# Assessing the impact of credit spread shocks on UK Gross Value Added: A SVAR-IV Approach

**N**ame: ARIF UDDIN PIYASH
STUDENT REGISTRATION NUMBER: 2310452
Supervisor: Dr. Kai Zhang

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**Abstract**

This study examines the impact of credit spread shock on UK Gross Value Added (GVA) index of services and its sub-sectors. As previous papers, mainly investigates the credit spread impact on GDP and monetary policy effect on credit spread. Employing the works of (Cesa-Bianchi, Thwaites, & Vicondoa, 2020) credit spread construction, I will use their monthly dataset on credit spread shock to understand its impact on UK service sectors. Furthermore, the paper uses SVAR-IV approach to look at the shock impacts and compares it with SVAR method. The finding shows that the 1 percentage change in standard deviation of credit spread shock doesn't affect the service sectors output only within 0.5 percentage point.

# 1 Introduction

Credit spread has been examined in several papers that look at the difference in yield between those securities issued by the government and private debt securities with equal maturity. Credit spreads have been proposed as a significant business cycle indicator in macroeconomics since they are often used as a major signal of how tight financial conditions are in the economy (Gourio, 2013); (Gilchrist & Zakrajšek, 2012). Credit spreads are known to provide useful prognostic information about future economic activity in forecasting (e.g., Gilchrist et al. (2009); Faust et al. (2013)). Furthermore, credit spreads are an important consideration for central bankers when implementing monetary policy, as stated by (Curdia & Woodford, 2010).

All these studies show a high correlation between credit spread and macroeconomic dynamics but do not provide a more detailed understanding of how different sectors in a particular industry respond to interest rates. However, in this paper, I will examine how the credit spread rate affects the Gross Value Added (GVA) of service sectors in the United Kingdom. Does credit spread shock impact service sectors of the economy?

To answer the above question, I have constructed a SVAR-IV approach that combines credit spread developed by (Cesa-Bianchi et al., 2020) with important macroeconomic variables and decomposition of several service sectors industries over the period 1997-2014. Prior research has primarily focused on identifying credit shocks through the implementation of short-term zero restrictions (Gilchrist & Zakrajšek, 2012); (Lown & Morgan, 2006) or sign restrictions (Gambetti & Musso, 2017); (Meeks, 2012), and analysing the effects on economic activities and financial markets. This paper, however, follows the method of (Mertens & Ravn, 2013); (Stock & Watson, 2012), where I will use Consumer Price Index (CPI) as an external instrument for credit spread shocks in a structural VAR to determine the reasons for their impacts on service sectors. Finally, I will be using four control variables because as suggested by (Stock & Watson, 2018) adding them reduces the sampling variance of the IV estimator and they help to lower the variance of the error component.

The reason for choosing the GVA service sector is because the service sector plays a major role in UK GDP output. In the United Kingdom, the service sector generated 81% of GDP (gross value added) and 83% of jobs between April and June 2024. In addition, a (Bell, Clark, Fry, Kelly, & Thwaites, 2023) analysis from 2023 assessing the strengths of the British economy found that UK economy is known for exporting financial and business services, which account for 7% and 9% of total exports, respectively. Other services, however, are also important. In fact, even while overall exports climbed from 44% to 47% over that period, financial services suffered a fall in their percentage of exports, from 12% in 2009 to 9% in 2019.

I find that responses of the index of services and its main eleven sectors to a structural credit spread shock within one standard deviation are inconsequential.

The results that are obtained show that the responses of the shock for all service sectors are within the 0.5% range. Importantly, impulse response suggests that shock does not lead to a significant reduction in service sectors.

The negligible movement of service sector activities indicates that the underlying sources of capital cost to this service industry are not much affected by credit spread changes. In particular, a slightly relevant literature (Gilchrist & Zakrajšek, 2012) looks at the response of GDP when hit by a change in corporate bond credit spread, their work found that shocks to excess bond premium lead to a statistically significant decline in output.

The first section of this paper provides a background of the study and a snapshot of the paper. While the remaining part of this paper is structured as follows. Section 2 shows the related literature which have been studied on this subject along with the recent methodologies used. Section 3 shows the econometric method used providing SVAR-IV specification, identification strategy and estimation. Section 4 begins with providing detail explanation of data used, then providing OLS estimation and various robustness checks for the choice of instruments and concluding by explaining results of the shocks. Finally, in Section 5 the paper concludes.

# 2 Related Literature

In dynamic macroeconomics, it is essential to determine the causal influence of economic events or policy actions (Frisch & Waugh, 1933). Related variables that concurrently drive the study's causative and outcome variables provide a significant barrier to causal inference research. Confounding factors might be "partial out" of an influence by being included as control variables in a regression with the result variable. A different approach, however, has generally been adopted by the macroeconomics literature. It involves two steps: first, estimating "shocks" as the residuals from a regression of the relevant causal variable on the set of confounding factors; second, integrating these shocks in a local projection (LP) or vector auto-regression (VAR) (Lloyd & Manuel, 2024).

In any study of the VAR and SVAR models, a fundamental question arises regarding how shocks impact macroeconomic variables such as GDP, inflation, and employment. There has been some ambiguity in explaining what exactly constitutes shocks some researchers called it innovation (Sims, 1980) and others have meant it as an instrument (Cochrane, 2011). However, in this paper, I will view shocks as adopted in the paper by (Mertens & Ravn, 2013) where treating the shock term as a vector of latent variables, it is estimated by enforcing identifying assumptions and using the information in the vector of lagged dependent variables to condition on the prediction errors of the dependent variable.

Research on credit spreads has employed various econometric models to understand their impact on macroeconomic variables. One widely used approach is the

Structural Vector Autoregression (SVAR) model, which allows for the identification of structural shocks within a system of interrelated economic variables. The SVAR model has been instrumental in disentangling the effects of credit spread shocks from other macroeconomic shocks.

For instance, (Mertens & Ravn, 2013) utilize an SVAR model with external instruments to identify tax shocks, a methodology that has been adapted in this study to analyze credit spread shocks. Similarly, (Cesa-Bianchi et al., 2020) employ a SVAR-IV approach to examine the impact of financial shocks on the UK economy, demonstrating the model's efficacy in isolating exogenous shocks.

