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The Impact of the COVID-19 Pandemic on Bank Lending – A Sectoral Analysis

Stephanie Kimani

Abstract

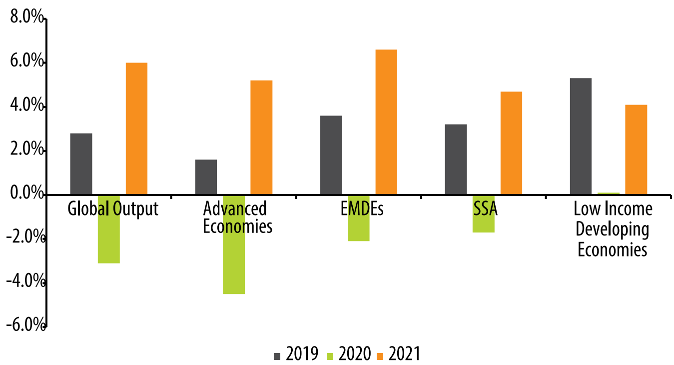
This study examined the impact of the COVID-19 pandemic on bank lending across various sectors in Kenya. Using a multivariate Vector Autoregressive (VAR) model within a time series data framework, the study established the existence of both direct and indirect COVID induced shocks on credit allocation to various sectors in the Kenyan economy. The main finding of the study was that the credit allocation response to the COVID-19 pandemic was through the demand channel. Therefore, any policy aimed at minimizing pandemic-induced economic damage by stimulating demand was not sufficient in catering for emerging supply distortions. Additionally, given that the COVID-19 pandemic induced uncertainty, resulting in a lagged response as revealed by the IRFs, most commercial banks would require to be incentivized, through prudential and supervisory bank regulations to extend and sustain positive credit allocation to the private sector

1.0 Introduction

The impact of shocks on bank lending has been a recurrent theme in discussions on the role that shocks and uncertainty play on the banking sectors' willingness to extend credit to the private sector. The discussions amplified at the onset of the global coronavirus (COVID-19) pandemic that extended beyond just being a public health crisis to one of the most notable synchronized economic fallouts of this century.

The consequent steep decline in activity, a result of twin shocks on both global demand and supply chains, was expected to wipe out nearly US$ 8.50 trillion in economic output over the periods 2020 and 2021 (World Economic Situation and Prospects, 2020) pushing more than 34 million people into extreme poverty.

Figure 1: Global GDP across Income Groups



Source: IMF World Economic Outlook Update, Author's Compilation

More specifically, the pandemic placed immense pressure on developing economies whom, prior to the COVID-19 crisis, were experiencing challenges in domestic revenue mobilization as well as volatility in capital/portfolio flows thereby constraining their ability to implement adequate fiscal stimulus measures. Saddled with high levels of public debt and persistent fiscal deficits, it is estimated that many developing countries only managed to provide fiscal packages worth less than 1.00% of their GDP (United Nations).

In light of soft fiscal policy responses and strained household and corporate incomes, central banks stepped up efforts to bridge liquidity gaps by establishing monetary stimulus packages that were intended to support banks accommodate the surge in liquidity demand (Li et al., 2020). However, the weakened economic environment had, and continues to have, material consequences for credit conditions thereby impacting banks' lending decisions despite the monetary support.

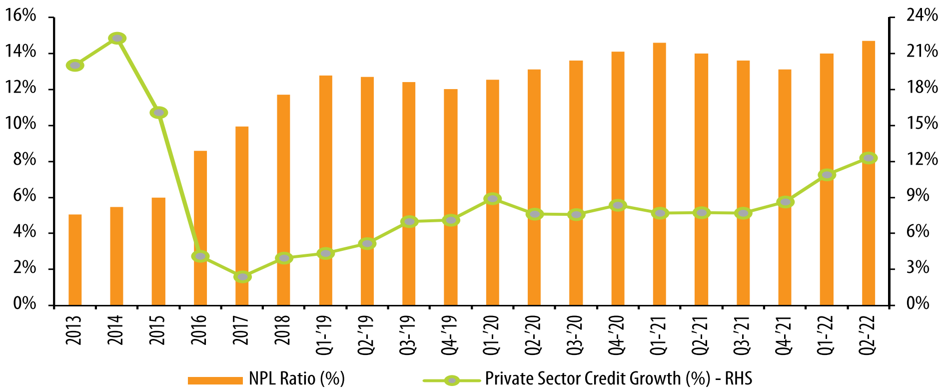
On the demand side of the credit function, constrained incomes impacted the capacity to access new as well as service existing loans. On the supply side, the uncertainty surrounding the depth and duration of the pandemic implied a substantial increase in non-performing loans (NPLs), due to a potential rise in household and company defaults, which resulted in reduced bank willingness to extend new credit.

The Kenyan Case

Even as the global economy emerges from the trenches of the turmoil, there remain challenges in the assessment of borrower credit quality in the banking sector. Concerns around poor credit risk management and credit quality identification, given some of the bold policy measures undertaken by authorities to support livelihoods, has raised credit risks in the banking sector.

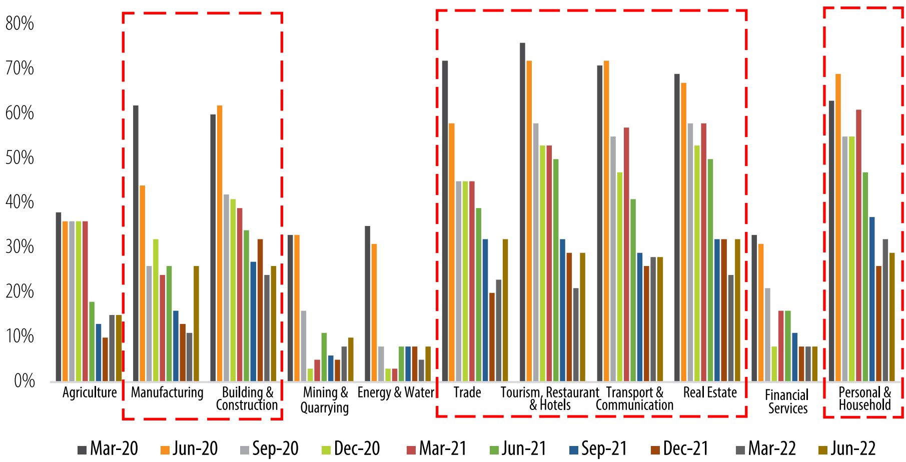
One of the concerns is that some of the residual policy support measures could mask true credit risk conditions. An immediate example in Kenya would be the suspension of the listing of loan defaulters on credit reference bureaus (CRBs) with a view of supporting borrowers amidst the COVID-19 induced economic shock.

