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A weekly index of economic activity to monitor the impact of COVID-19 in Rwanda

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Abstract

This paper discusses a weekly index of economic activity developed to track the economic impact of COVID-19 in Rwanda. The index is computed as a common component extracted using the principal component analysis from a number of high frequency indicators representing various economic sectors. The paper describes how these indicators were used to track the economic impact of COVID-19 in Rwanda, assisting policymakers in making appropriate decisions aimed at protecting the population and slowing the spread of the pandemic while minimizing the potential negative economic impact. The study demonstrates the extent to which the COVID-19 pandemic had a detrimental effect on Rwanda's economic activity and the speed at which it recovered once the pandemic was contained and temporary restrictions were lifted.

KeyWords: High frequency indicators, Weekly economic index of economic activity, Principal component analysis, COVID-19, Rwanda.

JEL Classification Numbers: C63, C65, E32, E66.

1. Introduction

The global health crisis caused by the COVID-19 pandemic has taken a toll on human lives and brought major disruptions to economic activity across the world. Faced with the pandemic, countries around the world quickly reacted by imposing measures to prevent the spread of infection, such as lockdowns, social distancing, and quarantines, among other measures. Though these measures were necessary to limit infections and the death toll, they had a negative impact on the economic performance of many economies around the world.

On the global scale, the world economy contracted by 3.1 percent in 2020 compared to a growth of 2.8 percent in 2019, the worst recession since the Second World War. In Rwanda, the Covid-19 pandemic has also substantially weakened economic performance through demand and supply shocks. This resulted in a real GDP growth contraction of 3.4 percent in 2020, the first recession since 1994, after a long-term average growth of 7.8 percent between 2000 and 2019. In 2021, however, the economy started recovering, recording real GDP growth of 10.9 percent, supported by the easing of containment measures thanks to a massive vaccine rollout and continued Government support to hard-hit businesses and vulnerable households.

Throughout the evolution of the pandemic, timely economic data and analysis were needed to assess the impact of the pandemic as well as the policy response. Indeed, prompt and appropriate monitoring of economic performance is a fundamental aspect of economic analysis and a key requirement for policymakers. However, assessments based on usual economic indicators, including Gross Domestic Product (GDP) and monthly frequency indicators, such as total business turnovers, purchasing manager index (PMI), index of industrial production, consumer confidence indicator ,business confidence indicator, etc; were of little use during the crisis when decisions had to be taken on a weekly or even daily basis. In addition, due to the uncertainty, any economic assessment had to be revised much more often during the pandemic. To monitor the economic impacts of the pandemic and provide a well-informed policy response, new types of economic indicators were thus needed.

Regarding the usually available data, the Gross Domestic Product (GDP) is the most widely used and most important and appropriate indicator capturing economic activities (OECD, 2015) since it measures economic activity from an aggregated, homogeneous, and relatively comparable perspective among countries. However, it is usually compiled every quarter and is available after a considerable time delay after the reference period. In Rwanda for instance, the quarterly GDP figures are released at least 75 days after the end of the quarter, to which they refer. This poses a challenge for real-time assessment of economic conditions that are needed for policymakers, especially in times of crisis.

Nevertheless, some economic indicators are available at a higher frequency (monthly, weekly and daily) and can be used to assess economic performance. These high-frequency indicators (HFIs) became particularly popular in the wake of the COVID-19 outbreak. For the case of Rwanda, reliable high-frequency indicators available include turnover data of Value Added Tax (VAT)-registered companies operating in the industry and services sector (using real-time information from Electronic Billing Machines (EBM), exports, imports, electricity production, cement (imported and domestically produced) as well as credit to the private sector. It is also possible to combine them into a composite index of economic activities. However, some of these indicators were available only on a monthly basis and often with a lag, therefore not useful in times when health and economic conditions evolve rapidly and policy decisions need to be taken with a sense of urgency. In times like this, there is need for data availability on a weekly or daily basis.

