The Effects of Macroeconomic Shocks on Formal Employment Outcomes

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Abstract

This paper analyses the relationship between formal employment and real GDP in Belize by measuring the employment elasticity of industrial groupings before and after the pandemic. In addition, vector autoregression (VAR) techniques are used to assess how shocks to output and other macroeconomic variables impact formal employment. The study uses a novel data set of active insured workers who directly or indirectly contributed to the Social Security Board between 2000 and 2022 as a proxy for formal employment. The employment elasticity analysis revealed that there was less formal employment per unit of economic output after the pandemic, indicating a high persistence of informal work arrangements during the recovery stage. Furthermore, employment elasticities were higher and positive in the manufacturing and services industries than in agriculture. The VAR analysis revealed that formal employment within the tourism industry was more susceptible to exogenous macroeconomic shocks than agriculture. The rise in informal employment per unit of output combined with a greater concentration of formal workers in service industries sensitive to external shocks is a worrisome post-pandemic trend that may require government intervention to mitigate any resulting social pitfalls.

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1. Introduction

The severe economic fallout from the COVID-19 pandemic in 2020 led to increased unemployment, underemployment, and informal working arrangements. The impact on the workforce was uneven, disproportionately affecting women, youths, and individuals in the informal economy without social protection. In particular, workers in contact intensive industries like tourism and distributive trade were severely impacted due the impracticability of working-from-home and sudden falloff in aggregate demand. By the end of 2022, Belize’s real gross domestic product (GDP) had marginally surpassed pre-pandemic levels, while the unemployment rate improved to a historic low of 5.0% in October 2022. The unemployment rate dropped further in April 2023 to a record low of 2.8%, following an 11.5% year-on-year output increase for the first quarter of 2023. This significant increase in employment pushed unemployment well below its long-run natural rate for a small open economy like Belize. Would the unemployment rate fall even further if the economy continues to outpace potential growth? This puzzle could be investigated by studying the relationship between output and unemployment.

In his seminal work, Charles Okun (1962) identified an inverse relationship between the unemployment rate and the output gap. More recently, other economists have investigated the adverse effects of macroeconomic shocks on labour markets. For example, Campos-Vasquez (2010) found that young and unskilled workers were the demographic group most affected by macroeconomic shocks and suggested lowering labour regulations to accelerate job creation in the recovery period. Verick (2009) came to a similar conclusion, suggesting wage subsidies, training programs, and job search assistance programs to alleviate downward fluctuations in the labour market. However, Voda et al. (2019) found that increasing investments would not boost employment, owing to technological advancements in labour-intensive sectors.

This paper aims to analyse the relationship between formal employment and real GDP in Belize using an employment elasticity approach. Additionally, a VAR model will be used to assess how formal employment responds to shocks to output and other macroeconomic variables. The results from the employment elasticity analysis supported findings from Ramoni-Perazzi & Orlandoni-Merli (2019) in Colombia, where higher values were observed in manufacturing and service industries relative to agriculture. Meanwhile the results from the VAR were similar to Mordecki & Ramirez (2014) as GDP preceded employment and a positive statistical relationship was observed between the two variables.

The rest of the paper is divided into five sections. Section 2 reviews the literature on how employment responds to macroeconomic shocks. Section 3 describes the data and employment elasticity and VAR methodologies used. Section 4 provides the main results. Section 5 discusses the implications of the VAR results, while section 6 concludes.

2. Literature Review

The relationship between economic growth and employment is typically analysed within the context of the aggregate production function. This theory relates total output of an economy to total employment, assuming that all other factors of production are fixed. It postulates that increases in employment leads to increases in output at a decreasing rate, yielding diminishing marginal returns.

The production function can be viewed from the supply or demand side. From the supply side, output depends on the amount of labour available, while the demand perspective emphasises how much labour is needed for a given output. Keynes (1936) emphasised the demand side, postulating that employment could be increased by raising consumption and investment. Twenty-six years later, Okun (1962) posited that there was a negative statistical relationship between real GDP growth and the unemployment rate. Corollary, the relationship becomes positive when employment is substituted for unemployment. From this perspective, the production system requires more workers to meet demand in periods of expansion, causing employment to rise and unemployment to fall simultaneously.

Interactions between employment and economic growth have been studied using employment elasticities and econometric techniques, such as impulse-response functions to measure the dynamic nature of this employment-growth relationship. The arc elasticity of employment measures "the percentage change in the number of employed persons in an economy or region associated with a percentage change in economic output, measured by gross domestic product" (Kapsos, 2006, p. 2). Furthermore, Kapsos (2006) utilised a multivariate log-linear regression model to calculate the point elasticity of employment instead of the method mentioned above after citing concerns from Islam and Nazara (2000) regarding high fluctuations in using year-over-year estimates. Notwithstanding, the interpretation of the results is similar to that of the arc elasticity of employment as an "elasticity of 1 implies that every 1-percentage point of GDP growth is associated with a 1-percentage point increase in employment" (Kapsos, 2006).

From 1991 to 2003, global employment elasticity trends revealed that employment grew at about one-third of the pace of total output, but from 1999 to 2003, the employment intensity of growth declined (Kapsos, 2006). When disaggregated by demographic groups, he found that youth employment elasticities were low and insufficient to prevent a sizable increase in youth unemployment without substantial GDP growth. Meanwhile, higher employment elasticities were observed for females than males, indicating a "catching up in terms of women's labour force participation" (Kapsos, 2006). He concludes by stating that more insights could be obtained from country-specific and comparative case studies to better inform policy discussions (Kapsos, 2006).

Ramoni-Perazzi & Orlandoni-Merli (2019) also conducted a log-linear regression to analyse the employment elasticity for Colombia. They estimated a 1.03 elasticity for the country, which indicated a near-proportional relationship between employment and output. Moreover, at the sectoral level, a principal component analysis was performed, where the highest values were observed in the manufacturing (2.39) and services (1.14) subsectors relative to agriculture (0.89), which suggested inter-sectoral labour movements (Ramoni-Perazzi & Orlandoni-Merli, 2019). The difference in elasticity outcomes underscored a shift in the labour market toward more productive, higher-paying jobs (Ramoni-Perazzi & Orlandoni-Merli, 2019), reducing poverty and increasing economic growth in the process.

The interaction between output and employment is also investigated using a VAR approach. Voda et al. (2019) used a VAR model and impulse-response functions to study the effects of investments on economic growth and employment for Romania. Their results revealed that the interdependence between investments and GDP positively impacted the economy, supported by the business environment (Voda et al., 2019). However, increased investments did not lead to increased employment due to technological advancements that reduced production costs (Voda et al., 2019).

Zhou (2020) utilized a VAR approach to measure employment changes in China on sectoral GDP data spanning from 1981 to 2019. Variables used included China's employment elasticity coefficient, per capita GDP, the value added of the secondary sector to GDP, the value added of the tertiary sector to GDP, and fixed asset investments to GDP. His results demonstrated that shocks to the value added of the secondary and tertiary sectors had differing effects on short-term and long-term employment. In the short run, a shock to the value added of the secondary sector leads to increasing levels of unemployment as manufacturing industries require investments to modernise technological capacities to support expansion (Zhou, 2020). Labourers would be adversely impacted as firms tighten wages and limit hiring due to heightened capital expenditures (Zhou, 2020). In the long run, firms would continue to strive toward maximising efficiency gains, while limiting production costs through "capital and knowledge-intensive" development (Zhou, 2020), thereby negatively affecting employment.

Conversely, a value-added shock to the tertiary sector will positively affect employment in both the long run and the short run, as the demand for labour within service industries outweighs capital investments. Furthermore, the initial labour requirements for these types of industries are low, leading to heightened employment levels. As time progresses, the demand for high-skilled labourers will increase, while that of low-skilled labourers will decline, reflecting the development of the tertiary sector. It was also revealed that capital investments can influence employment in the short term. However, the effect weakens significantly in the medium and long term as firms begin to utilise technology as a substitute for labour to maximise profits (Zhou, 2020). He concludes by stating that “the role of economic growth in promoting employment has gradually weakened” and that optimising the industrial structure could enhance labour market conditions. Furthermore, the labour market should be improved by increasing investments in education and providing social security to labourers (Zhou, 2020).

Alternatively, Mordecki & Ramirez (2014) estimated a VAR with error correction mechanism (VECM) for Uruguay. They utilised a quarterly time series from 1988 to 2011 comprising GDP (excluding agricultural activities), gross fixed capital formation, and urban employment. Based on the presence of a cointegrating vector in the series and a long-run relationship between the variables, the VECM was appropriately chosen. The empirical results showed a “positive relationship between GDP and the other two variables, where GDP precedes both employment and investment” (Mordecki & Ramirez, 2014). Conversely, the relationship between employment and investment was negative in some instances and was attributed to labour-saving investments or investments targeted toward “less labour-intensive sectors” (Mordecki & Ramirez, 2014).

In summary, Kapsos (2006) reiterated that employment elasticities “serve as a useful way to examine how economic output and employment growth evolve together over time”. It can explain how employment generation varies in different economic sectors and “assist in detecting and analysing structural changes in employment over time.” However, this methodology “only takes into account information pertaining to historical employment and output growth,” and “suffer(s) from omitted variable bias, as no other variables that may influence either employment performance or overall economic performance” are included. To this point, studying the dynamic interactions between formal employment and other macroeconomic variables using an atheoretical econometric framework would build our standing of the impact of shocks on the labour market.