The Cholesky identification method assumes that some variables do not respond to shocks within the same period by imposing a recursive structure on the contemporaneous interaction between variables. This method makes identification easier, but it could miss the rapid impacts of monetary policy shocks, especially in Dynamic New Keynesian (DNK) models where production and inflation are supposed to respond instantly. The possible variations in impulse responses produced from SVAR models have raised concerns due to this difference, since these may not adequately reflect the underlying dynamics of the economy under specific identification methods.

Credit spread shocks have become more integrated into the larger macroeconomic analysis in recent years, especially with the use of Structural Vector Autoregressions (SVARs). This analytical technique has been very helpful in separating out the intricate linkages between macroeconomic variables and is frequently used to quantify the impact of monetary policy shocks. But as several studies—such as those by (Hanson, 2004)and (Boivin & Giannoni, 2006), and others—have shown, SVARs frequently provide subdued responses of production and inflation when applied to stable macroeconomic eras, like the "Great Moderation." Traditional SVAR models face difficulties during this time of lower volatility in macroeconomic variables, especially when attempting to use the Cholesky decomposition approach to find monetary policy shocks.

SVAR-IV technique is applied in this study to assess credit spread shocks, providing an improved methodology that tackles some of these issues. The work addresses the problems related to the "zero short-run restrictions" of the Cholesky approach by improving the detection of exogenous shocks through the use of the Consumer Price Index (CPI) as an external instrument. This strategy is consistent with research suggesting that classic Cholesky-SVAR models could underestimate the effects of shocks on important macroeconomic variables, as demonstrated by the notable changes seen in experiments using pseudo-data derived from DNK models (Castelnuovo, 2010).

In macroeconomic research, the use of Structural Vector Autoregressions (SVARs) to analyze monetary policy shocks is commonly used. Several studies have looked at how important economic variables like production and inflation respond to these shocks. Nevertheless, recent research has shown important distortions that may occur in SVAR models, especially when using Cholesky decomposition to identify these shocks (Carlstrom, Fuerst, & Paustian, 2009). The accuracy of impulse responses plays a critical role in comprehending the transmission mechanisms of various shocks, especially credit spread shocks, which are fundamental to this thesis. Therefore, these distortions are particularly concerning in dynamic macroeconomic analysis.

This study uses a SVAR-IV technique to examine the effects of credit spread shocks on the Gross Value Added (GVA) of the UK service sector. The approach has been selected to tackle the possibility of misspecifications that have been noted in the literature to arise in ordinary SVAR models. The authors (Carlstrom et al., 2009) specifically highlight how structural parameters—like interest rate smoothing and shock persistence—play a part in the errors seen in SVAR-based impulse reactions. Because they are essential to the dynamics of credit spread shocks and how they affect the macroeconomic variables, these characteristics are especially pertinent to this research.

One important factor influencing economic agent's expectations for anticipated monetary policy measures is interest rate smoothing. The extent of interest rate smoothing can have a major influence on how credit spreads affect the service sector in the setting of my study, when these spreads are used as a gauge of financial circumstances. The body of research indicates that the immediate effects of monetary policy shocks on variables like as production and inflation are more noticeable when interest rate smoothing is strong. The impulse responses, however, could underestimate the actual consequences of these shocks in a Cholesky-SVAR framework as it does not properly account for this smoothing. This problem relates to this research since it highlights the necessity for a different identification technique to capture the true impact of credit spread shocks on the UK service sector, such as the SVAR-IV approach that I have used in this thesis.

Moreover, this study by (Castelnuovo, 2010) emphasizes the long-lasting effect of technical shocks and monetary policy shocks as important contributions to the distortions shown in SVAR models. Credit spread is the persistence parameter used in this article, and it is important to understand how credit spread shocks affect various subsectors of the UK service economy over the long run. Due to its dependence on Cholesky decomposition, a normal SVAR model may not adequately reflect the long-term effects of shocks like these on economic variables. This study is better positioned to account for these enduring impacts by using an SVAR-IV technique, offering a more realistic depiction of how credit spread shocks move across the economy.

The literature is rich with studies that explore the transmission of credit spread shocks to macroeconomic outcomes. (Gilchrist & Zakrajšek, 2012) provide evidence that shocks to the excess bond premium, which is a component of the credit spread, lead to significant declines in economic output. Their findings suggest that credit spread shocks can be as influential as monetary policy shocks in driving economic fluctuations.Moreover, the work of (Gilchrist & Zakrajšek, 2012) on the differential impact of credit spread shocks on manufacturing versus service sectors provides a comparative framework for understanding this paper results. Their findings that manufacturing sectors are more adversely affected by credit spread shocks supports my conclusion that the service sector's resilience could be due to its lower reliance on external financing.

Furthermore, research by (Lown & Morgan, 2006) highlights the role of credit conditions in influencing real economic activity, particularly through their impact on investment and consumption. These studies emphasize the importance of understanding how credit spread shocks propagate through the economy, affecting variables such as GDP, inflation, and employment.

In the context of the UK economy, (Gambetti & Musso, 2017) employ a SVAR model with sign restrictions to analyze the impact of credit shocks. Their results indicate that credit spread shocks have significant effects on economic activity, particularly in sectors that are more sensitive to changes in financial conditions. This is consistent with my findings that the service sector, which constitutes a substantial portion of the UK economy, responds modestly to credit spread shocks. While much of the literature focuses on aggregate macroeconomic outcomes, there is a growing body of research that examines the sectoral impacts of credit spread shocks. This is particularly relevant to my study, which disaggregates the service sector to analyze the differential responses of various sub-sectors to credit spread shocks.

Finally, studies such as those by (Kwon, 2020) delve into the sector-specific effects of financial shocks, finding that industries with higher financial leverage are more vulnerable to credit spread shocks. This resonates with my findings that the UK service sector, despite its large contribution to GDP, shows limited responsiveness to credit spread shocks, suggesting that the cost of capital in this sector may be less sensitive to fluctuations in credit spreads.

