The Drivers of Inflation Dynamics during the Pandemic in Rwanda: Evidence from Disaggregated Consumption Data

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Abstract

This research seeks to examine the behavior and/or dynamics of inflation during the pandemic, using monthly disaggregated consumption data for Rwanda covering the period 2005 to 2021. This article specifically examines the dynamics of inflation during the pandemic and the effect of consumption on these patterns. The study used the Sum of Autoregressive Coefficients (SARC), estimated using the ADF method as in Andrews and Chen (1994) as well as the Grid bootstrap method as in Hansen (1999), to measure inflation persistence. Inflation persistence helps to show how the pandemic shock affects different components of CPI and overall inflation and how long it takes for this shock to dissipate. The results show that inflation persistence before the pandemic is generally high compared to inflation persistence during the COVID-19 pandemic. However, the persistence of headline inflation is higher compared to other groups of inflation, mainly driven by the persistence of inflation for volatile CPI components. Thus, the Central Bank should always monitor movements in the inflation of these volatile components, especially during shocks similar to the pandemic.

Keywords: COVID-19 Pandemic, Inflation, Consumption, Inflation Persistence

JEL Classification: E32, E31, E21

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1 Introduction

The COVID-19 pandemic had far-reaching effects on human life and economic development in general. By 2022, globally, more than 480.9 million cases and 6.06 million deaths had been recorded (Ritchie et al., 2022). Though the pandemic has generally stopped, the world is still grappling with its effects, compounded by the recent emergence of new COVID-19 variants in China. The pandemic not only devastated the health sector but also led to economic recessions across the world. An estimated 31 million people were pushed into poverty around the world, of which more than 26 million are from sub-Saharan Africa, including Rwanda, and this number could even be as high as 62 million people (Lakner et al., 2021).

The pandemic and its collateral impacts negatively affected a majority of economies as supply chain disruptions from the pandemic resulted into a rise in consumer demand, and higher commodity costs, which altogether pushed inflation upwards in several countries (World Economic Forum, 2022). Inflation, which had been consistently low for a while prior to the pandemic, fluctuated drastically, having a significant impact on the economies and momentarily lowering prices. Not only that, but also in 2021, as the economic recovery accelerated, inflation increased above levels seen prior to the pandemic. The supply shocks have been propagating within the other sectors of the value chain, which also created a decline in aggregate demand of the households due to a rise in precautionary savings resulting from uncertainty. Moreover, households and firms were forced to reduce private spending and employment, respectively, due to a shortage in money balances (IMF, 2021).

From a transmission point of view, households' increased consumption stimulates demand. That increased demand often leads to businesses raising their prices [1]. Hence, increased consumption can push prices upward. Cavallo (2023) shows that during COVID-19 changes in expenditure patterns (demand behaviors of households) distorted the inflation dynamics because some consumer goods became more important than others. In this case, the underlying patterns of inflation can become complex to be measured from the general indices, which can pose serious risks to monetary authorities and policymakers. Consequently, there is a need for empirical research that bases on disaggregated consumption data in order to understand the clear dynamics of inflation levels because it improves the clarity in the drivers of inflation dynamics (Lunnemann & Mathä, 2004).

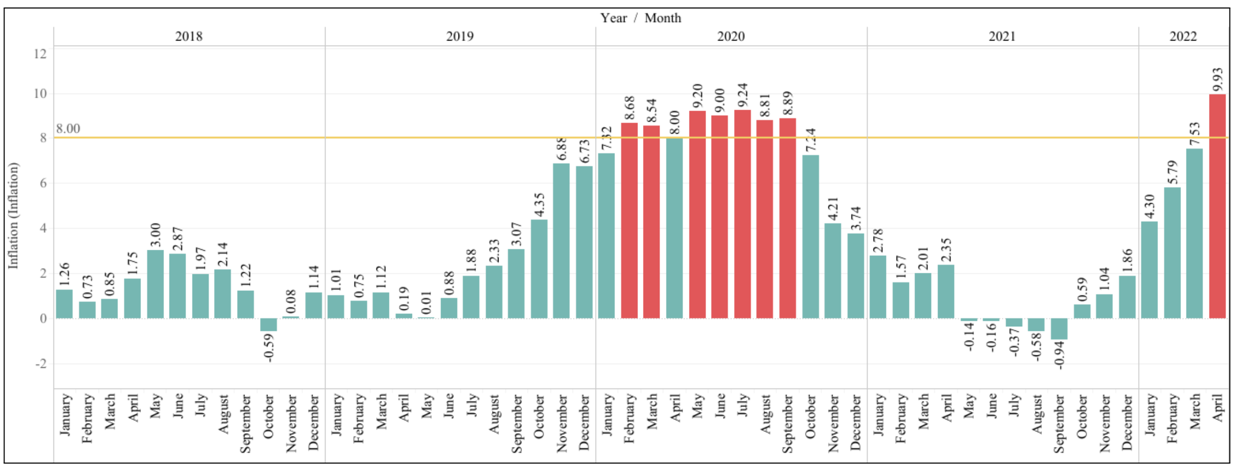
In 2020, Rwanda had a negative Gross Domestic Product (GDP) growth rate of 3.4% below zero (i.e., -3.4%) from a 9.5% growth rate in 2019. Additionally, there was a decline in households' consumption expenditure from 9% in 2019 to 3% in 2020, however, the consumption rebounded instantly in 2021 to 10% due to recovery in economic activities. Despite the lower levels of output that caused stagnation in economic activities, the average inflation rate of was 7.72% compared to 2.43% from 2019 (NISR, 2020). The negative effects of COVID-19 twisted the behaviors of both consumers and producers, causing inflation to exhibit unusual trends. Existing literature indicates that if inflation increases because aggregate demand keeps rising, stabilization policies can still reach their goals without putting constant recovery measures at risk. On the other hand, when inflation is caused by inadequate aggregate supply, stabilization policies might face possibly costly contradicting choices and diversion within consumption patterns due to excess demand because supply shocks are small contributors and reduce the overall variance of real GDP growth and inflation,

[1] Consumption and inflation are interrelated in the literature; see, for example, Ryngaert (2022) and Coibion et al. (2023)

respectively, compared to demand shocks (Bekaert et al., 2020).

Figure 1 shows the inflation trend in Rwanda on a monthly basis from January 2018 to April 2022. The yellow line shows the upper bound of the inflation target for the National Bank of Rwanda. The year-on-year (y-o-y) inflation was highest in 2020, reaching levels above the upper bound, notably in the months of February (8.68%), March (8.54%), May (9.20%), June (9.00%), August (8.81%), and September (8.89%), with a peak recorded in July (9.24%).

Figure 1: **Rwandan headline inflation (y-o-y)**



Source: *BNR (2022)*

Inflationary pressures recorded in 2020 are deemed to be a combination of the effects of increased demand and supply chain disruptions due to the COVID-19 pandemic (BNR, 2022). During the pandemic, lockdowns led to the closure of several businesses, thus hampering production, which resulted into demand-supply mismatches. The restrictions on movements as well as other containment measures, also negatively impacted production and supply chains and led to an increase in public transport fares. Even though the first case of coronavirus in Rwanda was recorded on March 14th, 2020, by the Rwanda Biomedical Center (RBC) Ndishimye et al (2020), the global supply chain was already under pressure following the rapid spread of COVID-19 after the first case was reported in Wuhan, China, in late 2019. As depicted in figure 1, the year 2021 was characterized by declining inflation. In fact, deflation was recorded throughout the months of May to September. However, inflation picked up again in 2022, with April 2022 recording the highest inflation (9.98%) since 2009. The rapid increase in inflation in 2022 was attributed to the effects of the emergence of the Omicron variant Anghelache et al. (2022). Later, the war between Russia and Ukraine amplified these inflationary pressures Diop and Asongu (2022).

Inflation dynamics were generated from various sources, and there was a growing need to collect data from different sectors to understand what may have had a major influence on inflation dynamics during this period. Thus, this paper uses disaggregated consumption data to study the inflation dynamics and to assess inflation persistence due to the COVID-19 shock. This study will only examine the effect of the COVID pandemic on inflation, where the effect of the Russian-Ukraine war will be controlled for by using a sample excluding the Russia-Ukraine war. The objectives of this study are to examine the drivers of inflation dynamics during the pandemic and analyze the effect of consumption on the dynamics of inflation. The stated research objectives will be achieved by using the Sum of Autoregressive Coefficients (SARC) and the Grid Bootstrap methodologies, which will be applied to data for the Rwandan economy covering the period January 2005 to December 2021. To the best of our knowledge, this is the first study to have used the SARC and Grid Bootstrap methods in the scope of the Rwandan economy to try to examine the dynamics of inflation during the pandemic using disaggregated consumption data.

Apart from the general background given in section 1, the rest of the paper is organized as follows: section 2 discusses the relevant literature on the inflation dynamics and debates throughout the time; section 3 presents the methodological approach, and estimation techniques; section 4 presents the empirical estimations, analysis and findings; while Section 5 provides the conclusion and policy implications.

2 Literature Review

There is scanty literature on the analysis of inflation dynamics for Rwanda using disaggregated consumption data and the underlying shocks that may arise in the economy. For the rest of the World, many economists have studied the behavior of inflation dynamics in the context of shocks as well as the dynamics of different components of inflation. For example, Duca et al. (2021) used the ordered logit and VAR models to reveal that when consumers expect higher inflation in the future, they increase their current spending patterns. This observation is consistent with Acunto et al. (2016), Manasseh et al. (2018) and Sheremirov et al. (2021), However, according to some studies, the effect of inflation expectations on current expenditure varies between durable and non-durable goods (Weber, 1975; Coibion et al., 2019). This explains why inflation projections and inflation expectations are important inputs into monetary policy decisions and why it is important to analyze inflation dynamics using different components of the CPI basket.

Additionally, Cavallo (2023) shows that the effect of inflation may also differ depending on the income of households, whereby during a crisis like COVID-19, low-income households are more likely to suffer from high inflation compared to high-income households. Using Carlson and Parkin (CP), and VAR methods, Soric (2013) found that consumers plan to lower future spending when they experience a shock in both actual and perceived inflation because they feel that inflationary pressures erode away their real income and wealth, which makes them spend-averse. The study also reveals that a change in inflationary expectations motivates consumers to increase their expenditures before the period of inflation takeoff happens.

Ha, Kose and Ohnsorge (2021) applied the Factor-Augmented Vector-Autoregressive (FAVAR) model on monthly data for the 2001-2021 period for a sample of 30 advanced economies and 55 emerging market and developing economies (EMDEs) as well as on quarterly data for the 1970-20 period for up to 35 advanced economies and 52 EMDEs to examine the drivers of the observed inflation dynamics during the pandemic and the likely trajectory in the near-term. They found that expectations play a crucial role in determining inflation during the pandemic where the inflation expectations of the current year would increase the expectations by more than one percent for the following year. Their take is that if inflation expectations are well anchored, it may not warrant any monetary policy response, otherwise tight monetary policy may be necessary. These findings are similar the one by Tenreyro (2020) that it is a crucial to anchor inflation expectations to ensure price stability. Indeed, inflation expectations have been cited to be an important driver of inflation persistence (Vijlder, 2022).

