weights for the inflation stabilisation parameter between 38% and 63%. Thus the weights estimated for Ghana and South Africa in this Chapter are well within this range.

The second research question is to find out whether the other policy options are important for AFITs. The results lead to the conclusion that output stabilisation with a policy weight of 38% is second to inflation stabilisation as a policy preference for Ghana. This is the highest weight among IT central banks according to results as shown in in Table 4.16. Interest rate smoothing is not as important for Ghana but is of significant consideration with a policy weight of 14%. For South Africa, aside inflation stabilisation, interest rate smoothing is the next important policy consideration with a policy weight of 26%, this is followed by output stabilisation with a weight of 15%. South Africa's focus on interest rate smoothing is only surpassed by Australia (36%) and Brazil (30%). Ghana and South Africa as expected of IT central banks, placed the least weight out of the four policy options on exchange rate stabilisation, with South Africa placing no weight on this policy option.

The AFIT average weight for the inflation stabilisation parameter of 50% is higher than the average weights of 46% and 43% recorded for LAIT and ASOE countries respectively. AFIT's weight on inflation stabilisation is heavily influenced by South Africa's high inflation stabilisation parameter estimate.

The results show that AFITs second preferred policy option after inflation stabilisation is output stabilisation with an average weight of 27% followed by interest rate stabilisation with a policy weight of 20%. The least policy preference for AFITs is exchange rate stabilisation, recording an average policy weight of 3%, the lowest among the IT central bank groupings relative to LAIT and ASOEs.

ASOEs most preferred policy objective is price stability, followed by interest rate smoothing with an average weight of 22%, and then output stabilisation with an average policy weight of 21%. Unlike previous results in the literature where ASOEs did not care at all about exchange rate stabilisation, the results in this study show a significant weight of 14%, this is a clear departure from results in earlier research.

LAIT central banks second policy preference after inflation stabilisation is output stabilisation with a policy weight of 23%. This preference is followed by interest rate smoothing with an average policy weight of 17%, the least preferred policy choice is exchange rate stabilisation (14%). Compared with previous results in in the literature, I observe a drop in preference for interest rate smoothing and an increase in preference for exchange rate stabilisation.

The order of policy preferences was the same for AFITs and LAITs; with inflation stabilisation, output stabilisation, interest rate stabilisation, and then exchange rate stabilisation in descending order of preference. ASOES order of policy preference was slightly different, after inflation stabilisation, interest rate stabilisation was the next preferred policy choice followed by output stabilisation and exchange rate stabilisation in descending order of preference. LAITs and ASOEs show more preference to exchange rate stabilisation with revealed average policy weights of 14% compared to 3% by AFITs.

An area for future research will be to pool the data from the various studies and countries and conduct a panel data analysis using a DSGE theoretical framework and Bayesian econometric methods. Given the significant shifts in policy preferences observed in this research compared to results from previous research panel data analysis becomes even more crucial.

Chapter 5

Conclusions

Chapter 2 of my thesis is an empirical analysis in which I compare the Bank of Ghana's forecasts to the actual out-turn to assess forecast accuracy using Mincer Zarnowitz regressions. This Chapter examines the efficiency of the Bank of Ghana's inflation forecasts relative to a benchmark forecast using a random walk model proposed by Atkeson and Ohanian (2001) and the International Monetary Fund World Economic Outlook forecasts. Indicator saturation variables are incorporated into the regression functions to address possible shifts in the data.

Chapter 3 is a combination of a theoretical and empirical framework, which uses a time-varying trend NKPC-based inflation forecast, and compares this forecast with selected time series-based benchmark forecasts.

In Chapter 4, I assess the commitment of African Inflation targeting central banks to their inflation mandates and compared the results with previous research of other regional groupings using Bayesian estimation methods.

5.1 Results of Chapter 2 and Chapter 3

In general, an accurate inflation forecast serves as an effective vehicle for the MPC to communicate the economic outlook to the public and to explain the implications for monetary policy in a transparent and accountable way.

In Chapter 2, using a Mincer-Zarnowitz regression, I conclude that the one-quarter ahead BoG inflation forecast with SIS variables provides the strongest evidence in support of forecast efficiency. The Bank of Ghana's one-quarter ahead inflation forecast is efficient with or without the incorporation of SIS variables, however, a stronger efficiency is exhibited when SIS variables are incorporated in the forecast. The stronger efficiency exhibited by the forecast that incorporates the SIS variables is of policy relevance as it points to the importance of addressing outliers and structural breaks in evaluating inflation forecasts, especially in developing economies prone to structural shocks.

The central bank's immediate term forecast outperforms the random walk and the IMF WEO forecasts. This finding is also of relevance to monetary policy formulation, as typically central bank's forecast have some subjective considerations that time-series model-based forecasts and other institutional forecasts, such as the IMF WEO, may not have sufficient information on to incorporate into their forecasts.

The two-quarters-ahead Bank of Ghana inflation forecast is inefficient even with the inclusion of SIS variables. This conclusion is also of policy relevance as it reveals that forecasts beyond the immediate quarter may be less reliable and should be used with some caution for monetary policy-making.

Using the concept of forecast encompassing in chapter 2, I note that the Bank of Ghana's inflation forecasts (both one-quarter ahead and two-quarters ahead) are robust and reflects all information embedded in the random walk forecast at the time of forecast but the same cannot be said of the random walk benchmark forecast.

There is evidence that the Bank of Ghana's forecasting performance improves as the central bank gets more experienced in forecasting inflation. The policy implication of this finding is that Monetary Policy Committees should expect inflation forecasts for the immediate time horizon to become more reliable with more experience of the central bank in the forecasting of this indicator. Finally, I note by the inspection of the scatter plots of the inflation forecast errors against actual inflation in Chapter 2 that outliers tend to occur at higher levels of inflation. As inflation increases the forecast error increases through the tendency of the forecasting framework to underestimate the inflation forecast. This finding supports earlier results of Zarnowitz and Mincer (1969) who concluded that "there is also evidence that increases in the series with strong upward trends are likely to be under-predicted". The policy implication of this finding is that at higher levels of inflation the inflation forecast error tends to increase, therefore it is prudent to factor the reduced accuracy of the inflation forecast in the decision-making process.

In chapter 3, I conclude that for the policy relevant immediate forecast horizon, one-quarter- ahead, the pseudo random walk forecast, referred to here as the AO inflation forecast is the most accurate forecast when compared to the random walk forecast and the four variants of the TVT-NKPC forecasts. There is not a statistically significant difference in forecast accuracy between the AO-RW inflation forecast and the TVT-NKPC forecast which was based on a real unit labour cost real marginal cost proxy and a recursive window sample(RULC RMC (rec) forecast). This result for the one-quarter ahead forecast is like Duncan and Martínez-García (2019) who concluded that in emerging market economies, it was difficult to add-value beyond AO forecasts without adding subjective judgement to account for structural shifts in the data.

For the policy relevant one-quarter ahead forecast, the RULC RMC(rec) TVT-NKPC forecast provides a theoretical and empirical justification for its use for inflation forecasting. However, if the computational cost and time required to generate the RULC-REC TVT-NKPC inflation forecast is significant, then the use of the AO inflation forecast is well justified.

For the 4, 8, 12, 16 and 20-quarters ahead forecast horizons, the empirical results shows a more accurate RW inflation forecast, but there is not a statistically significant difference in forecast accuracy among the TVT NKPC and the two benchmark inflation forecasts. The policy implication of this finding is that beyond the policy-relevant horizon, the random walk forecast provides a sufficiently accurate forecast for monetary policy-making in Ghana. In a more general perspective, the central bank's immediate-term forecast produces the least forecast error when compared to all the forecasts analysed in Chapter 2 and 3. Chapter 2 does not analyse the central bank's medium to long term forecasts due to data constraints, however the medium to long-term inflation forecasts in Chapter 3 reveal that, the random walk inflation forecast is the most accurate but there not a statistically significant difference in forecast accuracy between this forecast and the AO-RW forecast and TVT-NKPC inflation forecasts.

The research detected a statistically significant impulse indicator saturation variable in the first quarter of 2021, pointing to an outlier observation for that quarter. While the inclusion of this indicator saturation variable improves the model fit, it does not lead to an improvement of forecast performance but rather leads to a rejection of a null hypothesis of an unbiased and efficient forecast according to the joint test of the null hypothesis using Mincer-Zarnowitz regressions. The key policy lesson from this finding is that a model that fits the data well does not necessarily lead to a better forecast performance.

An area for further research will be to investigate whether the findings in Chapter 3 apply to other inflation targeting emerging or frontier open economies, such as South Africa.

5.2 Results of Chapter 4

The empirical results of chapter 4 confirm that Ghana and South Africa are committed to their price stability mandates. Ghana's weight placed on inflation stabilisation is 42% compared to South Africa's weight of 59%. This result is consistent with previous research recorded weights for the inflation stabilisation parameter between 38% and 63%. The AFIT average weight for the inflation stabilisation parameter of 50% is higher than the average weights of 46% and 43% recorded for LAIT and ASOE countries respectively. AFIT's weight on inflation stabilisation is heavily influenced by South Africa's high inflation stabilisation parameter estimate. AFIT countries average weight of inflation stabilisation is heavily impacted by South Africa's high inflation stabilisation weight.