# 3 Estimation and Identification

## 3.1 Identification

The core concept of identifying structural shocks in a structural VAR model using external instruments is that the structural shock is determined as the predicted value from the population regression of the instrument denoted as Z on the VAR innovations. For this approach to be valid, the instrument must meet certain criteria: it needs to be relevant (i.e., it must be correlated with the specific structural shock being studied) and exogenous (i.e., it must be uncorrelated with all other structural shocks). Additionally, the structural shocks themselves must be uncorrelated with each other. This paper works on this methodology developed by (Mertens & Ravn, 2013), and (Stock & Watson, 2012).

$Y_{it}$(i = 1, ..., 12)represents the vector of endogenous variables. In this study, there are 12 distinct sets of variables, each corresponding to a different primary variable of interest, denoted by the subscript i (e.g., the indexes of different service sectors). Moreover, $Y_{it}$contains six variables corresponding to the subscript j (j = 1, . . . ,6). Here, let credit spread interest rate be the endogenous regressor of interest, denoted by Real credit Index (RCI). Instrument variable ($Z_{jt}$) is monthly consumer price index. Control variables (C) chosen are (chained UK GDP monthly, monthly LIBOR rate , Exchange rate GBP/USD, and Unemployment rate.) $Y_{it}$ can be expressed as :

$$Y_{it} = [IndexofServices_{it}, RCI_t, C_{it}, C_{2t}, C_{3t}, C_{4t}] \tag{1}$$

The Structural VAR (Vector Autoregression) model is,

$$AY_{it} = \sum_{n=1}^{q} \alpha_n Y_{i,t-n} + \delta_{it} \tag{2}$$

In this setting, $\delta_{it}$ refers to a vector of structural disturbances that are uncorrelated over time and with each other. These latent variables of $\delta_{it}$ are determined using the prediction errors of $Y_{it}$, based on the information provided by the lagged dependent variables in the vector $X = [Y_{i,t-1}, \ldots, Y_{i,t-n}]$. The matrix $A$ is a $6 \times 6$ matrix of contemporaneous coefficients, and $\alpha$ consists of $6 \times 6$ coefficient matrices. By multiplying both sides of Equation (2) by $A^{-1}$, we obtain the reduced-form VAR model. The reduced-form error term can then be written as $\gamma_{it} = K\delta_{it}$, where $K = A^{-1}$.

The criterion for E[$\gamma_{it}\gamma_{it}'$] = KK$'$ imposes j (j-1) /2 = 30 identifying constraints, but we require extra identifying constraints for the elements in the last column of K. Assuming, the partition of structural shocks $\delta_{it}$ = [$\delta_{it}^{j-1}$, $\delta_{it}^{RCI}$], where $\delta_{it}^{RCI}$ is the shock of interest and $\delta_{it}^{j-1}$, is a vector comprising all other (j-1) shocks.

Using (Mertens & Ravn, 2013) work I will apply covariance limitations based on the proxy for latent shocks. These are my main identifying assumptions, with an additional requirement:

$$E[Z_t \delta_{it}^{RCI}] = \alpha \neq 0] \tag{3}$$

$$E[Z_t \delta_{it}^{j-1} = 0] \tag{4}$$

$$E[Z_t Q_{it}' = 0] \tag{5}$$

The third criterion is that the instrument should be orthogonal to the lagged data of $Y_{it}$, albeit this assumption can be modified. The external instrument can be adopted to determine elements K as long as Equations (3) and (4) are met. Here, I will assume partitioning K for a single VAR(n) system of $Y_{it}$.

K = , $\begin{vmatrix} \beta_1 & \beta_2 \\ (6\times1) & (6\times5) \end{vmatrix}$

$B_1$= , $\begin{vmatrix} \beta'_{11} & \beta'_{21} \\ (1\times1) & (1\times5), \end{vmatrix}$

$B_2$ = $\begin{vmatrix} \beta'_{12} & \beta'_{22} \\ (5\times1) & (5\times5), \end{vmatrix}$

Here, equation 2 to 5 expresses

$$\alpha\beta'_1 = \theta_{Z_t,\gamma\,'} \equiv E[Z_t, \gamma'](6)$$

Further Separation of $\theta_{Z_t,\gamma'}$ results,

$\theta_{Z_t,\gamma'}$ = $\begin{vmatrix} \theta_{Z_t}, \gamma'_1 & \theta_{Z_t}, \gamma'_2 \\ (1\times1) & (1\times5), \end{vmatrix}$

As a result, these limitations provide the following:

$$\beta_{21} = (\theta_{Z_t{}'_{\gamma_1}}{}^{-1}\theta_{Z_t\gamma'_1})'\beta_{11} \tag{7}$$

Henceforth, in this paper the SVAR-IV identification approach is given below in three steps:

Firstly, determine the residuals of $\gamma_{it}$ by estimating the reduced form VAR(n) using n-lagged values of $Y_{it}$ as controls.

Secondly, using the regression of $\gamma_{it}$ on $Z_t$, I have estimated $\theta^{-1\prime}_{Z_t\,\gamma_1}\theta_{Z_t\gamma'_1}$.

Thirdly, apply the restriction in equation 6 into practice and estimate the dynamic causal impact of $\delta^j_{it}$, specifically looking at $\delta^{RCI}_{it}$ (credit spread shock)[1].

## 3.2 Estimation

The number of lags for the baseline VAR is set to be 1 based on the selection of the Akaike Information Criterion (AIC) those introduced in (Ivanov & Kilian, 2005) which appropriately shows the dynamics of endogenous variables. The selection of lag lengths suggests that approximately 204 observations will be required for determining a significant number of system parameters. Thus, to effectively resolve this matter and enhance the accuracy of the estimation, I take the SVAR-IV method to estimate the VAR model based on the works of (Stock & Watson, 2012). Finally, I have included 95% confidence bands which were generated through bootstrapping over 100 iterations.

