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The impact of Covid-19 shocks in the US real economy and the availability of credit: A VAR model approach

André Redol de Sousa

Master (MSc) in Economics

Supervisor:

Ph.D. Luís Filipe Farias de Sousa Martins, Associate Professor (with aggregation), ISCTE Business School, ISCTE-IUL

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Resumo

A seguinte tese apresenta uma análise empírica de como o Covid-19 afetou a atividade económica, o crédito e a taxa de juro da Federal Reserve nos EUA, entre 4 de março de 2020 e 9 de março de 2022. Outra questão é se o crédito ajudou a impulsionar a atividade económica. Para atingir tal objetivo, são aplicados modelos VAR. Para estimar o impacto do Covid-19 nestas variáveis, utilizamos funções de Resposta a Impulsos Ortogonais.

Os resultados indicam que, após um choque de um desvio-padrão na taxa de crescimento do número de casos ou mortes do Covid-19 haverá uma resposta negativa na variação do índice de atividade económica, entre 0,3% e 0,16%. A taxa de crescimento do crédito total e a taxa de juro do Federal Reserve apresentam um efeito perto de zero. Sobre duração a do impacto, existe um efeito negativo médio de 0,3% até quinze semanas na variação do índice de atividade económica, causado pela taxa de crescimento de mortes por Covid-19.

Nos modelos com o crédito discriminado, verificamos os seguintes tipos de crédito que mais contribuíram para a atividade económica: crédito ao consumidor, e crédito comercial e industrial, que geram um efeito semanal de 0,2% e 0,15% respetivamente, quatro semanas após o choque inicial de um desvio-padrão. Sobre o efeito acumulado, o crédito ao consumidor é o único tipo de crédito que é eficaz para impulsionar a atividade económica, com o pico dois meses após o choque inicial, com um efeito médio semanal de 0,24%.

Finalmente, concluímos que nossos modelos VAR inadequados para prever futuros valores das variáveis.

Código JEL: C32 C53

Palavras-chave: Modelo VAR, Covid-19, Atividade económica, Crédito, Taxa de juros da Reserva Federal, Decomposição de Cholesky;

Abstract

The following thesis presents an empirical analysis of how Covid-19 affected the real economic activity, credit, and the Fed funds rate in the US between March 4th, 2020, and 9th, 2022. Another question of interest is whether the credit helped boost real economic activity in this period. To achieve the objective, VAR models are employed. To estimate the impact of Covid-19 on these variables, we use OIRF’s.

The results indicate that, there will be a negative response in the real economic activity index to the new confirmed cases or deaths growth rate Covid-19 one-standard deviation shock, between 0.3% and 0.16%. Also, the total credit growth rate and the Fed Funds rate are not considerably affected, with an effect close to zero. Moreover, in terms of impact duration, there is a negative effect for fifteen weeks on the real economic activity index caused by the Covid-19 deaths growth rate with an average effect of 0.3%.

In the models with the discriminated credit, we see which types of credit most contributed to the short-term economic activity: consumer and commercial and industrial loans, which create a positive effect of about 0.2% and 0.15%, on average one month after the initial shock. Regarding the accumulated impact, consumer loans are the only type of credit that seems effective in boosting real economic activity, with the peak occurring two months after the initial shock with an average effect of 0.24%.

Finally, we conclude that our VAR models are not suited to predict future variables values.

JEL Code: C32 C53

Keywords: VAR model, Covid-19, Real economic activity, Credit, Fed Funds Rate, Cholesky decomposition;

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Acronym Glossary

ADF: Augmented Dickey-Fuller test

ADFc: Augmented Dickey-Fuller test with a constant

ADFct: Augmented Dickey-Fuller test with a trend

AIC: Akaike Information Criterion

AR: Auto regressive

BEA: Bureau of Economic Analysis

BLS: Bureau of Labor Statistics

CARES: Coronavirus Aid, Relief, and Economic Security

Cases: Covid-19 new confirmed cases

Casesgrowth: Covid-19 new confirmed cases weekly growth rate

CIL: Commercial and industrial loans

CILgrowth: Commercial and industrial loans weekly growth rate

CL: Consumer loans

CLgrowth: Consumer loans weekly growth rate

COIRFs: Cumulative orthogonalized impulse response functions

CPFF: Commercial Paper Funding Facility

CPI: Consumer Price Index

CSSE: Center for Systems Science and Engineering

Deaths: Covid-19 new confirmed deaths

Deathsgrowth: Covid-19 new confirmed deaths weekly growth rate

DGSE: Dynamic stochastic general equilibrium

DSP: Difference-Stationary Process

dWeiInterp: Interpolated Weekly economic index in first differences

EU: European Union

FED: Federal Reserve

FEVD: Forecast error variance decomposition

FF: Federal Funds Effective Rate

FIMA Repo Facility: Repurchase Agreement Facility for Foreign International Monetary Authorities