Regarding the measurement of the inflation persistence on disaggregated data, Clark(2006), used the Sum of Autoregressive Coefficients (SARC) of the consumer price indices from 1984 to 2002. His findings indicated that, unlike other similar studies, the differences in inflation persistence between durable goods, nondurable goods, and services seem to not be substantially changing just like in the case of non-housing inflation, compared to overall inflation.

Phiri (2012) investigated how the threshold levels of inflation can affect its persistence in South Africa on monthly data from February 2000 to December 2010. Using threshold autoregressive roots (TAR) models and SARC, they found that inflation in headline CPI exhibits the highest persistence in regimes of higher inflation rates, and this is similar for the core inflation which can be persistent to more than a unity when it is between 4.7 and 8.5 percent, whereas it has the lowest SARC if the rate is below 4.7 percent. Phiri (2016) also used monthly inflation from 2003 up to 2016 for the Reserve Bank of South Africa (SARB) to study the effect of financial crisis on inflation. He used the univariate autoregressive model and estimated the persistence level of inflation using SARC [2]. Disaggregating inflation into 5 main sub-components (total CPI of memorandum item, administrative prices, total, goods and services), he found that the persistence was higher before the crisis but significantly lower in periods subsequent to the financial crisis. However, Phiri (2016) does not mention the persistence during the financial crisis itself [3].

Anguyo et al. (2020) investigated the inflation persistence in both headline and core inflation in the Ugandan consumer prices using monthly and quarterly data from 1993 to 2015 for headline inflation and 1998 to 2015 for core inflation. The research uses quantile regression approach [4]. Results reveal that the inflation rate is not characterized by a unit root, which implies that the effect of the shocks dies out over time and the inflation returns to its long-run value.

[2] He disaggregated the series of the inflation into five (5) main categories

[3] He did not construct any sample that exclusively takes into account the period of financial crisis.

[4] This research uses full sample and subsamples for both the headline and core inflation based on structural breaks from the series

Author	Period	Underpinning Theories	Methodology/Estimation Techniques	Variables of interest	Key Findings
Knotek II, E. S., Zaman, S. (2017)	1999 - 2017	Phillips Curve	Time-Varying Parameter -VAR with Stochastic Volatility	Inflation, Unemployment	Reduction in inflation persistence level
Paya, I.Duarte, A., Holden, K. (2007)	1947 - 2005	Temporal Aggregation	Cumulative Impulse Response (CIR)	Inflation (CPI, PCE)	Lower frequency time-series implies higher inflation persistence.
De Soyres, F., Franco, S. (2019)	1970 - 2017	Market Size, Trade, and Productivity	Correlation regressions with Fixed Effects	Inflation (CPI), GDP Deflator, Global Value Chains (Trade Flows)	High level of correlation between production linkages and inflation.
Coleman, S. (2010)	1989 - 2002	Optimum Currency Area, Aggregation	Fractional Integration	Food and non-food Inflation prices	Some evidence of long memory (persistence) in food and non-food inflation
Nguyen, A. D. M., Dridi, J., Unsal, F. D., Williams, O. H. (2017)	1988 - 2013	Inflation Persistence	Global Vector Autoregressions (GVARs)	CPI, nominal effective exchange rate, broad money, nominal interest rates, real GDP	Domestic demand pressures, global shocks, and shocks to output have played a larger role in driving inflation recently.

Table 1: Literature Summary on Dynamics of Inflation

3 Methodology and Data

3.1 Models for inflation persistence

The reason behind the sum of AR coefficients is that more persistent inflation has a higher sum of autoregressive coefficients (ρ_i). This shows that shocks to the inflation process do not go away quickly and that prices keep more of the initial shock (i.e., persistence). For example, this parameter would show how much of an immediate pandemic shock keeps influencing inflation for a particular sub-component of the CPI basket or of the overall CPI basket, and for how long before the effect of this shock dissipates. This research uses disaggregated consumption data to assess whether, during the pandemic, inflation for some CPI sub-components was more persistent compared to others, relative to the pre-pandemic periods and hence, to indicate which components may have influenced the general inflation persistence. The generic model for inflation persistence can be written as follows:

$$\Delta\pi_t = \alpha + \sum_{i=1}^{q-1} \phi_i \pi_{t-i} + (\rho - 1)\pi_{t-1} + \varepsilon_t \tag{3.1}$$

In equation (3.1), the change in the inflation rate between two periods is expressed as $\Delta\pi_t = \pi_t - \pi_{t-1}$. This equation corresponds to the well-known Augmented Dickey Fuller (ADF) regression suggested by Dickey and Fuller (1979; 1981), which can be used to determine whether a time-series process is stationary [5].

This methodology was justified by Andrews and Chen (1994) as accurate and robust to measure the persistence of inflation. The method was used by various authors to investigate the persistence of headline inflation and of its sub-components, for example, Sheremirov (2021) for the U.S. and Figueiredo and Machado (2017) for Brazil.

[5] See also Paya et al. (2007)

Due to the concern of biasness that may arise from OLS estimators in finite/small samples, this research has extended the estimation methodology by using the mean unbiased estimator method proposed by Hansen (1999). This method obtains a mean unbiased estimator of the sum of autoregressive coefficients (SARC), where the lag order is chosen based on AIC/SIC information criterion. The SARC model (3.1) includes the intercept and trend components:

$$\pi_t = \alpha + \beta_t + \rho\pi_{t-1} + \sum_{i=1}^{q-1} \phi_i \Delta\pi_{t-i} + \varepsilon_t \tag{3.2}$$

The full sample (January 2005-December 2021) accounts for all the shocks that happened, such as the 2008 global financial crisis, the increase in international commodity prices (2008 and 2011/12), the decrease in international commodity prices (2015/16), the aid shock (2012/13), the various domestic agricultural shocks, and COVID-19 but excludes the Russian-Ukraine war (2022). We also define sub-samples to try and capture particular shocks: (1) the first sub-sample covers the January 2005 – December 2007 period, and this corresponds to the period before the global financial crisis; (2) the second sub-sample covers the January 2008 – December 2019 period, and this captures the global financial crisis, the fluctuations in international commodity prices, and the aid shock but excludes COVID-19; (3) the third subsample covers the January 2020 – December 2021 period and this caters for the COVID-19 shock but excludes the Russia-Ukraine war shock. Nevertheless, there is a downside in shock identification because the shocks outlined above are not the only ones present in the samples defined in this study, which means that all the shocks that occurred within the time frame of the samples are not fully known even though they may be captured in the empirical estimations.

3.2 Data

To measure and/or assess inflation persistence using the SARC model, we use disaggregated consumption data. The analysis discussed in this chapter relies on month-over-month and year-over-year changes in the twelve (12) major groups of the Consumer Price Index (CPI) and combines these groups to form a headline CPI and a core CPI. This paper was also interested in looking at food inflation and energy inflation as separate groups. The core CPI is the part of the headline CPI that does not include prices of fresh food and energy. The time span is from January 2004 to December 2021, for the inflation groups (216 observations). The year-on-year inflation rates are approximated by multiplying by 100 the difference between the natural logarithm of the CPI for a given month and that of the corresponding month of last year (100*[log difference of the same month of 2 consecutive years]). We use monthly Central Bank Rate (CBR) and CPI data, sourced from the NBR and NISR, respectively. The monthly time-series data is obtained from the BNR (CBR) and NISR (CPI) website. Though CPI data starts in 2004, y-o-y computations imply that we lose the first 12 observations, reducing the sample number of observations from 216 to 204.

4 Findings

4.1 Descriptive Analysis

Before estimation, it is necessary to review the reliability of the sample size. The mean of the headline inflation shows that the mean inflation rate (5.6%) for the whole sample is below the upper bound of the NBR inflation target band (8%). This implies that the NBR managed to keep inflation below the upper bound, at least on average, for the period ranging from January 2005 to December 2021. However, this average value masks a lot of realities since it is affected by outliers. Note that if inflation is persistently high, the NBR can face challenges while trying to stabilize prices. Though average inflation does not show the degree of inflation persistence, it is an indication that shocks to inflation were generally short-lived and the NBR managed to stabilize prices in general, despite the occurrence of such shocks. However, an empirical investigation of inflation persistence is needed.

Variable	**Mean**	**Std. Dev**	**Skewness**	**Kurtosis**	**Jarque-Bera**	**Obs**
Sample			**2005m01 - 2021m12**			
Headline	0.056	0.043	1.175	4.795	74.296** (0.000)	204
Core	0.048	0.040	2.023	7.339	299.229** (0.000)	204
Food	0.068	0.072	0.470	2.886	7.630** (0.022)	204
Energy	0.060	0.064	1.117	2.756	42.935** (0.000)	204
Transport	0.050	0.064	0.366	5.289	49.099** (0.000)	204

Source: Author's calculations. Std. Dev is the abbreviation of Standard Deviation, Obs. stands for the number of observations, JB stands for Jarque-Bera χ^2 statistic. ** Denotes the significance at 5% level. The letter M denotes months.

Table 2: Descriptive Statistics

4.2 Monthly inflation persistence

Using the SARC, we analyze the persistence of inflation for the various CPI components before and after the pandemic. Thereafter, we identify those components that had the biggest influence on the overall inflation persistence during the periods under review. The SARC results are compared to those from a benchmark model, notably the autoregressive (AR) of order 1 (AR(1)).

Table 7 gives the results of the AR(1) model. Note that the SARC model is presented as an AR (p) model and the sum of autoregressive coefficients shows the level of inflation persistence. The variables of interest are: (1) Headline inflation; (2) Core inflation; (3) Food and non-alcoholic beverages inflation, and; (4) Housing, energy, water, and fuel inflation. The results show relatively slight differences between AR(1) and SARC coefficient estimates [6]. The comparison of the AR(1) and the SARC models has been frequently utilized in the literature for the U.S and Euro area, Pakistan and Asia-Pacific, to name a few (Marques, 2004; Tillmann, 2011; Muhamad et al., 2012). As expected, the AR(1) shows higher inflation persistence compared to that

[6] When the component of AR(1) and SARC has a negative sign, the series shows an oscillating behavior. See. Micallef and Ellul (2020)

obtained using the AR(p) model. However, the results from the two models are not fundamentally divergent.