3. Data and Methodology

This study seeks to investigate the relationship between formal employment and output. It is expected that these two variables have a positive statistical relationship, with GDP preceding formal employment. The subsection below describes the proxy used for formal employment in this study.

3.1 Formal Employment Data: Source and Trends

The Active Insured Persons (AIPs) report, produced monthly by the Social Security Board (SSB), provides a good proxy for formal employment. AIPs are “individuals who are registered with Social Security, work eight or more hours in a week, and actively contribute toward their social security payments either as employees or self-employed persons” (SSB, 2022). The definition of an AIP sets a higher bar for productive employment and poverty reduction compared to the definition of an employed person for labour force statistics purposes. In the latter, an employed person (EP) is defined as “an individual who worked for pay or profit for at least one hour in the reference week or had a job but was not at work during the reference week” (SIB, 2020). Furthermore, using AIP data as an indicator of employment conditions has the added advantage of having a more extensive coverage of the population, a higher reported frequency, and a wider disaggregation at the industry level, see Table A-1. A Pearson correlation analysis was computed to assess the strength of the linear relationship between AIPs and EPs. The results show that a strong positive relationship existed between the two variables, $r = 0.92$, $p = 0.001$, implying that they respond to the same macroeconomic forces. However, a further investigation has to be done on which comes first.

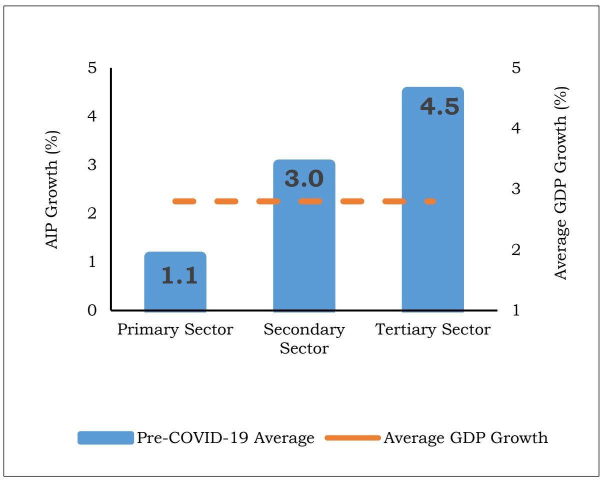
During the pre-COVID-19 period (2000-2019), the number of AIPs grew by 3.7%, significantly faster than the average GDP growth rate of 2.8% for the same period. A disaggregation by economic sectors, showed that formal employment grew at varying rates across sectors. Formal employment rose fastest in the tertiary sector (4.5%), followed by the secondary (3.0%) and primary (1.1%) sectors, see Chart 2.

Within the tertiary sector, formal employment was most heavily concentrated in the "*Public Administration and Defence; Compulsory Social Security*" (14.5%), "*Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles*" (12.2%), "*Accommodation and Food Service Activities*" (9.3%), and "*Education*" (7.9%) subcategories. The secondary sector outturn was driven by employment in "*Manufacturing*" (8.5%) and "*Construction*" (6.1%). Lastly, the share of formal employees in the primary sector was most pronounced in the "*Agriculture*" (11.8%) subcategory. These various industries accounted for 70.3% of the percentage distribution of AIPs during the pre-COVID-19 period.

After the COVID-19 outbreak, AIPs fell by 11.6%, declining slower than GDP, which nosedived by 13.4% in 2020. During the year, formal employment within the primary sector fell by only 2.0%, as local agricultural labourers were allowed to work during national curfew hours to safeguard food security under Statutory Instrument No. 62 of 2020. Secondary and tertiary formal employment contracted more deeply, down by 10.7% and 13.1%, respectively, as shown in Chart 3. Within these two sectors, movement and health restrictions severely disrupted employment in construction, tourism, and education activities, see Chart 4.

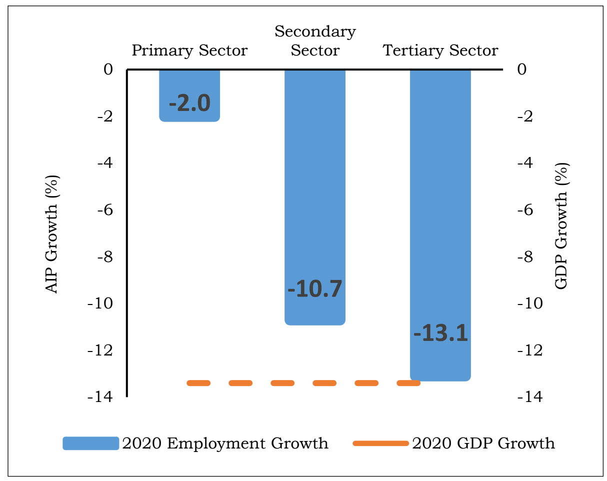
In 2022, formal employment surpassed 2019's pre-pandemic level by 2.8% to 90,033 labourers. This full rebound was stimulated by the resurgence of tourism, which, in turn, bolstered labour outcomes in the secondary and tertiary sectors. Conversely, formal employment in the primary sector declined marginally, partly due to labour shortages in the sugar, citrus, and banana industries, partly due to issues surrounding wage competitiveness, see Chart 5. In addition, the implementation of stricter border permit requirements, to limit the cross-border spread of COVID-19, dissuaded migrant workers from entering the country and exerted downward pressure on primary sector formal employment.