The results show that other policy options are important for AFITs. Output stabilisation with a policy weight of 38% is second to inflation stabilisation as a policy preference for Ghana. Ghana's output stabilisation weight is the highest among IT central banks obtained from previous research. Interest rate smoothing is not as important for Ghana but was of significant consideration with a policy weight of 14%. For South Africa, after inflation stabilisation, the next preferred policy preference for South Africa is interest rate smoothing with a policy weight of 26%, this is followed by output stabilisation with a weight of 15%. Ghana and South Africa, as expected of IT central banks, placed the least weight out of the four policy choices on exchange rate stabilisation, with South Africa placing no weight on this policy option.

Interest rate smoothing is not as important for Ghana but is of significant consideration with a policy weight of 14%. For South Africa, aside inflation stabilisation, interest rate smoothing is the next important policy consideration with a policy weight of 26%, this is followed by output stabilisation with a weight of 15%. South Africa's focus on interest rate smoothing is only surpassed by Australia (36%) and Brazil (30%). Ghana and South Africa as expected of IT central banks, placed the least weight out of the four policy options on exchange rate stabilisation, with South Africa placing no weight on this policy option.

AFITs second preferred policy option after inflation stabilisation is output stabilisation with an average weight of 27% followed by interest rate stabilisation with a policy weight of 20%. The least policy preference for AFITs is exchange rate stabilisation, recording an average policy weight of 3%, the lowest among the IT central bank groupings relative to LAIT and ASOEs.

ASOEs most preferred policy objective is price stability, followed by interest rate smoothing with an average weight of 22%, and then output stabilisation with an average policy weight of 21%. Unlike results in Kam et al. (2009) where ASOEs did not care at all about exchange rate stabilisation, the results in this study show a significant weight of 14%, this is a clear departure from results in earlier research.

LAIT central banks second policy preference after inflation stabilisation is output stabilisation with a policy weight of 23%. This preference is followed by interest rate smoothing with an average policy weight of 17%, the least preferred policy choice is exchange rate stabilisation (14%). Compared with previous results in McKnight et al. (2020) I observe a drop in preference for interest rate smoothing and an increase in preference for exchange rate stabilisation.

The order of policy preferences is the same for AFITs and LAITs; with inflation stabilisation, output stabilisation, interest rate stabilisation, and then exchange rate stabilisation in descending order of preference. ASOES order of policy preference is slightly different, after inflation stabilisation, interest rate stabilisation is the next preferred policy choice followed by output stabilisation and exchange rate stabilisation in descending order of preference. LAITs and ASOEs show more preference to exchange rate stabilisation with revealed average policy weights of 14% compared to 3% by AFITs.

Chapter four is of policy relevance for the evaluation of central bank monetary policies. It enables the assessment of the level of commitment of inflation targeting central banks towards their price stability mandates and also provides a framework to assess their alternative policy preferences. Since the data and computational power requirements to conduct this type of research could be high, it is important to gauge the cost of implementing this framework in comparison to its benefits especially since central bank policy preferences can also shift over time.

5.3 Possible limitations of the analysis

Chapter 2 uses CPI-based inflation forecast because this is the only type of inflation forecasts that the Bank of Ghana generates, but Chapter 3 is based on GDP deflator inflation forecasts, making the comparison of results of the two Chapters difficult. Another limitation of Chapter 2 is that the BoG started producing quarterly inflation forecasts in 2004 so the time series does not go far back, making the construction of pseudo out-of-sample forecast evaluation period for the evaluation of medium to long term horizon (4 quarter ahead to 12 quarters ahead) forecasts as done in Chapter 3 not feasible.

5.4 Routes for future research

Even though the data used in previous studies for the Latin American and advanced small open economies has been updated in Chapter 4 to match the same period of data used for the African economies, future research, which pools the data from the various countries and conducts a panel data analysis using a DSGE theoretical framework and Bayesian econometric methods, may offer some enhancements in results. Given the significant shifts in policy preferences observed in this research, compared to results from previous research, panel data analysis becomes even more imperative.

Kam et al. (2009) also point out areas of future research of Chapter 4, which include incorporating the potential effects of labour market behaviour and credit constraints on the estimates of central banks' objectives. A more careful and deeper calibration of the priors to align with country-specific characteristics of the economies sampled in this study would be worth pursuing in future research.

In Chapter 2, given that the length of the time series data is improving, future research which extends the pseudo forecast horizon to medium and long term forecasts will be useful.

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Appendix A

Appendix A

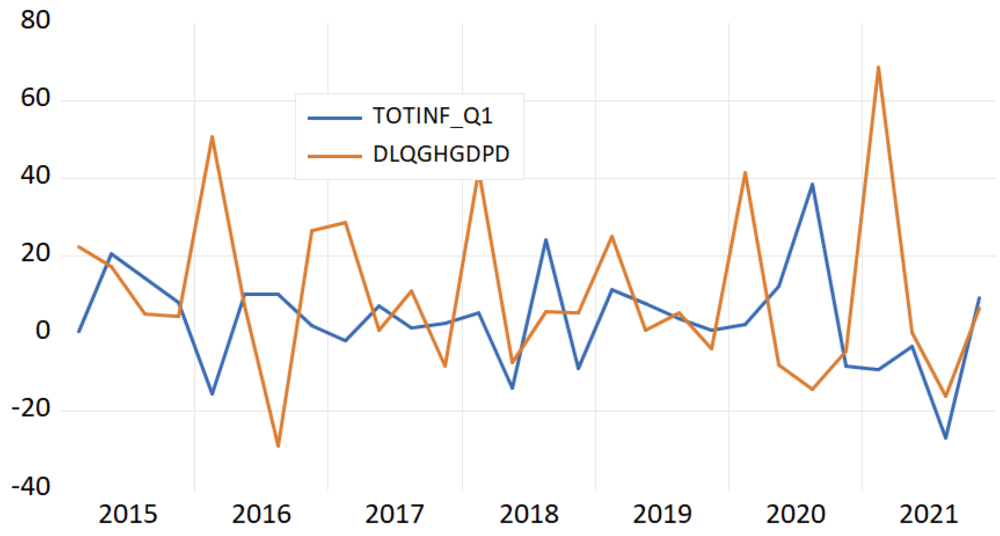

Figure A.1: One-quarter-ahead TVT-NKPC Inflation Forecast Versus Actual Inflation based on RULC Proxy and Rolling (ROLL) Window Samples, where TOTINF_Q1 = One-quarter-ahead TVT-NKPC Inflation Forecast and DLQGHGDPD = GDP-deflator Inflation.

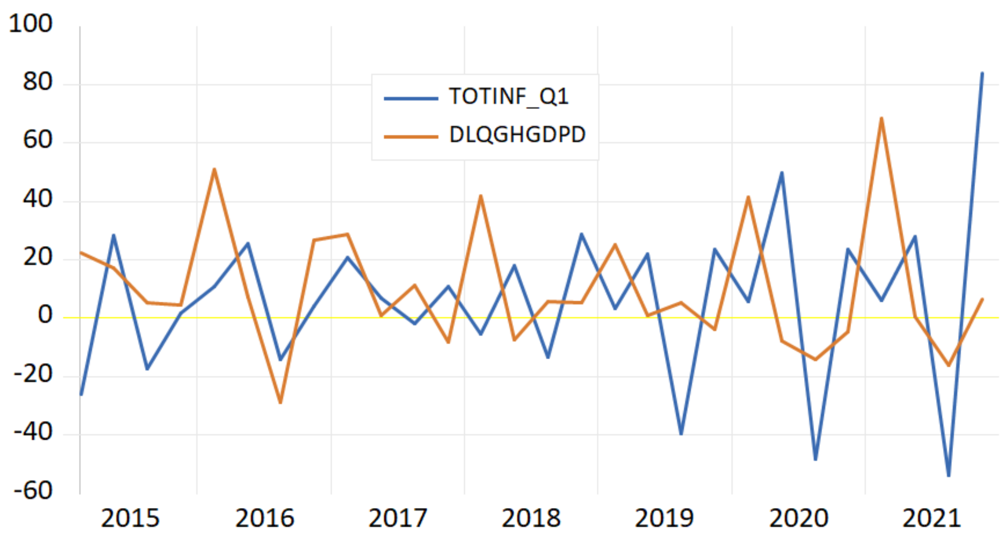

Figure A.2: One-quarter-ahead TVT-NKPC Inflation Forecast Versus Actual Inflation based on MOE Proxy and Rolling(ROLL) Window Samples, where TOTINF_Q1 = One-quarter-ahead TVT-NKPC Inflation Forecast and DLQGHGDPD = GDP-deflator Inflation.

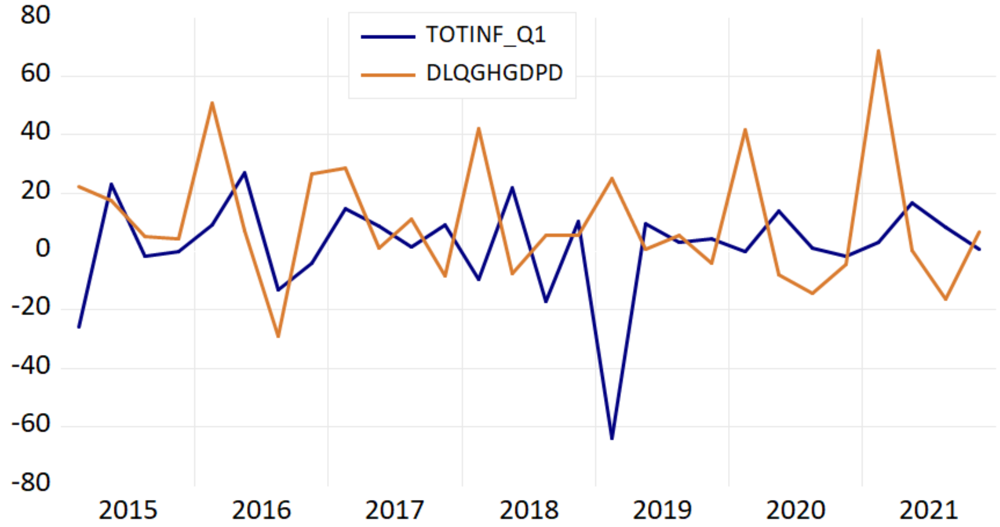

Figure A.3: One-quarter-ahead TVT-NKPC Inflation Forecast Versus Actual Inflation based on MOE Proxy and Recursive(REC) Window Samples, where TOTINF_Q1 = One-quarter-ahead TVT-NKPC Inflation Forecast and DLQGHGDPD = GDP-deflator Inflation.

