Credit Intensity of Economic Growth – A Sectoral Analysis: Case of Sri Lanka

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Abstract

This paper examines the dynamic relationship between credit and economic growth in Sri Lanka using aggregated and disaggregated data for the period 2003-2015 in an attempt to decipher the 'credit-GDP growth puzzle' experienced recently. The Unrestricted Vector Autoregression (UVAR) approach is followed to account for dynamics and causality tests conducted to determine the direction of the causality between real output and private credit. This is followed by a multiplier analysis to ascertain the direction, timing, magnitude and sensitivity of economic growth to unexpected shocks in private credit. We find evidence supporting the 'demand-following' hypothesis, and varying responses of real output to credit shocks at aggregate, sectoral and sub-sectoral levels imply the presence of sectoral heterogeneity to credit impulses. It is therefore imperative that policymakers account for these factors when formulating appropriate (stabilisation) policies to achieve its ultimate objective of price and economic stability.

Key Words: *(Sectoral) Credit, (Sectoral) Output, Vector Autoregression (VAR), Causality, Impulse Responses, Heterogeneity*

JEL Classification: *E50, E51, E52*

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1. Introduction

The credit-economic growth relationship has been a topic deliberated for over a century, but still stands out to be important to this day. Private credit and economic growth are said to have a close (positive) relationship, although the direction of causality is subject to debate. Nevertheless, it is widely accepted that the private sector is the engine of growth, especially for developing nations (OECD, 2006).

But what if it fails to fulfil this purpose? What if it fails to generate the economic stimulus that policymakers expect it to produce? Can this happen in the first place? This is the challenge that Sri Lanka has had to face from time to time. As a developing nation and a small open-economy with a GDP of around US dollars 82 billion (CBSL, 2016), Sri Lanka has predominantly relied on credit granted by commercial banks to finance investment and economic activity. More importantly, private credit to GDP has increased from 28.5 percent in 2003 to 30.8 percent by 2015.[1]

However, policymakers have been struggling lately to understand this *'credit-GDP growth puzzle'*, as the economy expanded only by 4.8 percent (year-on-year) in 2015 (as opposed to the growth of 4.9 percent in the previous year) in spite of the substantial growth of private sector credit by 25.1 percent in 2015 (compared to just 8.8 percent in the preceding year) (See Figure-1). Moreover, despite credit obtained by certain sectors or subsectors remaining elevated, growth of economic activity of those sectors or subsectors have been fairly dismal (and in some instances, contracted).

This gives rise to two important questions. Firstly, it is worth examining whether there exists a dynamic relationship between private credit and economic growth. Secondly, considering the diverse sectoral economic performances, it is worth investigating whether there are differential effects in economic activity to unanticipated shocks in credit, thereby providing evidence of sectoral heterogeneity.

The present study aims to bridge this gap in relevant literature by using aggregated and disaggregated data to analyse the credit-economic growth relationship in the context of Sri Lanka for the period 2003-2015. We follow the Unrestricted Vector Autoregression (UVAR) approach adopted by Ramaswamy and Slok (1998), and Ibrahim (2005), to account for dynamics, followed by conducting causality tests to determine the direction of the causal relationship between credit and economic growth, and multiplier analyses[2] to identify

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[1] Larger the private credit to GDP ratio, the higher the income boost that the poor get from growth (Beck and Demirgüç-Kunt, 2005).
[2] This involves analysis by way of Impulse Response Functions (IRFs) and Forecast Error Variance Decompositions (FEVDs).

the *direction, timing, magnitude* and *sensitivity* of economic growth to unexpected shocks in private credit. We then perform two checks to test for robustness and suitability of the benchmark model for our analysis.

We present two sets of findings. First, we find evidence of unidirectional causality running from economic growth to private credit, thereby supporting the 'demand-following' hypothesis. This posits that the influence of private credit on economic growth is weak in the case of Sri Lanka during 2003-2015. This, however, could have been the result of many events such as economic instability due to the three-decade long war and quantitative restrictions on private credit in 2012.

Secondly, we find evidence of sectoral heterogeneity as different sectors (and sub-sectors) of the economy responded differently to positive shocks in private credit. Services sector output is the fastest to respond positively to a favourable shock in private credit (i.e. after 6 months), while the industry sector takes close to two years for the same. Economic activity in the agriculture sector, however, responds positively to a favourable credit shock after about a year. We also find agriculture sector output to be the most sensitive to credit shocks, while the least sensitive is industry sector output.

Results of the sub-sectoral data analysis indicate that the tea sector output increases in the short-run following a positive credit shock, while output in the fisheries sector respond negatively during the shorter time horizon. On the contrary, the subsectors of textiles and apparel, and food, beverages and tobacco show a relatively subdued response of output to a credit shock, while the construction sector suffers a long and persistent decrease in output, and responds positively only after about 18 quarters. The subsectors of wholesale and retail trade, and transportation and storage display more of an erratic response in output to positive credit shocks, while output in the financial and business services subsector displayed a relatively minimal response. Nevertheless, output of food, beverages and tobacco, wholesale and retail trade, transportation and storage, and tea subsectors were more sensitive to unanticipated credit shocks compared to the other sectors.

It is worth mentioning that this area of research is largely uncharted due to the unavailability of a long series of disaggregated data. However, regardless of the challenge posed, the relevance and need for such analysis encouraged us to explore this line of research, as these findings are expected to make valuable additions to the arsenal of knowledge and understanding of the policymakers.

The rest of the paper is structured as follows: Section 2 provides a detailed review of pertinent literature, followed by Section 3, which explains the methodology employed by us to analyse causality and potential disparities in the effects of credit shocks on economic activity (at aggregated and disaggregated levels) in Sri Lanka. Section 4 presents the results of this study, complemented by a comprehensive analysis. The final section summarizes the key findings and gives policy implications.

2. Literature Review

Schumpeter (1911), a pioneering-advocate of the notion of finance-led growth, highlighted the importance of financial institutions and financial sector development, and its relationship with economic growth. He emphasised the importance of services provided by financial intermediaries in generating technological innovation and economic development.

More interestingly, Patrick (1966), classified the causal relationship between economic growth and financial development into the hypotheses of 'supply-leading' and 'demand-following'. The 'supply-leading' hypothesis is when financial development causes economic growth, while its opposite is referred to as 'demand-following'. The dichotomisation of these hypotheses, along with continuous financial sector developments, led researchers to investigate the finance-growth nexus extensively.

Analysing data in 35 countries, Goldsmith (1969), found that there was a positive correlation between financial development and economic growth, but made no claim that financial development caused economic growth. However, McKinnon (1974) and Shaw (1973) argued that repressed financial sectors (due to excessive government intervention and regulation) impede the growth potential of economies. They support the 'supply-leading' hypothesis as they claim that financial development fosters economic growth by increasing savings and enhancing allocative efficiency of credit.

Using data on 80 counties over a period of 30 years, King and Levine (1993), conducted a cross-country study to evaluate the finance-growth relationship. They used the ratio of private credit to GDP, among other variables, as an indicator of the level of financial development and found that financial development promotes economic growth. Similarly, Bayoumi and Melander (2008), found that credit causes changes in economic activity. Analysing data from the US, they found that a decline in overall credit by 2.5 percent causes the level of GDP to decline by 1.5 percent.

Abu-Bader and Abu-Qarn (2008), using the augmented VAR methodology to test for Granger causality, examined the causal relationship between economic growth and financial development for six Middle Eastern and North African (MENA) countries.[3] They found evidence of unidirectional causality running from financial development to economic growth in five out of the six countries, with Israel being the only exception showing evidence of causal effects originating from economic growth.[4]

However, evidence from several other studies supported the 'demand-following' hypothesis of financial development and growth. Robinson (1952), claimed that causality stems from economic growth (causing growth to lead finance), and the role of finance and financial

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[3] Algeria, Egypt, Israel, Morocco, Syria, and Tunisia.
[4] Several other studies by Hicks (1969), and Fry (1988), supported the 'supply-leading' hypothesis.

development is largely exaggerated. Kuznets (1955), Friedman and Schwartz (1963), Lucas (1988) and Kar and Pentecost (2000) shared the same thought.

In contrast to all of the above, some researchers found evidence of bidirectional causality between financial development and economic growth. Demetriades and Hussein (1996), after analysing data from 13 countries, found mixed evidence of unidirectional causality from credit to GDP, GDP to credit and also bidirectional causality. They claimed that the direction of causality is more country-specific.

Drawing evidence from Turkey, Ünalmiş (2002)[5] and Yucel (2009) found signs of bidirectional causality between financial development and economic growth in the long run.[6] However, Yucel (2009), found that financial development has a negative effect on economic growth. On the contrary, analysing data of 95 countries, Ram (1999), found no evidence of a positive relationship between financial development and economic growth.

More evidence of the positive relationship between financial development and economic growth can be found in different types of empirical studies: 1) firm-level studies (Demirgüç-Kunt & Maksimovic, 1998), 2) industry-level studies (Rajan & Zingales, 1998), 3) cross-country studies (Levine & Zervos, 1998), and 4) panel studies (Beck, Levine & Loayza, 2000).

In addition to the plethora of studies that have analysed the finance-growth nexus and its causal relationships, we also found interesting literature on response(s) of economic growth to innovations in credit. Using a Structural VAR (SVAR) model for Australia, Berkelmans (2005), examined the relationship between credit and other key macroeconomic variables. He found that monetary policy plays an important role in stabilising the economy (in terms of reining in inflation and reducing the overall impact on GDP and exchange rate), following a credit impulse. Nevertheless, impulse responses indicate that GDP would increase substantially and persist following a positive innovation to credit, in the absence of any monetary response.

Shan and Jianhong (2006), conducted a VAR analysis to assess the impact of financial development on economic growth in China, with total credit been used as the measure of financial development. They found that the response of GDP to a labour (employment) impulse is more persistent and stronger than the response of GDP to a shock on total credit, and hence referred to credit as the 'second force' that affects economic growth. Nevertheless, the effect of a credit shock on GDP growth lasts for nearly 3 years, before reaching its baseline.

A similar analysis for Vietnam was conducted by Hoang (2011), employing VAR models to estimate the response of GDP to shocks in different monetary policy instruments, which includes domestic credit among interest rates and exchange rates. She found that following a positive shock to domestic credit, nominal GDP responds positively during the first 3 quarters

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[5] He also found evidence of unidirectional causality from financial development to economic growth in the short-run.
[6] Standard Granger causality tests and Vector error correction models (VECM) were used in their analyses.

followed by a negative response in the next. However, responses changed substantially when real GDP was considered. Real GDP responded negatively to an innovation in domestic credit, which turned positive after about 4 quarters. Also, Granger causality tests indicated bidirectional causality between domestic credit and real GDP.

Konečný and Kucharčuková (2013), in a somewhat similar analysis done for the Czech Republic, employing a Bayesian Threshold VAR (BTVAR) model, found that industrial production responded positively to a favourable innovation on credit.