[1]For use of the SVAR-IV Identification method and the application of my data to R code has been learned from the works of (Perez, 2020)

# 4 Data, Instrument Choice and Results

## 4.1 Baseline Specification and Data

The present work uses data from Office for National Statistics (ONS) spanning from January 1997 to June 2024. I have collected time series data on Gross Value Added for the index of services and main sectors. There are almost 18 sectors in (main sectors) among which I have selected 11 based on their respective higher weights and discarding those with lower weights. The 11 sectors which are accounted for in this study are: Distribution, Hotels and Restaurants, Transport, Storage and Communications, Business Services and Finance, Wholesale, retail and motor trade, Transportation and storage, Accommodation and food service activities, public administration and defence, Financial and insurance activities, Real estate activities, Education, and other Service Activities.

Gross Value Added informs about how much value has been generated by any unit when producing any goods and services. The UK (ONS) provides a chained volume measured prices of GVA. For, the purpose of this paper a real GVA which removes the effects of inflation thus been used. Therefore, showing more apt evidence of how the service sector provides a marginal improvement or decline over the years when credit institutions interest rate spread increases or decreases.

The baseline VAR model uses monthly UK Gross value added and credit spread data over the period 1997 to 2014. While the imperative data is the measure of credit spread and the data has been used from the works of (Cesa-Bianchi et al., 2020). Credit spread is "a measure of total credit extended by financial institutions to the private non-financial sector" (Cesa-Bianchi et al., 2020). The data for credit spreads has been collected from the above-mentioned authors work who exploits monthly data on UK credit spread from the major lending institutions across the country.

Gross Value Added for the index of services and its main 11 sectors has been collected from the Office of National Statistics (ONS). This variable has been measured in terms of log real GVA. Furthermore, four control variables has been chosen which are measured in terms of log of real GDP, monthly LIBOR rate, Exchange rate GBP/USD, and Unemployment rate. Data for unemployment is available in the Bank of England website which publishes data on unemployment, CPI and GDP. However, data for the monthly LIBOR rate are extracted from trading economics website. The inclusion of Consumer price Index (CPI) as an Instrumental variable is motivated by the close relation of financial instruments with the inflation rate. Inflation rate is inherent while pricing almost all financial instruments. While setting yields for corporate bonds, setting loan rate or other interest measure inflation is inherent in any pricing of financial securities. There is a crucial linkage working between asset prices and inflation which is manifested in various financial securities. Several papers looked at the evidence of how investors feed inflation in their asset return. Firstly, a useful metric which provides a measurement of how their asset are affected when inflation goes up or down, i.e., they attach a discount rate to the financial asset which tracks movement of inflation. In traditional beta-pricing model, beta is found through regressing return on inflation see (Bekaert & Wang, 2010). Furthermore, research by (Hamilton, 2013) shows that the oil price movement affects the financial market which is relevant to understanding that inflation affects many firms which in turn affects the pricing of financial instruments.

## 4.2 OLS estimation and Instrument Choice

To evaluate the choice of the credit spread indicator along with the instrumental variable for the credit spread shock, I will use several measures to test the validity and usefulness of the instrument. Specifically, I will examine the responses of the Index of Services to changes in the real credit spread. Here, the dependent variable in this regression exercise is the Index of Services. The various tests and estimations will demonstrate whether the instrument has strong explanatory power, providing justification for its selection in the monthly VAR data.

Let $r_t^n$ be be the real credit spread on n month that serves as an independent variable and is in terms of log-difference , let $\Delta I_t$ be the change in Index of services in terms of log-difference.

Hence, the regression we consider is given as follows $\Delta R_t$ is related to $i_t^n$ as follows:

$\Delta I_t = \alpha + \beta i_r^n + \mu_t$

I will estimate this equation using two stages least squares with monthly consumer price index as an instrument. Under the identifying assumptions, the instrumental variables estimation isolates variation in $r_t^n$ due to Consumer Price Index (CPI) which is orthogonal to the error term $\mu_t$, thus providing a consistent estimator of $\beta$.Here, I have considered three variables: independent variable with endogeneity present, dependent variable and instrumental variable which provides a consistent estimator of $\beta$. Firstly, for independent variable real credit spread is chosen which is unable to capture all the disturbances and bound to have endogeneity problem, thus I will introduce an instrumental variable. Next, for instrumental variable there are two yardsticks under which one needs to choose an instrumental variable as noted by (Stock & Watson, 2018) in his paper, where he uses SVAR-IV methods and requires two fundamental assumptions to be met by the external instruments. First, in the below equation the instrument must have correlation with the shock of interest which is the relevance condition Second, the instrument must satisfy exogeneity condition, which is instrument must be uncorrelated with other current shocks. Finally, for the dependent variable I have chosen the Index of Services.

(1)Relevance Condition: E(Z$\mu = \alpha \neq$0)

(2)Exogeneity Condition: E(Z$\mu$ =0)