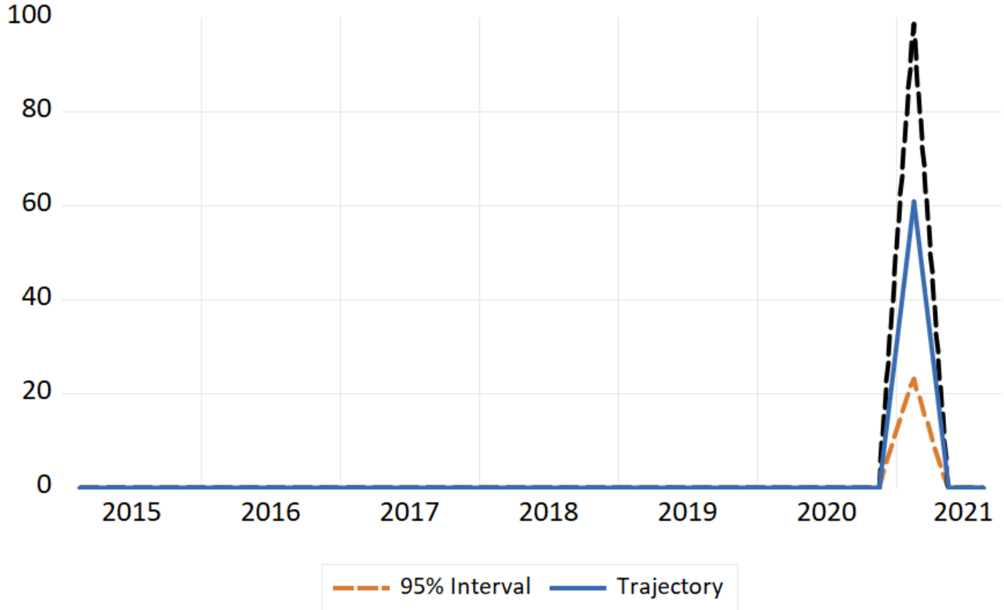

Figure A.4: 95 Percent Confidence Interval Trajectory of the Coefficient of the IIS Variable.