Figure 2: Private sector credit and asset quality dynamics



Source: Central Bank of Kenya (CBK), Author's Compilation

Bank respondents that noted a rise in the NPL ratio across various sectors

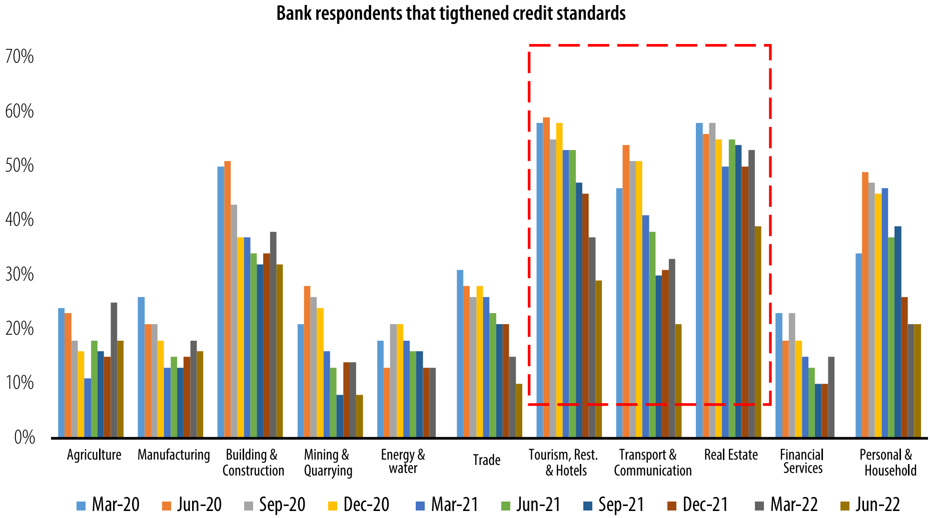


Source: Central Bank of Kenya (CBK), Author's Compilation

During the CRB listing 'freeze', data for 99% of the 4.60 million loan accounts negatively listed with CRBs were frozen following the suspension of reporting of defaults on loans valued lower than KES 5 million. There is evidence of a subsequent bank risk aversion, as noted by a dip in private sector credit growth in Q2-2020. This fueled the need for prudence as banks maintained and/or adopted high quality lending practices as well as approaches to ensure that bank provisions remained adequate in light of projected credit losses. This included but was not limited to banks suspending unsecured lending, requiring higher value collaterals and higher lending rates for shorter maturities.

The multifaceted impact of the pandemic on bank customers across various sectors has increased scrutiny of the banking sector loan book. Fundamental changes in the business environment have strengthened the need for a remediation of loan portfolios so as to remain financially viable. This has undoubtedly had an impact on banks' risk appetite towards some segments which has resulted in a disproportionate allocation and extension of credit. To this end, the consequent tightening of credit conditions towards some economic sectors could have clear micro and macro-economic consequences posing the risk of undermining the sustainability of the country's economic growth potential.

It is therefore of interest for policymakers to understand how bank lending decisions are affected during times of uncertainty/shocks, such as that of the COVID-19 pandemic. This is understandably so given



Source: Central Bank of Kenya (CBK), Author's Compilation

that the banking sector remains an important source of funds for many businesses, and one that is not easily substituted for funds obtained through other types of intermediaries or by debt directly placed in credit markets (Himmelberg and Morgan, 1995).

In this paper, we provide novel evidence of changes in banks' lending decisions, as proxied by the supply of bank loans to the private sector, as they face significant uncertainty during the pandemic. Specifically, the paper uses pandemic features to assess its causal impact on the supply of bank loans to the private sector across key sectors in Kenya.

Specifically, the paper seeks to test the below key hypotheses:

Hypothesis 1: Pandemic-related shock and uncertainty is negatively related to bank lending to the private sector.

Hypothesis 2: Pandemic-related shock and uncertainty resulted in a realignment of banks' loan portfolio.

2.0 Literature Review and Contributions

Financial theory highlights uncertainty and risk as prominent factors in the willingness of investors and financial intermediaries to provide capital (Pástor and Veronesi, 2013). It is therefore not far-fetched to expect economic uncertainty to have adverse effects on the supply of bank credit.

In a recent study by Nair et.al (2022), unexpected events with a global impact such as the COVID-19 pandemic created conditions of ambiguity and carried a high risk of decision failures. This in part may explain banks' risk aversion and conservatism in extending credit to the private sector at the onset and height of the COVID-19 pandemic.

Moreover, a study by Shao Wu (2021) revealed that heightened economic uncertainty resulted in more conservative non-price credit terms. These non-price credit terms included reducing the average loan size which would shorten the average loan maturity and increasing the proportion of loans that were secured by collateral.

There was also evidence that economic uncertainty affected the allocation of banks' loanable funds as well as decreased loan demand. The study by Shao Wu (2021) utilized the natural logarithm of volatility risk premium (VRP) framework as a proxy of economic uncertainty. Results from the study suggested that there was a negative association between economic uncertainty and the supply of bank credit.

Certainly, economic uncertainty and changes in bank lending decisions may be informed by the inherent threat of bank failures as a result of emerging credit risks linked to poor management as captured by low efficiency, low capital and excess lending. Low cost efficiency suggests badly managed portfolios where poor loan underwriting, poor monitoring and controls resulted in increased non-performing loans (NPLs) Berger & De Young, 1997, Podpiera & Neill, 2018).