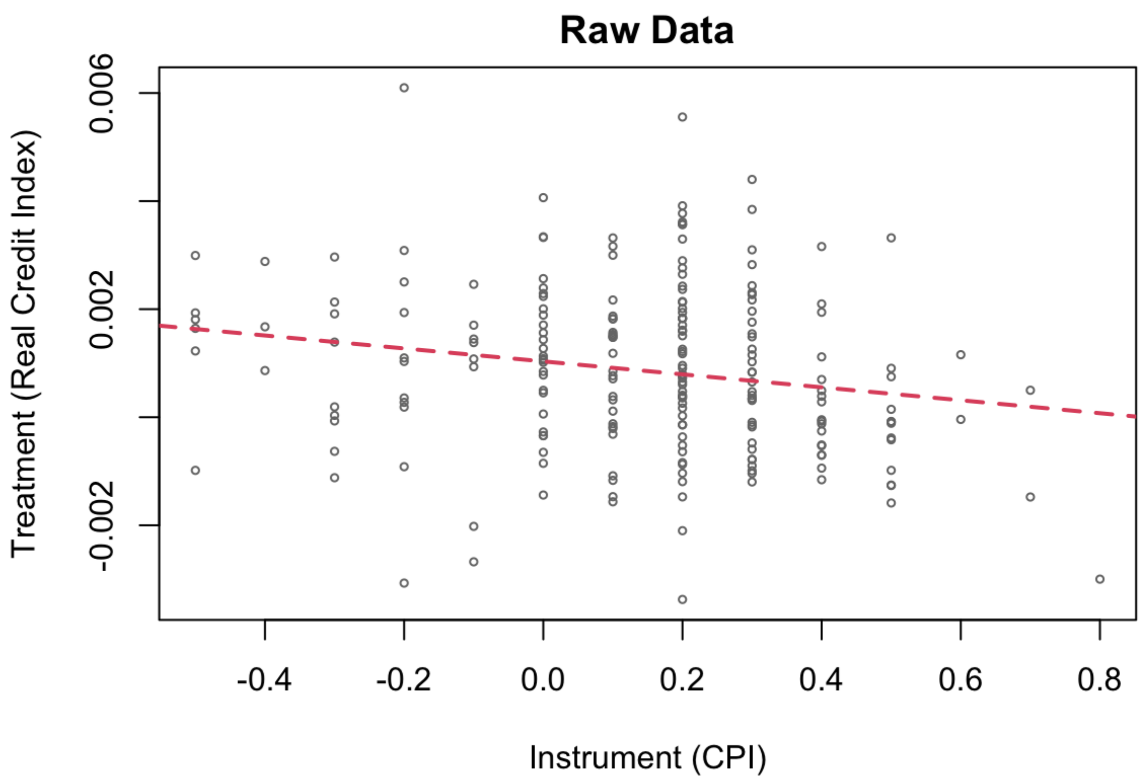


Figure 1: OLS

Figure 1 represents the results from an Ordinary Least Squares (OLS) regression analysis. The table (1) in appendix provides coefficients, standard errors, t-statistics, confidence intervals, and p-values for three different estimation methods: Analytic, Boot.c (bootstrap-c), and Boot.t (bootstrap-t). The coefficient for the OLS estimation is consistently -0.027 across all three methods. This suggests a negative but very small relationship between the independent variable and the dependent variable.The standard errors are nearly identical across the different methods, with minor variations. The Analytic method has a standard error of 0.089, Boot.c has 0.092, and Boot.t matches the Analytic at 0.089. The similarity of these values indicates that the model's variance does not change significantly when different methods are applied, implying that the model is stable. The t-statistic is approximately -0.3 for all methods, leading to p-values that are well above the conventional significance level of 0.05 (specifically 0.759, 0.717, and 0.754). This suggests that the relationship between the independent variable and the dependent variable is not statistically significant. The 95% confidence intervals (CI) for the coefficient further support the lack of statistical significance, as they include zero (-0.202 to 0.147 for Analytic). This means that we cannot reject the null hypothesis that there is no relationship between the variables. Overall, the OLS results indicate that the independent variable does not have a statistically significant effect on the dependent variable. The consistent findings across different estimation methods (Analytic, Boot.c, and Boot.t) reinforce the robustness of this conclusion, suggesting that the model is well-specified but that the effect size is too small to be meaningful in this context.

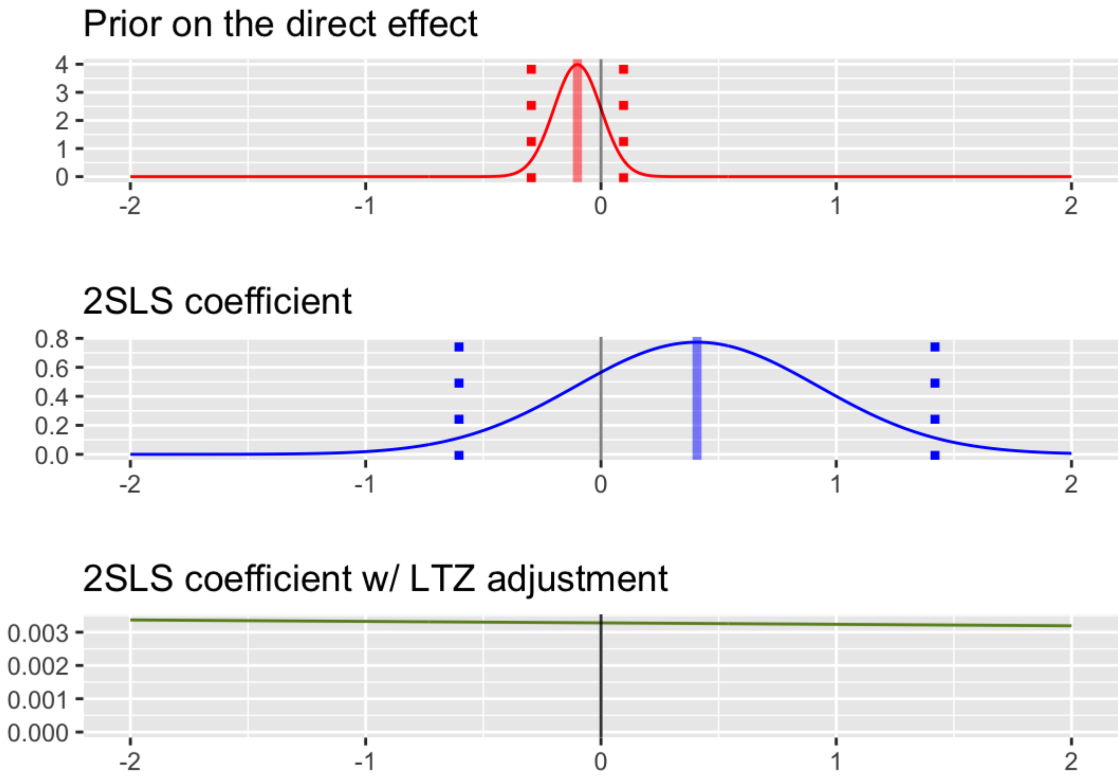


Figure 2: 2SLS Estimates Before and After LTZ Adjustment

Figure 2 provides the results from a Two-Stage Least Squares (2SLS) regression, which uses an instrumental variable (the Consumer Price Index, CPI) to address potential endogeneity issues. Additionally, the figure explains (2SLS) estimated sample distribution is shown in this figure both before and after the Local-to-Zero (LTZ) adjustment (Conley, Hansen, & Rossi, 2012). Furthermore, an illustration of the previous distribution based on the ZFS test is shown. The 95% confidence intervals are shown by the dotted lines, which emphasize how strong the initial 2SLS findings are even after the LTZ modification. This robustness supports the validity of the preliminary findings by showing that the LTZ adjustment does not significantly change the causal impact calculated by the 2SLS model.