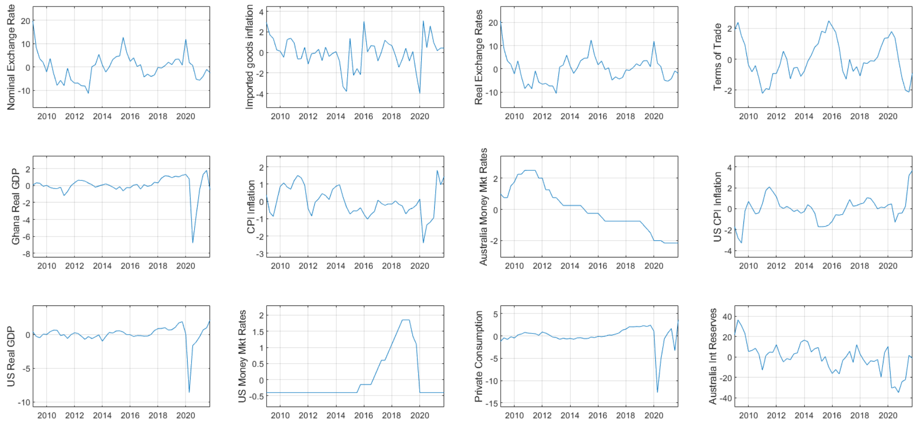

Figure A.5: Raw Data for Australia

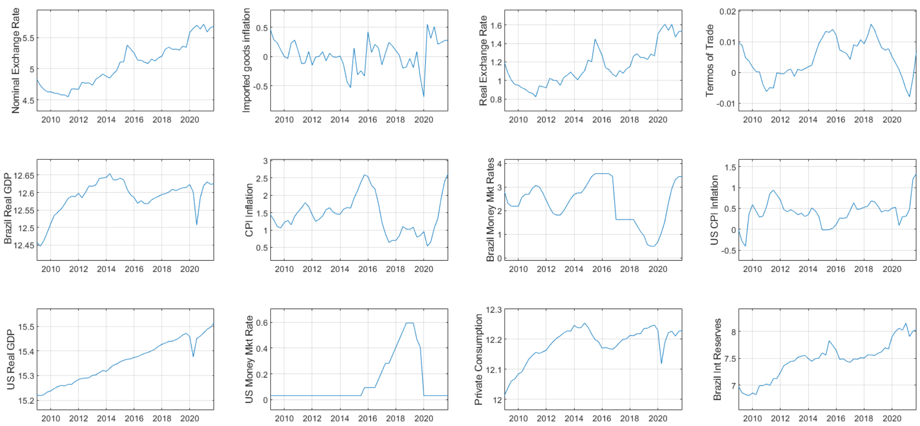

Figure A.6: Raw Data for Brazil

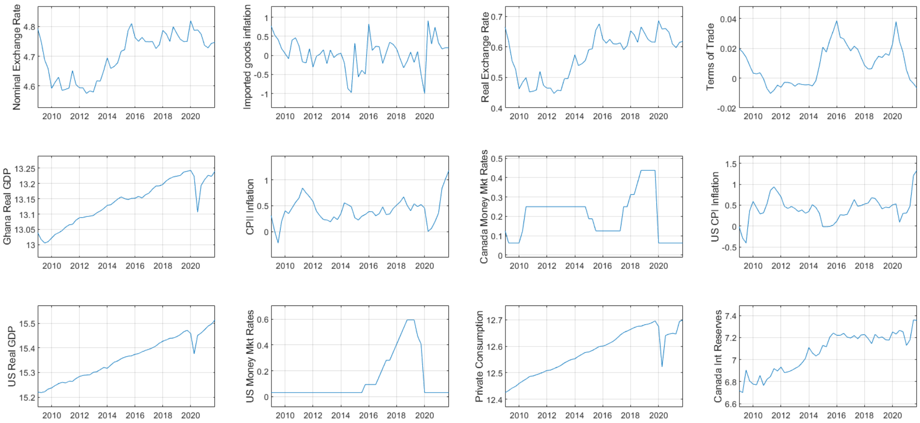

Figure A.7: Raw Data for Canada

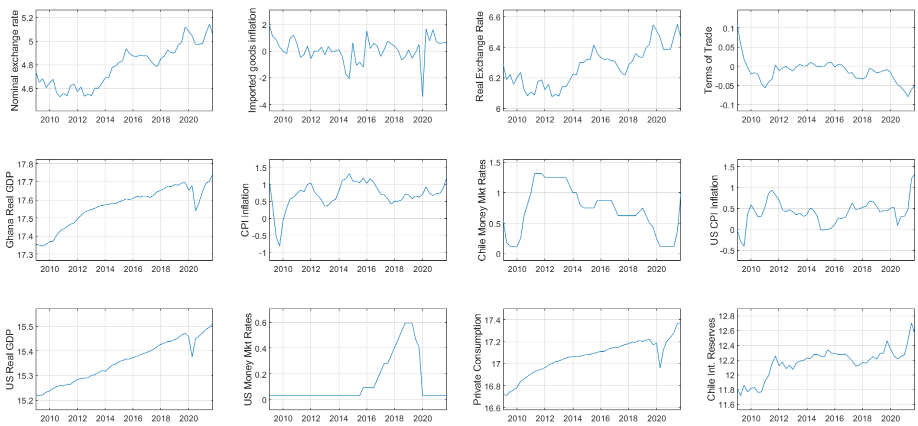

Figure A.8: Raw Data for Chile

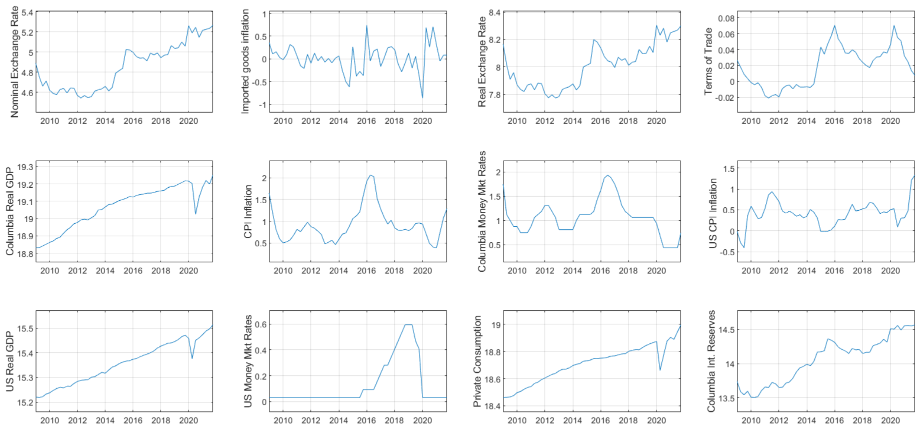

Figure A.9: Raw Data for Columbia

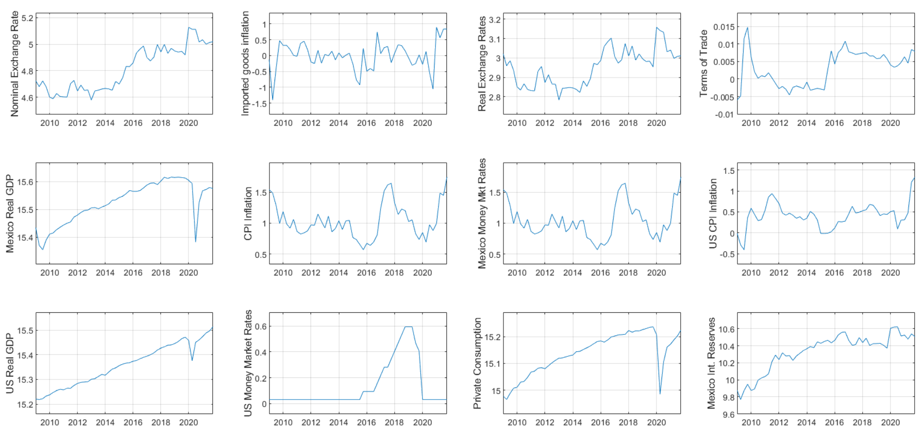

Figure A.10: Raw Data for Mexico

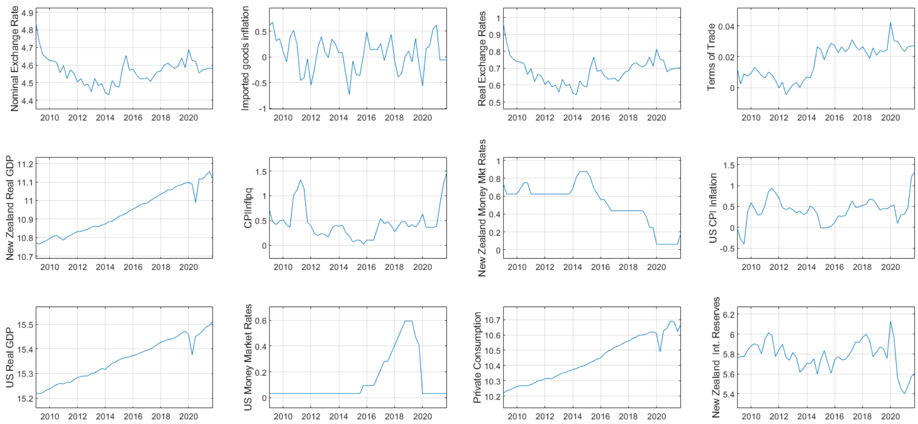

Figure A.11: Raw Data for New Zealand

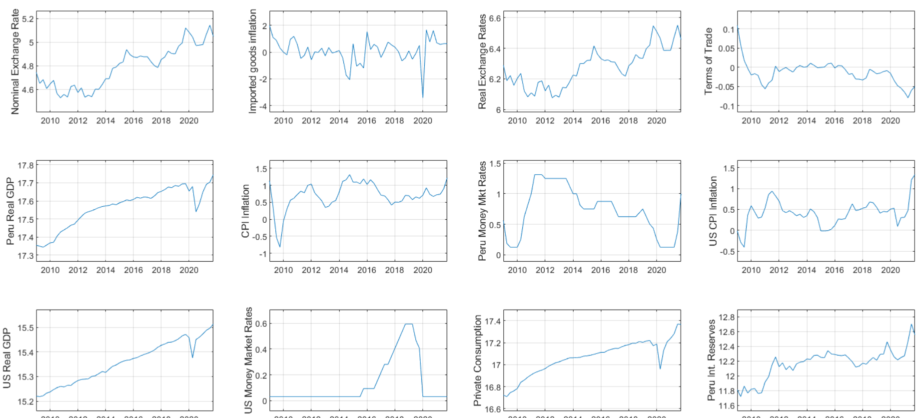

Figure A.12: Raw Data for Peru

Prior Distributions

Parameters	Description	Prior Mean	Prior Std
h	degree of habit persistence	2.00	0.38
σ	inverse of elasticity of intertemporal substitution of consumption	2.000	0.75
ϕ	inverse of Frisch elasticity of intertemporal labor supply	2.00	0.75
η	elasticity of substitution between home made and foreign goods	1.000	0.5
δ_H	degree of indexation in domestic-output markets	0.700	0.2
δ_F	degree of indexation in imported-goods markets	0.700	0.2
θ_H	degree of inflation persistence in domestic-output markets	0.500	0.2
θ_F	degree of inflation persistence in imported-goods markets	0.500	0.2
a_1	degree of persistence in foreign inflation	0.500	0.2
b_2	degree of persistence in foreign output	0.500	0.2
c_3	degree of persistence in foreign interest rate	0.500	0.2
ρ_a	degree of persistence in technology shock	0.500	0.2
ρ_q	degree of persistence in risk premium	0.900	0.2
ρ_s	degree of peristence in terms of trade	0.250	0.2
	Relative Policy Target Weights		
μ_q	real exchange rate stabilization	0.5	0.3
μ_y	output gap stabilization	0.500	0.3
μ_r	interest rate smoothing	0.500	0.3
	Standard Deviation of Shock Innovations		
σ_H	domestic-output cost-push shock	0.5	0.25
σ_F	imported-goods cost-push shock	0.5	0.25
σ_a	technology shock	1.0	0.4
σ_q	risk premium shock	2.0	0.5
σ_s	terms of trade shock	1.0	0.4
$\sigma_{\pi*}$	foreign inflation shock	0.3	2.0
σ_{y*}	foreign output shock	0.2	2.0
σ_{r*}	foreign interest rate shock	0.1	2.0
σ_r	interest rate shock	0.13	2.0

Table A.1: Prior Distributions, based on Akosah (2020). The parameters were calibrated to a value common for both countries:$\beta = .99$, $\chi = 0.5, \alpha$ was calibrated based on the average share of imports of goods and services in consumption over the sample period for each country, Ghana =.29, South Africa =.20.

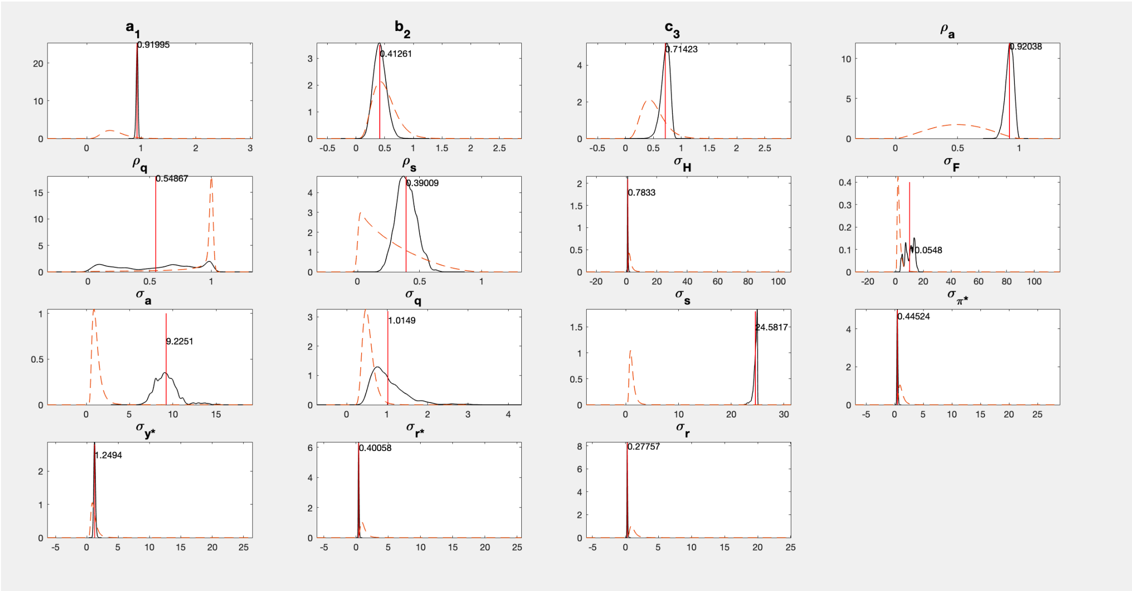

Figure A.13: Posterior Distributions of Key Parameters: Ghana, CAM and $\mu_q = 0$. Posterior (solid) and Prior (dashed).