Despite the fact that there is a large amount of literature on credit and economic growth, only a handful of research has been conducted to analyse the credit and economic growth relationship at a disaggregated level. Tang (2003), examined the above for Malaysia and found that bank credit on commercial, manufacturing and housing stimulates economic activity, while agriculture and real-estate related lending do not. Similar studies were also conducted by Cecchetti and Kharroubi (2012)[7] and Ananzeh (2016)[8].

Nevertheless, to our knowledge, we have found no literature that analysed how shocks to credit propagated to the real sector of the economy at a sectoral and sub-sectoral level; hence unexplored. However, there is a vast amount of literature that focus on how monetary policy (shocks) affect different sectors/regions of the economy. Bernanke and Gertler (1995), found that residential investment and durable consumption expenditures drop more strongly than its counterparts[9] in response to a monetary policy shock. Ramaswamy and Slok (1998), found evidence of differential effects of monetary policy among the EU nations. Ibrahim (2005) examined the impact of monetary policy on sectoral output in Malaysia and found that some sectors were impacted more by tight monetary policy.[10]

The contribution of this study to the existing literature is manifold. Despite there being a plethora of studies examining the credit-economic growth relationship, a sector-wise (and subsector-wise) multiplier analysis (of both private credit and GDP in a single study), to our knowledge, has not been performed yet. Also, this study focuses on Sri Lanka, for which a similar study has never been done before. Additionally, the new (and improved) data series on GDP (base 2010) will be used for this analysis, providing the most up-to-date work on this issue.

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[7] Cecchetti & Kharroubi (2012), analysed just the industry sector of 50 countries and find that credit booms harm R&D-intensive industries.

[8] Ananzeh (2016), conducted a study on Jordan and finds that there exists a long term relationship between total credit, sectoral credit and economic development. Moreover, he finds unidirectional causality from economic growth to bank credit in the Agriculture sector, while also concluding that there exists bidirectional causality between economic growth and bank credit in the Construction sector.

[9] Business fixed investment and non-durable consumption, respectively.

[10] Studies by Carlino and DeFina (1998), for the US, Arnold and Vrugt (2002), for Netherlands, and Ganley and Salmon (1997), for the UK found similar evidence of differential effects of monetary policy.

3.   Data and Methodology

3.1.   Data

This study employs time-series (quarterly) data from 2003-2015, with each variable containing 52 observations. The availability of sectoral and sub-sectoral data of key variables in this study became available from 2003 onwards, causing us to limit the study to the above period. The variables used in this study include: real Gross Domestic Product (GDP), real Private Sector Credit by commercial banks (PSC), the Consumer Price Index (CPI) and the Average Weighted Call Money Rate (AWCMR)[11], which is used as a proxy for the policy rate. As this study ventures into the analysis of sectoral and sub-sectoral developments, disaggregated data on real GDP and real PSC were also obtained;

1.   Sectoral – 1) Agriculture and Fisheries; 2) Industry; and 3) Services

2.   Sub-sectoral – 1a) Tea; 1b) Coconut; 1c) Fisheries; 2a) Construction; 2b) Food, Beverages and Tobacco; 2c) Textiles and Apparel; 3a) Wholesale and Retail Trade; 3b) Financial and Business Services; and 3c) Transportation and Storage.

Data on real GDP and CPI were obtained from the Department of Census and Statistics – Sri Lanka (DCS), while data on real PSC and AWCMR were obtained from the Central Bank of Sri Lanka (CBSL). As data on real GDP and CPI were constructed in different base years, appropriate data modifications were conducted to bring both series to a uniform base year.[12] Moreover, both series of real GDP and real PSC were seasonally adjusted using the Census X12 quarterly seasonal adjustment method.[13] All variables, except AWCMR are log-transformed.

3.2.   Methodology

In the past and even to date, a commonly used econometric tool to analyse multiple time series has been Vector Autoregressive (VAR) models, founded by Sims (1980). More importantly, it is one of the most popular methods used by monetary economists to unravel the impact of monetary policy on real economic activity (Walsh, 2010).

We follow the Unrestricted VAR (UVAR) approach adopted by Ramaswamy and Slok (1998) and Ibrahim (2005), as the primary focus of this study is to assess the dynamic responses of real economic activity to shocks in private credit at aggregate, sectoral and sub-sectoral levels.

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[11] This variable is used later to test for the robustness of the benchmark VAR model.

[12] As this study focuses on the period of 2003-2015, we had to construct a single series of both GDP and CPI by way of splicing (and backcasting) as GDP had two series of data with base years 2002 and 2010, while CPI also had two series of data with base years 2002 and 2006/07. In order to bring both series to a uniform base year, the series of CPI was rebased to 2010.

[13] We used EViews 8 (statistical software) for this purpose.

The Toda-Yamamoto approach will be used to determine causality among these variables, while a multiplier analysis involving Impulse Response Functions (IRFs) and Forecast Error Variance Decomposition (FEVDs) will be conducted to measure the *direction, timing, magnitude* and *sensitivity* of real economic activity to an unanticipated innovation in credit.

Since our study involves analysis of data at three levels,[14] three major VAR systems will be estimated.[15] However, due to the limited number of observations available for this study, careful effort has been taken to build a well-suited, tractable and parsimonious model to evaluate the research question. As such, VAR systems for the sectoral and sub-sectoral levels will follow the technique adopted by Arnold and Vrugt (2002) and Ibrahim (2005), with the aim of saving valuable degrees of freedom.[16] As a result, the VAR model for the aggregate system will contain 3 variables, while models for the sectoral and sub-sectoral systems will contain 5 variables, with each system estimating separate VAR models for its respective individual sectors.[17]

3.3. Model Specification and Diagnostic Tests

3.3.1. Stationarity Tests

It is imperative that we consider the data temporal properties before proceeding with the VAR model specification, as this would enable us to decide whether the VAR model should be specified using variables in levels, first differences or else using a Vector Error Correction Model (VECM).[18] We performed the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) and preliminary results discussed in Section 4.1 indicate that almost all variables are non-stationary, alternatively referred to as integrated of order 1 or I(1), while some models show evidence of cointegration. It is suggested that a VECM be used in this circumstance as it yields both consistent and efficient estimates, conditional on the fact that the precise cointegrating relationship is known and specified. If this condition, however, is not met, estimates of the VECM will be inconsistent.[19] On the contrary, a VAR specified in levels in a similar circumstance would generate inefficient but consistent estimates (Sims, 1980); a better outcome than a VECM that produces inconsistent estimates.

As the main focus of this study is to not find evidence of possible long run relationships among the variables in concern (but to determine causality and produce unbiased IRFs and

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[14] Aggregate, Sectoral and Sub-sectoral

[15] 13 VAR systems will be estimated in total: 1 Aggregate; 3 Sectoral and 9 Sub-sectoral systems

[16] More on this will be explained in section 3.3.2.

[17] The sectoral system will estimate 3 separate VAR models, while the sub-sectoral system will estimate 9.

[18] If the variables are stationary at levels (or integrated of order 0 i.e. I(0)), then run a VAR model using levels of variables. If on the other hand the variables are non-stationary (or integrated of a higher order, for example I(1)) and cointegrated, that suggests that a VECM should be used (Johansen, 1988). However, if the variables are non-stationary and not cointegrated, specifying a VAR model using first differences of variables is recommended. However, this is the case if one is interested in obtaining correct parameter estimates for interpretation.

[19] As a result, impulse responses generated will be biased and therefore, inaccurate.

FEVDs), and also since the accurate cointegrating relationships are unknown, a UVAR model in levels seems appropriate. Moreover, the choice of a UVAR model over other variants of VAR models are in line with the strategy adopted for similar studies by other authors, which includes Ramaswamy and Slok (1998), Ibrahim (2005) and Dabla-Norris and Floerkemeier (2006).

3.3.2. Benchmark VAR Model Specification (Model 1)

A basic Vector Autoregressive model of order p (VAR(p)) with $\boldsymbol{n}$ variables takes the following form:

$$\boldsymbol{y}_t = \boldsymbol{\alpha} + \sum_{j=1}^{p} \boldsymbol{\Phi}_j \boldsymbol{y}_{t-j} + \boldsymbol{\varepsilon}_t \qquad\qquad \boldsymbol{\varepsilon}_t \sim N(\boldsymbol{0}, \boldsymbol{\Sigma_\varepsilon}) \qquad\qquad (1)$$

where $\boldsymbol{y}_t$ is a ($\boldsymbol{n}$ x 1) column vector containing endogenous variables, $\boldsymbol{\alpha}$ is a ($\boldsymbol{n}$ x 1) vector of constants, $\boldsymbol{\Phi}_j$ are ($\boldsymbol{n}$ x $\boldsymbol{n}$) matrices of autoregressive coefficients and $\boldsymbol{\varepsilon}_t$ is a $\boldsymbol{n}$-dimensional vector of white noise terms $(\varepsilon_{1t}, \varepsilon_{2t}, \dots, \varepsilon_{nt})'$ with covariance matrix $\boldsymbol{\Sigma_\varepsilon}$, which is symmetric and positive definite.[20]

Considering the short series of data and the need to form parsimonious models due to the nature of the VAR framework, we followed the technique used by Arnold and Vrugt (2002) and Ibrahim (2005) when forming models for the sectoral and sub-sectoral systems. As these systems contained a relatively large number of control variables for both real GDP and private credit, several new series of data were generated, with a view to conserve degrees of freedom.[21]

Next, we used the Schwarz Bayesian Information Criterion (SBIC) and Hannan-Quinn Information Criterion (HQIC) to determine the lag order of the VAR model. The Lagrange multiplier (LM) test [22] for residual autocorrelation was conducted on the estimated VAR models to test for serial correlation. When we found evidence of serial correlation at that lag order, an extra lag of the variables was included until the residuals became serially uncorrelated.[23] This was consistent with the approach followed by Ibrahim (2005).

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[20] Hamilton (1994), Lutkepohl (2005)

[21] For example, if we consider the VAR model for the Agriculture sector, rather than including 4 additional variables, which are GDP and private credit for both the Industry and Services sectors, we only include 2 where one series is Aggregate GDP less Agriculture GDP (which is referred to as Non-Agricultural GDP), while the other series is Aggregate Private Credit less Credit to the Agriculture Sector (which is referred to Non-Agriculture related Lending).

[22] Introduced by Johansen (1995)

[23] Most VAR models overcame the issue of serial correlation with the inclusion of 2 lags. The maximum VAR order of the other models came to be 3. Financial and Business Services sector was the only other exception with a lag order of 1.