This paper intends to describe the constitution of a novel dataset of weekly indicators of economic activities as well the computation of a weekly composite index used in Rwanda to monitor the economic impact of COVID-19. A team of Rwandan Economists searched through all sources of data and found reliable and available data on a weekly basis for variables including EBM sales or turnover data, exports and imports, new authorized loans, and VAT. These indicators were accessible with a lag of one to two weeks and combined into a weekly index of economic activities (WIEA). Other indicators were people's movement trends, produced by Google, indicating mobility across different categories of places such as retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residential.

Using the aforementioned indicators, the country started producing a weekly report on economic activities. This analysis complemented regular reports on the health situation (number of cases, hospitalizations, deaths) and helped policymakers to take appropriate decisions aiming at protecting the population and limiting the progress of the pandemic while at the same time trying to minimize the potential negative economic impact. Some of the decisions taken included whether or not to start a total or partial lockdown, the length of a curfew, restrictions on public gatherings, working from home as well as the use of personal protective equipment.

The paper aims to contribute to the literature on the economic effects of COVID-19 and containment measures (Mascagni and Lees, 2022; Aragie et al., 2021; Bizoza and Sibomana, 2020)as well as the literature on the use of high daily and weekly frequency indicators to monitor economic activities. The contribution is through the demonstration of how HFIs can be used in the context of Low-Income Developing Countries (LIDCs) in Africa and elsewhere with limited data availability, using simple and well-known statistical techniques. Similar papers have been done only on advanced economies, mainly using advanced techniques such as principal component analysis and state space dynamic factor model (Lewis et al., 2020), expectation maximization algorithm (Eraslan and Götz, 2021), and wavelet transformation approach (Qureshi, 2022).

From a policy-making point of view, this paper is relevant for other countries as it documents how policymakers in Rwanda used high-frequency data to make important decisions during the pandemic and how they could evaluate the effectiveness of policies such as "working from home" or total or partial lockdowns, using satellite data made published by Google. Additionally, by enhancing tax compliance, nations can improve real-data sources that can be useful proxies of economic activity.

Looking at the analysis of these HFIs, this paper shows the extent to which the Covid-19 pandemic had a negative impact on Rwanda's economic activity, but also how quick economic recovery occurred as soon as the pandemic was under control and temporary restriction measures were relaxed.

The rest of this article is organized as follows, section 2 discusses the literature on covid-19 impact briefly and section three presents the methodology. Section four is about empirical findings while section five concludes.

2. Literature Review

Timely information is a prerequisite for good economic analysis and policy decision-making. Especially, during periods of shocks such as COVID-19, which have severely affected human health across the world and also had a negative impact on economies around the globe.

COVID-19 has had a significant effect on economic activity, by reducing economic growth, workforce, and human capital, thereby causing job losses, disrupting supply chains, increasing income inequalities, and worsening poverty traps, hitting investment and savings but positively impacting innovation and knowledge. However, the impact was mixed across countries depending on heterogeneity in the policy responses (Deb et al., 2022; Callegari and Feder, 2022; Calderon and Kubota, 2021). For instance, according to Deb et al. (2022), fiscal and monetary policies implemented during the COVID-19 crisis were crucial in reducing the negative effects of containment measures on economies, with the effects being more severe in countries where less fiscal stimulus was implemented and monetary policy easing was more restricted. Calderon and Kubota (2021) indicate that certain economic conditions contributed to a larger decline in economic growth during the COVID-19 pandemic crisis. These conditions include increased exposure to global markets, vulnerabilities to commodity price volatility, increased dependence on external financing, primarily Foreign Direct Investment (FDI); greater reliance on global value chains, and increased public debt exposure to private creditors. Contrary, they note that sufficient fiscal space and foreign savings served to buffer the steeper losses in economic growth.

COVID-19 affects the economy through three transmission channels (Carlsson-Szlezak et al., 2020). The first, which is direct, is related to the reduced consumption of goods and services. Prolonged lengths of the pandemic and the social distancing measures might reduce consumer confidence by keeping consumers at home, wary of discretionary spending and pessimistic about the long-term economic prospects. The second, pass through financial market shocks and their effects on the real economy. Household wealth will likely fall, savings will increase, and consumer spending will decrease further. The third channel is about supply-side disruptions. As COVID-19 keeps production halted, it will negatively impact supply chains, labor demand, and employment, leading to prolonged periods of layoffs and rising unemployment.