Chart 2: Pre-COVID-19 Employment Growth



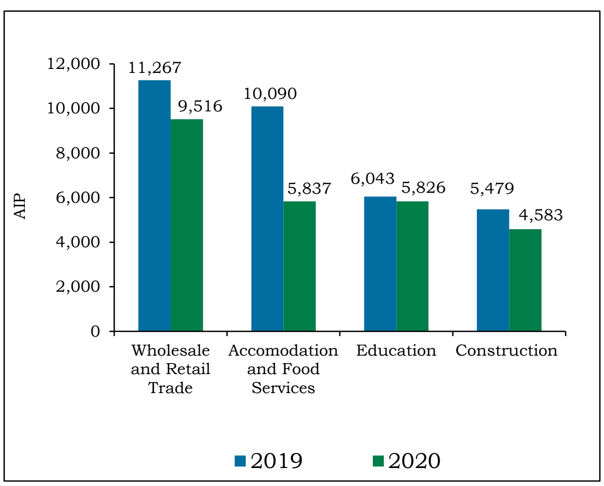
Sources: SSB and SIB

Chart 3: COVID-19 Employment Growth



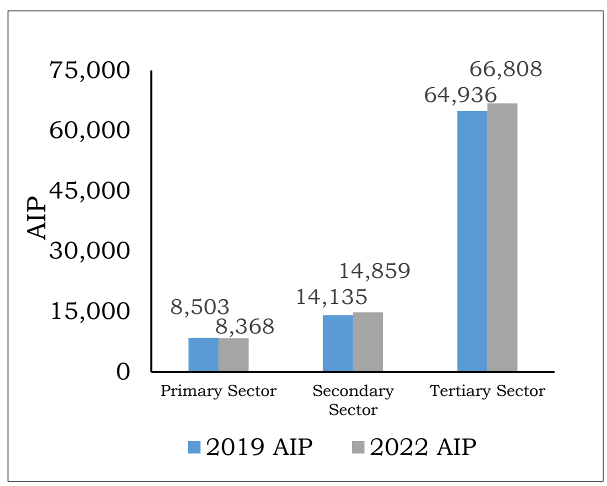
Sources: SSB and SIB

Chart 4: Employment Growth within Contact Intensive Industries



Source: SSB

Chart 5: Post-COVID-19 Employment Growth



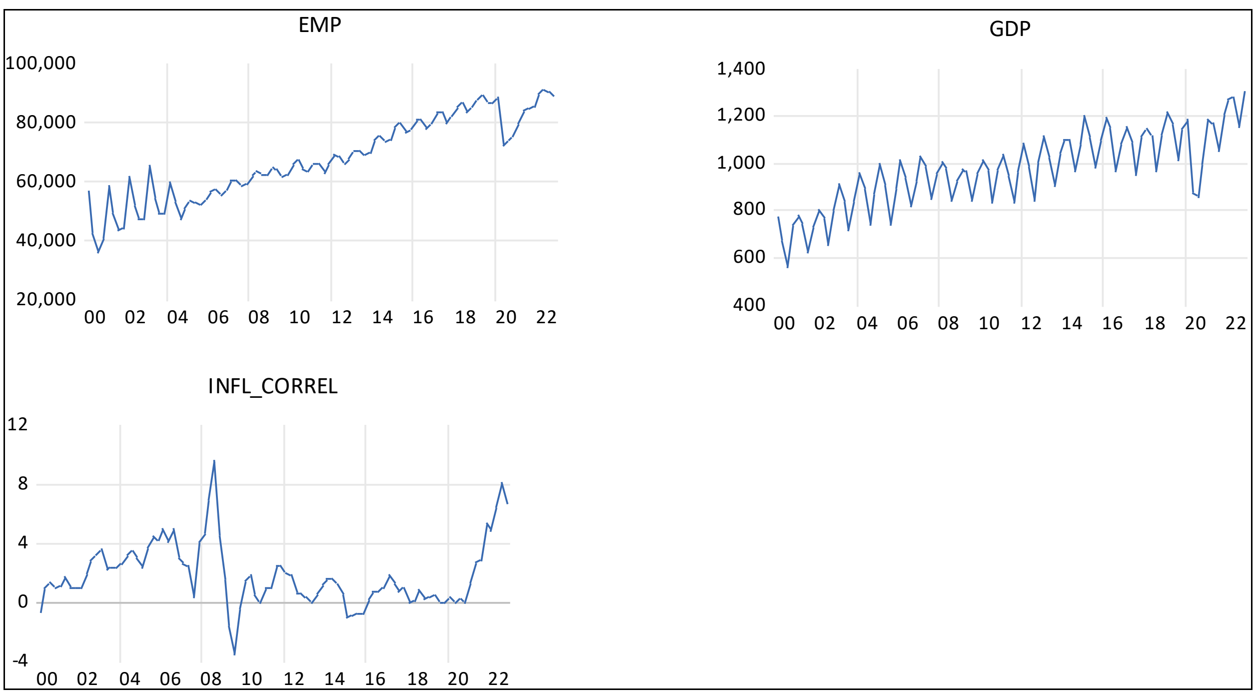
Source: SSB

3.1 Data Transformation

This paper used annual real GDP and formal employment data from 2000 to 2022 to measure employment elasticities. Real GDP was disaggregated at the sectoral level to examine select industries of interest. For the VAR analysis, quarterly data on formal employment, real GDP, and inflation were used. Real GDP and inflation were gathered from the Statistical Institute of Belize, while employment data was sourced from the Social Security Board (SSB).

From 2000 to 2022, real GDP rose by 3.1% on average, driven by services activities. Inflation has been low, averaging 1.9% over the period, although cost pressures averaged 4.8% in the two years after the onset of the pandemic.

Chart 6: Time Series Data



Source: SIB, CBB, SSB

The graphical representation of the data shows that the employment and real GDP series appeared to be fluctuating around a linear trend, while the inflation variable wandered around a non-zero mean. To correct for the non-normal distributions of the positive variables (formal employment and real GDP), a logarithmic transformation was applied. This reduces the skewness from the data and enhances the validity of the model. Furthermore, both the real GDP and formal employment time series appear to exhibit seasonal patterns owing to tourism. The variables were therefore seasonally adjusted to remove the influence of seasonal effects so that underlying trends in the data could be better analysed.

A correlogram analysis demonstrated that all the variables were serially correlated, suggesting that they did not follow a random process. Augmented Dickie-Fuller (ADF) and Philips-Perron (PP) tests were used to further examine the stationarity of the various time series to avoid obtaining spurious results. The null hypothesis of each is that the time series is non-stationary. Both tests included a constant and no trend as well as a constant and a trend, see Appendix Table A-2.

The ADF test confirmed that GDP, formal employment, and inflation were nonstationary at levels when a constant and no trend was included as well as a constant and trend. All variables became stationary at the first difference with a constant and no trend and a constant and trend.

Some of the results from the PP test differed from that of the ADF test, as the inflation time series was stationary at levels with a constant and no trend, while real GDP and formal employment remained non-stationary. Furthermore, once a constant and trend was included, formal employment became stationary at levels. This implied that no differencing would be required for formal employment and inflation. The contrasting results from the two tests could be attributed to sensitivities to structural breaks that may be present within the various time series. Furthermore, the statistical power of these tests tend to be weaker with smaller time series.

It was determined that the ADF test provided more reliable estimates relative to the PP test, as it corroborated the results from the various correlograms. Therefore, all variables were transformed to the first difference with a constant and no trend.

It is also necessary to analyse the data for possible structural breaks. This occurs when there is an unexpected change in a time series at a particular point in time. Failing to correctly account for these breaks can result in large forecasting errors and unreliable model estimations. The economic variables chosen for the study are prone to structural breaks owing to Belize's status as a "small, open and import dependent" economy that is "highly vulnerable to exogenous and weather-related shocks" (Garcia et al). Accordingly, several outlier periods can be observed in Chart 6.

For instance, between 2008-2010 and 2020-2022 inflation peaked beyond normal bounds owing mainly to price shocks on commodities and fuel prices that emanated from the Global Financial Crisis and the COVID-19 pandemic, respectively. The effects of the COVID-19 pandemic can also be observed on the formal employment and real GDP time series, as sharp declines take place in 2020. However, further investigation was needed to confirm the presence of structural breaks within the time series using a Bai-Perron multiple breakpoint test. The null hypothesis of this test states that there are no structural breaks within the time series. The results of the test revealed that there were two structural breaks (2008 Q1 and 2016 Q3), see Appendix Table A-3. The structural break identified in the third quarter of 2016 was due to negative GDP growth of 1.3%, as the primary sector was dragged down by damages caused by Hurricane Earl.

Interestingly, the COVID-19 shock was not identified as a structural break despite the large fluctuation in GDP that occurred. To ensure robustness, two models were estimated with dummy variables to capture the suggested structural break periods as well as the COVID-19 shock. The period for the COVID-19 shock[1] was determined to cover 2020 Q1 to 2021 Q2. A third model was estimated with no dummy variables for comparison purposes. The results are shown in Table 1 below.

Table 1: Regression Results

	I	II	III
GDP	1.2816 (0.0000)***	1.2664 (0.0000)***	1.2822 (0.0000)***
INFL	-0.0138 (0.0000)***	-0.0124 (0.0001)***	-0.0138 (0.0000)***
Dummy_1	0.0104 (0.8749)		
Dummy_2	0.0129 (0.8445)		
COVID_Dummy		0.0855 (0.0015)***	
C	2.3222 (0.0000)***	2.4191 (0.0000)***	2.3186 (0.0000)***
R-Squared	0.9057	0.9159	0.9056
Log Likelihood	123.5766	128.8261	123.5430
F-Statistic	209.0309	319.5367	427.3274

*,**,*** indicates statistical significance at the 90%, 95%, and 99% levels, respectively.

Based on the results shown in Table 1, the dummy variables that were identified in the Bai-Perron test (2008 Q1 and 2016 Q3) were not significant when included in the regression model. However, when the dummy variable that accounted for the COVID-19 shock was

[1] In the second quarter of 2021, value added output came within $12.7mn of the comparable period of 2019. Subsequently, value added growth surpassed 2019's level in the third quarter of 2021.

included in the model, it had a statistically significant effect on formal employment. Thus, the model was only estimated with the dummy variable that took into account the COVID-19 pandemic.

3.2. Empirical Approach

To conduct the investigation, employment elasticities were calculated to gain further insights into the interplay between formal employment and output. Additionally, a VAR was estimated to provide more comprehensive measurements on how formal employment responds to macroeconomic shocks. The two techniques are described below.

3.3. Employment Elasticity Analysis

The equation below represents the percentage change in active insured persons associated with a 1% change in real GDP. High and positive employment elasticities are associated with a high level of formal employment growth per unit increase of output. In contrast, low and positive employment elasticities are associated with a low level of formal employment growth per unit increase of output.

$$\varepsilon = \left(\frac{(E_1 - E_0 \;/\; E_0)}{(Y_1 - Y_0)/Y_0}\right) \qquad \text{..............................(1)}$$

Where ε = arc elasticity of employment, E = active insured persons, and Y = value added per economic industry.

It must be noted that the arc elasticity of employment approach provided more reliable estimates than the point elasticity method utilized by Kapsos (2006) and Ramoni-Perazzi & Orlandoni-Merli (2019), as the error terms in the Ordinary Least Squares (OLS) model were serially correlated. This violated one of the central assumptions of a classical linear regression model and would have provided biased estimations. Despite the simplicity of the arc elasticity of employment, it offered the advantage of measuring the responsiveness of formal employment to GDP growth over a range of time such as the pre-COVID-19 period. This proved useful in analysing the manner in which formal employment had evolved before and after the pandemic.

Be that as it may, elasticities were calculated for select industries within the primary, secondary, and tertiary sectors using annual data that spanned 2000 to 2022.

3.4. VAR

A Johansen Cointegration test was conducted to assess the suitability of employing a VAR or VECM model. A VAR model focuses on capturing dynamic short-term relationships among variables by representing each variable as a linear function of its own lagged values and the lagged values of other variables in the system. Meanwhile, VECM models are designed to capture both short-term and long-term equilibrium relationships among variables. In light of this, the variables need to be cointegrated in order for the VECM to be appropriately employed. The results of the cointegration test (see Appendix Table A-4) indicated that there was one cointegrating equation at the 0.05 level among the endogenous variables (formal employment, real GDP, and inflation), initially suggesting the VECM could be appropriately estimated.

However, the VECM model did not satisfy the stability condition as two inverse roots of the characteristic AR polynomial had a modulus greater than one and lied outside the unit circle, see Appendix Table A-5. This weighed heavily on the decision to utilize the VAR model in favour of the VECM owing to the instability of the coefficients over time. The estimation of a VAR model would still provide adequate estimations of the short-term relationships between formal employment and the independent variables. Furthermore, the VAR model would provide meaningful insights regarding the dynamic responses of formal employment to macroeconomic shocks by way of various impulse-response functions.