Historically, non-performing loans (NPLs) have been linked to bank failures, which coupled with other factors; act as a forerunner to banking crisis' (Ghosh, 2015). Kimani et.al (2019) found a strong and positive nexus between non-performing loans (NPLs) and banking sector stability in Kenya.

Traditionally, stable economic conditions as measured by real GDP growth implies better loan servicing and as such, lower non-performing loans (NPLs) (Ghosh, 2015; beck at. al, 2010). Deteriorating asset quality is therefore considered one of the channels for macroeconomic shocks on bank balance sheets (Nikolaidou, Vogiazas; 2017).

Fofack (2015) and Flamine et. al (2009), found macroeconomic volatility to be the main driver of non-performing loans (NPLs), whereas Fofack (2005) identified causality linkages between NPLs and GDP per capita. Glen, Steffen & Lea (2007) found that corporate write-offs to loan ratios increased following an adverse output shock.

Li et al. (2020) found that at the beginning of the COVID-19 pandemic, an influx of funds from liquidity injection programs and depositors, along with high pre-shock levels of bank capital, allowed banks to accommodate the surge in liquidity demand. Yet, a survey conducted the US Fed suggests that banks around the world were tightening lending standards, citing uncertain economic outlooks, worsening industry-specific problems, reduced risk tolerance, and other concerns.

Colak et. al (2020) confirmed a tightening of lending to the private sector providing evidence that bank loan growth declined globally in response to the pandemic shock - a proxy for COVID-19 cases and deaths. The decline in private sector credit growth was largely dependent the pandemic intensity across various countries. Additionally, the negative impact of the pandemic on credit allocation to the private sector was less pronounced in countries that were better prepared to handle a sudden health crisis. The study by utilized the difference-in-difference (DID) methodology.

In Kenya, the COVID-19 pandemic has had diverse effects across the economy as well as highlighted the limits of Kenya's growth model. FSD Kenya (2022) highlighted three key macroeconomic impacts of COVID-19 which are: (i) A deterioration in incomes and a contraction in aggregate demand; (ii) An increase in poverty levels; and (ii) Weakness in overall economic and business activity.

The sectors identified as hardest hit were those negative impacted by government enacted mitigation measures such as travel restrictions, lockdowns, social distancing and a shutdown of non-essential businesses (Kunt et.al, 2021). Some of the sectors identified were tourism, accommodation and food services, education, wholesale and retail trade and manufacturing.

Most concerning is that these sectors are an important source of formal employment. Further, a survey by FSD Kenya (2021) revealed that 20.00% of micro, small and medium sized enterprises (MSMEs) shut down during the pandemic while 45.00% of the remaining businesses were operating on less than half of their pre-COVID revenues by Q1-2021.

Motivation

This paper is motivated to investigate the drivers and heterogeneity of bank lending across various sectors as impacted by the COVID-19 shock. The paper seeks to use pandemic fear to inform behavioral changes in bank lending across various segments.

This suggests that a credit crunch is predicated on pandemic fear, as observed by a rise in COVID-19 cases, which induces uncertainty about the future thus increasing bank hesitation to enhancing lending. Studying this over time should provide clarity and some explanation on loan portfolio realignments pre-crisis as well as during the pandemic.

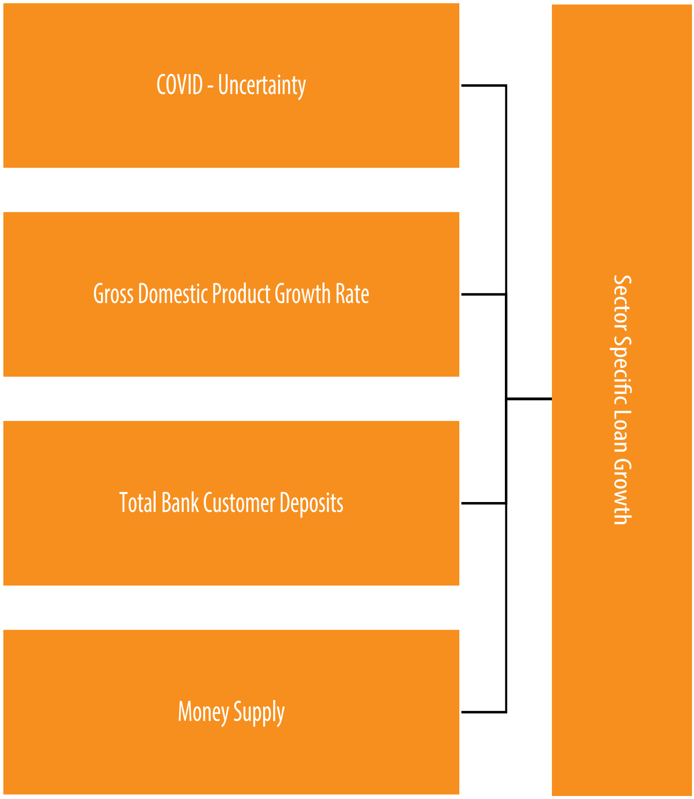
Understanding how banks alter their lending behavior in response to heightened uncertainty and risk is therefore a particularly important concern for policymakers (Colak, 2019).

The paper will evaluate the impact of the COVID-19 shock on bank lending using a VAR model which would enable derivation of the Impulse Response Function (IRF) to estimate the significance of the shock factor.'

This paper relates to growing literature on the impact of the COVID-19 pandemic on bank lending activities to the private sector and the filter through to the real economy. This paper as well seeks to study changes in bank lending decisions as informed by a realignment of banks' loan portfolio. The paper provides a novel contribution to literature on the impact of the COVID-19 pandemic on bank lending across various sectors in Kenya.

3.0 Research Methodology

3.1 Conceptual framework



The key variables of interest for this study are PSC: sector specific loan growth as the dependent variable and CVDUncert: COVID-Uncertainty which is the main explanatory variable of interest. GDP: gross domestic product growth rate, CustDepo: total bank customer deposits and M3: money supply are the control variables.