To assess the impact, different economic indicators have been used. Some papers used macroeconomic indicators such as Real GDP growth, inflation, unemployment rate, fiscal deficit, tax revenues, central bank rate, exports, imports, and FDI (UNDP-Rwanda, 2020; for Latin America and the Caribbean (ECLAC), 2020; Calderon and Kubota, 2021; UNCTAD, 2022; Bank, 2021; Cho et al., 2021) while authors like (Lewis et al., 2020; Blonz and Williams, 2020; Eraslan and Götz, 2021; Chen et al., 2020) prioritized the use of high-frequency indicators to fast track deteriorating economic conditions during the COVID-19 pandemic period and make timely and well-informed economic decisions to support COVID-19 economic policy response.

3. Methodology

To monitor the impact of COVID-19 in Rwanda, we followed the methodology used by Lewis et al. (2020), Wrynn and Bedogni (2020), Chen et al. (2020). They employed high-frequency indicators and created a composite index on weekly frequency for quick identification of the magnitude of the shock.

3.1. The High-Frequency Indicators

A survey of high-frequency economic indicators was conducted to choose readily available indicators on a weekly and daily basis. Table 1 provides an overview of the selected indicators.

To correctly assess the impact of the COVID-19 pandemic, we have to compare indicators of a particular week with their average value during the pre-COVID period. The latter span from the first week of 2019 (starting period of available data) to the eleventh week of 2020, as the countrywide lockdown was imposed from week 12 of 2020. In addition, we consider a four-week moving average trend to reduce the volatility of the series.

In addition to the high-frequency data, we use the google community Mobility data. Daily Google mobility has been used across the world to monitor the trend of Covid-19 and the responsiveness of different policies put in place to curb the effect of the pandemic (Yilmazkuday, 2021; Bravo and Jooste, 2020; Spelta and Pagnottoni, 2021)

Google published a new source of mobility data from late March 2020, based on the same location data used to indicate busy hours for restaurants and museums (Aktay et al., 2020). As data is only collected from users who have enabled 'location history' on their Android devices, it raises no new privacy concerns. To protect the privacy of the individuals whose data is used, the data is aggregated and anonymized. All metrics with a differential private count of contributing users (after noise addition) of less than 100 or a geographic region of less than 3 km^2 are discarded (Aktay et al., 2020).

The Google data indicate how the movements of people to different places, such as retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residential, vary in comparison to the baseline days. The latter represents normal values for that day of the week, computed as the median value over the period spanning from January $3^{rd}$to February 6^{th} 2020. The categorized places are retail & recreation (including restaurants, cafes, shopping centers, theme parks, museums, libraries, and cinemas); grocery & pharmacy (including grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies); parks (including national

Table 1: Indicators used in the WIEA

Indicator	Description	Frequency	Availability (t=week)
EBM sales	The total value of sales recorded by all businesses that use the EBM machines. They are compiled on a weekly basis as a sum of the sales between Monday and Sunday and are classified by economic sectors according to ISIC 2017.	Daily	t+2
VAT	Value Added Tax. This variable takes the total amount of VAT that is supposed to be levied on taxable sales recorded through the EBM system. It is compiled weekly, taking a total of Monday to Sunday.	Daily	t+2
NAL	New Authorized loans. This indicator is the total sum of the value of new authorized loans by the banking system every week.	Weekly	t+1
Traditional exports	The sum of coffee, tea, minerals (Cassiterite, Coltan, and Wolfram), and pyrethrum exports.	Weekly	t+1
Non-traditional exports	The sum of all other formal goods exports mainly Horticulture, Other minerals, and manufacture product.	Weekly	t+1
Imports	This indicator is the sum of the formal import of goods. In addition to the total import of goods, the index comprises the capita Good imports, Good consumer imports, Intermediary goods imports, and Fuel Imports.	Weekly	t+1

parks, public beaches, marinas, dog parks, plazas and public gardens); transit stations (public transport hubs such as subway, bus and train stations); workplaces and residential (Aktay et al., 2020).