3.5. Variable and Lag Selection

It is important to ensure that the VAR model does not contain too many variables or lags as it can result in overfitting. In this unfavourable scenario, the model becomes highly parameterized and captures unnecessary noise in the data. Variables and lag lengths must be guided by rational economic theory and prerequisite tests to ensure statistical significance.

3.6. Granger Causality Test

Thus, a key step in the VAR analysis is to conduct a granger causality test. This provides an empirical assessment regarding the causal relationships among variables in a multivariate time series model. These estimates will help to validate the inclusion of these variables in the model based on the degree of influence that they have on the dependent variable. Therefore, when applied to this study, insights could be obtained about how changes in real GDP and inflation will affect formal employment. Table 2 summarizes the results.

Table 2: Granger Causality Test

Pairwise Granger Causality Test Date: 10/10/23 Time: 13:32 Sample: 2000Q1 2022Q4 Lags: 2		
Null Hypothesis	F-Statistic	Prob.
GDP does not Granger Cause EMP	10.6084	8.E-05
INFL does not Granger Cause EMP	0.0295	0.9709

Based on the results, real GDP was found to Granger cause formal employment as the p-value was well below the 5% significance level. However, the inflation variable did not Granger cause formal employment. Notwithstanding, the decision was made to keep inflation in the model as it could moderate the relationship between real GDP and formal employment. During periods of cost-push inflation, firms may respond by reducing their staff complements to mitigate expenses.

However, if the reduction in employment leads to lower productivity, economic growth can also be negatively affected.

3.7. Lag Selection

The optimal lag length was determined to be 8 based on the Akaike Information Criterion, see Table 3. This decision was complemented by a lag exclusion Wald test, in which the null hypothesis states that including the selected lag length would not provide additional explanatory power in the model. As shown in Appendix Table A-6, the p-value for the eighth lag was below the 5% significance level, suggesting that it would have a significant impact on the model's fit. Finally, Table 4 confirms that the chosen lag length (8) did not have serial correlation.

Table 3: Lag Order Selection Criteria

Endogenous variables: DIF_EMP DIF_GDP DIF_INFL
Exogenous variables: C COVID_DUMMY
Date: 05/31/23 Time: 11:29
Sample: 2000Q1 2022Q4
Included observations: 83

Lag	LogL	LR	FPE	AIC	SC	HQ
0	200.1189	NA	1.87e-06	-4.6775	-4.5027*	-4.6073*
1	208.1497	15.0939	1.91e-06	-4.6542	-4.2170	-4.4785
2	210.6386	4.4980	2.24e-06	-4.4973	-3.7978	-4.2163
3	217.8332	12.4821	2.35e-06	-4.4538	-3.4921	-4.0674
4	238.8930	35.0151	1.76e-06	-4.7444	-3.5204	-4.2526
5	246.2865	11.7583	1.85e-06	-4.7057	-3.2194	-4.1085
6	252.3580	9.2169	2.01e-06	-4.6351	-2.8865	-3.9326
7	254.7127	3.4043	2.39e-06	-4.4750	-2.4641	-3.6671
8	278.6986	32.9445*	1.70e-06*	-4.8361*	-2.5629	-3.9228

* Indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Table 4: VAR Residual Serial Correlation LM Tests

VAR Residual Serial Correlation LM Tests Date: 05/30/23 Time: 14:31 Sample: 2000Q1 2022Q4 Included observations: 91						
Null hypothesis: No serial correlation at lag h						
Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	6.9491	9	0.6424	0.7717	(9, 126.7)	0.6426
2	9.2016	9	0.4188	1.0309	(9, 126.7)	0.4191
3	4.3532	9	0.8866	0.4786	(9, 126.7)	0.8867
4	10.8814	9	0.2839	1.2271	(9, 126.7)	0.2842
5	5.5475	9	0.7842	0.6127	(9, 126.7)	0.7843
6	7.9288	9	0.5413	0.8839	(9, 126.7)	0.5415
7	5.3363	9	0.8040	0.5889	(9, 126.7)	0.8041
8	7.8320	9	0.5511	0.8728	(9, 126.7)	0.5514

3.7.1 VAR Model Representation

The algebraic estimation of the VAR model is shown below:

$$\text{DIF\_EMP}_t = \beta_0 + \beta_1\text{DIF\_EMP}_{t-1} + \ldots + \beta_1\text{DIF\_EMP}_{t-8} + \beta_2\text{DIF\_GDP}_{t-1} + \ldots + \beta_2\text{DIF\_GDP}_{t-8} + \beta_3\text{DIF\_INFL}_{t-1} + \ldots + \beta_3\text{DIF\_INFL}_{t-8} + \beta_4\text{COVID\_DUMMY} + \varepsilon_t \quad \ldots\ldots\ldots(1)$$

$$\text{DIF\_GDP}_t = \beta_0 + \beta_1\text{DIF\_GDP}_{t-1} + \ldots + \beta_1\text{DIF\_GDP}_{t-8} + \beta_2\text{DIF\_EMP}_{t-1} + \ldots + \beta_2\text{DIF\_EMP}_{t-8} + \beta_3\text{DIF\_INFL}_{t-1} + \ldots + \beta_3\text{DIF\_INFL}_{t-8} + \beta_4\text{COVID\_DUMMY} + \varepsilon_t \quad \ldots\ldots\ldots(2)$$

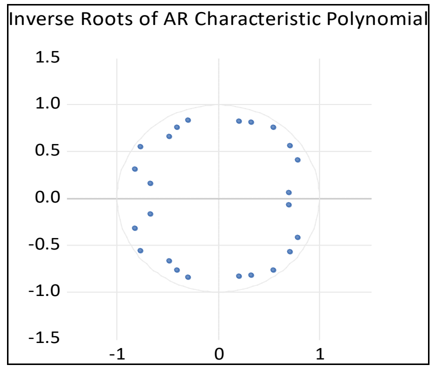
$$\text{DIF\_INFL}_t = \beta_0 + \beta_1\text{DIF\_INFL}_{t-1} + \ldots + \beta_1\text{DIF\_INFL}_{t-8} + \beta_2\text{DIF\_EMP}_{t-1} + \ldots + \beta_2\text{DIF\_EMP}_{t-8} + \beta_3\text{DIF\_GDP}_{t-1} + \ldots + \beta_3\text{DIF\_GDP}_{t-8} + \beta_4\text{COVID\_DUMMY} + \varepsilon_t \quad \ldots\ldots\ldots(3)$$

Where DIF_EMP = formal employment, DIF_GDP = real GDP, and INFL = inflation rate.

3.7.2 VAR Stability Test

The stability of the VAR models was then confirmed using the AR roots graphs shown below. All inverse roots of the characteristic AR polynomials had a modulus less than one and lied inside the unit circle as shown in Figure 1.

Figure 1: AR Roots Graph



3.7.3 VAR Sectoral Disaggregation

To gain further insights, employment and GDP data were disaggregated into the agriculture and tourism[2] industries. Consideration was given to also include the manufacturing industry; however the sectoral model failed the VAR stability test and would have produced unreliable estimations. Nevertheless, the two sectoral models for the agriculture and tourism industries satisfied the stability condition, see Figures 2 and 3.

Figure 2: Agriculture AR Roots Graph

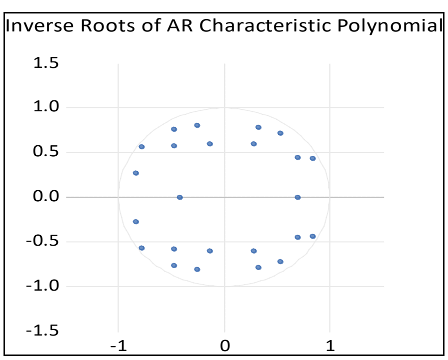
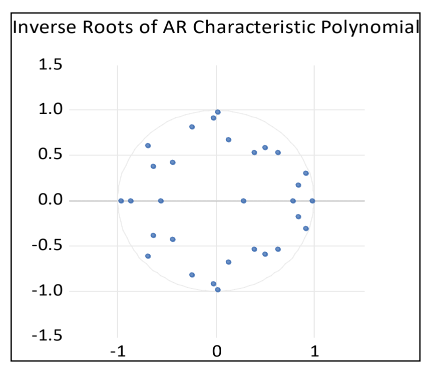