Table 1: Definition of Variables

Variable	Definition	Description and Source
Sector specific loan growth (PSC)	This is the change in the size of credit extended by banks to various sectors in the private sector. There is comprehensive literature to support the fact that a bank's allocation of credit is positively correlated to its risk appetite. During times of economic uncertainty, risk appetite diminishes thus tightening credit allocation.	Monthly growth rate of total bank loans to the private sector. **Source:** Central Bank of Kenya
COVID-Uncertainty (CVDuncert)	COVIDuncert will proxy implied pandemic fear that leads to bank uncertainty of the future	Changes in the Total number of confirmed COVID-19 cases **Source:** Ministry of Health (MOH)
Gross domestic product growth rate (GDP)	This is used as a proxy for the business environment. The business environment defines among other things the credit risk that banks may be exposed to. This measure represent factors beyond the firms that influence credit allocation decisions and the performance of loans. Khemraj and Pasha (2009) and Farhan et al. (2012) posit that real GDP has a significant and negative relationship on the level of NPLs. That is, a strong performance in the real economy is linked to a lower number of NPLs which should improve risk appetite and in turn enhance credit allocation to the private sector.	**Source:** Central Bank of Kenya
Total Bank Customer Deposits (CustDepo)	This will proxy banks' capacity to lend. In part, the lending capacity of bank is limited by the quantum of customer deposits.	**Source:** Central Bank of Kenya
Money Supply (M3)	This will be a proxy for liquidity. M3 is the broadest measure of money supply that includes currency, large time deposits and institution money market funds.	**Source:** Central Bank of Kenya

3.2 Functional model

A multiple regression model as specified below guided the study:

$$PSC_{t,j} = f(CVDUncert_t\ ,\ GDP_t\ ,\ CustDep_t\ ,\ M3_t,\ e_t)$$

Table 2: Model assumption

Variable Name	Notation	Expected Sign (Study)
Sector specific loan growth	PSC	
COVID-Uncertainty	CVDUncert	(-)
Economic growth	GDP	(+)
Customer Deposits	CustDepo	(+)
Money supply	M3	(+)

Empirical Model

In this study, the impact of COVID-uncertainty is classified as a shock. The study therefore analyzed the impact of this shock on bank lending across various sectors. To analyze this impact, the study utilized impulse response functions (IRFs) employed via vector autoregressive (VAR) models. Impulse response functions (IRFs) enable us trace the transmission of the pandemic shock on bank lending to which the paper derives useful tools in the assessment of economic policies.

The VAR model has proved useful in describing the dynamic behavior of economic and financial time series. The VAR model is also used for structural inference and policy analysis. In structural analysis, certain assumptions about the causal structure of the data under investigation are imposed, and the resulting causal impacts of unexpected shocks or innovations to specified variables on the variables in the model are summarized. These causal impacts are then summarized with impulse response functions (IRFs).

Target population

The main target population is the Kenyan banking sector as the main providers of credit to the private sector as well as policy makers (both the government and central bank) given the need to understand the relationship between shocks, policy intervention and the impact on credit supply to various sectors of the economy.

Data Collection

The sample for the study includes monthly data for the quantum of credit supplied to various sectors by Kenyan commercial banks between 2017 and 2020. Collectively the sample constitutes 44 data points. Private sector credit data was obtained from the entral bank of Kenya (CBK), macroeconomic data was sourced from the Kenya National Bureau of Statistics (KNBS) and COVID statistics was obtained from the Ministry of Health and Bloomberg.

Data Analysis

The collected data was analyzed using trend analysis with tabular representations that explicitly revealed trends among the different data sets. Diagnostic tests were performed to ensure no violation of assumptions of normality, homogeneity, stationarity, heteroscedasticity and serial correlation using the Stata software package version 16.

Econometric Processing and Analysis

Unit Root Test

This test established whether the data variables have a unit root or not. That is, whether the data variables are stationary and at what level of integration.

Correlation Test

The study employs the serial correlation described in Born & Breitung (2016) for the variables. The underlying concept of the test is to regress current demeaned residuals on past demeaned and bias-corrected residuals (up to order lags) using a heteroskedasticity and autocorrelation robust estimator. A Wald test is then performed on the estimated coefficients. The test calculates the Q (p) statistic that is asymptotically equivalent to this Wald test. Born & Breitung (2016) have verified that the test in its current form is also valid for unbalanced panels. It might be slightly oversized (rejects the null too often), but this is still a matter of debate).

Causality Test

The structure of the VAR model provides information about a variable's or a group of variables' forecasting ability for other variables (Granger, 1969). If a variable, or group of variables, y1 is found to be helpful for predicting another variable, or group of variables, y2 then y1 is said to Granger-cause y2; otherwise it is said to fail to Granger-cause y2. Formally, y1 fails to Granger-cause y2 if for all $s > 0$ the MSE of a forecast of $y_{2,t+s}$ based on ($y_{2,t}$, $y_{2,t-1}$,...) is the same as the MSE of a forecast of $y_{2,t+s}$ based on ($y_{2,t}$, $y_{2,t-1}$,...) and ($y_{1,t}$, $y_{1,t-1}$,...). The notion of Granger causality does not imply true causality, it only implies forecasting ability.

4.0 Research Findings and Discussion

This chapter presents the results of the econometric analysis. The variable are not transformed into logs, as they are percentages. Diagnostic tests were conducted. These tests included descriptive tests for normality of the data, unit root test for stationarity and the granger causality test to test the causal relationship between the variables.