3.2. The Weekly Index of Economic Activity (WIEA)

To capture all information available on a weekly basis, we compute a more comprehensive, representative, and reliable indicator called the weekly index of economic activity.

To compute the Weekly Index of Economic Activities (WIEA), We use the same methodology that the Federal Reserve Bank of New York, as well as the Irish Parliamentary Budget Office, employed to produce the weekly tracker for the economic activities (Lewis et al., 2020; Wrynn and Bedogni, 2020) using the principal component analysis (PCA) method. The PCA is a statistical procedure that reduces the dimensionality of large datasets by transforming a large set of variables into a smaller one that still contains most of the information in the large set (Jolliffe and Cadima, 2016; asan Karamizadeh et al., 2013).

In PCA, an original dataset of n correlated variables to various degrees is transformed to n numbers of uncorrelated principal components (PCs) which have equal sums of the variances with the original variables. Though the number of PCs is the same as the original variables, the transformation is made in such a way that the first few PCs explain the majority of the variance in the data set, hence reducing the dimensionality of the original data set. The PCs are sequenced from the highest to the lowest variance, i.e., the first PC describes the data's highest variance proportion. The next highest variance is explained by the second PC and so on. Let us denote by X the matrix of$x_1, x_2, ..., x_n$ original variables, $X_a = \sum_{i=1}^{n} a_i x_i$a linear combination of these variables, a is a vector of constants $a_1, a_2, ..., a_n$, S_a the sample covariance matrix associated with the dataset, and $a'$the transpose of a.

The variance of X_a is

$$Var\left(X_a\right) = a' S_a \tag{1}$$

The objective is to determine the linear combination $X_a$that maximizes the variance $Var\left(X_a\right)$. It is shown that the solution to that maximization problem is the one defined by a, which maximizes the quadratic form $a' S_a$ (Jolliffe and Cadima, 2016). To allow that problem to have a well-defined solution, a is imposed to be a unit norm vector: $a^{'}a = 1$.

Thus, the maximization problem is equivalent to

$$Max\left[Z\left(a\right) = a^{'}S_a - \lambda\left(a^{'}a - 1\right)\right] \tag{2}$$

First condition gives:

$$\frac{\partial Z\left(a\right)}{\partial\left(a\right)} = 0 \;\Leftrightarrow S_a - \lambda a = 0 \tag{3}$$

$$\Leftrightarrow S_a = \lambda a \tag{4}$$

Therefore, a must be a unit norm eigenvector and $\lambda$the corresponding eigenvalue of the covariance matrix S_a

It is important to note that λ are variances of X_a

$$Var\left(X_a\right) = a^{'}S_a = \lambda a^{'}a = \lambda \tag{5}$$

S is a $n \times n$real symmetric matrix with exactly n real eigenvalues $\lambda_k\left(k = 1, ..., n\right)$.

Their corresponding eigenvectors can be defined to form an orthonormal set of vectors,

i.e. $a^{'}_k a_{k^{'}} = 0,\ \forall k \neq k^{'};\left(k = 1\ if\ k = k^{'}\right)$.

With that restriction of orthogonality of coefficient vectors, the full set of eigenvectors of S are the solutions to the problem of obtaining up to n new linear combinations $X_{ak} = \sum_{j=1}^{n} a_{jk}x_j$, which successively maximize variance, subject to uncorrelatedness with previous linear combinations as $Cov\left(X_{ak}, X_{ak^{'}}\right) = a^{'}_k S_{ak} = \lambda_k a^{'}_k a_k = 0, \forall k \neq k^{'}$.

X_{ak} are called the principal components of the dataset.

a_k are called the principal component loadings, and elements of X_{ak} are called the principal component scores, values that each individual would score on a given principal component.