Figure 3: Tourism AR Roots Graph

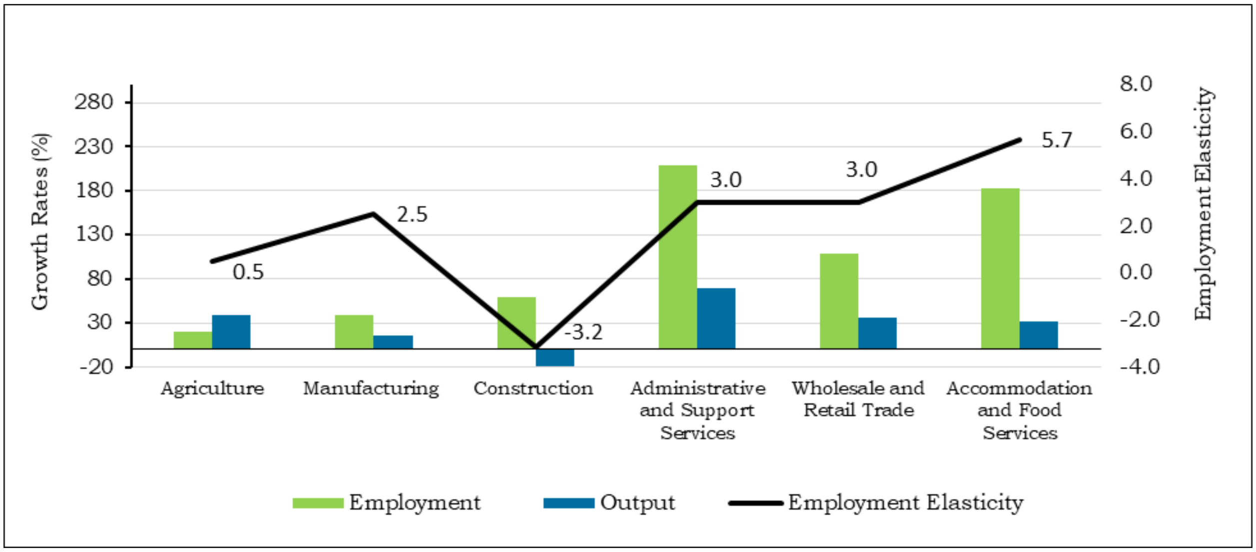


[2] Tourism industries included “Wholesale and Retail Trade; Repair of Motor Vehicles and Motor Cycles”, “Transportation and Storage” ,“Accommodation and Food Service Activities”, and “Arts, Entertainment and Recreation”.

4. Results

4.1 Employment Elasticity

Chart 7: Growth of Employment, Output, and Elasticity for Select Economic Sectors 2001-2019



Source: SSB, SIB, and Author's Calculation

Chart 7 illustrates various employment elasticities from select industries from the primary, secondary, and tertiary sectors. The results for the pre-pandemic period revealed that formal employment outpaced output in all the industries investigated except agriculture. Elasticities for most industries within the secondary and tertiary sectors were greater than one (implying that formal employment grew faster than the sectoral output), while that of the primary sector was less than one (suggesting that formal employment rose at a slower pace relative to the sectoral output). These factors were indicative of "a potential inter-sectoral shift" as the share of agricultural workers to total AIP had fallen from 16.3% in 2001 to 9.7% in 2019 (Ramoni-Perazzi & Orlandoni-Merli, 2019). Low and positive elasticities in agriculture, along with high and positive elasticities in services, potentially captured the "transition of workers to more productive and better-paid jobs in the services sector (Ramoni-Perazzi & Orlandoni-Merli, 2019). In addition, a high and negative elasticity was recorded for the construction industry (see Chart 7). This suggested that the share of formal employment per unit of construction output declined significantly over the two decades and that an increasing share of construction output was driven by informal employment. According to a report from the Organization for Economic Cooperation and Development and the International Labour Organization, individuals are considered informally employed if "his/her employer does not contribute to social security on his/her behalf" or if they don't "benefit from paid annual leave or sick leave" (OECD/ILO, 2019). Construction workers are often self-employed under contracts for service and aren't required by law to make social security contributions. This leads to an increased level of vulnerability relative to formal labourers who sign contracts of service and receive higher levels of social protection.

Table 5: Employment Elasticity by Economic Sector

	Total Employment Elasticity	Primary Sector Employment Elasticity	Secondary Sector Employment Elasticity	Tertiary Sector Employment Elasticity
2001-2019	1.3	0.2	13.3	1.7
2020	0.9	0.4	-4.6	0.8
2021	0.5	0.1	0.8	0.6
2022	0.6	0.4	1.0	0.6

Sources: SSB, SIB, and Author's Calculation

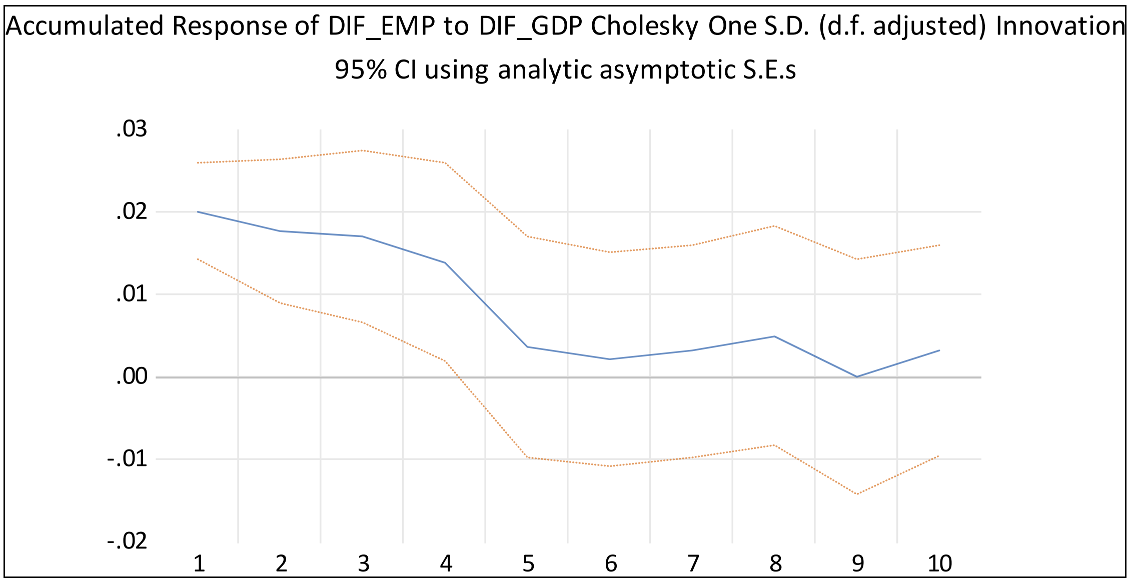
At the height of the pandemic in 2020, the arc elasticities for the primary sector increased from 0.2 to 0.4, swung from 13.3 to -4.6 in the secondary sector, and declined from 1.7 to 0.8 in the tertiary sector relative to the previous two decades as shown in Table 5. In the primary and tertiary sectors, where the elasticities ranged between 0 and 1, output fell faster than formal employment. In the secondary sector, the elasticity was substantially below 0, indicating that formal employment fell while output rose. This phenomenon was mainly due to heightened hydroelectricity generation after a prolonged drought the year before, resulting in jobless growth as employment in other industries waned.

In 2022, the arc elasticities for the primary and tertiary sectors were low and positive at 0.4 and 0.6, respectively. On the one hand, the elasticity for the primary sector generated a positive value because employment and output both fell. On the other hand, the low and positive elasticity for the tertiary sector indicated that formal employment lagged output growth. The highest observed elasticity was found in the secondary sector (1.0) and suggested that it was the most responsive to the upward fluctuation in output in the wake of the pandemic. According to Ramoni-Perazzi & Orlandoni-Merli (2019), these results facilitate pro-poor growth, as high employment elasticities in these sectors would increase the demand for labour, allowing workers to transition to higher quality jobs providing they acquire the requisite skills.

4.2 Impulse Response Functions

Impulse response functions were generated to analyse the dynamic relationships between economic variables. In more detail, the graphs below depict how a one-time shock[3] to real GDP and inflation will affect formal employment.

Figure 4: Response of formal employment to a GDP shock



In Figure 4, a positive shock to real GDP led to a 2.0% increase in formal employment on impact but declines to 1.8% in the second quarter. Formal employment then decreases sharply to 0.3% in the fifth quarter. The effect of the shock wanes further, as formal employment falls below 0 in the ninth quarter before settling at 0.3% in the final period.

[3] The shock was to one standard deviation and was applied to all the independent variables in the VAR to assess how formal employment would respond.