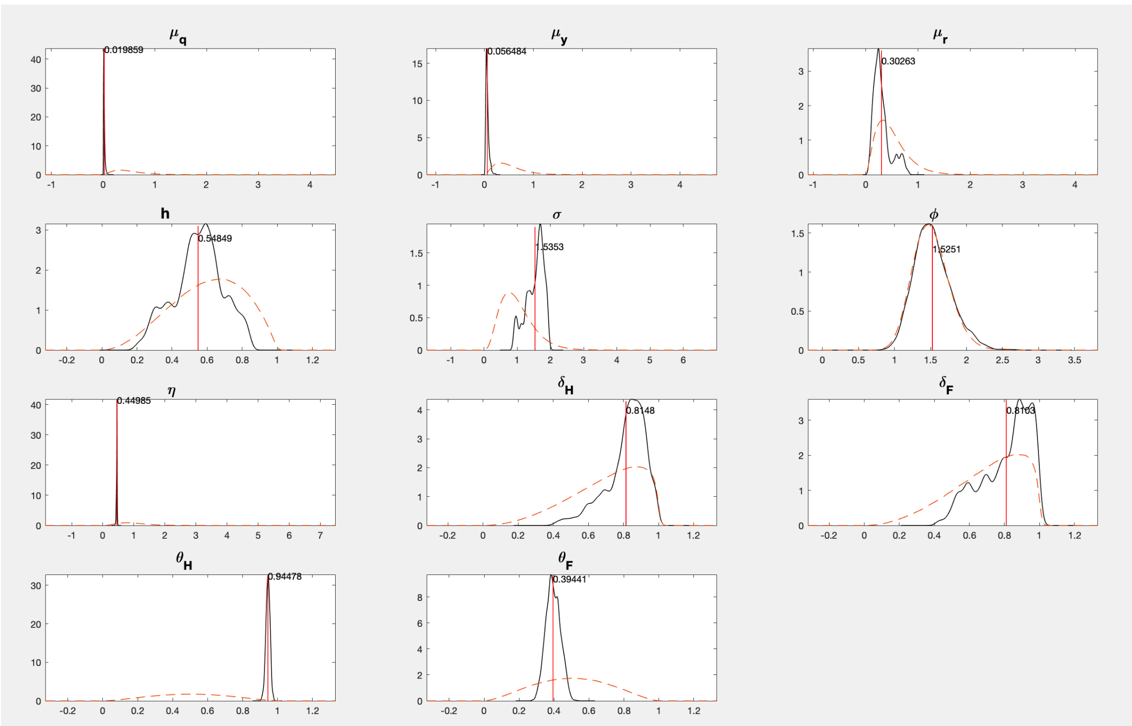

Figure A.14: Posterior Distributions of Key Parameters for Ghana, Assuming IAM and $\mu_q > 0$. Posterior (solid) and Prior (dashed).

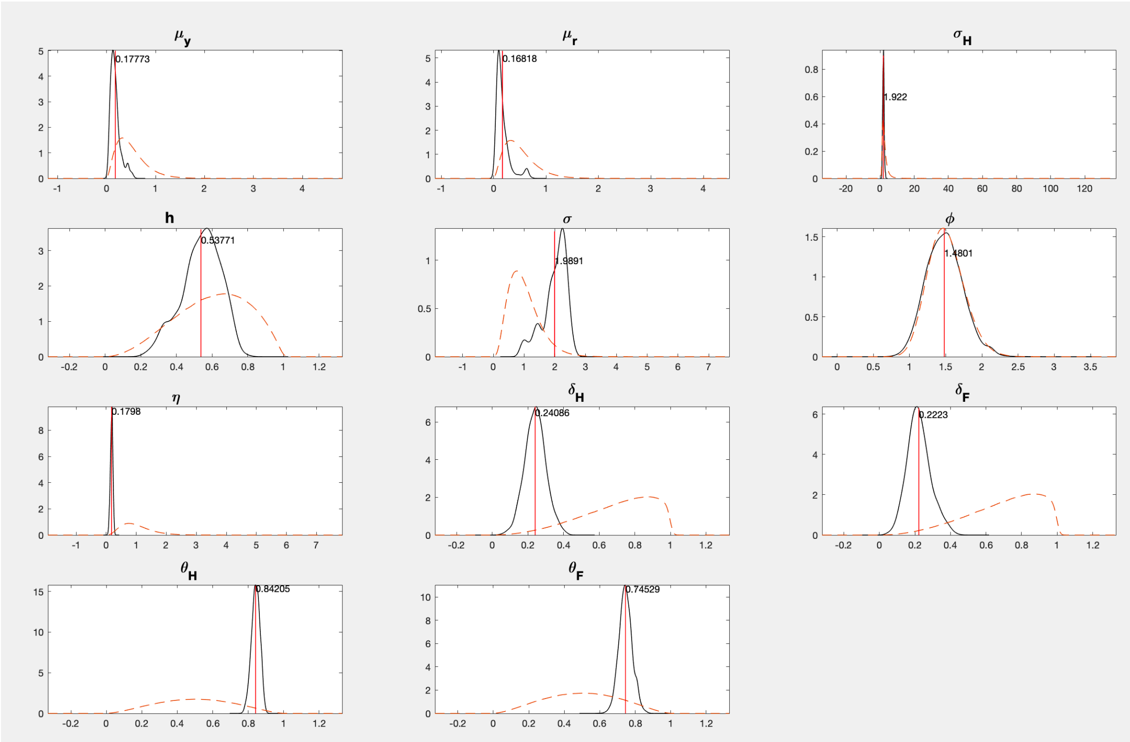

Figure A.15: Posterior Distributions of Key Parameters for Ghana, Assuming IAM and $\mu_q = 0$. Posterior (solid) and Prior (dashed)

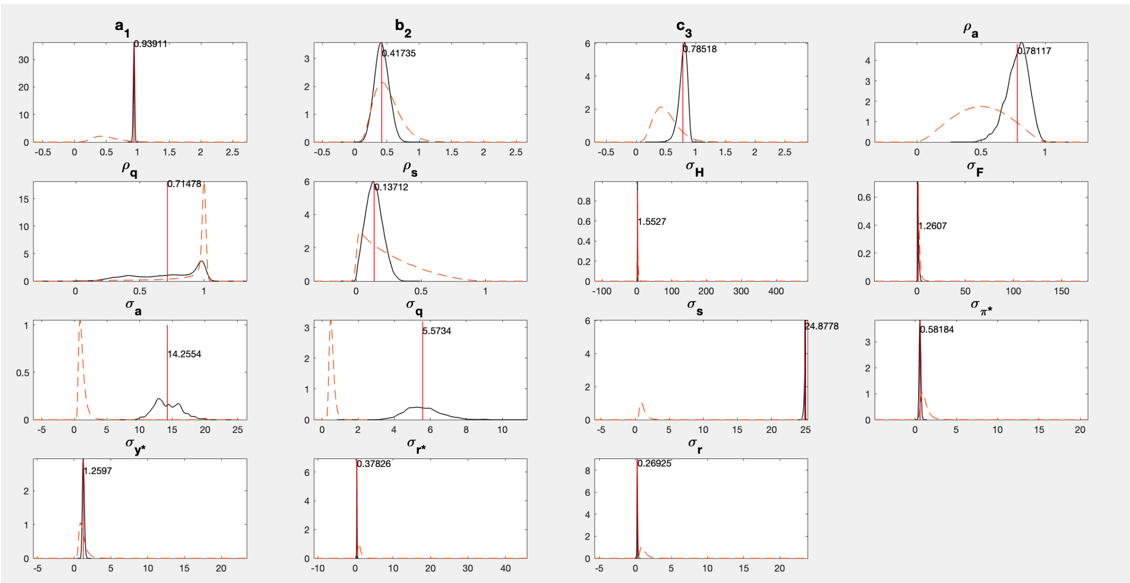

Figure A.16: Posterior Distributions of Key Parameters for South Africa, Assuming CAM and a Restricted Model ($\mu_q = 0$). Posterior (solid) and Prior (dashed)

Ghana - Posterior parameters and convergence diagnostics ($mu_q > 0$)

Parameters	Post Mean	Post SD	2.5%	97.5%	NSE(8%)	p-value	B-GF
h	0.548	0.141	0.194	0.932	0.031	0.751	1.002
σ	1.535	0.269	0.272	2.193	0.072	0.000	2.055
ϕ	1.525	0.260	1.051	2.029	0.017	0.094	1.010
η	0.450	0.013	0.273	2.196	0.002	0.000	1.245
δ_H	0.815	0.115	0.253	0.980	0.026	0.000	1.201
δ_F	0.810	0.142	0.254	0.980	0.034	0.000	1.589
θ_H	0.945	0.012	0.129	0.871	0.002	0.165	1.019
θ_F	0.394	0.041	0.129	0.871	0.009	0.000	1.337
a_1	0.987	0.009	0.188	0.962	0.002	0.817	1.001
b_2	0.382	0.102	0.188	0.962	0.006	0.541	1.001
c_3	0.620	0.123	0.188	0.964	0.007	0.481	1.002
ρ_a	0.706	0.097	0.129	0.871	0.021	0.274	1.020
ρ_q	0.417	0.181	0.235	1.000	0.043	0.000	1.467
ρ_s	0.284	0.107	0.007	0.726	0.022	0.045	1.061
μ_q	0.020	0.015	0.094	1.236	0.003	0.648	1.003
μ_y	0.056	0.033	0.094	1.236	0.005	0.357	1.009
μ_r	0.303	0.164	0.094	1.239	0.039	0.000	1.311
σ_H	9.777	2.010	0.911	7.355	0.532	0.000	2.251
σ_F	4.375	1.713	0.913	7.339	0.461	0.000	1.292
σ_a	12.997	1.114	0.520	2.657	0.279	0.000	1.387
σ_q	0.554	0.142	0.324	0.874	0.016	0.012	1.041
σ_s	11.989	0.909	0.520	2.662	0.226	0.000	1.248
$\sigma_{\pi*}$	0.219	0.026	0.520	2.658	0.001	0.005	1.008
σ_{y*}	1.353	0.143	0.520	2.664	0.011	0.968	1.000
σ_{r*}	0.199	0.023	0.520	2.656	0.000	0.009	1.002
σ_r	0.308	0.041	0.520	2.651	0.004	0.000	1.059

Table A.2: Posterior Parameters and Convergence Diagnostics under the Assumption of IAM and $\mu_q > 0$: Ghana. The prior means and standard deviations as well as the distributions remain the same as in Section 4.4 and therefore not repeated in the Appendix tables.