The principal component loading will be associated with selected high-frequency indicators to form the weekly economic activities index and this relationship is expressed by equation 6.

$$WIEA_t = W_{11}X_{1t} + W_{12}X_{2t} + W_{13}X_{3t} + \cdots + W_{1N}X_{Nt} \tag{6}$$

Where $W_{1i}$are the principal component loading from the principal components that capture the majority of information from the high-frequency indicators and X_{it} are the variables, aforementioned in table 1.

4. Empirical results

4.1. *High- Frequency Indicators Trends*

Rwanda has faced four main peak periods in terms of COVID-19 contamination, hospitalizations, and deaths. During these periods, economic activities were affected negatively, given the measures to save people's lives and limit the COVID-19 virus spread. The first happened in 2020; following the first case of COVID-19, a country-wide total lockdown was imposed to limit the spread of the virus. This lockdown spanned the second week of March 2020 to the end of April 2020. During this period, all unnecessary movements outside the home were banned except for movements related to essential services such as health care and shopping for groceries. Both public and private workers were ordered to work from home to help prevent the spread of the COVID-19 virus, and Rwanda's borders were completely closed, except for goods and cargo and returning citizens. Other peak periods were in January 2021 and July 2021, when the hike in pandemic infections caused the tightening of virus containment measures, including regional lockdowns. The latest period happened from the second week of December 2021 to January 2022, whereby no lockdown but a tightening of other restriction measures such as increasing curfew time, lowering staff working from the office as well the capacity of bus passengers, and limiting access to all business areas to no vaccinated people were imposed.

The selected economic indicators showed that during the period of tighter restriction measures, there was a weakening in economic performance. For instance, EBM sales fell by 42.5 percent on average during the first lockdown and improved gradually as restriction measures were eased, allowing the resumption of economic activities.

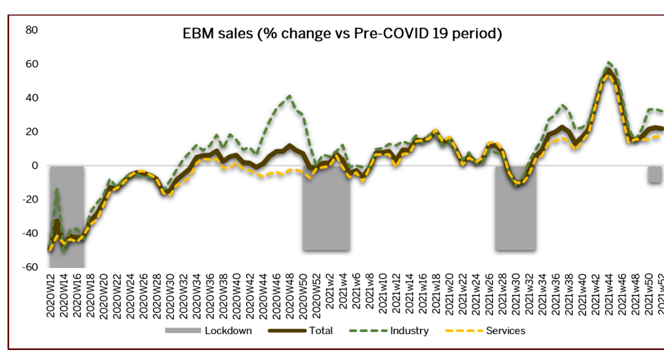

Figure 1: EBM sales

In this regard, they evolved from -30.9 percent recorded in the last week of the lockdown to a growth of 23.9 percent in the first week of December 2020. Turnovers further increased by 10.0 percent on average between February and June 2021 after dropping by 4.8 percent during the partial lockdown of January 2021. In July 2021, EBM sales fell by an average of 10.4 percent during the second lockdown, this time partially. Then, following the easing of containment measures that led to the resumption of all economic activities and the vaccination campaign, EBM sales recorded an average growth of 24.5 percent between August and December 2021. In the last two weeks of December 2021, COVID-19 restrictions were put in place following the surge in cases, but there was not much impact on economic activities. EBM sales growth decelerated during that period compared to November but overall growth of December was around 20 percent on a weekly basis, which is close to the August-December average.

The same economic conditions revealed by the EBM sales series are reflected by the evolution of the weekly VAT, New authorized loans, exports, and imports. These indicators declined in the period of crisis, and they picked up in the period of eased containment measures, evidencing severe economic conditions when COVID-19 cases were rising and economic recovery after the crisis period.