Table 2: Descriptive Statistics

Variable	Acronym	Mean	Std. Dev.	Min	Max
Credit to Agriculture	PSC(Agric)	0.02522	0.06485	(0.06548)	0.19277
Credit to Manufacturing	PSC(Manu)	0.10421	0.03500	0.01492	0.20054
Credit to Trade	PSC(Trade)	0.06154	0.02644	0.00912	0.10259
Credit to Building and Construction	PSC(Build)	0.02841	0.05702	(0.06990)	0.14650
Credit to Transport and Communication	PSC(Trans)	0.06469	0.10071	(0.14905)	0.21056
Credit to Finance and Insurance	PSC(Finan)	0.07221	0.04953	(0.03350)	0.17543
Credit to Real Estate	PSC(Real)	0.03133	0.03098	(0.02906)	0.09117
Credit to Mining and Quarrying	PSC(Min)	(0.04560)	0.12420	(0.23068)	0.42860
Credit to Private Households	PSC(PvtHouse)	0.04869	0.01909	0.02081	0.08863
Credit to Consumer Durables	PSC(ConsDur)	0.17425	0.05625	0.05535	0.28609
Credit to Business Services	PSC(Busi)	0.01735	0.07188	(0.17806)	0.11940
Credit to Other Activity	PSC(Other)	0.12867	0.18161	(0.07232)	0.65272
Total Banking Sector Credit to the Private Sector	PSC(Total)	0.06594	0.01682	0.03121	0.09618
Customer Deposits	CustDepo	0.08235	0.01918	0.04282	0.13658
Money Supply	M3	0.09075	0.02198	0.05464	0.14163
New COVID Cases	COVIDUncert	3,821.84	8,634.07	(2,780.00)	41,294.00
GDP Growth Rate	GDP	0.04407	0.03707	(0.04128)	0.10964

The study uses the mean as the standard measure of the center of distribution for all the data variables. The standard deviations of the data variables are close to 0 indicating that the variables are not volatile.

Table 3: Correlation Analysis

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
(1) PSC(Agric)	1.00													
(2) PSC(Manu)	-0.04	1.00												
(3) PSC(Trade)	-0.38	0.23	1.00											
(4) PSC(Build)	-0.11	0.46	-0.20	1.00										
(5) PSC(Trans)	0.62	-0.04	-0.02	-0.28	1.00									
(6) PSC(Finan)	-0.13	-0.33	-0.07	-0.43	-0.24	1.00								
(7) PSC(Real)	0.65	0.26	-0.28	0.33	0.59	-0.39	1.00							
(8) PSC(Min)	-0.04	0.50	0.42	0.10	0.32	-0.13	0.15	1.00						
(9) PSC (PvtHouse)	0.08	-0.42	0.20	-0.59	-0.05	0.20	-0.37	-0.25	1.00					
(10) PSC (ConsDur)	0.28	-0.26	0.15	-0.61	0.51	0.17	0.07	-0.06	0.21	1.00				
(11) CustDepo	0.47	0.16	0.26	0.02	0.50	-0.39	0.53	0.10	0.16	0.04	1.00			
(12) M3	0.49	0.10	-0.20	0.23	0.19	-0.01	0.44	-0.07	0.02	-0.36	0.64	1.00		
(13) COVIDUncert	0.28	-0.03	-0.21	0.05	0.36	-0.16	0.23	0.27	-0.25	0.01	-0.01	0.01	1.00	
(14) GDP	-0.26	-0.33	-0.32	-0.21	-0.43	0.42	-0.49	-0.36	-0.07	0.12	-0.80	-0.48	0.01	1.00

COVIDUcert has a weak correlation with the credit growth across various sectors.

Table 4: Unit Root Test

	Variables	*Equation*	*I(1)*
Dependent Variable	*PSC(Agric)*	*1*	*,**,***
	PSC(Manu)	*2*	*,**,***
	PSC(Trade)	*3*	*,**,***
	PSC(Build)	*4*	*,**,***
	PSC(Trans)	*5*	*,**,***

	Variables	Equation	I(1)
Dependent Variable	PSC(Finan)	6	*,**,***
	PSC(Real)	7	*,**,***
	PSC(Min)	8	*,**,***
	PSC(PvtHouse)	9	*,**,***
	PSC(ConsDur)	10	*,**,***
Independent Variables	GDP		***
	COVIDUncer		*,**,***
	M3		*,**,***
	CustDepo		*,**,***

*,**,*** variable is stationary at the 1%, 5% and 10% significance level

The results from the table indicate that all the variables are stationary at first difference.

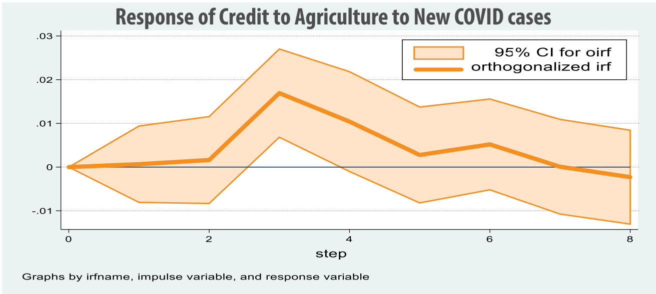
Table 5: Optimal Lag Order Selection

	Equation	Optimal Lag, MaxlLag(n) - using AIC
Equation 1	PSC(Agric) = f(CVDUncertt , GDPt , CustDept , M3t, et)	4
Equation 2	PSC(Manu) = f(CVDUncertt , GDPt , CustDept , M3t, et)	4
Equation 3	PSC(Trade) = f(CVDUncertt , GDPt , CustDept , M3t, et)	4
Equation 4	PSC(Build) = f(CVDUncertt , GDPt , CustDept , M3t, et)	4
Equation 5	PSC(Trans) = f(CVDUncertt , GDPt , CustDept , M3t, et)	4
Equation 6	PSC(Finan) = f(CVDUncertt , GDPt , CustDept , M3t, et)	4
Equation 7	PSC(Real) = f(CVDUncertt , GDPt , CustDept , M3t, et)	4
Equation 8	PSC(Min) = f(CVDUncertt , GDPt , CustDept , M3t, et)	4
Equation 9	PSC(PvtHouse) = f(CVDUncertt , GDPt , CustDept , M3t, et)	4
Equation 10	PSC(ConsDur) = f(CVDUncertt , GDPt , CustDept , M3t, et)	4

VAR models use the same lags so we shall use the equations' optimal lag selection of 4

5.0 Impulse Response Function and Granger Causality Results

Equation 1: PSC(Agric) = f(CVDUncertt , GDPt , CustDept , M3t, et)