The SARC (i.e. AR(p)) estimations show that the year-on-year headline inflation has the highest level of inflation persistence, standing at 90.8 percent., This means that, ceteris paribus, the weight of headline inflation for the previous 4 months in the current level of headline inflation is 90.8%, after a shock. Alternatively stated, the shock induced inflation dynamics for the past 4 months explain 90.8% of the current level of inflation. In addition, 88.8% of the current core inflation is explained by the inflation dynamics of the previous two months. For the other categories, the persistence of inflation for food and non-alcoholic beverages stands at 90.9%, whereas the inflation for housing, water, electricity, gas, and other fuels is persistent at 91.5%, each with a lag of months. Transport inflation exhibits the least persistence, standing at 84.9%. The high level of inflation persistence for headline inflation, relative to core inflation, confirms the importance of the persistence for food and non-alcoholic beverages and for housing, water, electricity, gas, and other fuels in driving overall inflation persistence/dynamics.

Variable	AR(1)	Lag	AR(p)
	2005m01 - 2021m12		
Headline	0.964543	4	0.908
Core	0.934699	2	0.888
Food	0.946615	2	0.909
Energy	0.919833	2	0.915
Transport	0.902702	2	0.849
SS1	2005m01 - 2007m12		
Headline	0.838505	1	0.834
Core	0.906844	2	0.830
Food	0.915792	2	0.829
Energy	0.961104	1	0.500
Transport	0.603317	1	0.522
SS2	2008m01 - 2019m12		
Headline	0.970240	2	0.933
Core	0.962990	3	0.912
Food	0.950864	2	0.910
Energy	0.906334	1	0.889
Transport	0.953137	3	0.901
SS3	2020m01 - 2021m12		
Headline	0.960139	1	0.750
Core	0.85235	1	0.690
Food	0.959103	1	0.521
Energy	0.841754	1	0.621
Transport	0.834434	1	0.691

Source: Author's calculations. "p" denotes the lag length order obtained using Schwartz Information Criterion (SIC)

Table 3: Sum of Autoregressive Coefficients (SARC)

The persistence of headline inflation can be relatively higher compared to core inflation due to the continuous persistence of energy and food inflation as can be seen from Table 3. The sub-groups of volatile components may exhibit high persistence after the shocks and this may cause what Cevik (2022) calls the aggregation effect, given that headline CPI is a weighted sum of the components. This is an indication that high inflation persistence in non-core components has an effect in the dynamics of headline inflation and must therefore be monitored by monetary authorities. Walsh (2011) argued that the importance of non-core CPI components in influencing inflation dynamics is more pronounced in developing economies where food prices are more volatile and persistent from shocks. Hence, the monetary policy decisions in developing countries should be tailored to such challenges, especially by mitigating second-round effects.

The AR(p) model estimations discussed were obtained using the Augmented Dickey Fuller (ADF) Method, which has been criticized on grounds that its OLS estimations tend to be biased, especially in finite samples (O'Reilly & Whelan, 2005; Capistrán & Ramos-Francia, 2009; Tillmann, 2011). For robustness check, we do the re-estimations using the Hansen Bootstrap method developed by Hansen (1999). This method obtains bootstrapped confidence intervals for an estimator of the sum of autoregressive coefficients (SARC) where the lag order (p) is chosen based on the SIC information criterion. Table 3 displays the SARC estimates based on Hansen (1999)'s grid bootstrap method:

Variable	SARC($\hat{\rho}$)	S. Err.	Confidence Interval
		2005m01 - 2021m12	
Headline	0.911513	0.021045	[0.887355, 0.965449]
Core	0.960514	0.015895	[0.949244, 1.011454]
Food	0.912941	0.022683	[0.888747, 0.974762]
Energy	0.911755	0.034888	[0.885870, 1.024283]
Transport	0.867485	0.030824	[0.835303, 0.943243]
SS1		**2005m01 - 2007m12**	
Headline	0.837207	0.094951	[0.807752, 1.126338]
Core	0.875963	0.071358	[0.865584, 1.117279]
Food	0.851445	0.066609	[0.806250, 1.064616]
Energy	0.500845	0.213428	[0.346369, 1.197065]
Transport	0.599216	0.139564	[0.478852, 1.087589]
SS2		**2008m01 - 2019m12**	
Headline	0.943861	0.023627	[0.926858, 1.018050]
Core	0.951952	0.016028	[0.937443, 1.007668]
Food	0.912089	0.027968	[0.884986, 1.011696]
Energy	0.898310	0.035930	[0.868064, 1.020376]
Transport	0.904344	0.023973	[0.878529, 0.968176]
SS3		**2020m01 - 2021m12**	
Headline	0.803864	0.145190	[0.760280, 1.214711]
Core	0.764000	0.147817	[0.717903, 1.204679]
Food	0.657341	0.182609	[0.542835, 1.203493]
Energy	0.521053	0.146436	[0.369634, 1.091886]
Transport	0.739492	0.148096	[0.674396, 1.198139]

Source: Author's calculations. [ ] denotes confidence interval brackets.

Table 4: Hansen's Grid Bootstrap

The table 4 above shows Hansen's (1999) median unbiased estimator of the sum of autoregressive coefficients and the bootstrapped 90% confidence bands based on 200 grid points and 1,999 replications to obtain bias-corrected confidence intervals for finite-sample OLS estimators. The interpretation of inflation persistence is based on the definition by Marques (2004) as the duration of shocks in inflation. The results show a higher persistence of inflation within the full sample. Both headline and core inflation have an inflation persistence rate of 91.2% and 96.1%, respectively. The remaining subgroups have 91.3%, 91.2%, and 86.7% inflation for food ((i.e., food and non-alcoholic beverages); energy (i.e., housing, water, electricity, gas, and other fuels inflations), and transport inflation), respectively.

The first subsample (SS1) is characterized by relatively high persistence in inflation compared to the period of the pandemic. Inflation persistence is especially higher in SSI for core inflation (87.6%) and food inflation (85.1%) compared to persistence during the pandemic which is 76.4% for core inflation and 65.7% for food inflation. The headline is persistent at 83.7% compared to 80.4% during the pandemic period. The energy and transport inflation exhibit the lowest persistence of 50.1% and 59.9%, respectively. However, the persistence in transport during the pandemic is relatively high (73.9%) compared to the period before the subprime crisis mainly due to shortage in transport [7] means during this period. (BNR, 2020)

The second sub-sample (SS2), exhibits more persistent inflation compared to other sub-samples other than the full sample. As stressed by Karangwa and Mwenese (2015), and Karangwa (2017), this period included various shocks, such as the demand shock (2009), the rise international commodity prices (2008 and 2011), and the aid shock (2012 – 13). These cumulative shocks caused delayed readjustment of prices, hence making inflation to be more persistent.

The third sub-sample SS3 captures the COVID-19 pandemic that broke out at the end of 2019. Estimation results show that SS3 exhibits the lowest persistence in headline and core inflation compared to other sub-samples. However, estimations for SS3 show that headline inflation is relatively more persistence (80.4%) than any other components mainly due to the supply chain disruptions caused by the coronavirus pandemic alongside with poor agricultural performance recorded in 2020 (where food inflation persistence is 65.7%) [8]. The core inflation also exhibits the lowest persistence in SS3 unlike in other sub-samples (and also in the full sample), implying that the effect of the pandemic shock to inflation was transitory.

In general, the dynamics of inflation during the pandemic does show characteristics of lower persistence where there is evidence from the results that the coefficients of SARC during the pandemic are lower compared to other samples. Paying special attention to SS3, the results show that persistence for all inflation groups drops relative to that from the other sub-samples. For example, compared to SS2 (2008-2019), inflation persistence for SS3 (2020-2021) drops, where the persistence in headline inflation falls by 10% from 94.4% to 80.4% percent; core inflation persistence drops by 18.8% from 95.2% to 76.4%; food inflation persistence drops by 25.5% from 91.2% to 65.7% percent, energy inflation persistence drops by 37.7% from 89.9 to 52.1 percent, while transport inflation persistence slightly declined from 90.4% to 73.9% which is the least among other subcomponents. Compared to SS1 (2005-2007), inflation persistence for SS3 (2020-2021) drops in the aggregate components (headline and core inflation). The persistence in headline inflation falls by 3.3% from 83.7% to 80.4%; core inflation persistence drops by 11.2% from 87.6% to 76.4%, food inflation persistence drops by 19.4% from 85.1% to 65.7%. Contrary, energy inflation persistence slightly increases by 2.0% from 50.1% to 52.1%, while transport inflation persistence increases from 59.9% to 73.9%.

These results show that the shocks from the pandemic were significantly transitory compared to other periods,

[7] Transport fees were revised downward in October 2020.

[8] Despite lower persistence in food inflation, the cumulative effects of this poor performance and supply chain disruption may significantly affect headline inflation.

implying that the shocks from the pandemic did not last longer, hence faster readjustments in prices during this period. These results also have an implication on how the monetary policy should respond; if the persistence in inflation is not large, monetary policy may not always choose to tighten since the price shocks are transitory and are probably going to remain for a relatively short time and dissipate onwards. However, this research gives evidence that accumulation of shocks in inflation may contribute to the persistence of inflation.

4.3 Robustness Check

This research carried out some robustness checks to understand how inflation persistence estimates would reflect the actual inflation for the whole period. The approach compares fitted values for the sample sizes set for the model using persistence coefficients and compare differences among those samples. The first test looks at the differences between estimation techniques, namely the ADF SARC and the Hansen's Grid Bootstrap to understand the differences between the estimates.

In the perspective of sample differences, the figures 9-13 in the appendix reveals that the divergences between estimates among the sample of 2005 – 2021 and sub-sample 2008 – 2019 are relatively closer compared to the estimates in the remaining sub-samples (i.e., 2005 – 2007 and 2020 – 2021). Maxwell, Kelly and Rausch (2008) emphasized the importance of sample size in the accuracy of the parameter estimates; this is confirmed by the large standard errors in small sizes and wide confidence intervals compared to the larger sample sizes.

From the perspective of inflation components, the estimates of Grid Bootstrap and SARC are closer in aggregate components than in individual components. For example, the components of energy and transport inflation have large differences in estimates for the sample of 2005 – 2007 with a difference of roughly 30% and 20%, respectively. Despite those differences, generally, the Grid Bootstrap and SARC are closer and generate consistent estimates among both aggregate and components of the inflation.

This paper calculated the differences between estimates and actual values using the popular measures of Root Mean Squared Errors (RMSE) [9] and Mean Absolute Errors (MAE) [10]. Despite that the sample size playing a big role in error minimization, it is not totally the case for all samples because the estimates of period 2008 – 2019 minimizes the errors compared to other samples and is followed by 2005 – 2021, 2005 – 2007 and finally the Covid-19 sample (2020 – 2021). Moreover, Figure 11 shows that the trends of the absolute values of deviations between estimated values (Grid Bootstrap) show differences among the samples during the pandemic compared to the deviations of other samples of the pre-pandemic period. To wrap up, this study has responded to the research questions as follows: (i) the inflation during the pandemic has shown lower persistence level, (ii) during the pandemic, headline inflation had a relatively high persistence than core inflation, and was influenced by mainly the food prices and global supply chain disruptions.