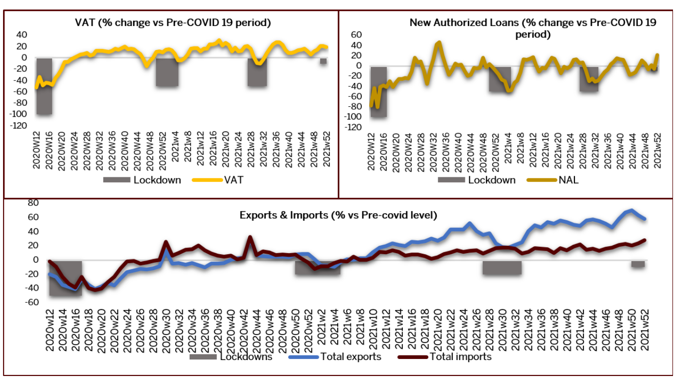

Figure 2: VAT, NewAuthorized Loans, Exports, and Imports

Regarding google community Mobility reports; we observe that the lockdown was strictly respected by the Rwandan population as mobility dropped drastically during the lockdown for recreation and retail. Since May 2020, mobility has been gradually increasing. In the period from Sept 10 to November 15, 2020, mobility for retail and recreation was higher than pre-COVID levels reflecting the relaxation of the curfew measures from 7 PM to 9 PM in an effort to promote domestic tourism. The surge of cases that made the government of Rwanda tighten measures is reflected in figure 3 where we see a negative trend due to the reduction of the curfew from 9 PM to 8 PM introduced on the 22nd of December and the closing of all business at 6 PM later from 5 January 2021.

The graphs below show how effective some of the measures taken by the government.

Mobility to workplaces was very low during the lockdown as every worker was asked to work from home. It still remains low due to the "50% work-from-home policy". Between the end of August and the end of October, there

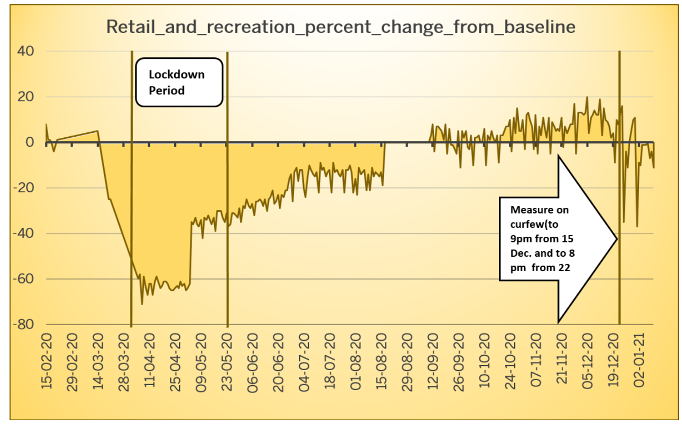

Figure 3: Google COVID-19 community reports Mobility for Retail and Recreation

was a change in Government guidelines from 50% to 30% and back to 50% in November regarding the share of workers allowed to work at their workplaces. The government took more stringent measures due to the surge in new cases and rising rate of mortality, where the share of workers allowed working at their workplace went from 30% from December 15^{th} to 15% from 5th January, this was strictly respected by Government institutions, and mobility levels remained relatively low. The fluctuations can be explained by the weekends when mobility is at almost similar levels compared to the pre-covid situation.

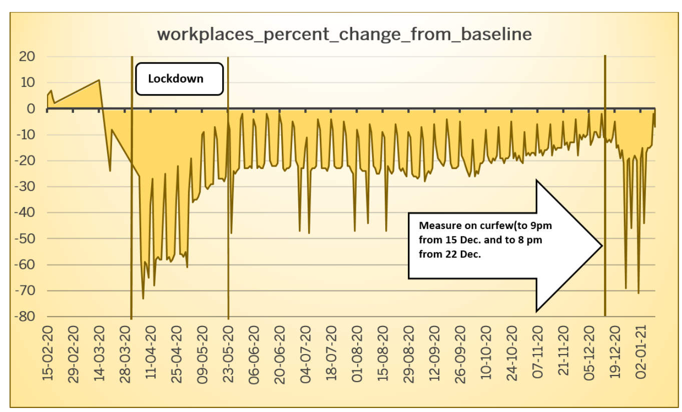

Figure 4: Google COVID-19 community reports Mobility for Workplaces

4.2. Weekly Index of Economic Activity

The starting point for computing the index is the assessment of the appropriateness of the aforementioned HFIs. These indicators accurately represent the GDP on the expenditure side. Table 2 shows that the indicators have a strong relationship with both the GDP and the Composite Index of Economic Activities (CIEA). The latter is a monthly composite index that has a strong track of Rwandan Real GDP, evidenced by a correlation rate of