Figure 5: Response of formal employment to an inflation shock

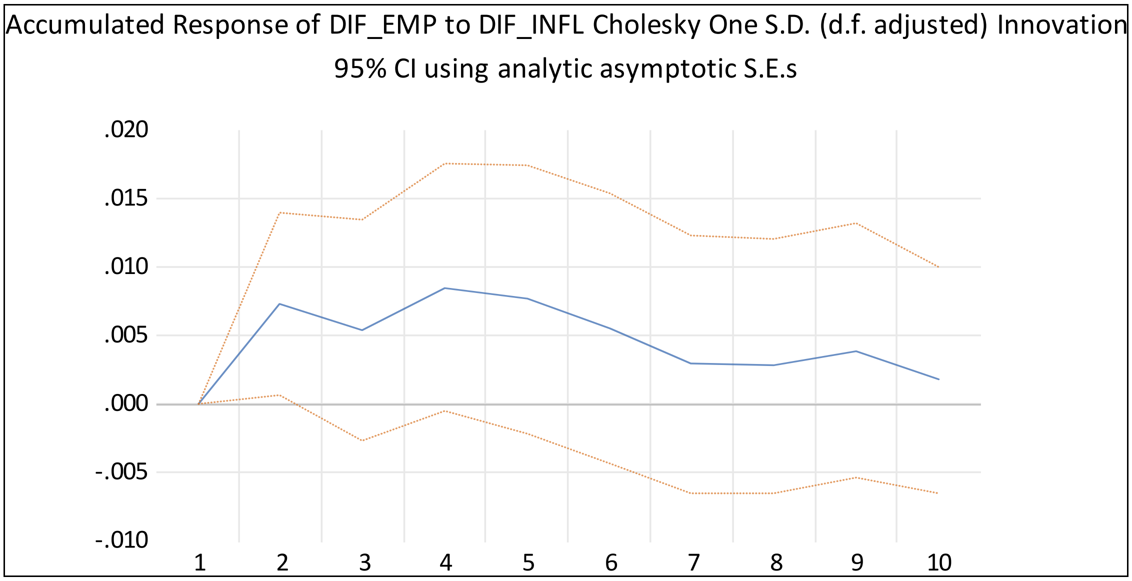
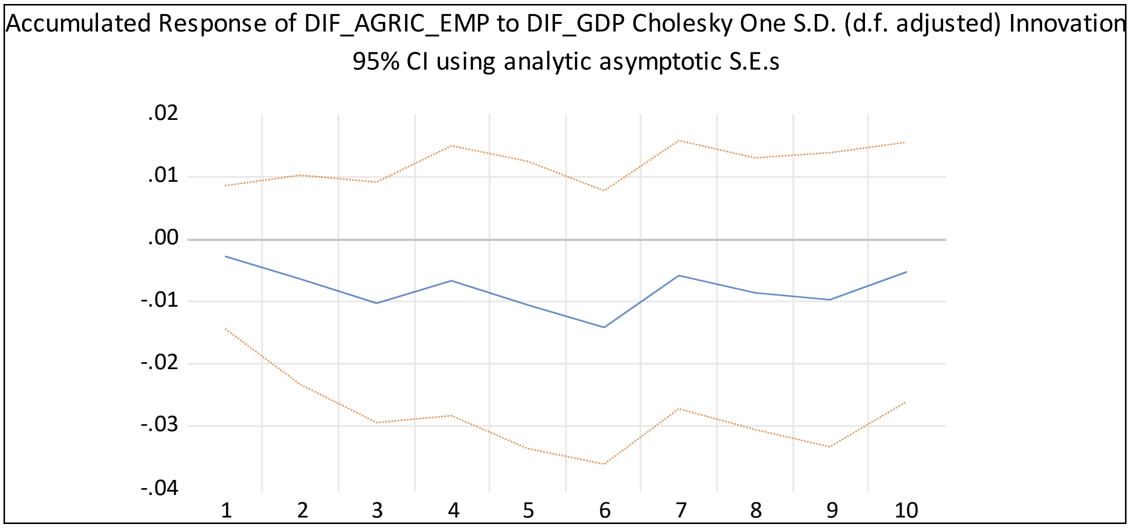


Figure 5 illustrates that formal employment's response to an inflation shock is weak upon impact (0.0%). In the second quarter, formal employment rises to 0.7% and increases to 0.8% in the fourth period. A declining trend is then observed for the remainder of the horizon where formal employment falls to 0.2% in the final period.

4.2.1 Sectoral Results

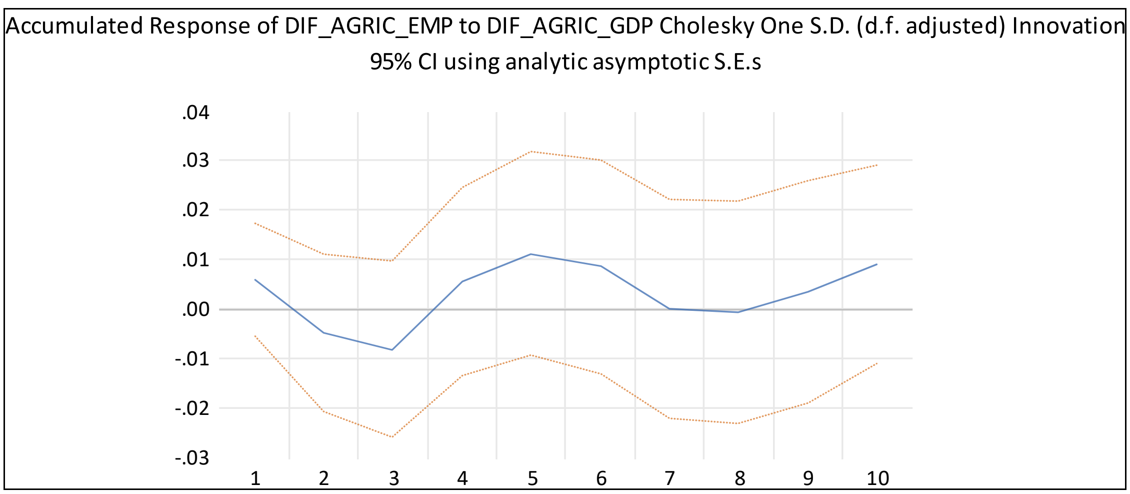
In order to gain more comprehensive insights, AIPs and real GDP were disaggregated into the agriculture and tourism industries. This would provide estimations on how shocks to the value-added output of selected sectors affect formal employment at the sectoral level. For comparative purposes, total real GDP was also measured.

Figure 6: Response of agriculture employment to a GDP shock



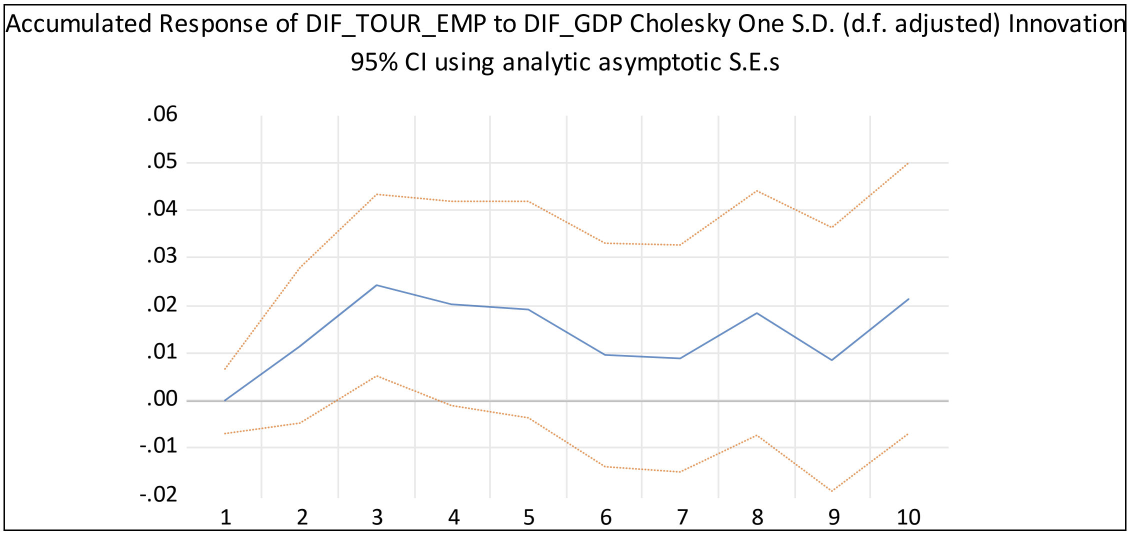
When real GDP was shocked, formal employment within the agricultural sector falls upon impact by 0.3% and remains below zero for the entirety of the horizon before settling at -0.5%.

Figure 7: Response of agriculture employment to an agriculture value added shock



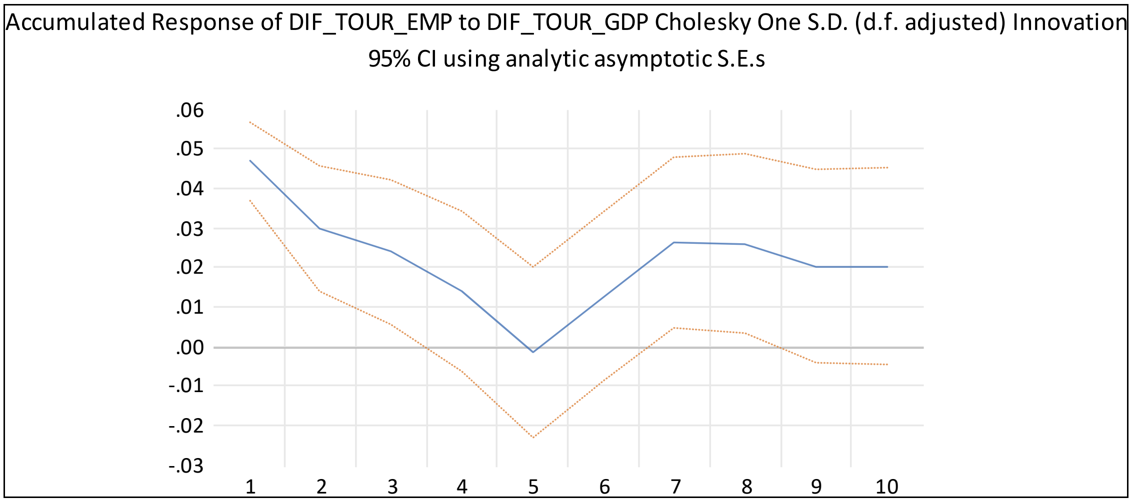
Upon impact, formal agricultural employment increases by 0.6% when the value added of agriculture was shocked. However, it falls to -0.8% in the third period before rising to 1.1% in the fifth quarter. A downward trend is then observed that pushes formal employment to -0.1% in the eighth quarter. Subsequently, formal employment surges upward and settles at 0.9% in the final period.