[9] See figure 13 in the appendix. The RMSE is by definition defined as the square root of the mean variance (squared deviations). i.e., $\sqrt{\frac{\sum_{i=1}^{n}(y-\hat{y})^2}{n}}$

[10] See figure 13 and 14 in the appendix. The MAE is by definition defined as the absolute value of the deviations mean. i.e., $\frac{\sum_{i=1}^{n}|y-\hat{y}|}{n}$

5 Conclusion and Policy Implications

The main objective of this research was to examine the drivers of inflation dynamics during the pandemic based on evidence from disaggregated consumption data for Rwanda. The results of this study adds more clarity in understanding the drivers of inflation dynamics during the pandemic. Results portray the following conclusions. First, the inflation persistence before the pandemic is generally high compared to the inflation persistence during the COVID-19 pandemic. Second, core inflation persistence is high compared to headline inflation in all samples, except during the pandemic period.

Furthermore, all components of inflation show lower persistence during the pandemic period (i.e., SS3) than in other sub-samples, except for transport and energy whose persistence is higher in the 2020m01 - 2021m12 sub-sample compared to the 2005m01 - 2007m12 sub-sample. The persistence in headline inflation for the 2020m01 - 2021m12 sample mainly results from the mixture of supply chain disruptions and persistence in volatile sub-groups of inflation, notably food inflation. Therefore, it is crucial that monetary policy takes decisions by considering both headline and core inflation to avoid biased decisions in case components of food and energy inflation become more persistent as it is evident that headline inflation during the pandemic tends to become relatively more persistent than does the core component due to COVID-19 along with bad agricultural performance.

This research bridges the gap between existing literature by emphasizing the need to use disaggregate data to assess the persistence of inflation for the case of Rwanda and in the context of an economic shock, such as COVID-19. A similar study could be undertaken to capture the Russia-Ukraine war shock and to better identify shocks in each of the sub-samples considered.

References

Andrews, D. W., & Chen, H. Y. (1994). Approximately median-unbiased estimation of autoregressive models. *Journal of Business and Economic Statistics*, *12*, 187-204. doi: 10.1080/07350015.1994.10510007

Anghelache, C., Anghel, M. G., Ștefan Virgil Iacob, Panait, M., Rădulescu, I. G., Brezoi, A. G., & Miron, A. (2022). The effects of health crisis on economic growth, health and movement of population. *Sustainability*, *14*(8), 4613. doi: 10.3390/su14084613

Anguyo, F. L., Gupta, R., & Kotzé, K. (2020). Inflation dynamics in uganda: a quantile regression approach. *Macroeconomics and Finance in Emerging Market Economies*, *13*(2), 161–187.

Bekaert, G., Engstrom, E., & Ermolov, A. (2020, 6). Aggregate demand and aggregate supply effects of covid-19: A real-time analysis. *Finance and Economics Discussion Series*, *2020*. doi: 10.17016/FEDS.2020.049

BNR. (2020). *Monetary policy report, november* (Tech. Rep.). National Bank of Rwanda.

BNR. (2022). *Monetary policy report 2022, august* (Tech. Rep.). National Bank of Rwanda.

Capistrán, C., & Ramos-Francia, M. (2009, 7). Inflation dynamics in latin america. *Contemporary Economic Policy*, *27*, 349-362. doi: 10.1111/J.1465-7287.2008.00128.X

Cavallo, A. (2023). Inflation with covid consumption baskets. *IMF Economic Review*, 1–16.

Cevik, S. (2022, 9). Breaking bad: A disaggregated analysis of inflation inertia. *IMF Working Papers*, *2022*. doi: 10.5089/9798400219689.001.A001

Clark, T. E. (2006). Disaggregate evidence on the persistence of consumer price inflation. *Journal of Applied Econometrics*, *21*(5), 563–587.

Coibion, O., Georgarakos, D., Gorodnichenko, Y., & van Rooij, M. (2019). *How does consumption respond to news about inflation? field evidence from a randomized control trial* (IZA Discussion Papers No. 12498). Institute of Labor Economics (IZA).

Coibion, O., Georgarakos, D., Gorodnichenko, Y., & Van Rooij, M. (2023). How does consumption respond to news about inflation? field evidence from a randomized control trial. *American Economic Journal: Macroeconomics*, *15*(3), 109–152.

Coleman, S. (2010, 3). Inflation persistence in the franc zone: Evidence from disaggregated prices. *Journal of Macroeconomics*, *32*, 426-442. doi: 10.1016/J.JMACRO.2009.08.002

D'Acunto, F., Hoang, D., & Weber, M. (2016). *Unconventional fiscal policy, inflation expectations, and consumption expenditure.* CESifo Working Paper Series.

De Soyres, F., & Franco, S. (2019). Inflation dynamics and global value chains. *World Bank Policy Research Working Paper*(9090).

Dickey, A. D., & Fuller, A. W. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica*, *49*, 1057-1072.

Dickey, D. A., & Fuller, W. A. (1979, 6). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, *74*, 427-431. doi: 10.1080/01621459.1979.10482531

Diop, S., & Asongu, S. A. (2022). The impact of covid-19 and russia-ukraine war on food prices in fragile countries: Misfortunes never come singly.
doi: 10.2139/ssrn.4210418

Duca, I., Kenny, G., & Reuter, A. (2021). Inflation expectations, consumption and the lower bound: Micro evidence from a large euro area survey. *SSRN Electronic Journal*. doi: 10.2139/ssrn.3285079

Figueiredo, F. M. R., & da Gama Machado, V. (2017). Assessing inflation persistence in brazil using disaggregate data. *Banco Central do Brazil*.

Ha, J., Kose, M. A., & Ohnsorge, F. (2021). Inflation during the pandemic: What happened? what is next?

Hansen, B. E. (1999). The grid bootstrap and the autoregressive model. *The Review of Economics and Statistics*, *81*, 594–607. doi: 10.1162/003465399558463

IMF. (2021). *Inflation scares.*

Karangwa, M. (2017). The impact of external shocks on effectiveness of monetary policy in rwanda. *BNR Economic Review*, *10*, 33-59.

Karangwa, M., & Mwenese, B. (2015). The forecasting and policy analysis systems (fpas) macro-model for rwanda. *BNR Economic Review*, *7*, 101-129.

Knotek II, E. S., & Zaman, S. (2017, 11). *Have inflation dynamics changed?* Federal Reserve Bank of Cleveland. Retrieved from `https://www.clevelandfed.org/newsroom-and-events/publications/economic-commentary/2017-economic-commentaries/ec-201721-have-inflation-dynamics-changed`

Lakner, C., Yonzan, N., Mahrer, D. G., Aguilar, C. A., & Wu, H. (2021, 1). *Updated estimates of the impact of covid-19 on global poverty: Looking back at 2020 and the outlook for 2021* (Tech. Rep.). World Bank.

Lunnemann, P., & Mathä, T. Y. (2004). How persistent is disaggregate inflation? an analysis across eu 15 countries and hicp sub-indices. *An Analysis Across EU*, *15*.

Manasseh, C., Okoro, O., Egele, A., Manasseh, C. O., Abada, F. C., Ogbuabor, J. E., ... Okoro, O. E. (2018). The effects of interest and inflation rates on consumption expenditure: Application of consumer spending model. *International Journal of Economics and Financial Issues*, *8*, 32-38.

Marques, C. R. (2004). *Inflation persistence: Facts or artefacts?* (Tech. Rep.). European Central Bank.

Maxwell, S. E., Kelley, K., & Rausch, J. R. (2008, 1). Sample size planning for statistical power and accuracy in parameter estimation. *Annual Review of Psychology*, *59*, 537-563. doi: 10.1146/annurev.psych.59.103006.093735

Micallef, B., & Ellul, R. (2020). How do estimates of inflation persistence in malta compare with other eu countries? *International Journal of Economics and Finance*, *12*(7), 1–31. doi: 10.5539/ijef.v12n7p31

Muhamad, H. N., Jahanzeb, M., & Iqbal, J. (2012). Intrinsic inflation persistence in a developing country intrinsic inflation persistence in a developing country. *Munich Personal RePEc Archive*.

Ndishimye, P., Nkeshimana, M., Hitimana, N., Turatsinze, D., Nahayo, E., Byiringiro, F., ... others (2020). Knowledge, attitudes and preventive practices towards covid-19 among frontline healthcare workers in rwanda. *Rwanda Public Health Bulletin*, *2*(1), 16–21.

Nguyen, A. D., Dridi, J., Unsal, F. D., & Williams, O. H. (2017, 10). On the drivers of inflation in sub-saharan africa. *International Economics*, *151*, 71-84. doi: 10.1016/j.inteco.2017.04.002

NISR. (2020). *Gross domestic product* (Tech. Rep.). National Institute of Statistics of Rwanda.

O'Reilly, G., & Whelan, K. (2005, 11). Has euro-area inflation persistence changed over time? *The Review of Economics and Statistics*, *87*, 709-720. Retrieved from `https://direct.mit.edu/rest/article/87/4/709/57653/Has-Euro-Area-Inflation-Persistence-Changed-Over` doi: 10.1162/003465305775098125

Paya, I., Duarte, A., & Holden, K. (2007). On the relationship between inflation persistence and temporal aggregation. *Source: Journal of Money, Credit and Banking*, *39*, 1521-1531.

Phiri, A. (2012, 7). Threshold effects and inflation persistence in south africa. *Journal of Financial Economic Policy*, *4*, 247-269. doi: 10.1108/17576381211245971

Phiri, A. (2016). *Changes in inflation persistence prior and subsequent to the subprime crisis: What are the implications for south africa?* (Tech. Rep.). Munich Personal RePEc Archive.

Ritchie, H., Mathieu, E., Rodés-Guirao, L., Appel, C., Giattino, C., Ortiz-Ospina, E., ... Roser, M. (2022). *Coronavirus pandemic (covid-19)* (Tech. Rep.). Our World in Data. Retrieved from `https://ourworldindata.org/explorers/coronavirus-data-explorer`

Ryngaert, J. M. (2022). Inflation disasters and consumption. *Journal of Monetary Economics*, *129*, S67–S81.

Sheremirov, V., Bräuning, F., Cooper, D., Garga, V., Olivei, G., Peek, J., ... Tootell, G. (2021). The drivers of inflation dynamics during the pandemic:(early) evidence from disaggregated consumption data. *Current Policy Perspectives, Federal Reserve Bank of Boston*.

Sorić, P. (2013, 12). Assessing the sensitivity of consumption expenditure to inflation sentiment in post-communist economies. *Post-Communist Economies*, *25*, 529-538. doi: 10.1080/14631377.2013.844932

Tenreyro, S. (2020). Monetary policy during pandemics: inflation before, during and after covid-19. *Bank of England*.