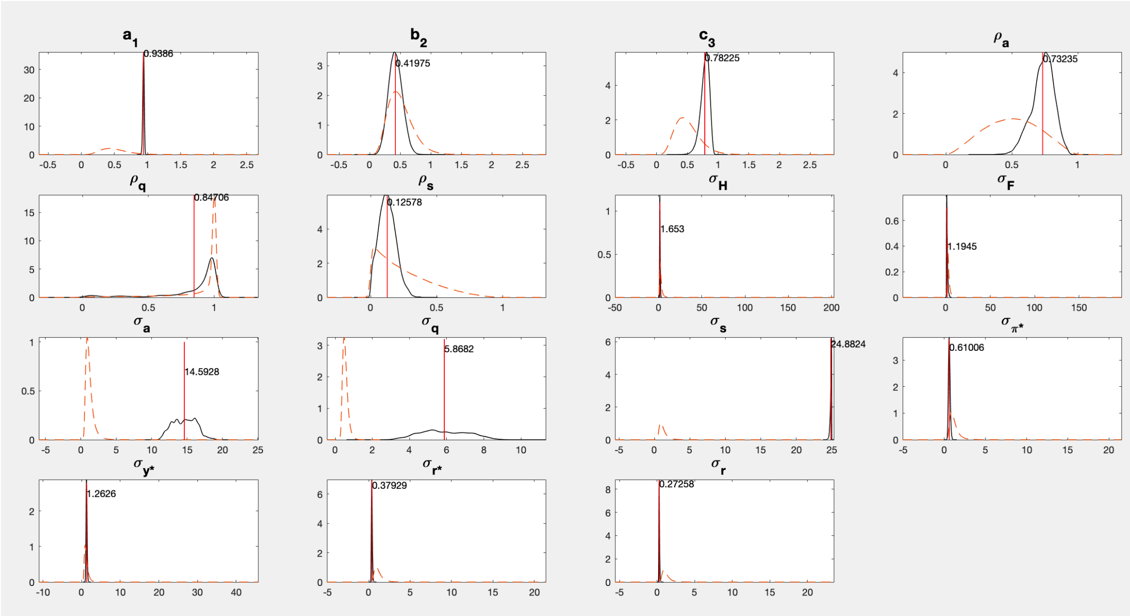

Figure A.17: Posterior Distributions of Key Parameters for South Africa, Assuming CAM and an Unrestricted Model($\mu_q > 0$). Posterior (solid) and Prior (dashed).

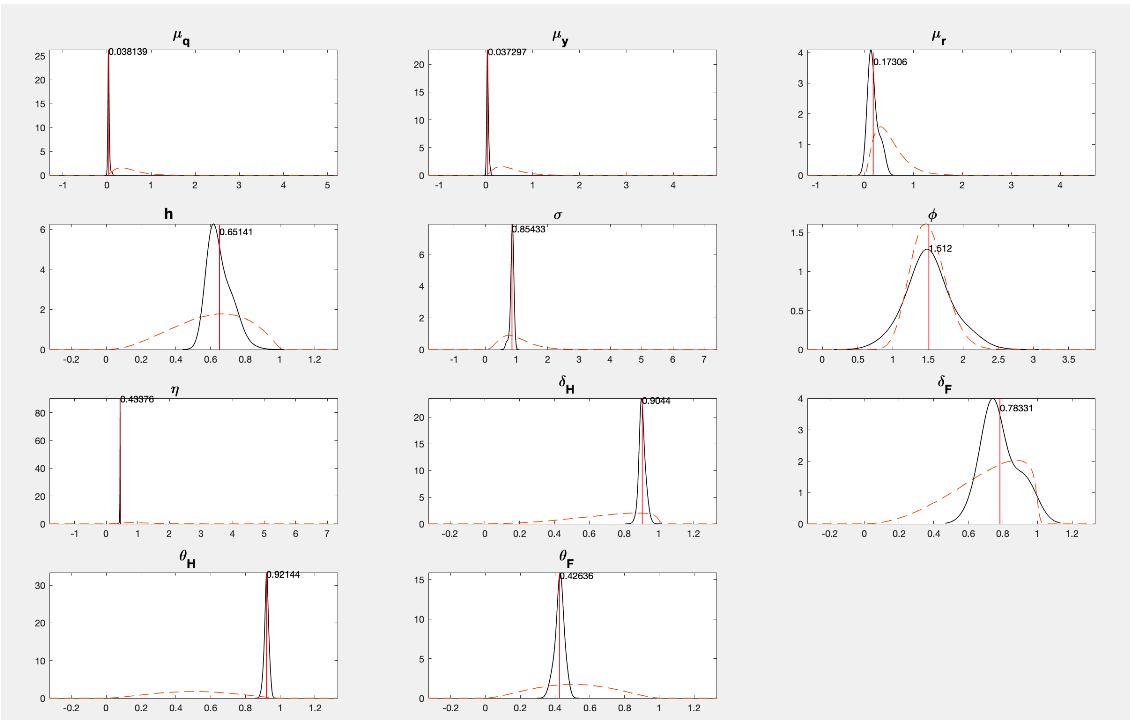

Figure A.18: Posterior Distributions of Key Parameters: South Africa, assuming IAM and an Unrestricted Model($\mu_q > 0$). Posterior (solid) and Prior (dashed).

Parameter	Description	Prior Distribution			Posterior Distribution						
		Type	Mean	S.D	Mean	S.D	2.50%	97.50%	NSE (8%)	p-value	B-GF
h	habit persistence	Beta	0.60	0.20	0.80	0.06	0.19	0.93	0.01	0.54	1.00
σ	inverse elasticity of intertemporal substitution of consumption	Gamma	1.00	0.50	0.56	0.15	0.27	2.19	0.03	0.02	1.07
ϕ	inverse of Frisch elasticity of intertemporal labour supply	Gamma	1.50	0.25	1.40	0.24	1.05	2.03	0.01	0.03	1.01
η	elasticity of substitution between home made and foreign goods	Gamma	1.00	0.50	0.71	0.15	0.27	2.19	0.01	0.18	1.01
δ_H	degree of indexation in domestic-output markets	Beta	0.70	0.20	0.22	0.11	0.25	0.98	0.02	0.09	1.03
δ_F	degree of indexation in imported-goods markets	Beta	0.70	0.20	0.65	0.21	0.25	0.98	0.03	0.55	1.01
θ_H	degree of inflation persistence in domestic-output markets	Beta	0.50	0.20	0.43	0.07	0.13	0.87	0.01	0.00	1.19
θ_F	degree of inflation persistence in imported-goods markets	Beta	0.50	0.20	0.11	0.04	0.13	0.87	0.01	0.17	1.02
a_1	degree of persistence in foreign inflation	Beta	0.50	0.20	0.92	0.02	0.19	0.96	0.00	0.00	1.02
b_2	degree of persistence in foreign output	Beta	0.50	0.20	0.41	0.11	0.19	0.96	0.00	0.05	1.00
c_3	degree of persistence in foreign interest rate	Beta	0.50	0.20	0.71	0.08	0.19	0.96	0.00	0.02	1.00
ρ_a	degree of persistence in technology shock	Beta	0.50	0.20	0.92	0.03	0.13	0.87	0.00	0.84	1.00
ρ_q,	degree of persistence in risk premium	Beta	0.90	0.20	0.86	0.17	0.23	1.00	0.03	0.54	1.01
ρ_s	degree of persistence in terms of trade	Beta	0.25	0.20	0.39	0.08	0.01	0.73	0.01	0.10	1.02
	Relative Policy Target Weights										
μ_y	output gap stabilisation	Gamma	0.50	0.30	1.14	0.61	0.09	1.24	0.16	0.00	1.43
μ_r	interest rate smoothing	Gamma	0.50	0.30	0.31	0.16	0.09	1.23	0.03	0.00	1.21
	Standard Deviation of Shock Innovations										
σ_H	domestic-output cost-push shock	Inverse Gamma	0.50	0.25	0.78	0.21	0.91	7.36	0.03	0.02	1.03
σ_F	imported-goods cost-push shock	Inverse Gamma	0.50	0.25	10.05	3.31	0.91	7.38	0.87	0.00	1.59
σ_a	technology shock	Inverse Gamma	1.00	0.40	9.23	1.35	0.52	2.66	0.27	0.00	1.15
σ_q	risk premium shock	Inverse Gamma	2.00	0.50	1.01	0.42	0.32	0.88	0.07	0.00	1.12
σ_s	terms of trade shock	Inverse Gamma	1.00	0.40	24.58	0.39	0.52	2.66	0.05	0.13	1.02
$\sigma_{\pi*}$	foreign inflation shock	Inverse Gamma	1.00	0.40	0.45	0.08	0.52	2.66	0.00	0.62	1.00
σ_{y*}	foreign output shock	Inverse Gamma	1.00	0.40	1.25	0.14	0.52	2.65	0.01	0.02	1.01
σ_{r*}	foreign interest rate shock	Inverse Gamma	1.00	0.40	0.40	0.14	0.52	2.66	0.00	0.52	1.00
σ_r	interest rate shock	Inverse Gamma	1.00	0.40	0.28	0.05	0.52	2.66	0.00	0.37	1.00

Table A.3: **Prior and Posterior Parameter estimates for Ghana under CAM and a restricted Model($\mu_q = 0$).** The prior means and standard deviations as well as the distributions remain the same as in Section 4.4 and therefore not repeated in the Appendix tables.