Figure 8: Response of tourism employment to a GDP shock



The effect of a shock to real GDP on formal employment is negligible impact. However, formal employment rises sharply to 2.4% in the third quarter. A downward trend is then observed, as formal employment falls to 0.9% in the seventh quarter. However, to close the horizon, formal employment rises to 2.1%.

Figure 9: Response of tourism employment to a tourism value added shock



When the value added of tourism output was shocked, formal employment in tourism increases by 4.7% upon impact. A declining trend is observed until the fifth quarter when the response settles at -0.2%. In the sixth and seventh periods, formal employment in tourism rises to 0.3%. Thereafter, formal employment hovers around 0.2% to close the horizon.

4.3 Variance Decomposition

A variance decomposition was estimated to provide a more comprehensive understanding about how shocks or changes in one variable will affect the behaviour of other variables. This allows the prioritization of certain variables based on their relative contribution to fluctuations in the system. Rational economic reasoning in tandem with the results from the Granger causality test are key for the Cholesky ordering as it determines the sequence in which variables are ordered in the VAR model.

It was determined that the ordering should be real GDP, formal employment, and inflation. This was supported by Keynes' belief that output and employment are largely dependent on changes in aggregate demand which are represented by consumption, investment, government spending, and net exports. The Granger causality test also supported this notion as real GDP was found to granger cause formal employment. Furthermore, the ordering was guided by the degree of influence that a variable has over the other variables in the system.

The results from the variance decomposition revealed that in period 1, a shock to real GDP explained 43.5% of the variation in formal employment, see Appendix Table A-7. The contribution then falls to 36.1% in the second period before rising to 41.0% in the third period. Subsequently, the contribution hovers around that level before settling at 41.9% in the final period. Concurrently, formal employment's contribution totalled 56.4% in period 1, but increases to 59.1% in period 2 and hovers around 58.0% in periods 3 and 4. Thereafter, a declining trend is observed, and the contribution settles at 51.8% in period 10. Meanwhile, the contribution of inflation begins at 0.0% but increases over the horizon and attains a peak of 6.3% in period 10.

In summary, the importance of shocks to formal employment and real GDP explained the highest percentage toward the overall variance decomposition of formal employment. Inflation contributed to a much lower extent but increased marginally over the horizon. Although formal employment had a higher contribution than real GDP, the Cholesky ordering was left unchanged. This was supported by economic theories such as Okun’s law which postulates that GDP is a key determinant of employment. Furthermore, the purpose of the study was to estimate the impact of macroeconomic shocks on formal employment. To that end, the results from the various impulse response functions would be more meaningful if real GDP precedes formal employment in the Cholesky ordering.

5. Discussion

This study attempted to investigate the effects of macroeconomic shocks on formal employment by way of an employment elasticity analysis and a VAR. A major finding is that a one-time shock to real GDP has a strong and positive effect on formal employment in the short run. However, the magnitude of the response weakens throughout the remainder of the horizon. This was in line with a-priori expectations as economic growth is “the combined result of increases in employment and increases in labour productivity” (ILO, 2015). Meanwhile, the response of formal employment to an inflation shock was weak. This supported findings from the granger causality test, as inflation did not have a statistically significant influence on formal employment.

The sectoral disaggregation revealed mixed results for agriculture and tourism. In the former’s case, when real GDP was shocked, formal employment within the agricultural sector demonstrated a negative response for the entire horizon period. The negative trend substantiated findings by Kapsos (2006) as he found that “GDP growth has been associated with a marginal decline in agriculture”. This could be due to more mechanized agricultural processes that reduced the dependence on field labourers.

Notwithstanding, when the value added of agricultural output was shocked, formal employment within the agricultural sector was stronger upon impact relative to the value obtained when real GDP was substituted. The remaining quarters demonstrated upward fluctuations before a peak was attained in the fifth quarter. These results revealed that formal employment conditions in the agricultural sector are more influenced by a sector-specific shock to the value-added output of agriculture as opposed to that of real GDP. This underscored the importance of the agricultural sector’s performance to formal employment in the same sector while demonstrating a lesser impact of a shock to real GDP.

The response of formal employment in tourism to a shock to real GDP was weak upon impact, but a peak was attained in the third quarter. The strong response toward the latter end of the horizon periods underscored the strong interlinkages that tourism has with the economy at large as it acts as a "generator of both employment and income, both directly and diffused through the economy" (Roldan, 1994). Furthermore, the foundations of Belize's economy are underpinned by services-related activities that are heavily influenced by tourism. Accordingly, the services sector employed 73.7% of total AIPs in 2022.

Concurrently, when the shock was applied to the value added of tourism output, formal employment in the tourism industry had the most significant response of all the impulse-responses investigated. The magnitude of the shock then weakened throughout the remainder of the horizon. The significant rise upon impact of the shock indicated a high level of pass-through effects to formal employment in the tourism industry when the sector's value-added increases. Notwithstanding, it must also be mentioned that these results highlighted the high level of vulnerability that this sector has toward exogenous shocks such as the COVID-19 pandemic.

To summarize, the sectoral analysis revealed that formal employment within the tourism industry is more susceptible to exogenous shocks relative to that of the agricultural sector. The government should foster an environment that is conducive to the sustainability of the tourism industry given its importance to economic growth. The cultivation of more public-private-partnerships (PPPs) can help to achieve this goal as it is "a mechanism for government to procure and implement public infrastructure and/or services using the resources and expertise of the private sector" (World Bank, 2022). Meanwhile, the relatively weak response of formal employment in the agricultural sector to the shock to real GDP demonstrated that there needs to be more investigation regarding the drivers of employment within that industry owing to the lack of pass-through effects from other sectors.

6. Conclusion

In conclusion, the assessment showed that formal employment demonstrated a strong and positive initial response to a real GDP shock, but the magnitude weakens thereafter. These results confirmed that formal employment in Belize is affected by fluctuations in GDP. Another key finding was that the COVID-19 shock caused a significant distortion in GDP that needed to be accounted for by way of a dummy variable before regression analysis could be conducted.

At the sectoral level, the response of formal agricultural employment to a shock to the value-added output of agriculture was relatively weak initially and endured heavy fluctuations before attaining a peak toward the middle of the horizon. This suggested that increases in the value added of agriculture output will not necessarily lead to a significant rise in formal employment within the sector in the short run. Conversely, formal employment within the tourism industry had a significant and positive response upon impact of a shock to the value added of tourism output. This revealed a high dependence between these two variables, which highlighted the vulnerability of formal employment in the tourism industry to exogenous shocks. Government officials are advised to expand the usage of PPPs with an aim to increase the resilience of the tourism industry against shocks.

Additionally, the employment elasticity analysis revealed that formal employment growth has slowed since the pandemic, giving rise to a larger informal sector. These findings raise concerns about the quality of employment in the post-pandemic period, given that healthy growth in formal employment is critical to achieving sustainable and inclusive macroeconomic growth. Policy makers should enforce stricter regulations relating to social security contributions. If left unchecked, these individuals could be forced to work past the retirement age owing to a lack of social safety nets. Furthermore, a large segment of society that is without social protections are at an increased risk of falling below the poverty line and can place downward pressure on tax revenues to the government while increasing potential welfare costs.

Lastly, the sectoral disaggregation indicated higher employment elasticities in the manufacturing and services sectors when compared to that of agriculture. Jobs in agriculture tend to be lower paying and a shift toward higher paying jobs in the aforementioned sectors would enhance the country's pro-poor growth prospects. To that end, government officials should foster an environment that is conducive to inter-sectoral labour movements by promoting higher education levels among low-skilled members of the workforce.

7. References

Campos-Vázquez, R. M. (2010). THE EFFECTS OF MACROECONOMIC SHOCKS ON EMPLOYMENT: THE CASE OF MEXICO. Estudios Económicos, 25(1 (49)), 177–246. http://www.jstor.org/stable/25790018

Craigwell, R. (2006). Foreign Direct Investment and Employment in the English and Dutch-Speaking Caribbean.

ILO. Decent Work Country Diagnostics - Technical Guidelines to draft the Diagnostics Report. Geneva : ILO, 2015.

Informal Workers - PATA Sustainability Resource Centre (previously CRC). (2023, June 29). PATA Sustainability Resource Centre (Previously CRC). https://src.pata.org/informal-workers/

Intraregional Labour Migration Flows: Current situation, challenges and opportunities in Central America and the Dominican Republic. Belize report. IOM, ILO, CECC/SICA, Network of Labour Market Observatories of Central America and the Dominican Republic, 2012. 94 p.

Islam, I. and Nazara, S. 2000. “Estimating employment elasticity for the Indonesian economy”. ILO Technical Note, Jakarta.

Kapsos, S. (2006). The employment intensity of growth: Trends and macroeconomic determinants. Palgrave Macmillan UK EBooks, 143–201. https://doi.org/10.1057/9780230627383_4

Keynes, J. M. (1936). The General Theory of Employment, Interest and Money. Macmillan.

Knotek, Edward. (2007). How useful is Okun's law?. Economic Review. 73-103.