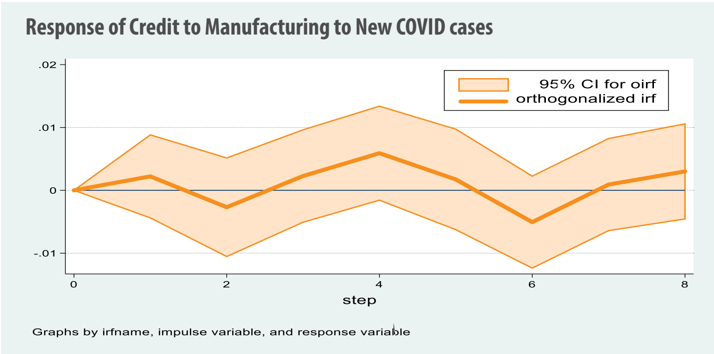
COVIDUncert granger causes Credit Allocation to the Agriculture Sector

The VAR results suggest that a 1.00% increase in new COVID cases results in a positive albeit very small (0.0000022) rise in credit allocation to the agriculture sector with the most significant impact being for the third lag of new COVID cases (p=0.005).

From the impulse response function (IRF), there is no immediate impact of new COVID cases on credit allocation to the agriculture sector. However, over time credit supply to the agriculture responds with a positive lagged response. This implies that an immediate COVID shock tends to filter through the system (credit to the Agriculture sector) and have the most significant impact by the third month. The positive relationship may reflect the impact of the various stimulus measures introduced by the government that helped anchor incomes in the agriculture sector and thus ease credit risks.

However, the temporary fiscal stimulus measures tended to mask risks in the sector and once these measures were withdrawn, credit supply to the agriculture sector contracted after seven (7) months. Credit risks were linked to unfavourable weather and elevated input costs such as fertilizer and certain chemicals due to disruptions to global trade

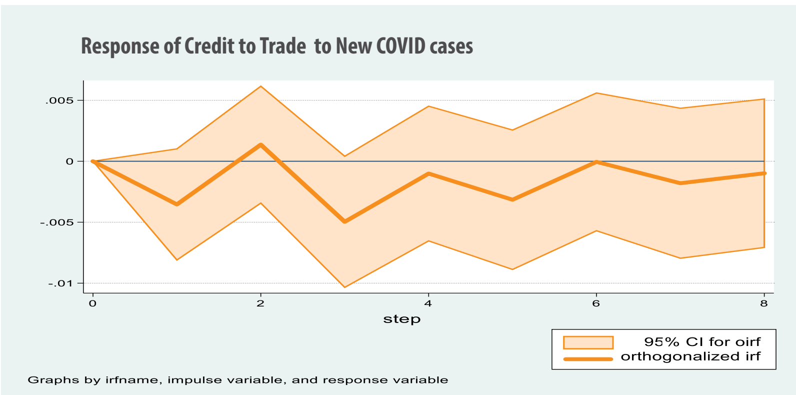
Equation 2: PSC(Manu) = f(CVDUncertt , GDPt , CustDept , M3t, et)



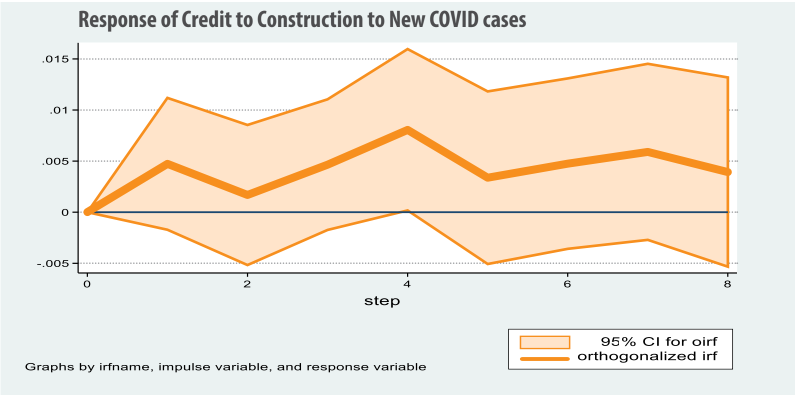
COVIDUncert does not granger cause Credit Allocation to the Manufacturing Sector:

The VAR results suggest that there is no significant relationship between new COVID cases and credit allocation to the manufacturing sector. That said, the impulse response function (IRF) suggests that a 1.00% shock due to new COVID cases results in a mixed response of credit allocation to the manufacturing sector. This may indirectly reflect the tightening and loosening of local containment measures over the sample period which constrained labour supply while disruptions to external trade elevated input costs. With a constrained ability to pass on higher costs to consumers at the time, manufacturing companies' reduced capacity as well as reduced/halted investments. This resulted in reduced demand and supply of credit.

Equation 3: PSC(Trade) = f(CVDUncertt , GDPt , CustDept , M3t, et)



Equation 4: PSC(Build) = f(CVDUncertt , GDPt , CustDept , M3t, et)



COVIDUncert does not granger cause Credit Allocation to Trade:

The VAR results suggest that a 1.00% rise in new COVID cases results in a 0.00000088 decline in credit to the private sector with the impact most significant for the first lag of new COVID cases (p=0.017).

The impulse response function (IRF) suggests that a 1.00% shock due to new COVID cases results in an overall contraction of credit to sectors in trade.

This may indirectly reflect the tightening and loosening of local containment measures over the sample period which constrained local activity while disruptions to external trade reduced the supply of imported goods/ parts (etc) amid depleting stock piles. This therefore resulted in reduced business activity thus raising credit risks.