Table 2: Variables used to compute the WIEA

Type		Correlation with GDP	Correlation with CIEA
Industry and services turnovers	**Total sales**	**83.9**	**90.0**
Export	**Total exports**	**75.0**	**94.1**
Imports	**Total imports**	**76.5**	**92.6**
Credit to the private sector	**New Authorized Loans**	**70.6**	**86.0**
Tax	**Value Added Tax**	**73.5**	**80.5**

90 percent on average in the last ten years.

To have a much clearer picture of the fit between the selected indicators and the reference variable, we plot the series of the chosen variables. Their monthly version is compared to the CIEA.

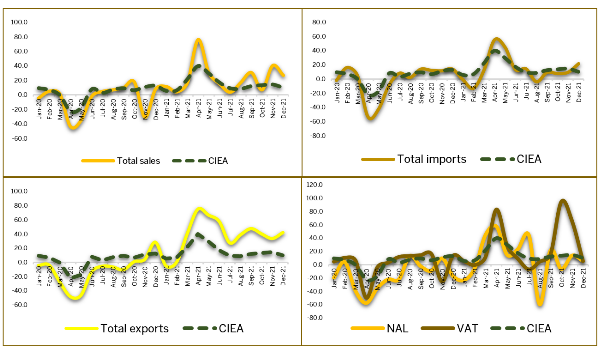

Figure 5: Selected variables and the CIEA evolution (Percent year-on-year)

Figure 5 presents the evolution of the selected variables, and the observed trends confirm the strong correlation between the chosen variables and the CIEA. Furthermore, they all reveal the economic fallout during the lockdown periods as well as the subsequent gradual recovery of economic activities after the resumption of economic activities.

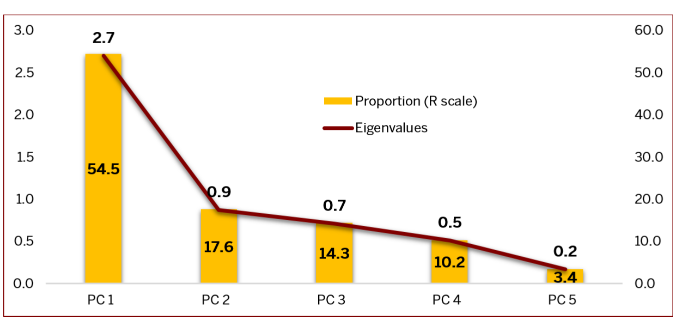

Figure 6: Scree plot and percentage variance for each principal component

After assessing the suitability of the variables, we combine these indicators in one index constructed using the principal component analysis (PCA). The computation of PCA shows that the first principal component contains rich information with a proportion of 54.5 percent, while the rest is shared between four principal components representing less information individually, as illustrated by figure 6.

Therefore, we proceed by computing the WIEA, following equation 6, using the first principal component. The associated weights for the chosen variable are presented in table 3. The weights are eignvector loading, which represent the correlation between the specific variable and the principal component.

Table 3: Weights derived from the first principal component

Variable	**eigenvector loading**
Total EBM sales	**0.53**
Total exports	**0.42**
Total imports	**0.45**
NAL	**0.26**
VAT	**0.52**

The computed index, which year-on-year growth is presented in figure 2, provides timely information on economic conditions, mostly during this period of the COVID-19 pandemic. The index indicates the extent of economic activities fallout in each period of lockdown and evidence also the recovery amid the easing of restriction measures. The index shows that economic activities contracted about 45 percent compared to the pre-pandemic level during the countrywide lockdown period and the recovery in the aftermath, improving to a decrease of 6.1 percent by end of December 2020 and an increase of 13.3 percent on average in 2021.