OECD/ILO (2019), Tackling Vulnerability in the Informal Economy, Development Centre Studies, OECD Publishing, Paris, https://doi.org/10.1787/939b7bcd-en

Mordecki, Gabriela & Ramírez, Lucía. (2014). Investment, growth and employment: VECM for Uruguay.

Okun A. M. (1962). Potential GNP: its measurement and significance. In: Proceedings of the business and economic statistics section of the American Statistical Association, Alexandria, VA: American Statistical Association (pp. 89–104).

PUBLIC-PRIVATE-PARTNERSHIP LEGAL RESOURCE CENTER. (2022, December 15). World Bank. https://ppp.worldbank.org/public-private-partnership/about-public-private-partnerships

Ramoni-Perazzi, J., & Orlandoni-Merli, G. (2019). LABOR ELASTICITY OF GROWTH BY SECTOR AND DEPARTMENT IN COLOMBIA: THE IMPORTANCE OF THE AGRICULTURAL EMPLOYMENT ELASTICITY. Agroalimentaria, 25(48), 19-34.

Roldán, J. M. (1994). The financing requirements of nature and heritage tourism in the Caribbean. https://portals.iucn.org/library/node/22416

Sánchez López. (2019). Unemployment and Growth in the Tourism Sector in Mexico: Revisiting the Growth-Rate Version of Okun's Law. Economies, 7(3), 83. MDPI AG. Retrieved from http://dx.doi.org/10.3390/economies7030083

Social Security Board. (2022). Social Security Board Annual Report. https://www.socialsecurity.org. bz/wp-content/uploads/2022/08/SSB_Annual-Report-2021_e.pdf

Statistical Institute of Belize. (2020). Labour force survey. https://sib.org.bz/wp-content/uploads/LabourForce_2020-09.pdf

Verick, Sher. (2009). Who Is Hit Hardest during a Financial Crisis? The Vulnerability of Young Men and Women to Unemployment in an Economic Downturn. SSRN Electronic Journal. 10.2139/ssrn.1455521.

Voda, Alina & Duguleana, Liliana & Dobrota, Gabriela. (2019). Investments, Economic Growth and Employment: VAR Method for Romania. Studies in Business and Economics. 14. 231-244. 10.2478/sbe-2019-0037.

Zhou, J. (2020) An Empirical Study on Employment Changes in China—Based on VAR Model. American Journal of Industrial and Business Management, 10, 1250-1262. doi: 10.4236/ajibm.2020.107083.

8. Appendix

Table A-1: Select AIP Indicators [1]

Year	Primary Sector		Secondary Sector		Tertiary Sector			
	Agriculture	Fishing and Aquaculture	Manufacturing	Construction	Public Administration and Defense	Wholesale and Retail Trade	Accommodation and Food Services	Administrative and Support Services
2019	7,728	566	6,839	5,479	12,562	11,267	10,090	5,129
2020	7,747	387	6,325	4,583	12,649	9,516	5,837	4,275
2021	8,013	355	6,738	5,394	12,336	10,355	7,195	5,050
2022	7,794	378	7,330	5,780	12,625	11,118	9,150	11,660

[1] Annual Figures represent an average of monthly Active Insured Persons.

Source: SSB

Table A-2: Stationarity Tests[1]

	Levels				First-differences			
Test	Constant, no trend	Conclusion	Constant, trend	Conclusion	Constant, no trend	Conclusion	Constant, trend	Conclusion
ADF								
GDP	-1.4965 [0.5310]	Non-Stationary	-3.3305 [0.0679]	Non-Stationary	-11.4212 [0.0001]	I(1)	-11.3745 [0.0000]	I(1)
EMP	-1.0254 [0.7414]	Non-Stationary	-3.4484 [0.0514]	Non-Stationary	-10.6420 [0.0000]	I(1)	-10.6253 [0.0000]	I(1)
INFL	-1.2063 [0.6685]	Non-Stationary	-0.9732 [0.9416]	Non-Stationary	-4.8679 [0.0001]	I(1)	-4.8938 [0.0007]	I(1)
PP								
GDP	-1.260 [0.6449]	Non-Stationary	-3.2239 [0.0863]	Non-Stationary	-11.7683 [0.0001]	I(1)	-11.7412 [0.0000]	I(1)
EMP	-0.9095 [0.7812]	Non-Stationary	-3.4709 [0.0487]	Stationary	-10.7455 [0.0000]	I(1)	-10.8034 [0.0000]	I(0)
INFL	-2.8995 [0.0493]	Stationary	-3.0295 [0.1301]	Non-Stationary	-8.2127 [0.0000]	I(0)	-8.1924 [0.0000]	I(1)

[1]ADF, PP test H_0: $(\rho-1)=0$, probability values in brackets using McKinnon (1996) one-sided p-values

Table A-3: Bai-Perron Multiple Breakpoint Test

Multiple breakpoint tests Bai-Perron tests of L+1 vs. L sequentially determined breaks Date: 10/05/23 Time: 16:13 Sample: 2000Q1 2022Q4 Included observations: 92 Breaking variables: LGDP INFL_CORREL C Break test options: Trimming 0.15, Max. breaks 5, Sig. level 0.01 Allow heterogeneous error distributions across breaks			
Sequential F-statistic determined breaks:			2
		Scaled	Critical
Break Test	F-statistic	F-statistic	Value**
0 vs. 1 *	48.6751	146.0253	18.26
1 vs. 2 *	19.9825	59.9475	19.77
2 vs. 3	4.9678	14.9035	20.75
* Significant at the 0.05 level. ** Bai-Perron (Econometric Journal, 2003) critical values.			
Break dates:			
	Sequential	Repartition	
1	2016Q3	2008Q1	
2	2008Q1	2016Q4	

Table A- 4: Johansen Cointegration Test

Hypothesized No. of Cointegrating Relationships	Trace Statistic[1]	0.05 Critical Value	Prob.** Critical Value
None*	31.1588	29.7970	0.0346
At Most 1*	8.2506	15.4947	0.4390
At Most 2	3.4643	3.8414	0.0627

[1]Trace Test indicates 1 cointegrating equation(s) at the 0.05 level
* Denotes rejection of the hypothesis at the 0.05 level

Table A-5: AR Roots Table for VECM

Roots of Characteristic Polynomial Endogenous variables: LEMP LGDP INFL Exogenous variables: COVID_DUMMY Lag specification: 1 2 Date: 07/04/23 Time: 16:14	
Root	Modulus
1.000000	1
1.000000	0.9999999999999998
0.136443 - 0.613779i	0.6287612298225304
0.136443 + 0.613779i	0.6287612298225304
-0.420390 - 0.348612i	0.5461299927026092
-0.420390 + 0.348612i	0.5461299927026092
-0.312318 - 0.445036i	0.5436907650312025
-0.312318 + 0.445036i	0.5436907650312025
-0.440488	0.4404880686982912

VEC specification imposes 2 unit root(s).

Table A-6: VAR Lag Exclusion Wald Test

VAR Lag Exclusion Wald Tests				
Date: 06/22/23 Time: 16:47 Sample (adjusted): 2001Q3 2022Q4 Included observations: 86 after adjustments				
Chi-squared test statistics for lag exclusion: Numbers in [ ] are p-values				
	DIF_EMP	DIF_GDP	DIF_INFL	Joint
Lag 1	14.4405	3.3195	6.6773	38.4002
P-Value	[0.0024]	[0.3449]	[0.0829]	[0.0000]
Lag 2	2.7556	1.6750	4.3411	12.2601
P-Value	[0.4308]	[0.6425]	[0.2269]	[0.1990]
Lag 3	4.8694	8.6052	1.1179	10.6424
P-Value	[0.1816]	[0.0350]	[0.7727]	[0.3010]
Lag 4	8.0258	3.8438	63.4914	85.7904
P-Value	[0.0455]	[0.2788]	[0.0000]	[0.0000]
Lag 5	6.3544	0.5724	5.5473	15.7457
P-Value	[0.0956]	[0.9027]	[0.1358]	[0.0724]
Lag 6	3.0776	1.6905	4.4707	15.7495
P-Value	[0.3798]	[0.6390]	[0.2149]	[0.0723]
Lag 7	3.1887	0.7045	2.5826	8.7949
P-Value	[0.3634]	[0.8721]	[0.4605]	[0.4564]
Lag 8	10.1630	4.3423	20.5581	39.4704
P-Value	[0.0172]	[0.2268]	[0.0001]	[0.0000]

Table A-7: Variance Decomposition

Period	S.E.	DIF_EMP	DIF_GDP	INFL
1	0.0302	56.4824	43.5175	0.0000
2	0.0334	59.1605	36.1398	4.6995
3	0.0335	58.9498	36.0239	5.0261
4	0.0339	58.2157	36.0137	5.7704
5	0.0356	53.6850	41.0176	5.2972
6	0.0357	53.4108	40.9536	5.6355
7	0.0358	53.0999	40.7744	6.1256
8	0.0359	52.9880	40.9059	6.1060
9	0.0363	52.1577	41.7903	6.0518
10	0.0366	51.7509	41.9482	6.3008

Cholesky One S.D. (d.f. adjusted) Innovations
Cholesky ordering: DIF_GDP DIF_EMP INFL
Standard errors: Monte Carlo (100 repetitions) standard deviations in parentheses