The estimated benchmark model for the different VAR systems takes the following form, with the vector $\boldsymbol{y}_t$ been defined as:

a) Aggregate system: $\boldsymbol{y}_t = (\boldsymbol{LGDP}_t,\ \boldsymbol{LCPI}_t,\ \boldsymbol{LPSC}_t)'$
b) Sectoral system: $\boldsymbol{y}_{jt}^S = (\boldsymbol{LGDP}_{jt}^S,\ \boldsymbol{LGDP}_{-jt}^S,\ \boldsymbol{LCPI}_t,\ \boldsymbol{LPSC}_{jt}^S,\ \boldsymbol{LPSC}_{-jt}^S)'$
c) Sub-sectoral system: $\boldsymbol{y}_{mt}^{SS} = (\boldsymbol{LGDP}_{mt}^{SS},\ \boldsymbol{LGDP}_{-mt}^{SS},\ \boldsymbol{LCPI}_t,\ \boldsymbol{LPSC}_{mt}^{SS},\ \boldsymbol{LPSC}_{-mt}^{SS})'$

where $j = 1, 2, 3$ denoting output and credit of each sector; and $m = 1,\dots, 9$ denoting output and credit of each subsector. [24]

Most importantly, we have used the method of Cholesky decomposition to identify impulse-responses in our recursive VAR systems. In the aggregate system, the variables are ordered as real output, consumer price level and real private credit.[25] Findings from the causality study (refer section 4.2.1.) suggest that real output causes real private credit but not vice versa; hence real GDP is considered the most exogenous. Consumer price level is placed after real output but before real private credit, since we believe that credit will have little to no contemporaneous impact on the price level due to price stickiness.[26]

3.3.3. VAR Stability Test

A key prerequisite for a well-specified VAR model is stability, as unstable models invalidates standard asymptotic theory (Hatemi-J, 2002). Moreover, multiplier analysis have known interpretations only if the estimated VAR model is found to be stable (Hamilton, 1994; Lutkepohl, 2005).

The VAR(p) process in (1) is considered stable if all roots of the reverse characteristic polynomial lie outside the complex unit circle.[27] That is;

$$\det(I_n - \Phi_1 z - \cdots - \Phi_p z^p) \neq 0 \qquad \text{for } |z| \leq 1$$

All VAR systems in this study were tested and verified to have satisfied the stability conditions. (See Table 3)

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[24] LGDP – log of real GDP; LCPI – log of CPI; LPSC – log of real private credit; ^{S} denotes 'Sector'; ^{SS} denotes 'Sub-sector'

[25] The ordering of the variables follows economic theory, with the idea that real GDP is the least responsive to shocks in other variables in the system, while real private sector credit is the most responsive.

[26] The ordering of variables remains unchanged in the sectoral and sub-sectoral VAR systems as we consider the recursive causal structure of the broader definitions to hold at the disaggregated levels (which is not unrealistic).

[27] For a more detailed explanation (including technicalities), see Lutkepohl (2005). Alternatively, we can reach the same conclusion of VAR stability, if all roots of the companion matrix lie inside the complex unit circle.

3.4. Causality Testing and Multiplier Analysis

The most important techniques that help us analyse our research questions are causality tests and multiplier analysis. We adopt a variant of the Granger causality test introduced by Toda and Yamamoto (1995), to determine the direction of causality between private credit and economic growth in the context of Sri Lanka. Since we are dealing with non-stationary variables in a levels VAR framework, using standard Granger causality tests to determine causal relationships will be inaccurate as standard asymptotic theory is inapplicable, causing Granger causality (Wald) test statistics to suffer from specification bias and spurious regression (Sims, Stock and Watson, 1990; Toda and Phillips, 1993).[28]

This is then followed by a multiplier analysis, which includes orthogonalised Impulse Response Functions (IRFs) and Forecast Error Variance Decompositions (FEVDs). The impact of the CBSL's [29] credit policy on economic growth at both aggregated and disaggregated levels can be gauged by analysing the IRFs as it displays the *direction, magnitude* and *timing* of GDP's response to credit impulses. The varied responses in output in different sectors would provide evidence of sectoral heterogeneity to credit shocks.

Lastly, we conduct FEVDs to determine the relative *sensitivity* of output (at the aggregated and disaggregated levels) to shocks in private credit. As with IRFs, diverse results across sectors and sub-sectors would imply heterogeneity that policymakers should be aware of when formulating policy.[30]

3.5. Checks for Model Robustness and Suitability

We conducted two experiments to test for the robustness (and suitability) of our benchmark model (Model 1). It should be reiterated that the limited amount of observations in this study leaves us little space for generous additions of other potentially important control variables. With that in mind, we define our first robustness check by introducing the Average Weighted Call Money Rate (AWCMR) as a new control variable in place of log CPI (Model 2). Inclusion of AWCMR, which is the interbank money market rate, is expected to (reflect and) control the monetary policy stance of the Central Bank.

Secondly, we defined a model excluding log CPI as a control variable from the benchmark model to ascertain the significance of CPI in the credit-real output analysis. We refer to this as Model 3.

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[28] More on the Toda-Yamamoto approach to test for causality can be found in Appendix D.
[29] Central Bank of Sri Lanka
[30] A detailed (general) explanation on IRFs on FEVDs can be found in Appendix E and F.

4. Empirical Findings

4.1. Preliminary results [31]

Prior to conducting a VAR analysis, it is important that we understand the data temporal properties. Therefore, the Augmented Dickey-Fuller (ADF) test was performed on the variables to identify their nature of stationarity, or in other words, their order of integration.

The results of the unit root tests, presented in Table 2, indicate that all variables associated with the aggregate and sectoral system are stationary in their first differences or I(1). Similarly, almost all of the variables in the sub-sectoral system are I(1) with the exception of Tea-GDP and Fisheries-Credit, which turned out to be stationary at levels or I(0). The results of the nature of stationarity of the above two variables were confirmed by the Phillips-Perron test (Phillips and Perron, 1988).

The Johansen Cointegration test (Johansen, 1988) was performed on those models involving purely I(1) variables. However, results of the above test have not been reported, as the main focus of this study is to determine causality and produce unbiased IRFs and FEVDs, and not to find evidence of possible long run relationships among those variables.

4.2. VAR results

4.2.1. Aggregate system results [32]

Prior to venturing into the main area of focus in this study, which is analysing the responses of aggregate output to shocks in private sector credit, it is prudent to determine the direction of causality, as it helps investigate whether lagged values of one variable help predict another. Also, results from the causality test would help determine the ordering of our variables in the system, (which is usually based on economic theory and fundamentals), when generating impulse response functions.

Table 5 presents results of the Toda & Yamamoto (1995), causality tests conducted on the aggregate system. It can be observed that the null hypothesis of *Real Private Credit does not cause Real GDP* cannot be rejected at the 5 percent level, implying that real private credit does not help predict real output in the Sri Lankan context. However, the null hypothesis of *Real GDP does not cause Real Private Credit* can be rejected even at the 1 percent level. This implies that real output significantly helps predict real private credit, and this result remains robust to longer lag lengths. Our findings therefore support the *'demand-following'* hypothesis evident in studies by Robinson (1952), Kuznets (1955) and Lucas (1988).

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[31] For Descriptive (Summary) statistics, please see Table 1
[32] Refer Appendix J (Table 4) for a more detailed discussion on the aggregate results.

Table 5: Causality Test Results (Toda-Yamamoto Procedure): Aggregate System

Null hypothesis	Chi²	Prob > Chi²
Real Private Credit does not Granger [T-Y] Cause Real GDP	0.497	0.78
Real GDP does not Granger [T-Y] Cause Real Private Credit	**14.226**	**0.00**

Notes: The above table reports the results of the causality test (Toda-Yamamoto [T-Y] procedure) performed on the variables of the aggregate system | Results pertaining to CPI are not shown as that is not the main focus. | Both Real Private Credit and Real GDP are in logs | Lag length of VAR is 2 | Interpretation: The null hypothesis of Real Private Credit does not Granger [T-Y] Cause Real GDP cannot be rejected, which implies that Real Private Credit does not help predict Real GDP. However, the null hypothesis of Real GDP does not Granger [T-Y] Cause Real Private Credit is rejected even at the 1% level, which implies that Real GDP helps predict Real Private Credit, when the aggregate system is concerned.

Then, we proceed to evaluate the aggregate output responses to shocks in private credit in our benchmark system, which includes (and is ordered as) real Gross Domestic Product (GDP), consumer price index (CPI) and real private sector credit (PSC).[33] The aggregate analysis is conducted with the purpose of determining the nature of response of economic growth to unanticipated shocks in non-bank private sector credit, which is crucial for policymakers, in general, as the credit channel is one medium through which monetary policy transmission takes place. This analysis would also provide useful insights to policymakers in Sri Lanka, in particular, to make sense of the *'credit-GDP growth puzzle'*, an issue often deliberated during the last few years. Moreover, results of the aggregate system would also serve as a benchmark when evaluating sectoral and sub-sectoral effects of private credit shocks.

The orthogonalised IRFs in Figure 2 illustrate the response of aggregate real output, CPI and aggregate real private credit to a one standard deviation shock to private credit. It is evident that following a positive credit shock, aggregate real output responds positively with the effect reaching a peak at the 18-19 quarters. This is comprehensible as credit obtained by the private sector would be used to engage in economic activity, which fuels economic growth. Moreover, we could also infer that private credit and economic growth has a positive relationship.[34]

Further, the price level also increases in response to the positive credit shock with the effect dissipating from quarter 7 onwards. This is true as increased credit disbursements are likely to increase demand, which exert upward pressure on the price level of the economy.

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[33] All of the variables mentioned herein were log transformed in this analysis.

[34] The response of private credit to an impulse in real output is positive and relatively more persistent (results of which are not shown in this study, but available from the author on request)

**Figure 2: The effects of a Private Credit shock
on Aggregate Real GDP, CPI and Aggregate Real Private Credit**

(a) Aggregate GDP – irf2   (b) CPI – irf2   (c) Aggregate Private Credit – irf2
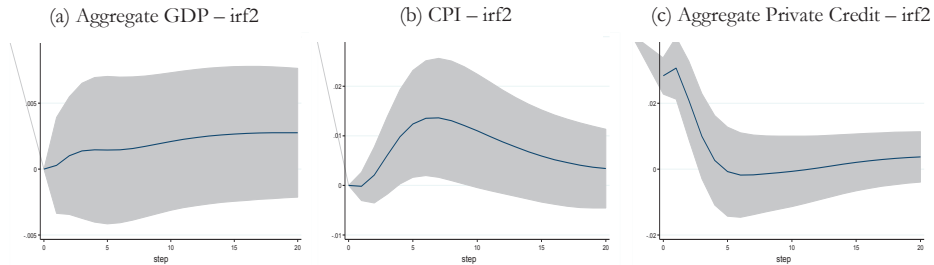
Notes: Graphed above is the orthogonalised impulse response function – the response of aggregate GDP, CPI and aggregate private credit to a one standard deviation shock in aggregate private credit. The shaded area represents the 95% confidence band for the response function.

However, careful inspection of the IRFs (See Figure 3) indicates the presence of a *'second wave'* of growth of real output, that commences after the inflationary effect in prices recede.[35] This implies that credit, in the case of Sri Lanka, has more of an *inflationary* aspect rather a *growth-stimulating* aspect, which policymakers should be mindful about when formulating policy.