Tillmann, P. (2011). Inflation targeting and regional inflation persistence: Evidence from korea. *Pacific Economic Review*, *18*(2), 147–161.

Vijlder, W. D. (2022). *Inflation persistence and why it matters.* BNP Paribas.

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

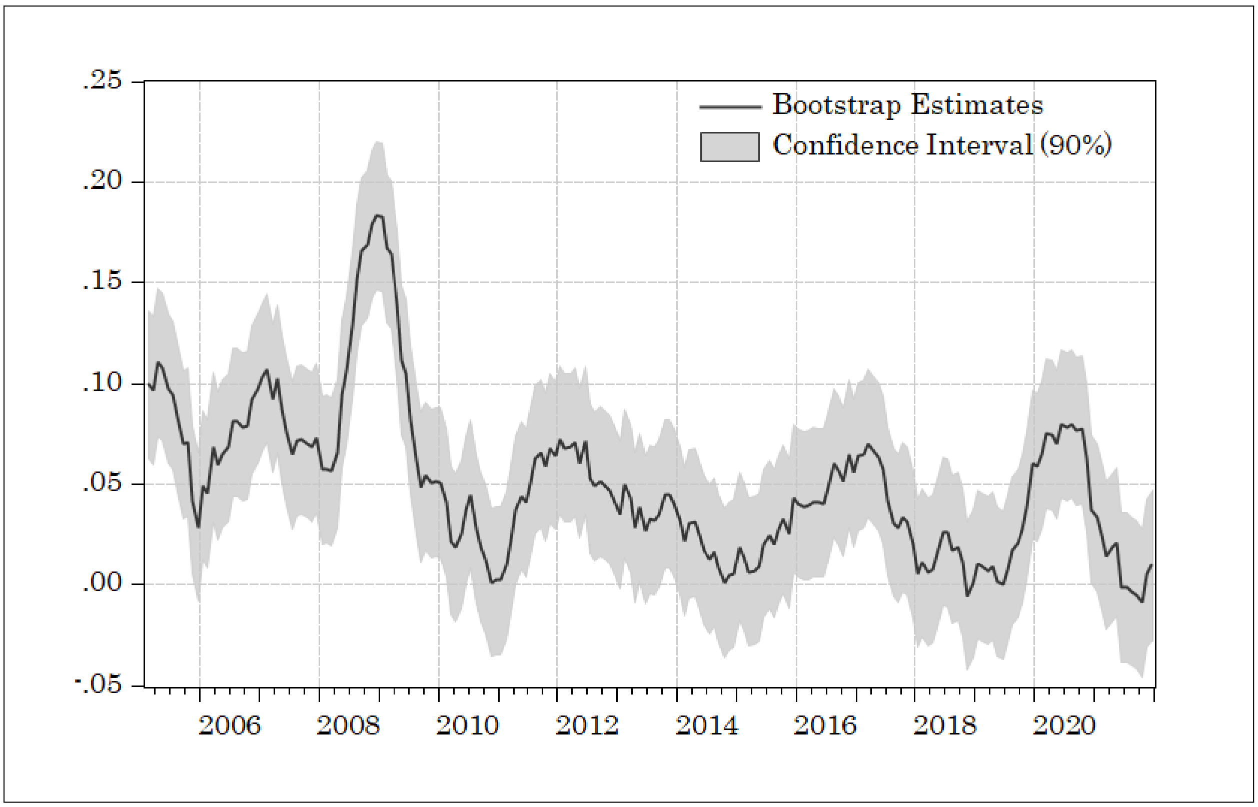
Weber, W. E. (1975). Interest rates, inflation, and consumer expenditures. , *65*, 843-858.

World Economic Forum. (2022). *The global risks report 2022* (17th ed.). World Economic Forum.

Appendices

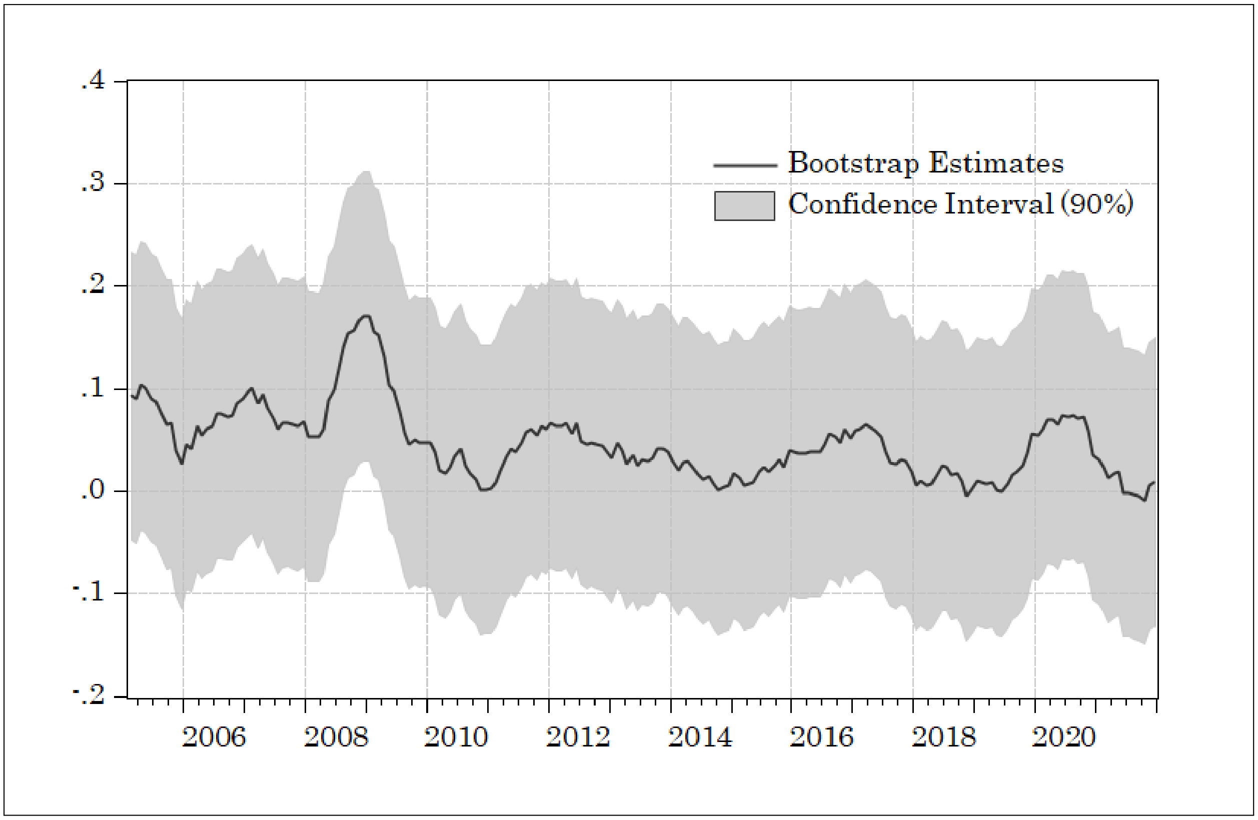
Appendix A Graphs and Charts

Figure 2: **Headline Inflation (fitted) from Hansen (1999) Grid Bootstrap. Grey Area is the Bootstrap Confidence Interval (2005 – 2021).**



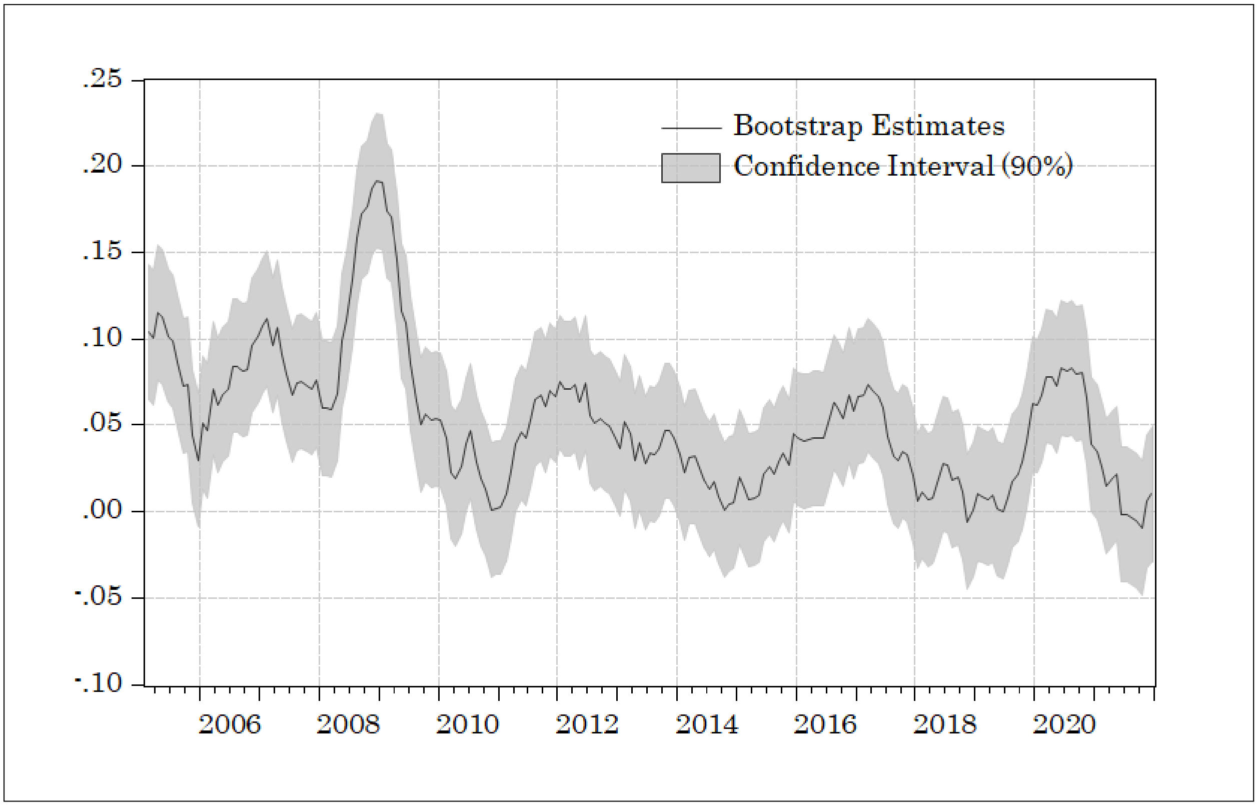
Source: *Author's Calculations*

Figure 3: **Headline Inflation (fitted) from Hansen (1999) Grid Bootstrap. Grey Area is the Bootstrap Confidence Interval (2005 – 2007).**