Ghana - Posterior parameters and convergence diagnostics ($mu_q = 0$)

Parameters	Post Mean	Post SD	2.5%	97.5%	NSE(8%)	p-value	B-GF
h	0.538	0.110	0.194	0.932	0.015	0.506	1.005
σ	1.989	0.393	0.272	2.193	0.099	0.000	1.440
ϕ	1.480	0.249	1.051	2.028	0.011	0.792	1.000
η	0.180	0.041	0.272	2.194	0.003	0.457	1.002
δ_H	0.241	0.059	0.253	0.980	0.007	0.001	1.067
δ_F	0.222	0.066	0.254	0.980	0.007	0.000	1.089
θ_H	0.842	0.024	0.130	0.870	0.002	0.896	1.000
θ_F	0.745	0.037	0.129	0.871	0.004	0.575	1.002
a_1	0.663	0.116	0.188	0.961	0.020	0.441	1.008
b_2	0.396	0.097	0.188	0.961	0.004	0.002	1.012
c_3	0.636	0.123	0.188	0.963	0.008	0.755	1.000
ρ_a	0.980	0.006	0.129	0.871	0.001	0.223	1.012
ρ_q	0.980	0.043	0.236	1.000	0.006	0.151	1.019
ρ_s	0.986	0.008	0.007	0.725	0.000	0.220	1.003
μ_y	0.178	0.103	0.094	1.239	0.021	0.000	1.251
μ_r	0.168	0.135	0.095	1.235	0.029	0.024	1.080
σ_H	1.922	0.420	0.913	7.364	0.076	0.000	1.161
σ_F	11.941	2.714	0.911	7.343	0.708	0.000	1.728
σ_a	23.496	1.197	0.520	2.652	0.260	0.649	1.004
σ_q	0.743	0.183	0.323	0.875	0.015	0.115	1.011
σ_s	13.308	1.169	0.520	2.665	0.284	0.000	1.735
$\sigma_{\pi *}$	0.269	0.034	0.520	2.655	0.001	0.895	1.000
$\sigma_{y *}$	1.171	0.122	0.521	2.657	0.006	0.457	1.001
$\sigma_{r *}$	0.205	0.024	0.520	2.652	0.001	0.734	1.000
σ_r	0.326	0.047	0.520	2.659	0.006	0.034	1.028

Table A.4: **Posterior parameters and convergence diagnostics, assuming IAM under a restricted model for Ghana**. The prior means and standard deviations as well as the distributions remain the same as in Section 4.4 and therefore not repeated in the Appendix tables.

South Africa - Posterior parameters and convergencce diagnostics ($mu_q > 0$)

Parameters	Post Mean	Post SD	2.5%	97.5%	NSE(8%)	p-value	B-GF
h	0.95	0.03	0.19	0.93	0.00	0.01	1.03
σ	1.25	0.32	0.27	2.19	0.07	0.01	1.11
ϕ	1.58	0.26	1.05	2.03	0.01	0.75	1.00
η	0.23	0.08	0.27	2.19	0.00	0.00	1.01
δ_H	0.63	0.20	0.25	0.98	0.03	0.98	1.00
δ_F	0.68	0.17	0.25	0.98	0.02	0.61	1.00
θ_H	0.17	0.05	0.13	0.87	0.00	0.50	1.00
θ_F	0.09	0.02	0.13	0.87	0.00	0.05	1.02
a_1	0.94	0.01	0.19	0.96	0.00	0.62	1.00
b_2	0.42	0.11	0.19	0.96	0.00	0.17	1.00
c_3	0.78	0.07	0.19	0.96	0.00	0.53	1.00
ρ_a	0.73	0.08	0.13	0.87	0.01	0.23	1.01
ρ_q	0.85	0.23	0.24	1.00	0.05	0.00	1.17
ρ_s	0.13	0.06	0.01	0.72	0.00	0.48	1.00
μ_q	0.06	0.05	0.09	1.24	0.00	0.31	1.01
μ_y	0.41	0.24	0.09	1.24	0.04	0.01	1.10
μ_r	0.64	0.24	0.09	1.24	0.04	0.25	1.02
σ_H	1.65	0.36	0.91	7.35	0.02	0.66	1.00
σ_F	1.19	0.70	0.91	7.35	0.09	0.04	1.04
σ_a	14.59	1.61	0.52	2.66	0.37	0.00	1.18
σ_q	5.87	1.27	0.32	0.87	0.23	0.04	1.06
σ_s	24.88	0.11	0.52	2.65	0.00	0.87	1.00
$\sigma_{\pi*}$	0.61	0.11	0.52	2.67	0.00	0.56	1.00
σ_{y*}	1.26	0.14	0.52	2.66	0.00	0.94	1.00
σ_{r*}	0.38	0.06	0.52	2.65	0.00	0.65	1.00
σ_r	0.27	0.05	0.52	2.66	0.00	0.10	1.00

Table A.5: **Posterior Parameters and Convergence Diagnostics, assuming CAM and an unrestricted model for South Africa**. The prior means and standard deviations as well as the distributions remain the same as in Section 4.4 and therefore not repeated in the Appendix tables.

South Africa - Posterior parameters and convergence diagnostics ($mu_q > 0$)

Parameters	Post Mean	Post SD	2.5%	97.5%	NSE(8%)	p-value	B-GF
h	0.651	0.060	0.195	0.933	0.015	0.003	1.154
σ	0.854	0.053	0.272	2.194	0.013	0.002	1.153
ϕ	1.512	0.289	1.050	2.029	0.056	0.000	1.208
η	0.434	0.005	0.272	2.193	0.001	0.004	1.122
δ_H	0.904	0.016	0.252	0.980	0.002	0.941	1.000
δ_F	0.783	0.094	0.254	0.980	0.025	0.000	1.599
θ_H	0.921	0.011	0.129	0.871	0.002	0.000	1.289
θ_F	0.426	0.024	0.129	0.871	0.004	0.000	1.162
a_1	0.912	0.029	0.188	0.963	0.005	0.070	1.050
b_2	0.423	0.094	0.188	0.962	0.018	0.586	1.004
c_3	0.575	0.106	0.188	0.962	0.019	0.762	1.001
ρ_a	0.512	0.025	0.128	0.871	0.005	0.101	1.040
ρ_q	0.999	0.004	0.234	1.000	0.000	0.072	1.024
ρ_s	0.270	0.086	0.007	0.724	0.022	0.018	1.100
μ_q	0.038	0.017	0.094	1.237	0.003	0.070	1.048
μ_y	0.037	0.017	0.095	1.236	0.003	0.790	1.001
μ_r	0.173	0.096	0.094	1.235	0.024	0.468	1.010
σ_H	10.188	0.696	0.916	7.323	0.177	0.000	1.298
σ_F	5.264	1.234	0.912	7.370	0.330	0.000	1.703
σ_a	13.810	0.353	0.521	2.662	0.090	0.008	1.121
σ_q	0.589	0.105	0.323	0.876	0.018	0.058	1.048
σ_s	11.195	0.186	0.520	2.657	0.040	0.583	1.005
$\sigma_{\pi*}$	0.235	0.029	0.519	2.656	0.005	0.442	1.006
σ_{y*}	1.159	0.091	0.520	2.657	0.014	0.389	1.009
σ_{r*}	0.206	0.021	0.520	2.659	0.002	0.408	1.004
σ_r	0.302	0.034	0.520	2.666	0.005	0.824	1.000

Table A.6: **Posterior Parameters and Convergence Diagnostics under the assumption of IAM and an unrestricted Model ($\mu_q > 0$) for South Africa**. The prior means and standard deviations as well as the distributions remain the same as in Section 4.4 and therefore not repeated in the Appendix tables.

South Africa - Posterior parameters and convergencce diagnostics (mu_q=0)

Parameters	Post Mean	Post SD	2.5%	97.5%	NSE(8%)	p-value	B-GF
h	0.92	0.07	0.19	0.93	0.01	0.14	1.02
σ	1.78	0.52	0.27	2.19	0.13	0.00	1.33
ϕ	1.54	0.25	1.05	2.03	0.01	0.04	1.00
η	0.22	0.08	0.27	2.19	0.00	0.00	1.02
δ_H	0.50	0.22	0.25	0.98	0.04	0.45	1.01
δ_F	0.61	0.20	0.25	0.98	0.03	0.55	1.00
θ_H	0.21	0.06	0.13	0.87	0.01	0.51	1.00
θ_F	0.10	0.03	0.13	0.87	0.00	0.48	1.00
a_1	0.94	0.01	0.19	0.96	0.00	0.00	1.02
b_2	0.42	0.11	0.19	0.96	0.00	0.03	1.00
c_3	0.79	0.07	0.19	0.96	0.00	0.32	1.00
ρ_a	0.78	0.09	0.13	0.87	0.01	0.10	1.02
ρ_q	0.71	0.25	0.24	1.00	0.06	0.86	1.00
ρ_s	0.14	0.06	0.01	0.72	0.00	0.48	1.00
μ_y	0.51	0.31	0.09	1.24	0.07	0.00	1.34
μ_r	0.31	0.15	0.09	1.23	0.02	0.62	1.00
σ_H	1.55	0.46	0.91	7.33	0.07	0.01	1.07
σ_F	1.26	0.75	0.91	7.35	0.13	0.00	1.12
σ_a	14.26	2.01	0.52	2.66	0.44	0.14	1.04
σ_q	5.57	0.97	0.32	0.88	0.14	0.38	1.01
σ_s	24.88	0.11	0.52	2.66	0.00	0.59	1.00
$\sigma_{\pi*}$	0.58	0.10	0.52	2.65	0.01	0.00	1.03
σ_{y*}	1.26	0.14	0.52	2.66	0.01	0.01	1.01
σ_{r*}	0.38	0.06	0.52	2.66	0.00	0.69	1.00
σ_r	0.27	0.05	0.52	2.65	0.00	0.26	1.00

Table A.7: **Posterior Parameters and Convergence Diagnostics, under the Assumption of CAM and $\mu_q = 0$: South Africa**. The prior means and standard deviations as well as the distributions remain the same as in Section 4.4 and therefore not repeated in the Appendix tables.