Results of the variance decompositions presented in Table 6 provide further insights to the above findings. Credit shocks account for only a small proportion of the variation in real output (less than 5 percent after 5 years) relative to that of CPI, where credit shocks explain about 21-27 percent of variation in the price level during the medium- to long-term. This implies that the aggregate output sensitivity to positive credit shocks are unexpectedly low in the Sri Lankan context, as in the case of Nigeria (Ifeakachukwu and Olufemi, 2012), highlighting a possible breakdown and the ineffectiveness of the credit (or bank lending) channel of monetary transmission.

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[35] i.e., real GDP, which increases up until quarter 4, witnesses a stabilisation of the positive effect from that point on till quarter 7, before taking-off again. The corresponding positive response of CPI changes course from quarter 7 onwards.

Table 6: Variance Decompositions: Aggregate System

Horizons	GDP	CPI	PSC
(a) Variance Decomposition of GDP			
4	99.1	0.3	0.6
8	98.4	0.3	1.3
12	96.8	1.0	2.2
16	94.7	1.9	3.4
20	92.8	2.6	4.5
(a) Variance Decomposition of CPI			
4	2.4	94.4	3.2
8	2.6	76.7	20.8
12	6.8	66.1	27.1
16	12.9	59.4	27.7
20	18.9	54.5	26.6
(a) Variance Decomposition of PSC			
4	23.7	2.9	73.4
8	46.7	4.5	48.9
12	55.0	4.4	40.7
16	59.6	4.0	36.4
20	62.2	4.1	33.7

Notes: This table presents the variance decompositions based on level VAR (with all variables in logs) | The lag order of the VAR is based on the Schwarz Bayesian Information Criterion/ Hannan-Quinn Information Criterion, while assuring that the error terms are serially uncorrelated | GDP = Real Gross Domestic Product ; CPI = Consumer Price Index ; PSC = Real Private Sector Credit | Cholesky ordering of the variables → [$LGDP_t$, $LCPI_t$, $LPSC_t$] | Private Sector Credit contains commercial bank lending to the private sector (excluding lending to other banking entities) | Time horizon in quarters | All values are in percent.

Moreover, the impulse responses depict that credit shocks appear to persist for about 4 quarters, and fade subsequently.

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4.2.2. Sectoral system results [36]

Following the analysis of the aggregate output response to shocks in private sector credit, we continue to evaluate the same at the sectoral level. The primary reason for such sectoral analysis is to determine the asymmetric responses of output of various sectors to sector-specific credit shocks, which aids us to identify sectoral heterogeneity, if that exists, and fashion policy accordingly. Therefore, we estimate separate VAR models for each sector and compare that with the aggregate output responses, which serve as the benchmark.

Figure 4 illustrates the impulse responses of output of the three main sectors of the economy to a one-standard deviation shock to sector-specific private credit. It can be observed that all sectors respond positively, with a lag, to a credit impulse. Results indicate that output of the agriculture and fisheries sector responds positively to a credit shock from quarter 4 onwards. Variance decompositions provided in Table 7 indicate that credit impulses explain nearly 9 percent of the variation in that sectors' output in the long-term.

Figure 4: The effects of sector specific credit shocks on sectoral GDP
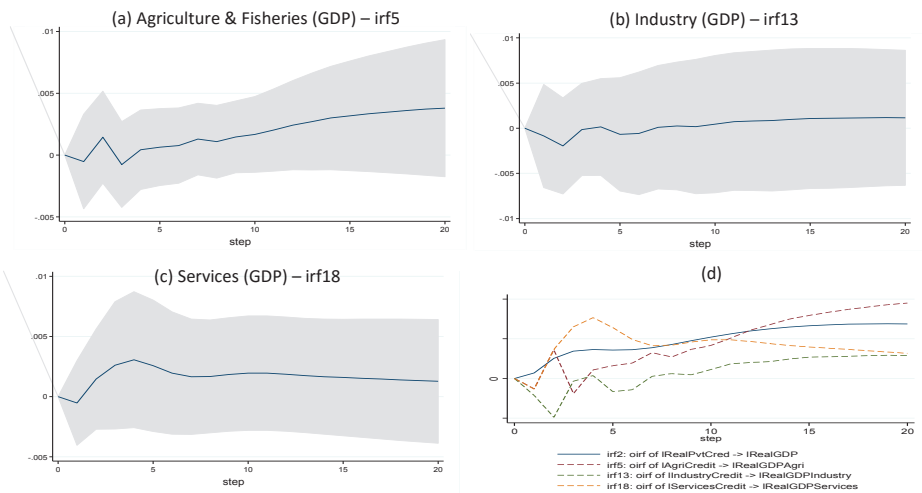
Notes: Graphed above are the responses of sectoral GDP, namely Agriculture, Industry and Services to orthogonalised (one standard deviation) shocks to sector-specific private credit. | The shaded area represents the 95% confidence band for the response functions. | Plot (d) denotes the asymmetric sectoral output responses to shocks in sector-specific credit.

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[36] Refer Appendix J (Table 4) for a more detailed discussion on the sectoral results.

Table 7: Variance Decomposition of Sectoral GDP to Sector-specific Private Credit Shocks

Horizons	Agriculture & Fisheries	Industry	Services
2	0.1	0.1	0.1
4	0.6	0.5	1.4
8	1.0	0.4	2.7
12	2.3	0.3	2.8
16	5.3	0.4	2.8
20	8.7	0.6	2.7

Notes: This table presents the variance decompositions based on level VAR (with all variables in logs) | The lag order of the VAR is established to obtain serially uncorrelated error terms | Cholesky ordering of the variables → $[LGDP_{jt}^S, LGDP_{-jt}^S, LCPI_t, LPSC_{jt}^S, LPSC_{-jt}^S]$ | $LGDP^S$ = Log Sectoral Real GDP; $LPSC^S$ = Log Sectoral Private Sector Credit | Private Sector Credit contains commercial bank lending to the private sector (excluding lending to other banking entities) | Time horizon in quarters | All values are in percent.

The response of industry sector output to shocks in credit directed to the sector appears to be unsteady at short horizons, but takes off from the seventh quarter onwards. However, results from the variance decomposition suggests that shocks to industry credit explains only a marginal variation in the output of the industry sector throughout the forecast horizon, highlighting the weak sensitivity of the industry sector output to sector-specific credit impulses.

The services sector, unlike the other two sectors, responds positively to shocks in services sector-related credit in the shorter horizon, which gradually tends towards the pre-shock output level from quarter 4 onwards. The sensitivity of services sector output to sector-specific credit shocks remain relatively subdued, albeit it being higher than that of the industry sector.

It can be inferred that the agriculture and fisheries sector output is the most sensitive to sector-specific credit shocks, while the industry sector is the least sensitive. The weak sensitivity of the industry and services sectors to credit shocks could be primarily due to the fact that firms in those sectors have access to alternate sources of funding in the domestic equity and capital markets and therefore are less susceptible to unanticipated shocks in credit disbursed by commercial banks, unlike their agriculture sector counterparts that are highly reliant on bank credit.

Furthermore, since agricultural production is more seasonal, an unexpected influx of credit is likely to take about a year to yield positive results as shown by the IRFs. Also, since most agricultural output producers are individuals and small scale enterprises, they have limited

access to alternate sources of funding, which makes them heavily dependent on bank credit. Moreover, as per a direction issued by the CBSL (CBSL, 2010), all licensed banks are required to lend a minimum of 10 percent of their lending portfolio towards agricultural activity. This could well be another reason why agricultural output responds the most to a positive credit impulse compared to the industry and services sectors in Sri Lanka.

4.2.3. Sub-sectoral system results [37]

The analysis is extended further by investigating the effects of shocks to private credit on output at the sub-sectoral level. Separate VAR models are estimated for each of the selected nine sub-sectors,[38] impulse response functions (Figure 5) and forecast error variance decompositions (Table 8) are simulated to identify the possible asymmetric responses of sub-sectoral output to sub-sector specific private credit impulses.

The response of the tea sector output to a credit impulse shows an immediate positive response in the short-term with the same effect resurfacing after about 6 quarters and remaining persistently above the baseline thereafter. Moreover, the tea sector output appears to be quite sensitive to a sub-sector specific credit expansion, with credit accounting for 8-10 percent of the variation in tea output during the forecast horizon. The short-term effect on tea sector output remains notably higher than the long-term effect following a credit impulse, which could largely be due to credit being used to meet working-capital requirements, that aid production to continue unaffected from adverse demand and supply conditions. Policymakers must pay careful attention to ensure that credit obtained by the tea sector is channelled efficiently to yield a sustainable growth in its production.

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[37] Refer Appendix J (Table 4) for a more detailed discussion on the sub-sectoral results.
[38] Sub-sectors were selected based on the availability of sub-sector specific GDP and private credit data and their importance to the Sri Lankan economy (based on the sub-sectoral share of GDP).

Figure 5: The effects of sub-sector specific credit shocks on sub-sectoral GDP
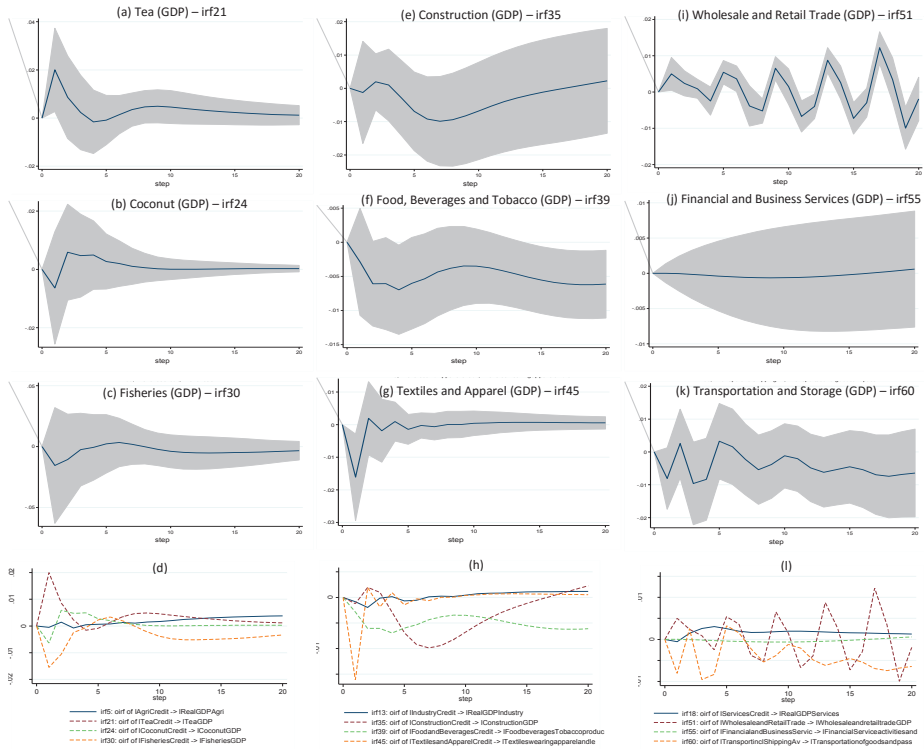
Notes: Graphed above are the responses of sub-sectoral GDP, (namely Tea; Coconut; Fisheries; Construction; Food, Beverages and Tobacco; Textiles and Apparel; Wholesale and Retail Trade; Financial and Business Services; and Transportation), to orthogonalised (one standard deviation) shocks to sub-sector specific private credit | The shaded area represents the 95% confidence band for the response functions | Plot (d), (h) and (l) illustrates the asymmetric sub-sectoral output responses to shocks in subsector-specific credit.