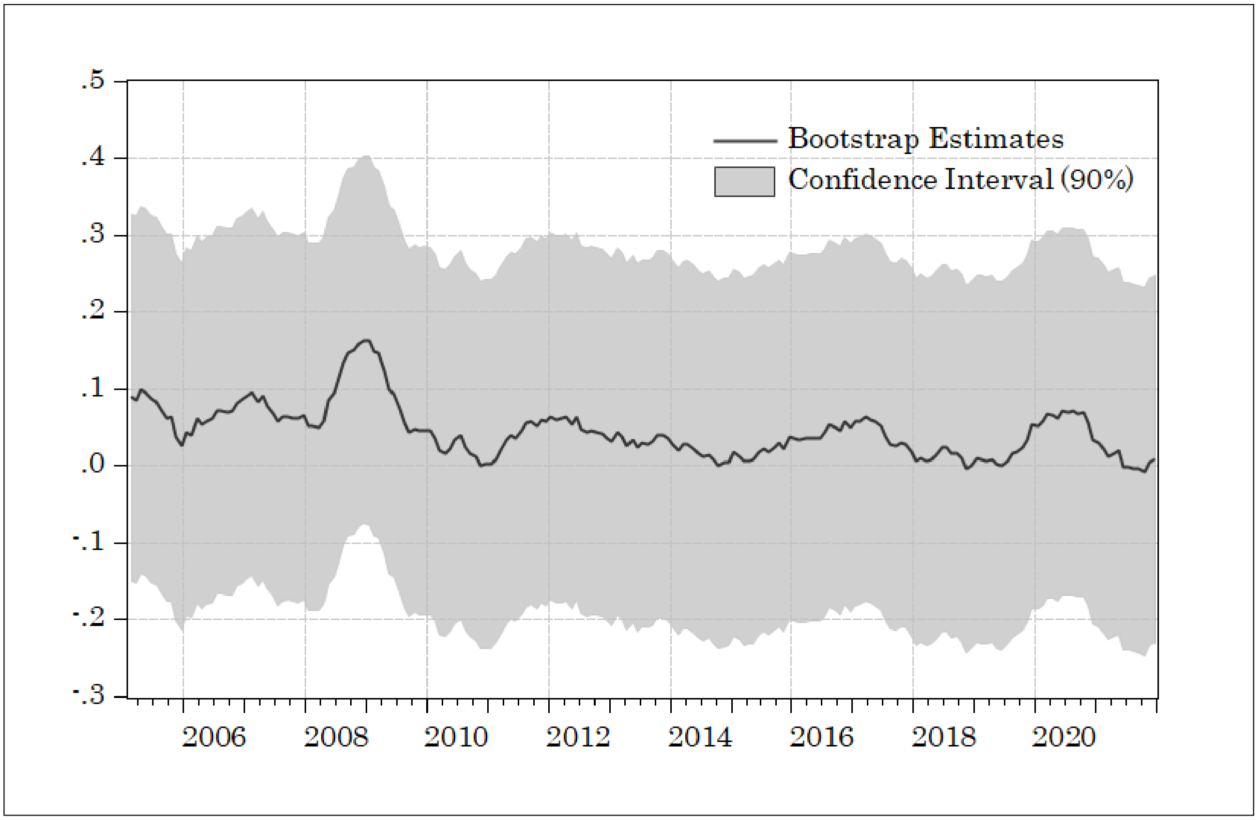
Source: *Author's Calculations*

Figure 4: **Headline Inflation (fitted) from Hansen (1999) Grid Bootstrap. Grey Area is the Bootstrap Confidence Interval (2008 – 2019).**



Source: *Author's Calculations*

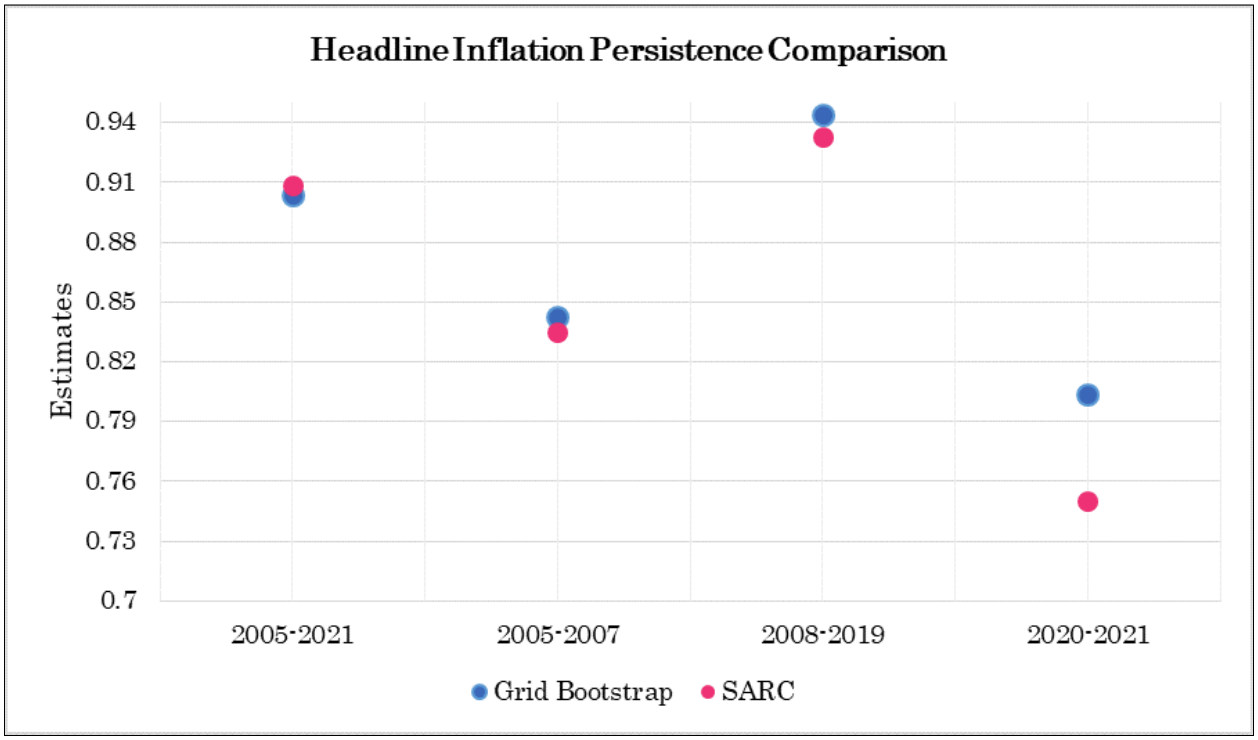
Figure 5: **Headline Inflation (fitted) from Hansen (1999) Grid Bootstrap. Grey Area is the Bootstrap Confidence Interval (2020 – 2021).**



Source: *Author's Calculations*

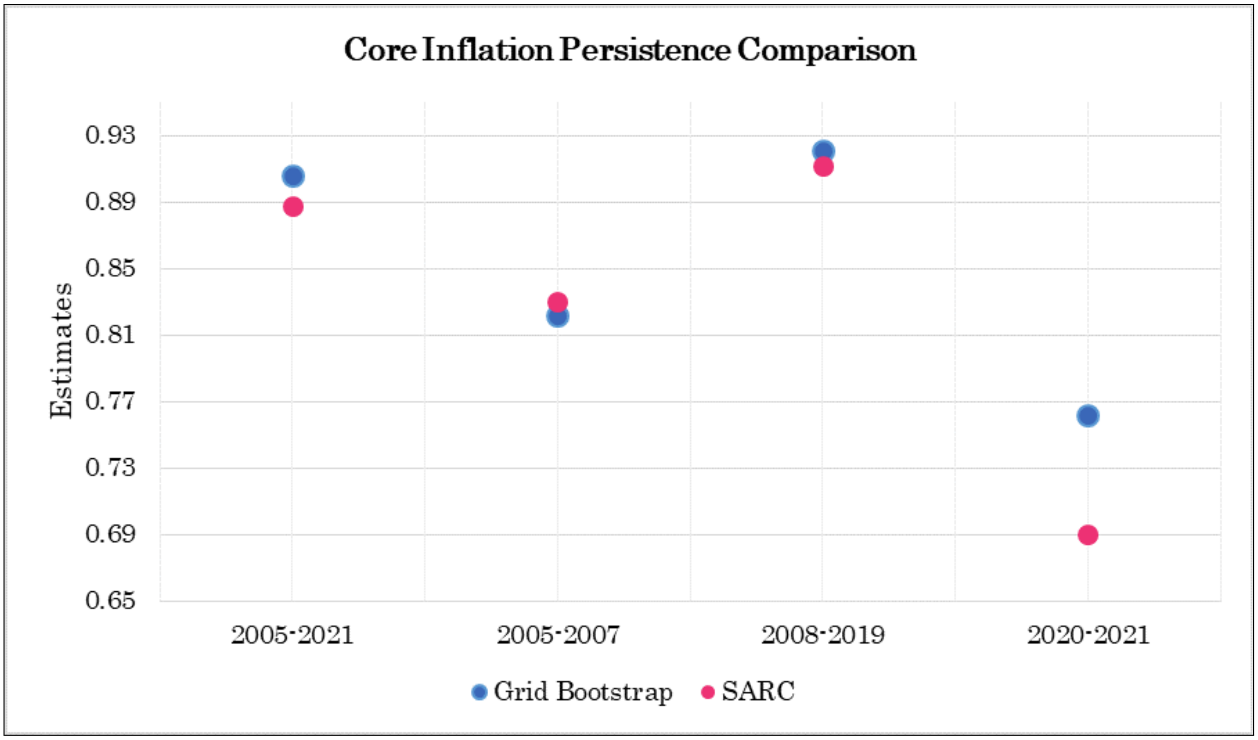
Appendix B Estimates Comparisons

Figure 6: **Comparison of headline inflation estimates (Red dots are SARC [ADF], Blue dots is the Grid Bootstrap).**