The 2SLS coefficient is 0.408 across all methods (Analytic, Boot.c, and Boot.t), indicating a positive relationship between the instrumented variable and the dependent variable. The standard errors here are larger than those in the OLS results, especially for Boot.c, which has a standard error of 0.839 compared to 0.516 for both Analytic and Boot.t. The larger standard errors suggest that there is more uncertainty in the 2SLS estimates, which is typical when using instrumental variables due to the additional layer of estimation. The t-statistics are lower than those in the OLS results (0.791 for Analytic and Boot.t, and 0.486 for Boot.c), and the p-values are still well above 0.05 (0.429, 0.461, and 0.415). This indicates that, like the OLS results, the 2SLS estimates are not statistically significant. The 95% confidence intervals for the 2SLS coefficient include zero, ranging from -0.603 to 1.420 for Analytic, again suggesting that we cannot reject the null hypothesis of no effect. The 2SLS results suggest that even after accounting for potential endogeneity using the CPI as an instrument, the relationship between the instrumented variable and the dependent variable remains statistically insignificant. The larger standard errors indicate that the instrument introduces more variability into the estimates, but this does not change the overall conclusion that the effect is not significant.

Henceforth, both the OLS and 2SLS results indicate that the relationship between the variables under study is not statistically significant. The use of the CPI as an instrument in the 2SLS model is justified by the F-statistic which is 11.427 marginally above the threshold of 10 suggested by (Stock & Yogo, 2002), but the results show that the effect size is small and not significantly different from zero, regardless of the method used. This consistency across different estimation techniques suggests that the findings are robust, though they also point to the possibility that the relationship being examined may not be substantively meaningful in this context.

## 4.3 Results

In this section, I will examine the impulse response function of the change in indexes of services and its main sectors to one-standard deviation structural credit spread shock over a horizon of 12 months. Here, I will add the credit spread to a standard

VAR that includes the following endogenous variables : (1) log-difference of Index of Services (2) log-difference of Other Service Activities, (3) log-difference of Real estate activities, (4) log-difference of Distribution, Hotels and Restaurants, (5) log-difference of Transportation and storage, (6) log-difference of Wholesale, retail and motor trade (7) log-difference of public administration and defence, (8) log-difference of Transport, Storage and Communications, (9) log-difference of Financial and insurance (10) log-difference of Accommodation and food service, (11) log-difference of Education (12) log difference of Business Services and Finance. The identifying assumption underlying this recursive ordering is that shocks to credit spread affect service activities and its main sectors contemporaneously and the VAR

### 4.3.1 Impulse Responses to Credit Spread Structural Shocks

As shown in section 3, I will extract the shock related to credit spread to a forecasting horizon of 12 months. The shock which is extracted is known here as credit spread shock and is the most significant shock in terms of quantitative changes in credit spread. To reflect the short- and medium-term variations of credit spreads, the prediction horizons are set to 0 to 12 months, with equal weights assigned to each projection.

I will start by analysing the response of the index of services, other service activities, public administration and defence, and Education service activities. First, index of services has a slight movement after the shock hits as it reverts to its original level at a shorter horizon within five months span. Second, other services activities have hardly had any impact as there are no movement only a small blip in the seventh month. Thirdly, public administration and defence depicts a fluctuation as there is a rise of 0.1% of these service activities and then fell to 0.5% and thereafter moving to its original level. Finally, education service activities hardly change with only slight increase of 0.1% after few months.

Furthermore, analysis of real estate activities, financial and insurance activities, transportation and storage, and business service and finance show more widespread fluctuation relative to those main sectors explained above. Firstly, shocks to real estate activities increases slightly and the drops to 0.05% and then recovering sharply to its initial level. Next, Financial and insurance activities saw swings around 0.2% and returning to its original level in the after 8 months. Additionally, the results emphasizes the dynamics specific to the service sector, demonstrating that certain subsectors — like real estate and financial services—respond more strongly to shocks to credit spreads. This finding aligns with the theory that sectors that are closely associated with capital flows and financial markets are more vulnerable to modifications in lending terms. Changes in interest rates and credit availability, for instance, have a direct impact on property values and investment decisions in the real estate sector. In a similar vein, the financial services industry is particularly susceptible to shocks originating in credit markets due to its tight ties to the larger financial system. Thirdly, transport, storage and communication saw a sharp rise in activities rising to 0.2% and then reverts immediately the following month to its base level. Finally, business services and finance responses to credit spread shock was swaying around 0.1% and moving to its original level in the sixth month.

The negligible responses of index of services and its main sectors suggests that the primary shock of credit spread does not impact service sector in UK as do the sector of manufacturing. In comparison to previous studies where the channel of transmission of credit spread shock was examined to responses of real GDP, inflation, and investment, (Kwon, 2020) this study differs, and its results decomposes the macroeconomic variable to understand sector wise responses. The panels in Figure 3 in (appendix) indicates that there exists weak linkage between services and credit spread shock. Particularly, the shock explains relatively a small percentage change in index of services and its main sectors for a brief forecast horizon, but its explanatory power declines over time as the period of forecasting increases.

Furthermore, the weak linkage between service sector activities and credit spread shocks, as highlighted in the analysis, might suggest that the transmission mechanism of credit shocks operates differently in the service sector compared to the manufacturing sector, where credit conditions more directly affect production and investment.

Upon closer examination of the results, it becomes evident that the impact of credit spread shocks is relatively muted across most service sectors. This finding aligns with prior literature, such as Gilchrist and Zakrajšek (2012), which highlights the modest impact of financial shocks on certain economic activities. However, the specific characteristics of the UK service sector might explain the limited reactions observed in this study.