Table 8: Variance Decomposition of Sub-sectoral GDP to Sub-sector-specific Private Credit Shocks

Horizons	Agriculture & Fisheries			Industry			Services		
	Tea	Coconut	Fisheries	Construction	Food, Beverages & Tobacco	Textiles & Apparel	Wholesale & Retail Trade	Financial & Business Services	Transport & Storage
2	7.6	0.7	0.6	0.0	0.7	9.2	4.5	0.0	4.3
4	8.7	1.5	0.8	0.1	5.7	9.1	3.7	0.0	5.9
8	8.6	2.0	0.8	3.1	12.0	8.5	5.8	0.1	6.7
12	9.7	2.0	0.9	4.8	13.4	7.9	9.1	0.1	7.1
16	10.0	2.0	1.1	4.3	16.2	7.8	12.5	0.1	8.7
20	10.1	2.0	1.3	3.7	20.5	7.7	15.4	0.1	11.0

Notes: This table presents the variance decompositions based on level VAR (with all variables in logs) | The lag order of the VAR is established to obtain serially uncorrelated error terms | Cholesky ordering of the variables → $[LGDP_{mt}^{SS}, LGDP_{-mt}^{SS}, LCPI_t, LPSC_{mt}^{SS}, LPSC_{-mt}^{SS}]$ | $LGDP^{SS}$ = Log Sub-sectoral Real GDP; $LPSC^{SS}$ = Log Sub-sectoral Private Sector Credit | Private Sector Credit contains commercial bank lending to the private sector (excluding lending to other banking entities) | Time horizon in quarters | All values are in percent.

Output in the coconut sector increases marginally following a shock to credit, with its effect then gradually dissipating thereafter. Also, credit shocks account for only a small fraction of the sector's output variation. This implies that credit only has a short-term impact on the output of the coconut sector and is relatively insensitive to credit impulses.

Conversely, the fisheries sector output declines instantaneously during the first 6 months, improves marginally during the short- to medium-term before turning negative again over the remainder of the forecast horizon following a positive credit impulse. Moreover, the output of the fisheries sector displays very low sensitivity to credit shocks. It is worth noting that the contribution of the fisheries sector output[39] (and even the coconut sector) to overall GDP remains higher than that of the tea sector, despite credit directed to the sector remaining comparatively lower (See Table 9). Therefore, this is one area policymakers should pay

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[39] In terms of both value and growth

attention to as this would imply that credit channelled to the fisheries sector might be insufficient to generate a sizeable increase in production.

The construction sector output increases in the short-term in response to a credit impulse, which is followed by a prolonged period of contraction between years 1-4. However, the construction sector output improves after 4 years, signifying the long-run effect of construction on economic growth. Moreover, output in this sector is barely sensitive to positive credit impulses, in the short run, albeit a small increase in sensitivity is visible in the medium- to long-term.

On the contrary, output of the food, beverages and tobacco sector tends to be negatively impacted by a positive credit impulse. This could be due to the fact that this sector primarily borrows on a very short term basis (such as temporary overdrafts), which has relatively less to do with the sector's output and its growth. Nevertheless, credit shocks account for a considerable proportion of output variation in the sector, making it the most sensitive sub-sector in our analysis.

The response of output of the textiles and apparel sector to a credit impulse appears to be erratic at short horizons, albeit the effect turns out to be positive from quarter 8 onwards. This indicates that credit has a lagged effect on this sector's output, which is typical of any industry-related sector, as credit-funded investments take time to generate returns. However, unlike other sectors, the sensitivity of this sector's output to positive credit shocks dissipates over time.

The wholesale and retail trade sector is the largest contributor to the economy's GDP. The IRFs indicate that the output of this sector behaves erratically during the entire forecast horizon to a credit impulse, which could be attributed to the short-term nature of activity in this sector in the case of Sri Lanka. The cyclical nature of output responses indicates that credit does not have a persistent effect on the output of this sector. However, this sector's output is relatively more sensitive to credit impulses, where credit accounts for 6-15 percent of the output variation in the medium- to long-term.

Output of the financial and business services sector shows only a marginal response to a sector-specific credit impulse. This result, though quite alarming, makes sense due to shortcomings in the data. GDP data pertaining to this sector includes all bank and non-bank financial business services, while credit data includes only that of non-banks, and therefore is not fully comparable. Most importantly, since the banking sector accounts for nearly 70 percent of assets of the financial system (CBSL, 2016), credit excluding interbank lending, will prove less useful to our analysis. It is due to this reason we observe that output of this sector is insensitive to credit impulses.

Lastly, the response of the transportation sector output to a positive credit shock is erratic. In the shorter horizon, we can observe positive responses occasionally, but turns negative in the

medium-term and lasts thereafter till the end of the forecast horizon. This could largely be due to the transportation sector in Sri Lanka being predominantly state-run and a positive private credit impulse, therefore is unlikely to impact this sector's output notably. Nevertheless, 11 percent of the variations in the output of this sector is due to credit impulses.

Most interestingly, careful inspection of plot (d) in Figure 4 and plots (d), (h) and (l) in Figure 5 depicts the differential effects of sector/ sub-sector specific credit shocks on the output of those respective sectors/ sub-sectors. In other words, there is clear evidence of sectoral heterogeneity and identification of these potential differences in the effects of credit shocks on output at the sectoral and sub-sectoral levels, will provide policymakers valuable guidance and understanding when fashioning and implementing policies to achieve their ultimate objective of price and economic stability.

One important observation is that overall agricultural output appears to be responding well to a positive credit shock in the long run, while its sub-sectors respond positively as they should in the short- to medium-run, unlike the other sectors. However, the agriculture share of GDP has averaged only about 8 percent during the last 5 years, while the share of agriculture-related credit has increased to 12.2 percent (See Table 9). This could imply that too much credit has been channelled to a sector that is relatively less productive and contributes less to overall GDP.

However, (CBSL, 2016) provisional statistics indicate that the agriculture sector has recorded the highest sectoral growth in 2015 and a satisfactory level of growth in 2014.[40] One could argue that the agriculture sector received the *right amount* of credit (if not more), unlike its other sectoral counterparts (especially the industry sector), as banks increasingly channel credit to the agriculture sector possibly due to higher demand, the mandatory lending requirement or simply because banks are able to charge relatively higher rates of interest (for e.g. lending for agricultural purposes via pawning of gold articles at rates of around 20-24 percent per annum), which they find lucrative from their perspective. This practice crowds out credit available for industry and services sectors, which are relatively more productive and contributes more towards overall GDP, which could be the reason why the expected response of output of these two sectors to credit impulses are imperceptible. Therefore, a careful attempt to redirect credit to non-agricultural sectors (predominantly, the industry sector) should be evaluated and acted upon.

Moreover, due to uncertainty in the global and domestic financial markets, a majority of the banks focused more on short-term lending, rather than medium- or long-term lending. Certain sectors require long-term funds and careful attention by policymakers to reverse this said phenomenon by ensuring financial stability would enable these sectors (e.g. construction sub-

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[40]Real GDP growth of the agriculture sector was 5.5 percent in 2015, compared to 3.0 percent (industry) and 5.3 percent (services). Agriculture recorded the second highest growth rate in 2014 (which was 4.9 percent), compared to 3.5 percent (industry) and 5.2 percent (services).

sector under industry) to obtain funds on a longer-term basis, which would generate sustainable economic growth.

Also, in the Sri Lankan context, policymakers (predominantly the Central Bank), in different occasions have adopted strategies such as quantitative restrictions on credit (to slow credit growth when credit is buoyant) and the use of moral suasion (to encourage lending when credit is depressed or needs to be directed to certain sectors), apart from the use of interest rates. Awareness of potential disparities in the effects of credit impulses on disaggregated output will aid policymakers in many respects. They will be able to evaluate the *direction*, *magnitude, timing* and *sensitivity* of responses of output of relevant sectors and sub-sectors of the economy to credit impulses, and when used in conjunction with a similar analysis on sectoral output responses to interest rate shocks, policymakers will be able to make well informed decisions.

5.   Checks for Model Robustness and Suitability

5.1. Introducing AWCMR as a New Control Variable in place of CPI (Model 2)

The analysis done so far was based on the benchmark VAR model, which features log of CPI as a key control variable. To assess the robustness of the model, we introduce the variable of AWCMR, replacing log of CPI and refer to this as Model 2.

IRFs generated from Model 2 are illustrated in column 2 of Figure 6. Responses of output to credit impulses in Model 2 appear to be quite similar to the responses of the benchmark VAR (Model 1), especially in the shorter horizon, while some deviation in the magnitude of responses could be observed thereafter. The only exception is the financial and business services sub-sector, where Model 2 demonstrates a somewhat different output response. Nevertheless, as the responses of Model 2 are broadly qualitatively similar to that of Model 1, it suggests that our benchmark VAR model is robust to alternate model specifications.

5.2. Excluding CPI as a Control Variable (Model 3)

Further to the above, a separate exercise was conducted to assess the suitability of the benchmark VAR model to estimate output responses to credit impulses. For this purpose, a VAR model without log of CPI as a control variable was formed (referred to as Model 3) and impulse responses were drawn to test for the appropriateness of the benchmark model for this study.

The inclusion of CPI (Model 1) as an additional control variable appears to add more explanatory content to Model 3, as factoring in the price level when dealing with real variables produce realistic results. Moreover, output responses of Model 2 move quite closely with those of Model 3. This implies that excluding log CPI from the benchmark model would have biased the impulse responses generated in this study, while also suggesting that including AWCMR

in place of log of CPI as a control variable would have had less value addition to the model in terms of explanatory power.[41]

6. Concluding Remarks and Policy Implications

The relationship between credit and economic growth has been a long discussed topic over the past century. In this paper, we investigate the causal nexus between economic growth and private credit in Sri Lanka, and the response of output to innovations in private credit, using data from 2003-2015. The analysis is carried out using 3 levels of data: aggregate, sectoral and sub-sectoral, with the aim of determining possible disparate effects of output to credit impulses.