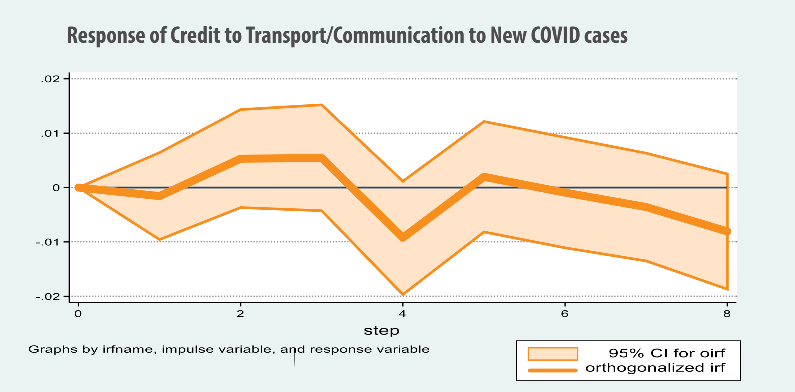
COVIDUncert does not granger cause Credit Allocation to Building and Construction:

The VAR results suggest that there is no significant relationship between new COVID cases and credit allocation to the building and construction sector.

That said, the impulse response function (IRF) suggests that 1.00% shock due to new COVID cases over time results in an overall expansion of credit supply to building and construction.

This may indirectly reflect the public spending on infrastructure during the COVID period. Infrastructure spending was primarily concentrated on roads e.g. the Nairobi Expressway and other major roads as the administration ramped up efforts to complete pending infrastructure projects prior to the August 2022 general election. The positive spillover to the private sector ie among contractors helped sustain the expansion of credit to the sector – the payment of pending bills notwithstanding.

Equation 5: PSC(Trans) = f(CVDUncertt , GDPt , CustDept , M3t, et)



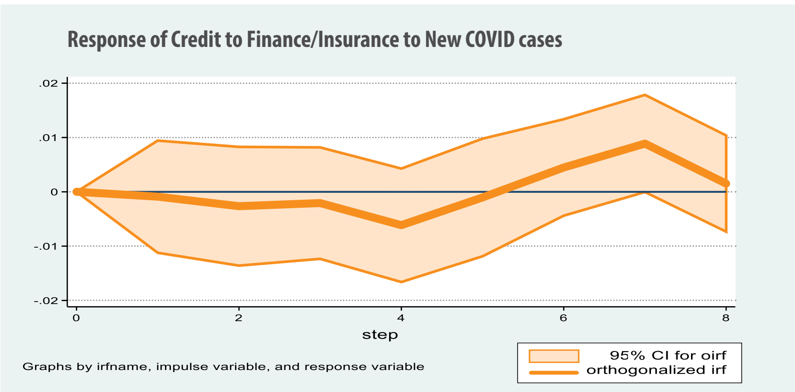
COVIDUncert granger causes Credit Allocation to the Transport Sector

The VAR results suggest that a 1.00% rise in new COVID cases results in a 0.00000199 and 0.00000277 decline in credit to the transport sector with the impact most significant for the first and fourth lag of new COVID cases, respectively (p=0.019 and p=0.003).

The impulse response function (IRF) suggests that a 1.00% shock due to new COVID cases results in a mixed response on credit allocation to the transport sector.

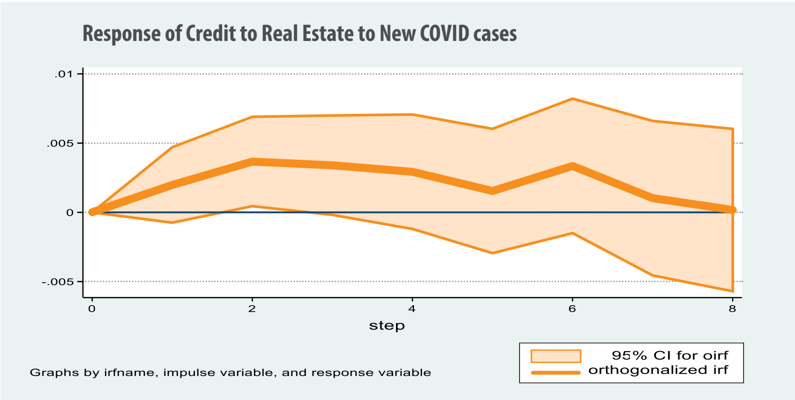
This may directly reflect the tightening and loosening of local containment measures over the sample period which reduced mobility while work from home (WFH) policies reduced demand for transport. This overall impaired activity in the sector thus raising credit risks and conservative lending practices to the sector.

Equation 6: PSC(Finan) = f(CVDUncertt , GDPt , CustDept , M3t, et)



COVIDUncert granger causes Credit Allocation to the Finance and Insurance sector

Equation 7: PSC(Real) = f(CVDUncertt , GDPt , CustDept, M3t, et)



The VAR results suggest that there is no significant relationship between new COVID cases and credit allocation to the finance and insurance sector.

The impulse response function (IRF) however suggests that a 1.00% shock due to new COVID cases over time results in a contraction in credit supply to the finance and insurance sector after 1 month.

This may directly reflect a slowdown in consumption/ investments which resulted in capex constraints for companies in the finance and insurance sector.

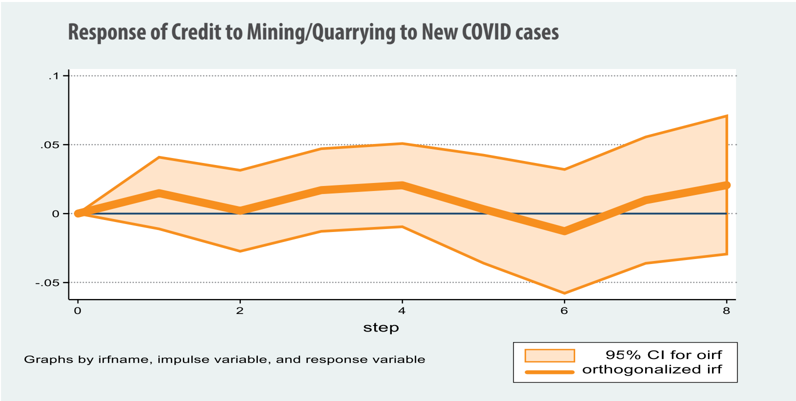
Over time, the need for working capital support improved bank business while investments in bonds/ government securities helped boost income – this then helped ease credit risks in the sector thus the positive response of credit supply after 5months. However, the sector still remained vulnerable to second-round effects which necessitated caution.