The findings of this study contribute to the broader understanding of how financial conditions impact different sectors of the economy. By decomposing the service sector's response to credit shocks, the analysis provides valuable insights for policymakers and economists interested in stabilizing economic activity in the face of financial volatility. Future research could further explore these dynamics, perhaps by incorporating additional variables or by extending the analysis to other sectors of the economy.

Finally, the impulse response study highlights the relatively small impact of credit spread shocks on the UK service sector. This resilience reflects the sector's diverse structure and, presumably, the effectiveness of existing financial buffers that protect it from short-term financial disruptions. Understanding these patterns is critical for developing policies that promote economic stability in the face of financial shocks.

### 4.3.2 Comparison with Cholesky method SVAR

When discussing the comparison with the Cholesky technique SVAR, it is critical to analyze the larger implications of the variations between this method and the SVAR-IV approach to assess the economic shocks. The Cholesky decomposition, while popular due to its simplicity, imposes an unchangeable repetitive structure on the variables that may not necessarily correspond to the underlying economic theory or the real dynamics of the variables. This method implies that the first variable in the ordering is contemporaneously exogenous, influencing all subsequent variables while not being impacted by them during the same period.

In contrast, the SVAR-IV technique provides a more flexible identification strategy by isolating exogenous shocks utilizing external instruments, such as the Consumer Price Index (CPI) in this paper. This strategy addresses possible endogeneity difficulties, resulting in a more accurate portrayal of the causal connections between variables. For example, using the CPI as an indicator helps to verify that the credit spread shocks are not having other economic disturbances present, resulting in more dependable impulse response functions.

Furthermore, when evaluating impulse responses, the distinctions between the two techniques become clear across different time horizon. The Cholesky approach may have smaller or less long-lasting impacts, possibly due to its reliance on the imposed structure rather than reflecting the underlying dynamics of the economic system. In contrast, the SVAR-IV technique frequently reveals stronger and prolonged reactions, allowing for a more complete understanding of the shocks' long-term impacts.

Here, I will contrast the findings with a baseline conventional SVAR model in which Cholesky decomposition is used to identify the shocks. The basic model retains the similar vector of endogenous variables and the lag order of p=1, as recommended by AIC; however, the external instrument, monthly consumer price index (CPI), no longer identifies the shocks. The SVAR impulse response functions of the change in indexes of services and its main sectors to structural credit spread shock with a one-standard deviation over a 12-month period are displayed in Figure 4.

A notable different image appears when looked at the difference between the results of the two SVAR model. Overall, Cholesky-identified SVAR in contrast to SVAR-IV model signals more variation. This result is different from those found by the works of (Stock & Watson, 2018), who found that the responses received from the SVAR-IV re-evaluation were greater than the Cholesky-identified findings by (Kilian, 2009). For the index of service and from main sectors (other service activities) responses to credit spread shocks has remained same in both SVAR model. Figure panel shows that the distribution, hotel and restaurants, financial and insurance, business services and finance, education and transportation and storage sectors responses to shock is more striking than those of the SVAR-IV. Firstly, distribution, hotel, and restaurants services responses to credit spread shock saw a sharp drop of about 0.8% when shock hit and rose again to its original level in the following month. Secondly, financial and insurance activities saw a spike in activities with an increase in activities to more than 0.8% and then gradually, moving to its initial level in the sixth month. Next, business services and finance similarly had a sharp rise in activities following credit spread shock it rose to above 0.4%. Finally, transportation and storage activities increased to 0.6% immediately when the shock hit and reverting to its original level in the fifth month. Henceforth, the responses of shock in Figure 3 and Figure 4 provides a sense on how the Gross Value Added of indexes of services and its main sectors responses to credit spread shocks are diminutive.

To summarize, while the Cholesky technique provides a simple way for finding shocks in an SVAR model, its limitations in dealing with complicated, interdependent interactions make it unsuitable for some economic evaluations. The SVAR-IV method, which employs external instruments and rigorous validation techniques, provides a more nuanced and accurate framework for evaluating the effects of credit spread shocks, especially in a sector as complex as the UK service industry. The unique qualities of the data and the research topics at hand may impact the selection of these methods, with a preference for more flexible and theoretically sound approaches such as SVAR-IV in complicated circumstances.

# 5 Conclusion

The results of this research paper provide a substantial contribution to the current discussion on how financial shocks—particularly credit spread shocks—affect the macroeconomic environment in the United Kingdom. The study's novel method of breaking down the service industry into its primary sub-sectors provides a detailed insight of how various service sector industries react to variations in credit spread shocks. This breakdown of service sector to study is essential, particularly in light of the service sector's significant GDP contribution to the UK and its function in the larger economy.

The use of the SVAR-IV approaches, which is ideal for determining the impacts of credit spread shocks on economic variables while accounting for potential endogeneity problems, is one of the thesis's primary contributions. The study successfully separates the exogenous component of credit spread shocks by utilizing the Consumer Price Index (CPI) as an external instrument. This helps to ensure that the impacts found on the Gross Value Added (GVA) of the service sector are not confused with other macroeconomic variables. The results are more robust due to the methodological study applied such as OLS estimation and local-to- zero estimation method, which also provides a better understanding of the causal link between credit conditions and economic activity. Since, OLS and LTZ method provides shows the validity of the instrument.

Based on the empirical analysis, it appears that the service sector is less affected by credit spread shocks than other industries, including manufacturing. This result is consistent with the literature, which frequently emphasizes how financial shocks have distinct effects on various sectors. For example, sectors like manufacturing that depend significantly on outside funding are typically more vulnerable to changes in lending terms. On the other hand, because of its wide variety of businesses, the service sector could profit from a combination of finance arrangements that act as a shock absorber.

This thesis contributes by investigating the temporal dynamics of credit spread shocks. The impulse response functions show that most sub-sectors recover to pre-shock values in a matter of months, indicating that the impacts of these shocks are often transient. This temporal trend indicates that credit spread shocks have a limited long-term impact on the service sector, despite their ability to temporarily disrupt economic activity. This conclusion is especially related to policymakers because it emphasizes the resilience of the service sector and the need for prompt actions to lessen the short-term disruptions brought on by financial shocks.