We follow the unrestricted VAR (UVAR) approach using techniques such as Toda-Yamamoto causality testing and multiplier analysis, which includes generating Impulse Response Functions (IRFs) and Forecast Error Variance Decompositions (FEVDs). We find evidence supporting the *'demand-following'* hypothesis in the case of Sri Lanka, with unidirectional causality running from economic growth to private credit.

The multiplier analysis involving IRFs and FEVDs are estimated for 3 VAR systems. Results of the aggregate system indicate that both aggregate output and the price level responds positively to credit impulses. However, a *second wave* of growth in output can be observed as the effect of the credit shock on the price level starts dissipating. This indicates that credit in Sri Lanka tends to have more of an *inflationary* aspect rather than a *growth-stimulating* aspect. Moreover, sensitivity of aggregate output to credit shocks is unexpectedly low in the case of Sri Lanka.

Similarly, sectoral output responds favourably to positive credit impulses in the long run. However, varying responses of the three sectors in the short run demonstrates evidence of sectoral heterogeneity to credit shocks. Services sector output responds quickly and positively to a credit impulse, while agriculture and fisheries sector's outputs respond positively in the medium-term. Output of the industry sector behaves erratically in the shorter horizon. With respect to sensitivity, agriculture and fisheries sector output is the most sensitive to credit shocks, while the industry sector output is the least sensitive.

Further evidence of sectoral heterogeneity to credit shocks was found when the study was extended to analyse responses of output of the sub-sectors. Within the agriculture and fisheries sector, output of both tea and coconut sectors responded positively to credit impulses at different magnitudes, while the fisheries sector output suffered a decline.

Sub-sectors belonging to the industry sector showed equally diverse responses with construction output responding negatively in the short-term, which eventually turned positive

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[41] See columns 3 and 4 in Figure 6

at the end of the forecast horizon. Output of the food, beverages and tobacco sector responded negatively throughout the entire forecast horizon, while that of the textiles and apparel sector was unsteady during the short-term, but turned marginally positive over the medium-term.

Responses of those sub-sectors under services to a credit shock were irregular. Response of output of the wholesale and retail trade, and transportation and storage sectors were erratic, while that of the financial and business services sector was marginal.

Output of the food, beverages and tobacco, wholesale and retail trade, transportation and storage, and tea sectors were the most sensitive to credit shocks, while output of financial and business services, fisheries, coconut and construction sectors were the least sensitive.

The above findings have important implications to both literature as well as policymakers in several ways. Although the literature focuses extensively on analysing the causal relationship between credit and economic growth, little attention has been paid to analyse the disparate effects of credit policy on different sectors and sub-sectors of the economy. While this study focuses on Sri Lanka, conducting similar studies for other countries in the future could yield interesting and varying results due to cross-country variations in terms of the structure of the economy and the financial system. Moreover, future research can also focus on regional output disparities of credit policy, as all these would imply the need for a careful approach for policy.

Moreover, findings of this study provide valuable insights to policymakers both in Sri Lanka and globally. Since there is evidence of differential effects of output to private credit impulses in the context of Sri Lanka, careful attention should be given when formulating policies to ensure that each sector or sub-sector of the economy benefits from the policy actions taken.

Also, policymakers in Sri Lanka should fashion policy to encourage more medium- to long-term lending, particularly to the industry and services sectors, which would help improve the *growth-stimulating* aspect of private credit, while also allowing them to achieve their core objective of price and economic stability. Such changes to the lending structure (in terms of sectors lent to and tenure of loans) would be an appropriate policy, over quantitative restrictions on overall credit during periods when credit expands beyond the desired level.

The significance and relevance of these findings and policy recommendations not only applies to Sri Lanka, but to all policymakers globally. Heterogeneity in sectoral output responses to credit requires policymakers to be mindful of the disparate effects that policy actions could entail. Even countries like the US, the UK and the European Union can find relevance to this study as policymakers in those nations would have to be conscious about how unconventional monetary policy, particularly credit easing, affects different sectors (and regions) in disproportionate ways, thereby warranting a careful approach to credit that stimulates economic growth.

It should be mentioned that the sample period of this study, 2003-2015, was eventful in terms of policy measures and economic background, both locally and globally, and the results are likely to have been affected by those incidences.[42] It should also be noted that employing superior methodologies such as structural VARs (SVARs), along with the inclusion of more control variables to analyse this issue would have been more appropriate.

Nevertheless, the present study and its findings are likely to generate discussion and interest on the credit-growth nexus and this approach to analyse such relationship at disaggregated levels (sectoral and regional) for different countries will be an area for future research.

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[42] Policy measures such as quantitative restrictions on credit (in 2012), the 3-decade long civil war (ending in 2009) and turmoil in the global financial market (in 2008/09) are some events that are likely to have affected credit and economic growth in numerous ways in Sri Lanka.

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Appendices

A.   Figure 1: Real Credit Growth Vs. Real GDP Growth
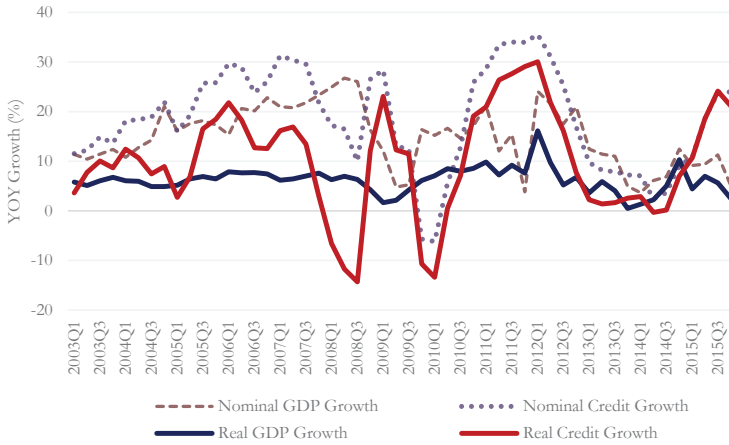
B.   Figure 3: Response of log GDP and Log CPI to a Credit Impulse
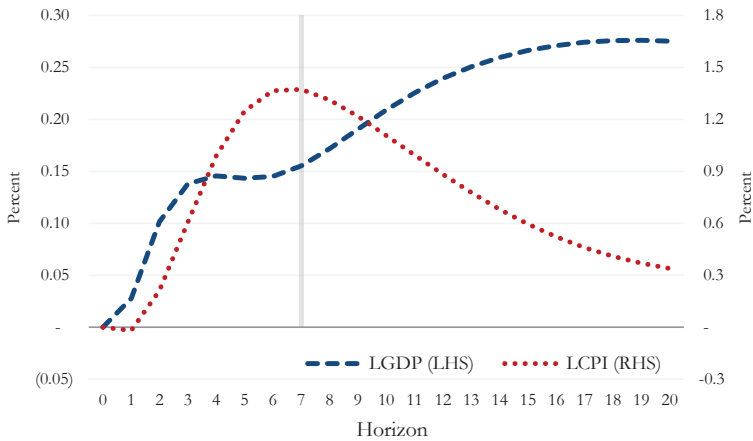
C. Table 1: Definitions, Sources and Descriptive Statistics

Variable	Definition/ Description	Source	Mean	Std. Deviation
Real GDP	Real Gross Domestic Product - Seasonally adjusted (Base: 2010=100)	DCS	1,558,622	364,535
Real Private Sector Credit (PSC)	Seasonally adjusted credit granted by commercial banks to non-bank private sector (adjusted for inflation)	CBSL	1,475,514	494,309
Consumer Price Index (CPI)	Colombo Consumers Price Index (rebased, so that Base: 2010=100)	DCS	90.9	28.0
Average Weighted Call Money Rate (AWCMR)	Interbank money market rate for unsecured lending	CBSL	10.1	3.9
Agriculture & Fisheries (GDP)		DCS	130,385	22,523
Industry (GDP)			413,206	100,678
Services (GDP)			862,683	213,104
Agriculture & Fisheries (Credit)		CBSL	173,655	63,838
Industry (Credit)			555,503	173,841
Services (Credit)			332,539	143,685
Tea (GDP)		DCS	17,419	1,371
Coconut (GDP)			19,133	1,680
Fisheries (GDP)			21,054	6,615
Construction (GDP)			91,598	36,929
Food, Beverages & Tobacco (GDP)			104,267	21,489
Textiles & Apparel (GDP)			61,263	6,425
Wholesale & Retail Trade (GDP)			175,701	38,357
Financial & Business Services (GDP)			167,971	47,476

Transportation & Storage (GDP)		158,266	47,657
Tea (Credit)	CBSL	40,155	5,822
Coconut (Credit)		3,738	1,721
Fisheries (Credit)		5,382	2,094
Construction (Credit)		238,325	79,625
Food, Beverages & Tobacco (Credit)		40,855	8,236
Textiles & Apparel (Credit)		76,570	15,035
Wholesale & Retail Trade (Credit)		175,809	37,312
Financial & Business Services (Credit)		75,151	30,299
Transportation & Storage (Credit)		17,538	10,399

Notes: This table reports the definitions/descriptions, sources and summary statistics of all the variables used in our analysis | DCS: Department of Census and Statistics - Sri Lanka; CBSL: Central Bank of Sri Lanka | GDP and Private sector credit figures (aggregate, sectoral and sub-sectoral) are in Millions (Sri Lanka Rupees); CPI contains index values; AWCMR is in percent.

D. The **Toda-Yamamoto Approach to test for Granger Causality**

Toda and Yamamoto (1995), introduced an alternative approach to test for Granger causality, which could be applied on VAR models, irrespective of their order of integration or cointegration; hence requiring no pre-testing. It generates a modified Wald test statistic (MWALD) [43] based on the estimation of an augmented VAR model.

The Toda-Yamamoto (TY) procedure involves two steps:

    I.   Determine the maximum order of integration (d_{max}) of the series in the VAR model (by performing the ADF test)

    II.   Form a well-specified levels VAR model of order k (VAR(k)) [44]

As we test for causality only in the aggregate system, the VAR($k + d_{max}$) model will take the following specific form:

$$
\begin{bmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \end{bmatrix} = \begin{bmatrix} \beta_{10} \\ \beta_{20} \\ \beta_{30} \end{bmatrix} + \sum_{i=1}^{k} \begin{bmatrix} \beta_{11,i} & \beta_{12,i} & \beta_{13,i} \\ \beta_{21,i} & \beta_{22,i} & \beta_{23,i} \\ \beta_{31,i} & \beta_{32,i} & \beta_{33,i} \end{bmatrix} \begin{bmatrix} y_{1t-i} \\ y_{2t-i} \\ y_{3t-i} \end{bmatrix}
$$
$$
+ \sum_{j=1}^{d_{max}} \begin{bmatrix} \beta_{11,k+j} & \beta_{12,k+j} & \beta_{13,k+j} \\ \beta_{21,k+j} & \beta_{22,k+j} & \beta_{23,k+j} \\ \beta_{31,k+j} & \beta_{32,k+j} & \beta_{33,k+j} \end{bmatrix} \begin{bmatrix} y_{1t-k-j} \\ y_{2t-k-j} \\ y_{3t-k-j} \end{bmatrix} + \begin{bmatrix} v_1 \\ v_2 \\ v_3 \end{bmatrix}
$$

(2)

where, $y_1 = LGDP$; $y_2 = LCPI$; $y_3 = LPSC$

We focus on testing for variable-to-variable causality, with the purpose of identifying causal relationships among (just) two variables, where we test the following null hypothesis [45] (e.g. causality from LPSC to LGDP):

$$H_0: \beta_{13,1} = \beta_{13,1} = \cdots = \beta_{13,k} = 0$$

---

[43] When a levels VAR of order $k + d_{max}$ is estimated, the MWALD test statistic has an asymptotic chi-squared (χ^2) distribution.