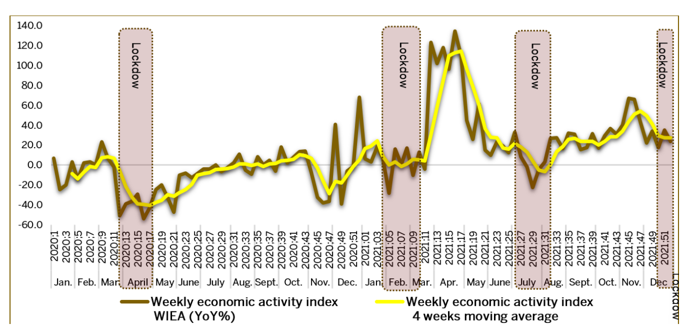

Figure 7: Weekly Index of Economic Activities

The comparison of the WIEA with the real GDP as well as the CIEA, reveals that the index conveys the same message about the recent evolution of the Rwandan economy. Therefore, the index is a powerful early warning indicator. It has a correlation of 87.0 percent and 85.1%

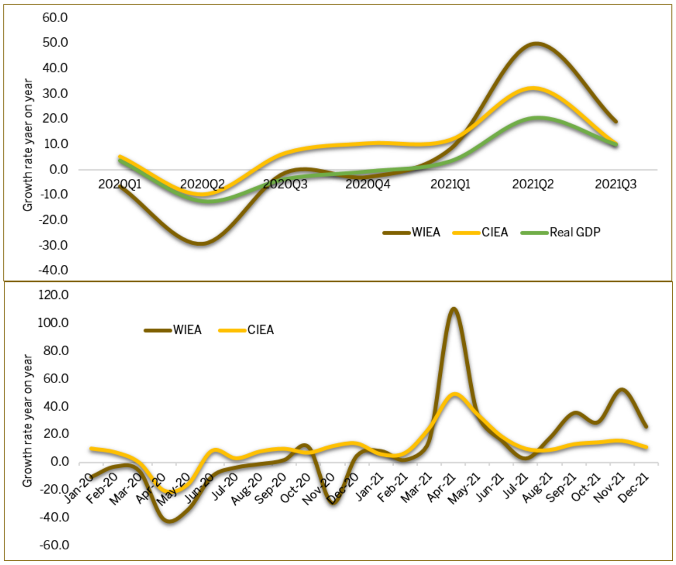

Figure 8: Relationship between WIEA, Real GDP, and CIEA

percent vis-à-vis the CIEA and Real GDP, respectively.

Given its overall performance, it can be used to inform the monetary policy process about the current and near-future trends of overall economic activity.

5. Conclusion

Comprehensive economic indicators that provide accurate descriptions of economic conditions are normally accessible with a modest delay. This can complicate the process of economic decision-making, specifically when conditions evolve rapidly from day to day and week to week, as is the case of the COVID-19 period where governments around the world have to take quick measures to fight the health and negative economic consequences of COVID-19 pandemic.

This paper presents high-frequency indicators and a simple approach to generate an index of economic activities on a weekly basis which can help to track economic conditions and the economic impact of COVID-19 in Rwanda. The constructed weekly index of economic activities demonstrates a strong correlation with real GDP and the Composite Index of Economic Activities, making a valuable measure of economic activities and an early warning index that facilitates policy decision-making. The economic analysis based on these indicators has complemented other health reports and assisted policymakers in taking appropriate measures and decisions to safeguard populations and stop the spread of the pandemic while minimizing the potential negative economic impact.

This paper contributes to the literature and the policy-making environment by showing how HFIs can be used in the context of Low-Income Developing Countries (LIDCs) in Africa and elsewhere with limited data availability. This paper is particularly relevant for other developing economies because it shows that with some indicators usually available on a more regular basis, a reliable index can be computed in a relatively simple way. However, it is important for Rwanda and for other countries to keep investing in the automation of various processes such as tax payment and declarations, economic transactions to avail more HFIs for economic analysis. The Google mobility data also offers a good opportunity to measure the impact of mobility restriction measures put in place during the pandemic.

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