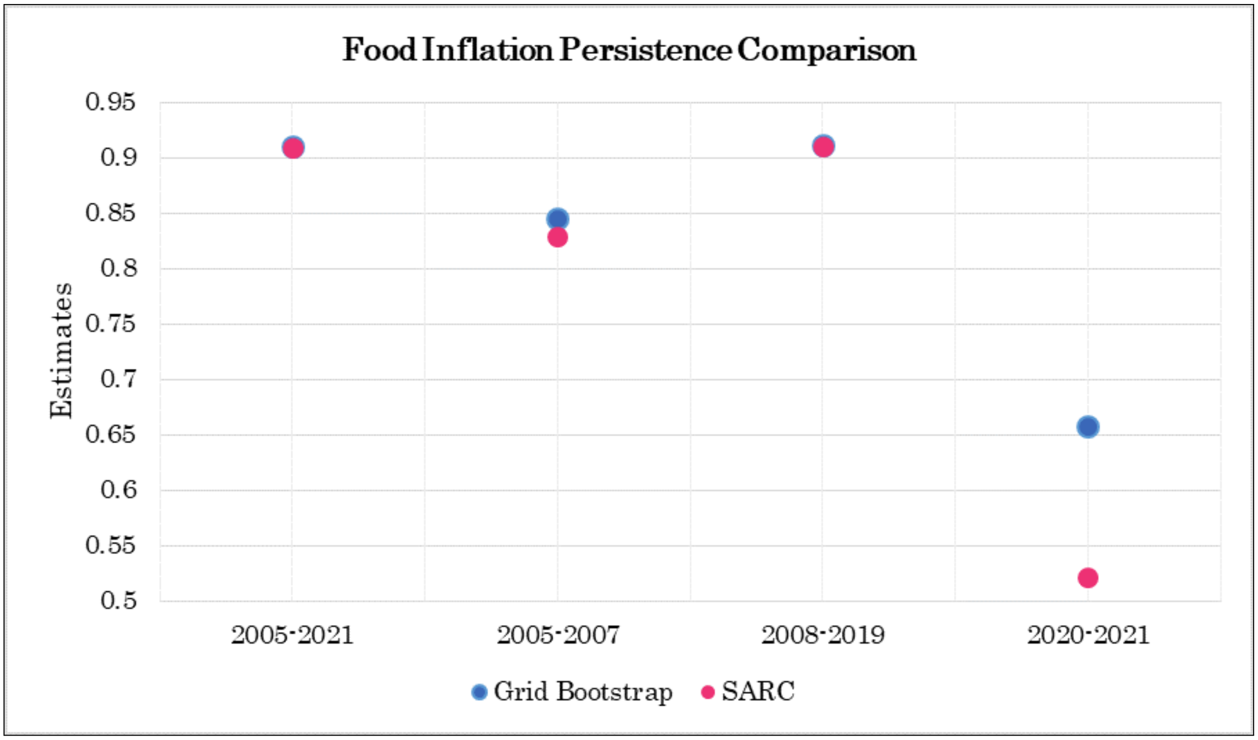
Source: *Author's Calculations*

Figure 7: **Comparison of core inflation estimates (Red dots are SARC [ADF], Blue dots is the Grid Bootstrap).**



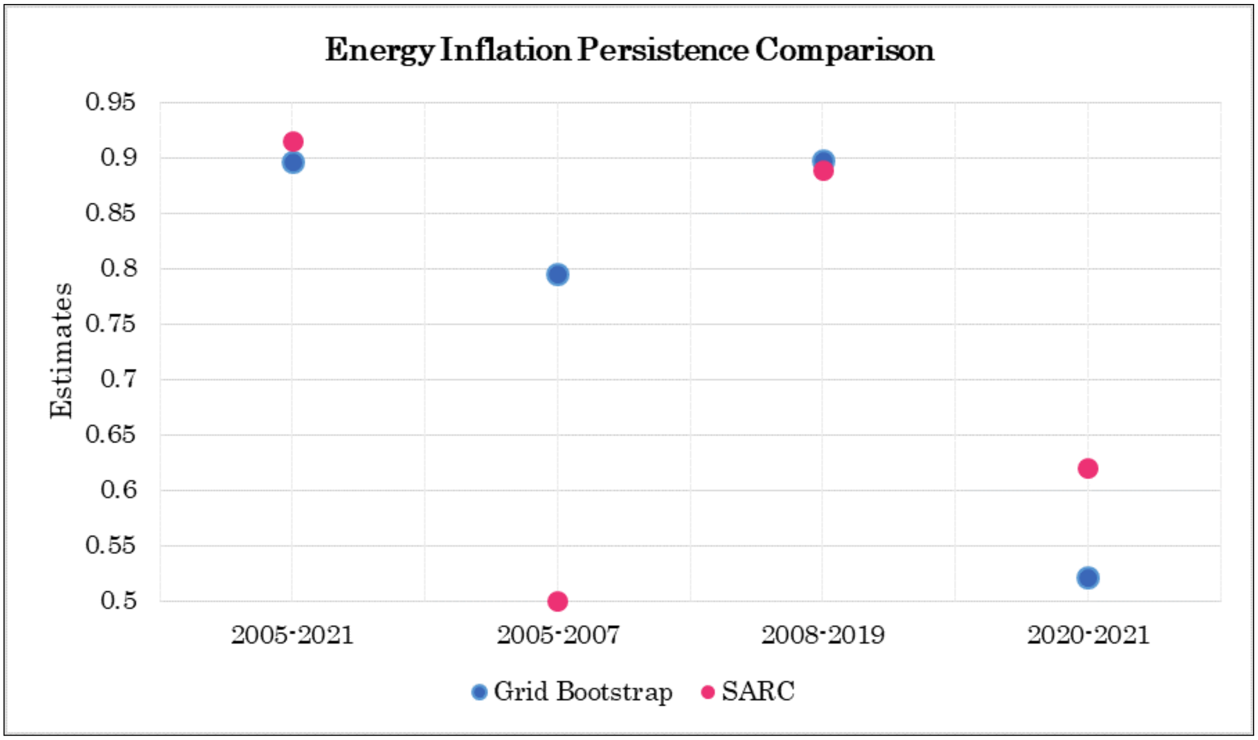
Source: *Author's Calculations*

Figure 8: **Comparison of food inflation estimates (Red dots are SARC [ADF], Blue dots is the Grid Bootstrap).**



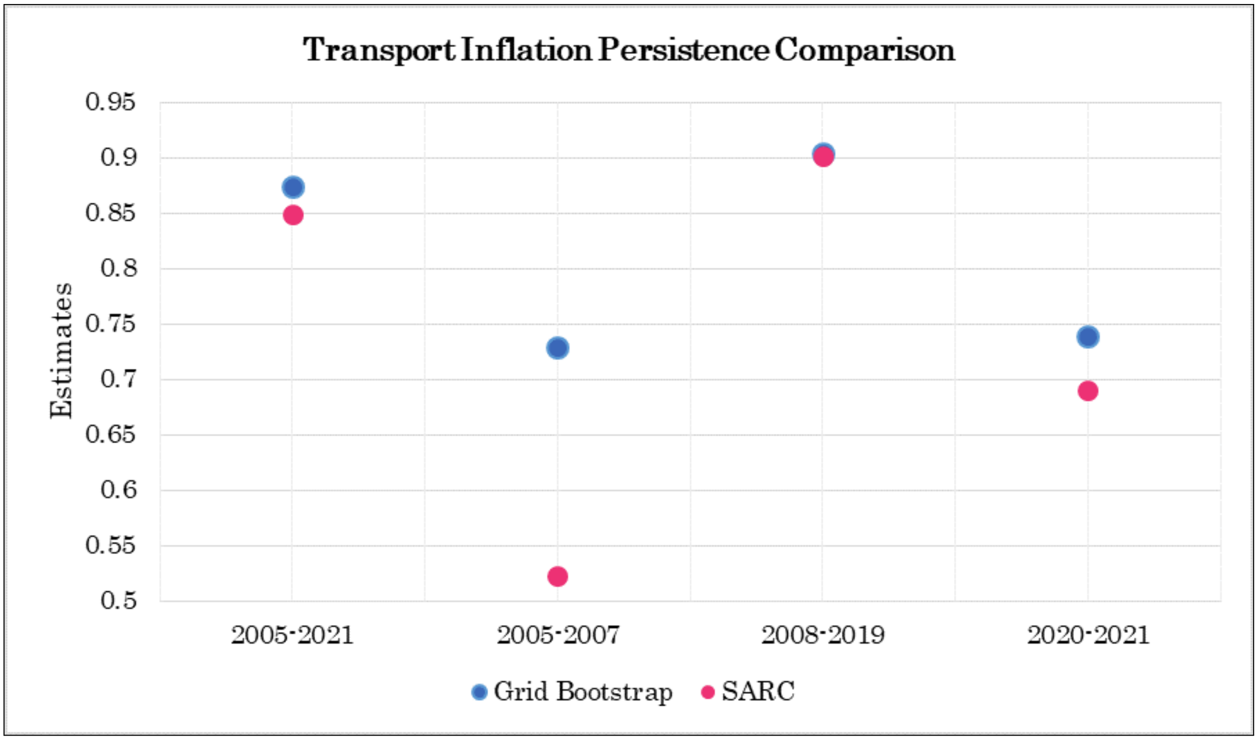
Source: *Author's Calculations*

Figure 9: **Comparison of energy inflation Estimates (Red dots are SARC [ADF], Blue dots is the Grid Bootstrap).**



Source: *Author's Calculations*

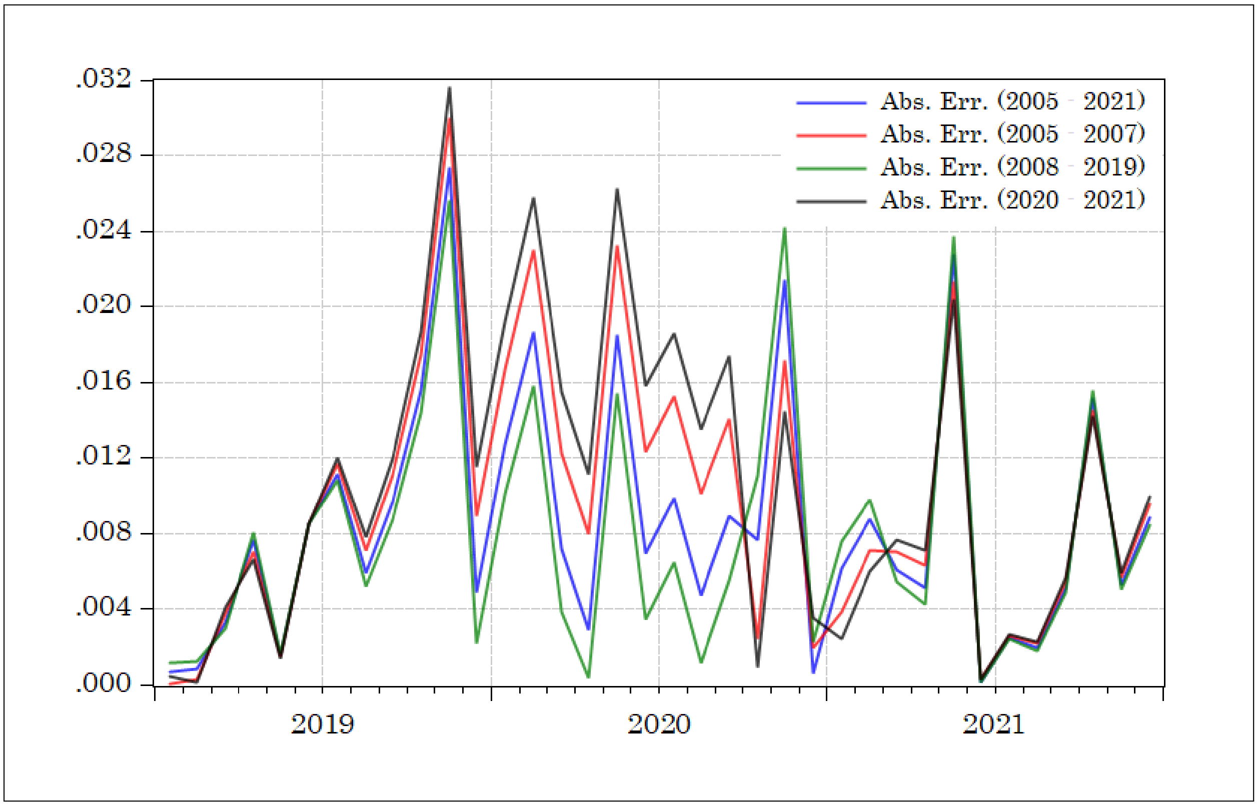
Figure 10: **Comparison of transport inflation estimates (Red dots are SARC [ADF], Blue dots is the Grid Bootstrap).**