[44] Determine the optimal lag length by using selection order criteria such as Akaike Information Criterion (AIC), Hannan-Quinn Information Criterion (HQIC) or Schwarz Bayesian Information Criterion (SBIC) and ensure that the VAR model is well-specified by testing for stability and serial correlation.

[45] The null hypothesis implies that one variable (LPSC) does not cause the other (LGDP), while its rejection presents evidence of causality.

E. Orthogonalised Impulse Response Functions (IRFs)

Impulse Response Functions help trace out the responses of one variable (e.g. real GDP) to an unanticipated shock in another variable (e.g. real private credit) in the VAR system. The impulse responses are obtained by rewriting the VAR in its moving-average (MA) form. The MA(∞) representation of the VAR(p) model in (1) can be written as:[46]

$$y_t = \mu + \sum_{i=0}^{\infty} \phi_i \varepsilon_{t-i} \tag{3}$$

where, $\mu = E(y_t)$; $\phi_i = J\Phi^i J'$; and $J = [I_n : 0 : \dots : 0]$

Unreasonable assumptions, such as the occurrence of shocks only in one variable at a particular point in time, and shocks among variables being independent, warrant for the generation of orthogonalised impulse responses. By decomposing the original innovations in the VAR,[47] we are able to represent our VAR(p) model in its MA form:

$$y_t = \mu + \sum_{i=0}^{\infty} \Psi_i \eta_{t-i} \tag{4}$$

where,

$\Psi_i = \phi_i P$

$\eta_t = P^{-1}\varepsilon_t$ (a vector of orthogonal residuals) [48]

μ is the mean of y_t, which is constant $\forall\ t$.

The components in the vector η_t are contemporaneously uncorrelated as these orthogonalised shocks hold the property of $\varepsilon_t \sim (0, I_n)$.[49] In addition, the Ψ_i matrix contain information on the impulse responses.

---

[46] We broadly follow notation by Lutkepohl (2005). The same source could be referred for a more detailed explanation (including technicalities).

[47] We decompose the covariance matrix Σ_ε, which is symmetric and positive definite as: $\Sigma_\varepsilon = PP'$ (where P is a lower triangular matrix). This is the Cholesky decomposition of matrix Σ_ε. Using this equality, we rewrite equation (3) as: $y_t = \mu + \sum_{i=0}^{\infty} \phi_i PP^{-1}\varepsilon_{t-i}$

[48] Its covariance matrix takes the form $\Sigma_\eta = P^{-1}\Sigma_\varepsilon(P^{-1})' = I_n$

[49] A unit shock to any component in the vector η_t is equal to a one standard deviation shock since $\Sigma_\eta = I_n$. See Lutkepohl (2005) for a detailed explanation.

F. Forecast Error Variance Decompositions (FEVDs)

Forecast Error Variance Decompositions (FEVDs) provides information on the proportion of the total h-period ahead forecast error variance of an endogenous variable resulting from orthogonalised shocks to itself as well as to other variables in the VAR system.

Using equation (4) in conjunction with orthogonalised shocks ($\Sigma_\eta = I_n$), the optimal h-step ahead forecast error can be shown as;

$$\boldsymbol{y}_{t+h} - \bar{\text{y}}_t(h) \ = \ \sum_{i=0}^{h-1} \boldsymbol{\phi}_i \boldsymbol{\varepsilon}_{t+h-i} \tag{5}$$

where, $\boldsymbol{y}_{t+h}$ = actual value at time $t+h$

$\quad\quad \bar{\text{y}}_t(h)$ = h-period ahead forecast value of $\boldsymbol{y}_t$ made a time t

Then, with a bit of algebra, equation (5) can be modified as;

$$\boldsymbol{y}_{t+h} - \bar{\text{y}}_t(h) = \sum_{i=0}^{h-1} \boldsymbol{\Psi}_i \boldsymbol{\eta}_{t+h-i} \tag{6}$$

Most importantly, the forecast error of each individual component will therefore possibly contain all the shocks.[50]

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[50] We have followed the methods and expressions outlined by Lutkepohl (2005).

G. Table 2: Results of the Augmented Dickey-Fuller (Unit Root) Tests

Variable	Level		First Difference		Remarks	Model Specification at Level	ADF Lags
Real GDP	-2.038		-4.738	*	I(1)	C&T	2
Real Private Sector Credit (PSC)	-3.039		-3.597	*	I(1)	C&T	2
Consumer Price Index (CPI)	-0.672		-3.096	**	I(1)	C&T	2
AWCMR	-1.160		-4.216	*	I(1)	C	2
Agriculture & Fisheries (GDP)	-3.394		-6.590	*	I(1)	C&T	1
Industry (GDP)	-2.114		-6.197	*	I(1)	C&T	2
Services (GDP)	-1.992		-4.699	*	I(1)	C&T	2
Agriculture & Fisheries (Credit)	-1.244		-6.754	*	I(1)	C&T	1
Industry (Credit)	-0.902		-3.861	*	I(1)	C&T	2
Services (Credit)	-1.729		-3.467	*	I(1)	C&T	2
Tea (GDP)	-3.393	**			I(0)	C	2
Coconut (GDP)	-2.615		-5.768	*	I(1)	C	1
Fisheries (GDP)	-1.324		-5.046	*	I(1)	C	2
Construction (GDP)	-2.326		-5.118	*	I(1)	C&T	2
Food, Beverages & Tobacco (GDP)	-2.241		-4.176	*	I(1)	C&T	2
Textiles & Apparel (GDP)	-2.698		-6.688	*	I(1)	C&T	2
Wholesale & Retail Trade (GDP)	-2.937		-9.572	*	I(1)	C&T	2
Financial & Business Services (GDP)	-0.458		-4.226	*	I(1)	C&T	1
Transportation & Storage (GDP)	-3.252		-7.011	*	I(1)	C&T	2
Tea (Credit)	-0.984		-3.696	*	I(1)	C	2
Coconut (Credit)	-2.556		-3.831	*	I(1)	C&T	2
Fisheries (Credit)	-3.706	**			I(0)	C	2
Construction (Credit)	-0.686		-3.419	**	I(1)	C&T	1
Food, Beverages & Tobacco (Credit)	0.067		-3.311	**	I(1)	C	2
Textiles & Apparel (Credit)	-2.605		-4.314	*	I(1)	C&T	2
Wholesale & Retail Trade (Credit)	-1.808		-5.109	*	I(1)	C&T	2
Financial & Business Services (Credit)	-2.330		-3.400	**	I(1)	C&T	1
Transportation & Storage (Credit)	-2.262		-4.639	*	I(1)	C&T	2

Notes: This table presents the unit root test results for 28 variables | The null hypothesis is that the variable follows a unit root process | * - significant at 1% ; ** - significant at 5% | I(0): Stationary at levels; I(1): Stationary at first difference | C: ADF test with constant; C&T: ADF test with trend and constant

H. Table 3: Optimal Lag Order of VAR Models

VAR Model	Model 1 (Benchmark VAR)	Model 2	Model 3
Aggregate System			
Base VAR - Aggregate	2	2 $^\Delta$	2
Sectoral System			
VAR 1 - Agriculture & Fisheries	3	3	3
VAR 2 - Industry	2	2 $^\Delta$	2
VAR 3 - Services	2	2	2
Sub-sectoral System			
VAR 4 - Tea	2	3	3
VAR 5 - Coconut	2	1 $^\Delta$	2
VAR 6 - Fisheries	2	2	2
VAR 7 - Construction	2	2 $^\upsilon$	2
VAR 8 - Food, Beverages & Tobacco	2	2 $^\Delta$	2
VAR 9 - Textiles & Apparel	2	2	2
VAR 10 - Wholesale & Retail Trade	2	2 $^\Delta$	2 $^\Delta$
VAR 11 - Financial & Business Services	1	1	1
VAR 12 - Transportation & Storage	2	3	3

Notes: This table presents the optimal lag order of the different, stable VAR models | The lag order of the benchmark VAR (Model 1) is established to obtain serially uncorrelated error terms (at the 5% level), while the lag order of other models are decided to match the lag order of the benchmark VAR (Model 1) provided the VAR model is stable | Δ indicates presence of serial correlation at that lag order; υ indicates that the VAR model is unstable at that lag order | Model 1: Benchmark VAR, which includes log CPI as a control variable; Model 2: includes AWCMR in place of log CPI as a control variable; Model 3 excludes log CPI from the benchmark VAR model.

I. **Table 4: Results of Multiplier Analyses**

VAR Models – Benchmark VAR	Findings Explained	
	IRFs	**FEVDs**
Aggregate System		
Base VAR - Aggregate	*GDP:* Following a positive credit shock, aggregate real output responds positively with real output increasing by around 0.15% above baseline after 1 year. It remains at that level for about 2 more quarters before increasing again and peaks at the 18-19 quarters with real output remaining around 0.28% above baseline. However, this effect is not statistically significant.	*GDP:* Credit shocks account for only about 2% of the fluctuations in aggregate output by the end of 3 years, with this proportion increasing to less than 5% after 5 years.
	CPI: In response to the positive credit shock, the price level increases by around 1% above baseline within 4 quarters, peaks at 1.4% at quarter 7 before dissipating towards the steady state level, with effects from quarter 4 to 9 remaining significant.	*CPI:* Credit shocks explain about 3 percent of variation in the price level during the first year, which subsequently increases to 21% at the end of 2 years and around 27% (on average) during the 3- to 5-year horizon.
Sectoral System		
VAR 1 - Agriculture & Fisheries	The sector responds positively from quarter 4 onwards with the increase being marginal in quarter 4, but persists to end up at 0.4% above baseline at quarter 20.	Shocks to credit explains only around 1% of the variation in output of the sector during the first 2 years, while it increases to nearly 9% by the end of 5 years.
VAR 2 - Industry	Output responses appears to be unsteady at short horizons, starting off negatively and bottoming out at 0.2% below baseline in quarter 2. However, from the seventh quarter onwards, industry sector output takes off and peaks at 0.1% above baseline in quarter 19.	Shocks to credit explains only about 0.5% of the variation in output of the industry sector from the first year till the end of the forecast horizon on average.