COVIDUncert does not granger cause Credit Allocation to the Real Estate Sector

The VAR results suggest that a 1.00% rise in new COVID cases results in a 0.000000746 rise in credit to the real estate sector with the impact most significant for the second lag of new COVID cases (p=0.012).

That said, the impulse response function (IRF) suggests that a 1.00% shock due to new COVID cases over time results in an overall expansion of credit supply to the real estate sector.

Equation 8:
PSC(Min) = f(CVDUncertt , GDPt , CustDept, M3t, et)



This may indirectly reflect delays in mortgage disbursements related to existing challenges in land registration and titling processes that are necessary for underwriting mortgages.

Therefore, the mortgages disbursed during the first 8 months of the pandemic sample period could be mortgages approved before.

After 8 months, the response of credit to the real estate sector as a result to the pandemic shock starts to turn negative perhaps reflecting a reduction in mortgage applications at the time due to constrained incomes and a halt of mortgage approvals given the COVID induced uncertainty.

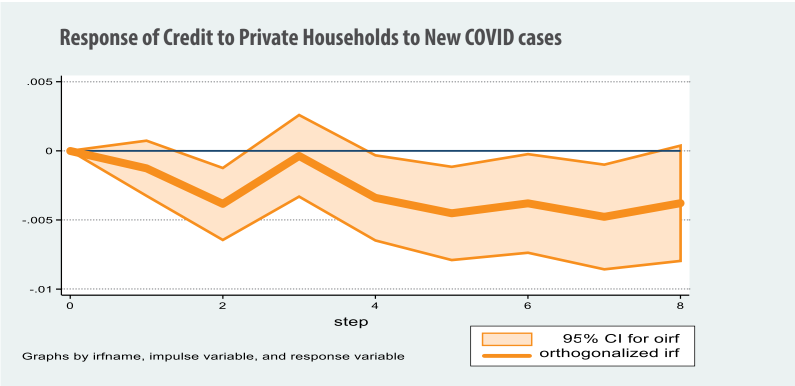
COVIDUncert granger causes credit to the mining sector

The VAR results suggest that a 1.00% rise in new COVID cases results in a 0.0000065 rise in credit to the mining sector with the impact most significant for the fourth lag of new COVID cases (p=0.003).

That said, the impulse response function (IRF) suggests that a 1.00% shock due to new COVID cases results in a mixed response on credit supply to the mining sector.

This may directly reflect the tightening and loosening of local containment measures over the sample period which constrained labour supply and thus weakened activity in the sector.

Equation 9: **PSC(PvtHouse) = f(CVDUncertt , GDPt , CustDept , M3t, et)**

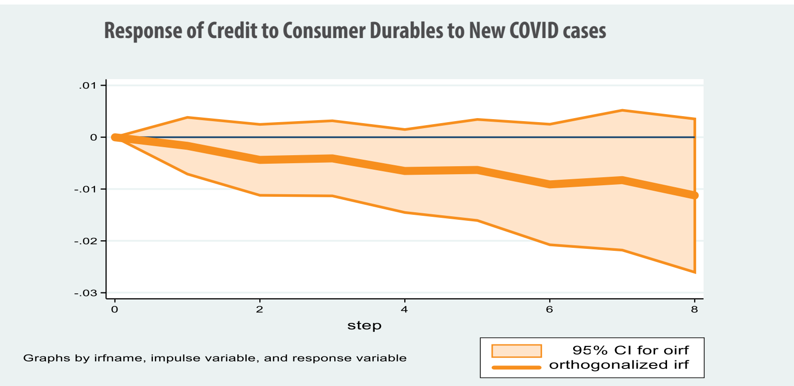


COVIDUncert granger causes Credit Allocation to Private Households

The VAR results suggest that a 1.00% rise in new COVID cases results in a rise in credit allocation to private households with the impact most significant for the third lag of new COVID cases (p=0.001). The impulse response function (IRF) suggests that 1.00% shock due to new COVID cases over time results in an overall contraction in credit supply to private households. The response immediately turns negative even before 1 month lapses.

This could reflect a sudden dent in incomes caused by layoffs as COVID-uncertainty rises and lockdowns become more broad-based thus denting business activity. Both demand and supply of credit contracts.

Equation 10: **PSC(ConsDur) = f(CVDUncertt , GDPt , CustDept , M3t, et)**



COVIDUncert does not granger cause Credit Allocation to Consumer Durables

The VAR results suggest that there is no significant relationship between new COVID cases and credit to consumer durables.

That said, the impulse response function (IRF) suggests that 1.00% shock due to new COVID cases over time results in an overall contraction in credit supply to consumer durables. The response immediately turns negative even before 1 month lapses.

This finding may be demand driven consistent with findings from Tauber and Zandweghe, 2021 (US Fed, Cleavland). The study revealed that an increase in disposable incomes due to reduced consumption of services indirectly resulted in a durable goods boom thus reducing demand for credit to purchase consumer durables.

6.0 Conclusion and Policy Recommendations

From the study, the impact of the pandemic shock was moderated by various policy actions that helped avoid further damage to key sectors – helping maintain the flow of credit to the economy.

However, these 'interventions' have generally been short-lived given emerging constraints on fiscal space as well as an ineffective transmission of monetary policy to credit markets - resulting in a shift in bank lending strategies.

Work from home strategies had an indirect positive impact on disposable incomes for those (i) still employed and (ii) had stable incomes – resulting in a shift in consumption patterns that influenced the decline in credit to some segments (e.g. consumer durables).

The main finding is that the credit allocation response to the COVID-19 pandemic was through the demand channel.

Therefore, any policy aimed at minimizing pandemic-induced economic damage by stimulating demand was not sufficient in catering for emerging supply distortions.

More positively, the central bank of Kenya (CBK) should find comfort in the strength of the banking system given healthy capital and liquidity ratios before and during the pandemic that enabled them remain resilient to shocks.

In conclusion, given that the COVID-19 pandemic induces uncertainty, resulting in a lagged response as revealed by the IRFs, most banks would require to be incentivized, through prudential and supervisory bank regulations to extend and sustain positive credit allocation to the private sector.

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