Source: *Author's Calculations*

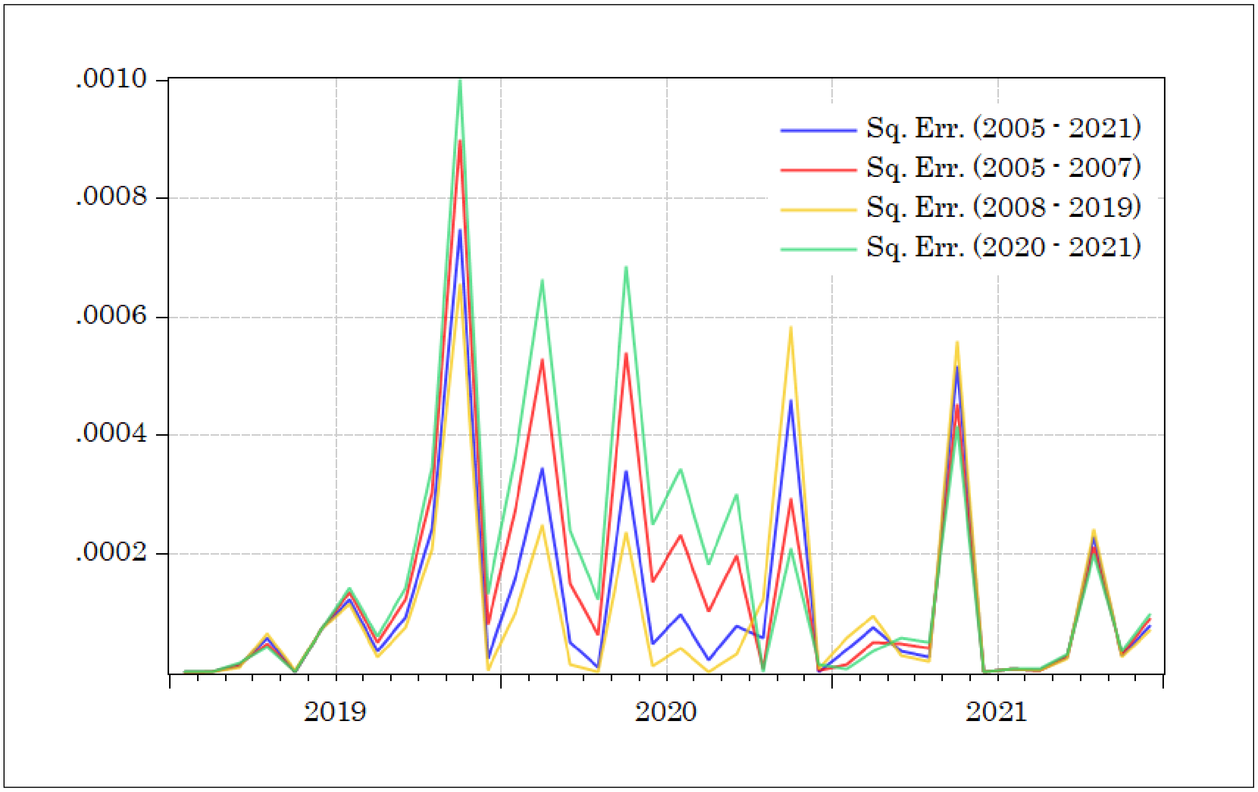
Appendix C Errors

Figure 11: **Comparison of Absolute Errors between samples.**



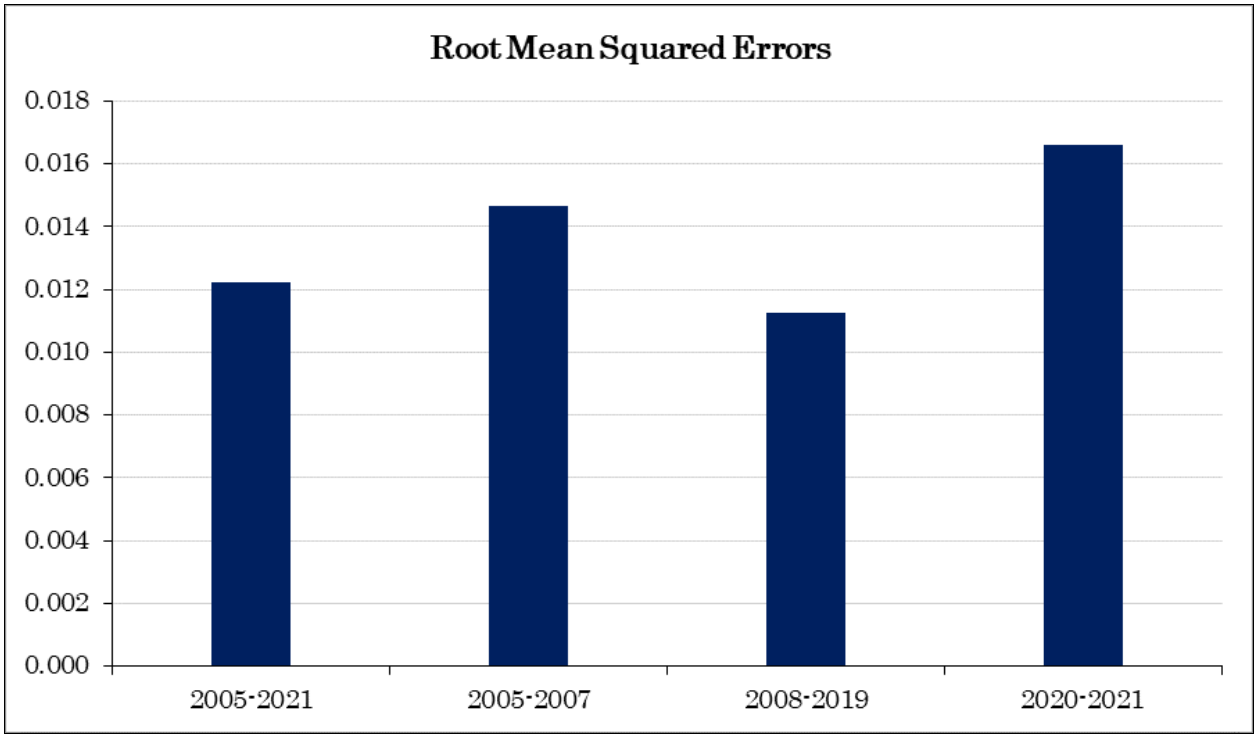
Source: *Author's Calculations*

Figure 12: **Comparison of Squared Errors between samples.**



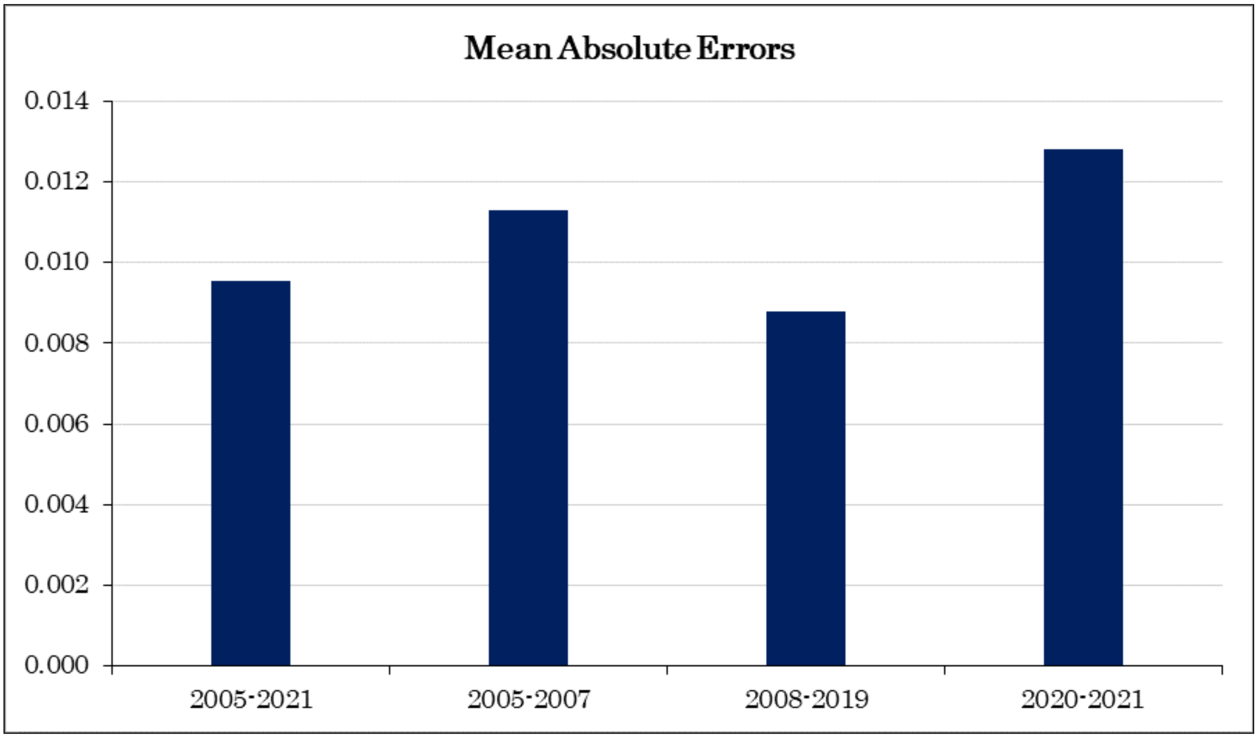
Source: *Author's Calculations*

Figure 13: **Comparison of Root Mean Squared Errors between samples.**



Source: *Author's Calculations*

Figure 14: **Comparison of Mean Absolute Errors between samples.**



Source: *Author's Calculations*