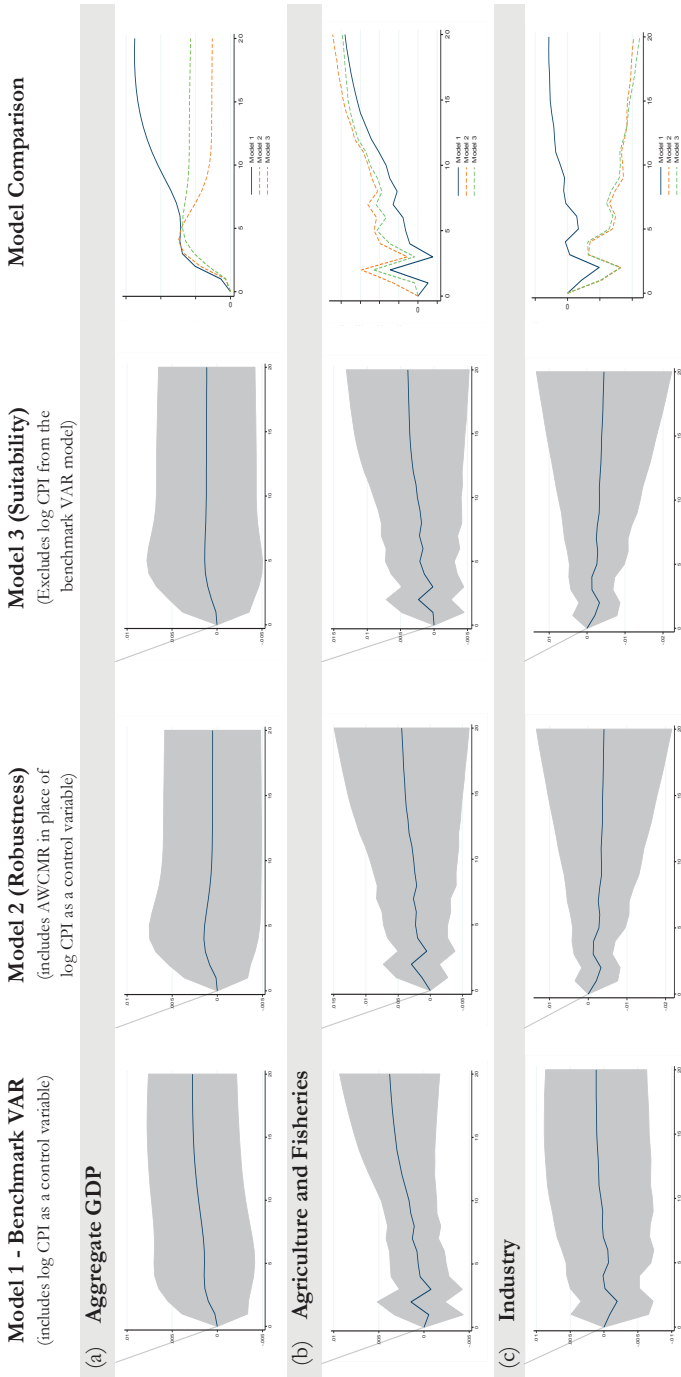| VAR Models - Benchmark VAR	Findings Explained	
	IRFs	FEVDs
VAR 3 - Services	The sector responds positively to shocks in services sector-related credit in the shorter horizon, where it peaks at 0.3% above baseline in quarter 4, after which it gradually tends towards the pre-shock output level over the forecast period of 5 years	Sensitivity of services sector output to sector-specific credit almost doubles after the first year, where shocks to services sector credit explains around 3% of the variation in services sector output, on average, during years 2-5.
Sub-sectoral System		
VAR 4 - Tea	The sector shows almost an immediate positive response to a credit shock, peaking at 2% above baseline in quarter 1, which is statistically significant. However, this effect fades out gradually and reaches baseline by about quarter 4 before the positive effect re-appears in quarter 6 and remains persistently above baseline by around 0.1-0.5% over the forecast horizon.	Credit account for nearly 8% of the variation in tea output during the first 2 quarters, which then increases to around 9-10% thereafter.
VAR 5 - Coconut	Output increases marginally to about 0.6% above baseline in quarter 2, following a shock to credit, with its effect then gradually dissipating thereafter.	Only a minuscule fraction of the sector's output variation is attributable to credit shocks.
VAR 6 - Fisheries	Output of the sector declines instantaneously by about 1-1.6% below baseline during the first 2 quarters, and only turns positive during quarters 5-7 recording a 0.3% increase on average. This effect then fades away and remains negative thereafter.	Output of the sector displays very low sensitivity to credit shocks, with credit impulses accounting for only around 1% of the variation (on average) in this sector's output.

Findings Explained

VAR Models – Benchmark VAR	IRFs	FEVDs
VAR 7 - Construction	Output in the sector increases by about 0.1-0.2% percent in the shorter end of the spectrum. However, output seem to suffer from the quarter 4 onwards till the sixteenth quarter, where the largest drop (of around 1%) takes place at the end of the second half of year 2. This, however, gradually improves and reaches positive territory from year 4 onwards.	Output in this sector is hardly sensitive to positive credit impulses, in the short run, while credit shocks only account for about 3-4%, on average, in the longer term.
VAR 8 - Food, Beverages & Tobacco	Output of this sector tend to be negatively impacted by a positive credit impulse. It declines by about 0.7% below baseline after 1 year, with the negative effect fading away to last only for 5 more quarters, before it starts declining again.	Credit shocks account for 12% of output variation in the sector after 2 years, and almost 21% after 5 years, making it the most sensitive sub-sector in our study.
VAR 9 - Textiles & Apparel	Response of output of this sector to a credit impulse appears to be erratic at short horizons, although the effect turns out to be positive from quarter 8 onwards. However, the maximum positive effect can be quantified to be around 0.1% above baseline in quarter 14.	Credit shocks account for 9% of output variation in the shorter horizon, followed by a gradual slowdown to about 7.7% by the end of 5 years.
VAR 10 - Wholesale & Retail Trade	Output of this sector is quite erratic during the entire forecast horizon. A positive credit shock has a positive effect on this sector's output for about 2 to 3 quarters before it turns negative for another couple of quarters and this cyclical trend continues.	Credit shocks account for 6% of the output variation by the end of 2 years, doubles to around 13% at the end of 4 years, before ending at 15% after 5 years.
VAR 11 - Financial & Business Services	Output of this sector tends to decline to a maximum of 0.1% below baseline up until the end of 4 years, after which a slight positive effect could be seen towards the end of the forecast horizon.	Credit shocks causes almost no variation in output of this sector.

VAR Models - Benchmark VAR	Findings Explained	
	IRFs	**FEVDs**
VAR 12 - Transportation & Storage	Output of this sector displays a somewhat erratic behaviour to a positive credit shock. Occasional positive effects of credit shocks could be witnessed in this sector's output in the shorter horizon, but moves on to the negative territory from quarter 7 onwards and persists thereafter till the end of the forecast horizon.	Credit shocks account for 6% of the output variation by the end of 1 year, which increases to around 11% after 5 years.

Notes: This table provides a detailed report of findings from the multiplier analysis.

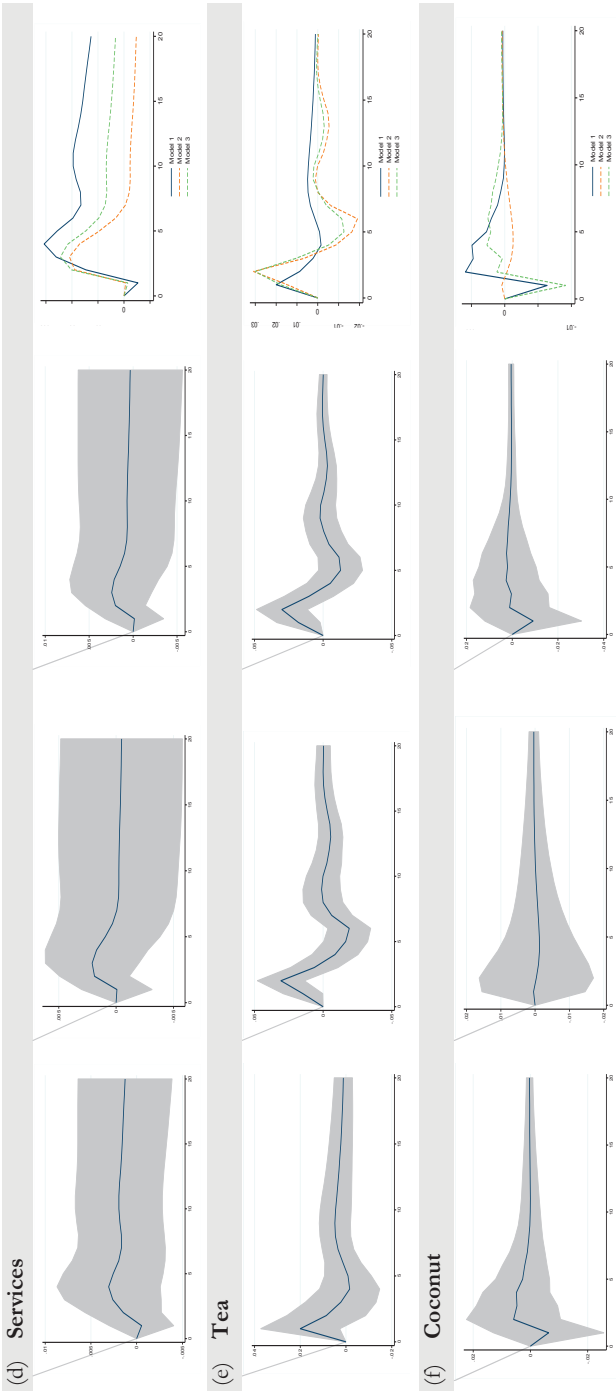**J. Figure 6: Model Robustness and Suitability**

Model 1 - Benchmark VAR
(includes log CPI as a control variable)

Model 2 (Robustness)
(includes AWCMR in place of log CPI as a control variable)

Model 3 (Suitability)
(Excludes log CPI from the benchmark VAR model)

Model Comparison

(d) **Services**

(e) **Tea**

(f) **Coconut**

Model 1 - Benchmark VAR
(includes log CPI as a control variable)

Model 2 (Robustness)
(includes AWCMR in place of log CPI as a control variable)

Model 3 (Suitability)
(Excludes log CPI from the benchmark VAR model)

Model Comparison

(g) Fisheries

(h) Construction

(i) Food, Beverages and Tobacco

Model 1 - Benchmark VAR
(includes log CPI as a control variable)

Model 2 (Robustness)
(includes AWCMR in place of
log CPI as a control variable)

Model 3 (Suitability)
(Excludes log CPI from the
benchmark VAR model)

Model Comparison

(j) **Textiles and Apparel**

(k) **Wholesale and Retail Trade**

(l) **Financial and Business Services**