Lastly, this thesis provides a few helpful contributions for further study. Examining how credit spread shocks affect other economic sectors, like manufacturing or technology, might be one way to find out if the conclusions drawn from the service sector apply to other businesses. Examining how financial innovation and digitalization affect the service sector's resistance to credit spread shocks is a stimulating subject for future research. Policymakers and practitioners alike will find it more important to comprehend how the changing financial landscape affects the way in which financial shocks spread to the real economy.

# 6 Limitation of the study

Although this study offers valuable insights into how credit spread shocks affect the UK service industry, it should be noted that it has several limitations. Firstly, the study's time frame is restricted to the years 1997 to 2014, which could not adequately represent the long-term dynamics of credit spread shocks, especially considering the latest developments in finance and the state of the economy. Including more current data in the research might lead to a more thorough understanding of these patterns, particularly in the aftermath of the financial crisis.

The SVAR-IV technique is predicated on a few claims that might not hold true in all situations. For instance, using the Consumer Price Index (CPI) as an external tool to identify shocks assumes that there is a certain link between inflation and credit spreads, which may not hold in various economic conditions. In addition, the short-term volatility and quick changes that define financial markets could not be well captured by using monthly statistics. Adding more frequent data or using other identification techniques might make the results more reliable.

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# 7 Appendix

Table 1

| | Coef | SE | t | CI 2.5% | CI 97.5% | p.value |
|---|---|---|---|---|---|---|
| Analytic | -0.027 | 0.089 | -0.307 | -0.202 | 0.147 | 0.759 |
| Boot.c | -0.027 | 0.088 | -0.310 | -0.193 | 0.146 | 0.772 |
| Boot.t | -0.027 | 0.089 | -0.307 | -0.190 | 0.135 | 0.764 |

Table 2

| | Coef | SE | t | CI 2.5% | CI 97.5% | p.value |
|---|---|---|---|---|---|---|
| Analytic | 0.408 | 0.516 | 0.791 | -0.603 | 1.420 | 0.429 |
| Boot.c | 0.408 | 0.753 | 0.542 | -0.900 | 1.825 | 0.434 |
| Boot.t | 0.408 | 0.516 | 0.791 | -0.439 | 1.255 | 0.398 |

Figure 3: Impulse Response to credit spread shock (SVAR-IV) method 1997 - 2014

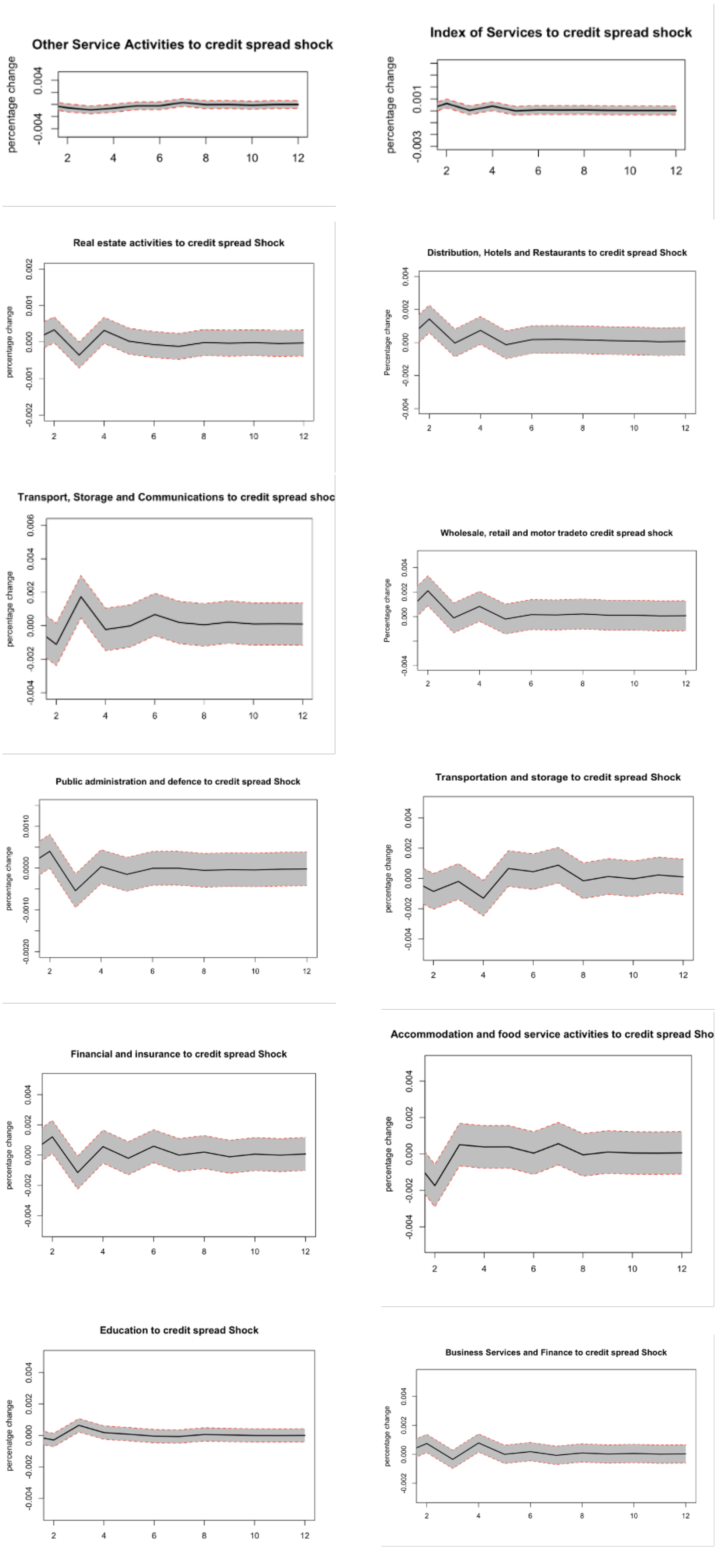

Figure 4: Impulse Response to credit spread shock SVAR cholesky method 1997 - 2014