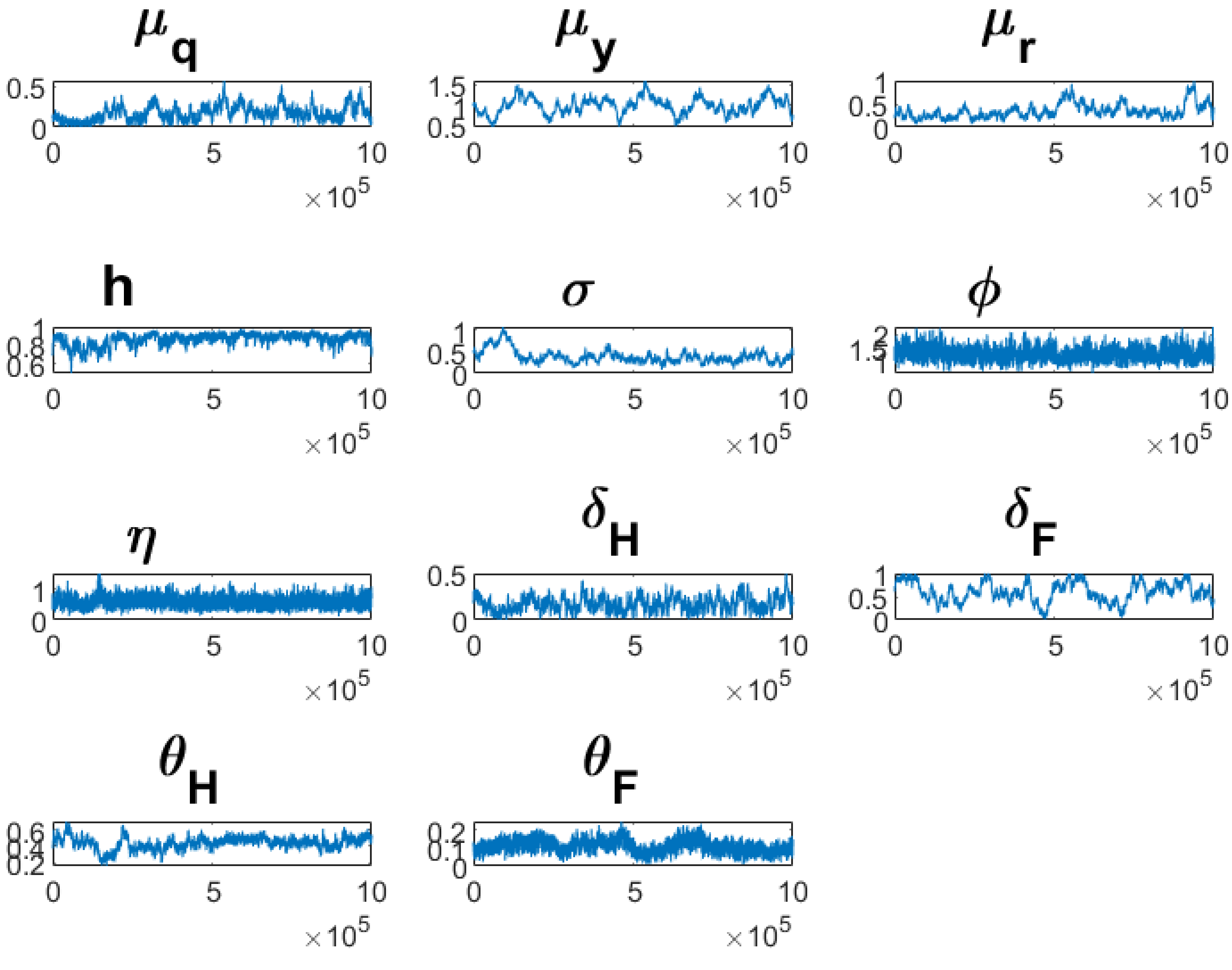

Figure A.19: Distribution of Deep Parameters Over One Million draws for Ghana.

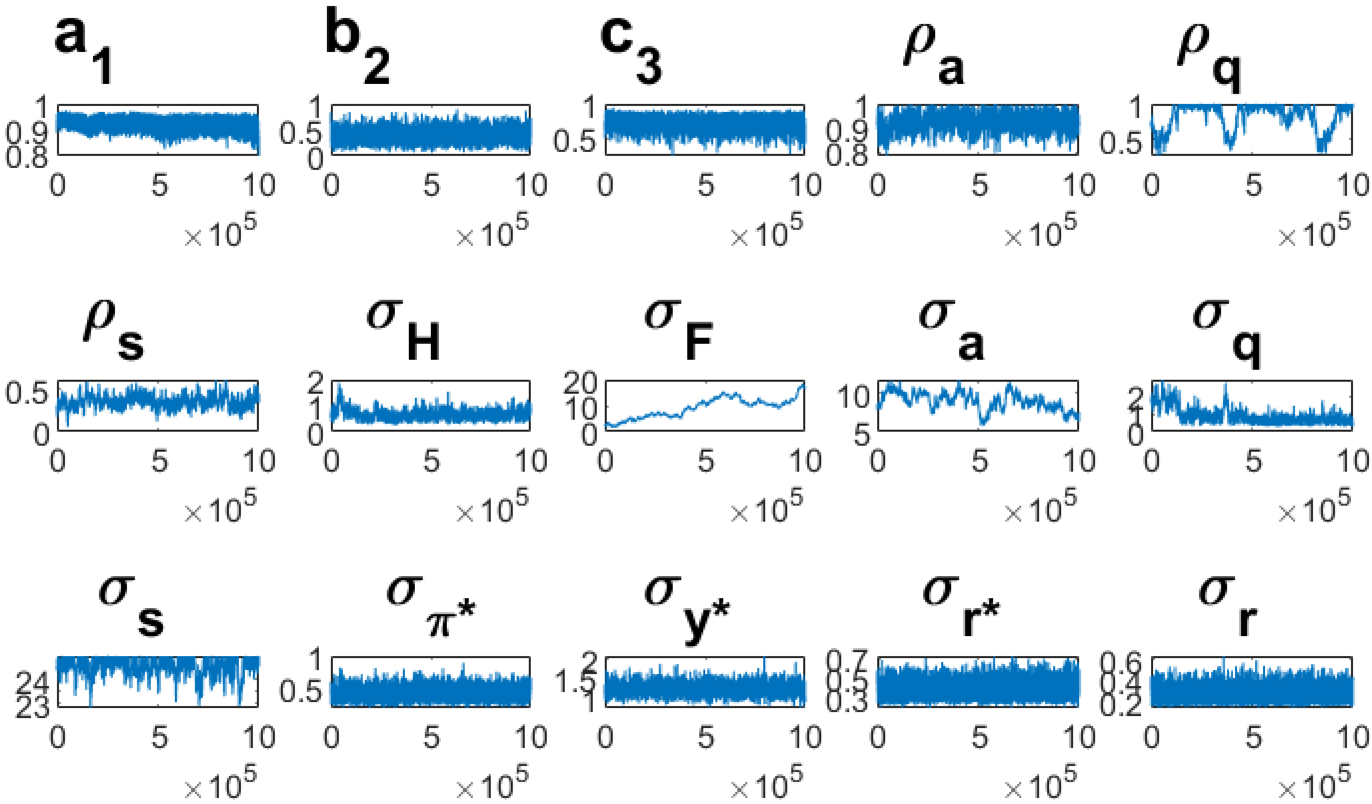

Figure A.20: Distribution of Exogenous Parameters Over One million draws for Ghana.

Category	**Country**	**Period**	μ_π	μ_y	μ_r	μ_q
Advance SOE	Australia	1990Q1-2005Q3	49%	20%	30%	0%
Advance SOE	Canada	1990Q1-2005Q3	50%	8%	42%	0%
Advance SOE	New Zealand	1990Q1-2005Q3	47%	13%	40%	0%
LAIT	Brazil	2009Q1-2021Q4	39%	28%	21%	12%
LAIT	Chile	2009Q1-2021Q4	38%	6%	44%	12%
LAIT	Columbia	2009Q1-2021Q4	53%	23%	19%	5%
LAIT	Mexico	2009Q1-2021Q4	63%	6%	27%	4%
LAIT	Peru	2009Q1-2021Q4	39%	24%	33%	4%

Table A.8: Estimated Policy Weights from Previous Studies for the Advance SOEs and LAITs