FRED: Federal Reserve Economic Data

GC: Granger Causality

GDP: Gross Domestic Product

HQIC: Hannan-Quinn Information Criterion

IP: Industrial production

IRFs: Impulse response functions

JHU: Johns Hopkins University

LLBC: Loans and leases in bank credit

LLBCgrowth: Loans and leases in bank credit weekly growth rate

LCB: Loans to commercial banks

LCBgrowth: Loans to commercial banks weekly growth rate

MAE: Mean Absolute Error

MAPE: Mean absolute percentage error

MF-VAR: Mixed frequency vector autoregressive

MLF: Municipal Liquidity Facility

MMLF: Money Market Mutual Fund Liquidity Facility

MSE: Mean squared error

NARDL: Nonlinear cointegrating autoregressive distributed lag

OLL: Other loans a leases

OLLgrowth: Other loans and leases growth rate

PDCF: the Primary Dealer Credit Facility

PMCCF: Primary Market Corporate Credit Facility

PPPLF: Paycheck Protection Program Liquidity Facility

QE: Quantitative Easing

RMSE: Root mean square error

RMSPE: Root mean square percentage error

SBIC: Schwartz Bayesian Information Criterion

SMCCF: Secondary Market Corporate Credit Facility

SVAR: Structural Vector autoregression

TALF: Term Asset-Backed Securities Loan Facility

TSP: Trend-Stationary Process

U.S: United States

Vac: total number of people who received at least one vaccine dose per 100 people in the total U.S population

Vacgrowth: total number of people who received at least one vaccine dose per 100 people in the total U.S population weekly growthrate

VAR: Vector autoregression

VIX: Implied Stock Market Volatility

WEI: Weekly economic index

WeiInterp: Interpolated Weekly economic index

WHO: World Health Organization

WWII: World War II

1. Introduction

SARS-CoV-2 began in China, with the first Covid-19 known case identified in December 2019. The virus immediately spread to the rest of the world at an increasingly fast pace, with the first registered case in the U.S. recorded at the end of January 2020. Each day the number of confirmed cases and infections increased exponentially and, in March 2020, the World Health Organization (WHO) identified Covid-19 as a pandemic. Amid there was no vaccine, most countries' healthcare systems showed incapacity to deal with the exponential increase of cases; as a result, preventive measures such as curfew restrictions and lockdowns had to be implemented by governments worldwide, reducing the production capacity to produce goods and services, Brinca, Duarte, and Faria e Castro (2020); Gupta, Simon, and Wing (2020). These measures affected welfare and the world economy. The movement of people became restricted, and supply chains were disrupted. At the same time, it originated a partial shutdown of economic activity and immediate losses in output, Pellegrino, Ravenna and Züllig (2021). Moreover, hit labor markets with a drop in employment and a cut in wages, Cajner et al. (2020) and Kurmann et al., (2020), reaching values tantamount to those in the worst recessions. Also, in most countries, the unemployment rate increased, interest rates fell or turned negative, and prices decreased, Younes and Altug (2020).

At this early stage, volatility and uncertainty were very high, and it was difficult to measure the social and economic impacts of the pandemic since it depended on the success of containing the pandemic and restarting economic activity. The first hit was in the stock market. At the end of 2019, the volatility index (VIX) reached similar values to the global financial crisis. In the first months of 2020, equity markets posted their worst losses since the 2008 financial crisis, with the S&P500 index dropping 20% in the first quarter of 2020.

The pandemic has led to companies' bankruptcy, a decline in private investment, reduced integration into value chains, and less productive capabilities and human capital. Particularly in the U.S., the Covid-19 contraction is comparable to the one in the Great Depression of the 1930s, which was the most significant and prolonged slump in economic activity history.

According to the Bureau of Economic Analysis (BEA), Gross Domestic Product (GDP) went down 31.4% from its peak in the second quarter of 2020, which was the highest drop ever occurred in U.S. history since 1947, Weinstock (2021). At the same time, imports and exports of goods and services fell by 13% on average in the first five months of 2020. As for the unemployment rate, the Bureau of Labor Statistics (BLS) registered an incredibly 14.7%, reaching its highest value since 1948.

With the surge of the economic downturn, the U.S. Federal Reserve (FED) immediately used forward guidance and implemented unconventional monetary policy measures, such as lowering interest rates to zero lower bound, offering unlimited quantitative easing (QE), and maintaining credit flow. Moreover, to support the flow of credit, the FED opened its discount window to commercial banks by lowering the rate to 0.25%, re-established liquidity swap line arrangements, eliminated reserve requirements, and expanded repurchase agreement operations. It has also reintroduced facilities used during the global financial crisis and created new ones. The reintroduced facilities were the Commercial Paper Funding Facility (CPFF), the Primary Dealer Credit Facility (PDCF), the Money Market Mutual Fund Liquidity Facility (MMLF), and the Term Asset-Backed Securities Loan Facility (TALF). As for the new ones, Primary Market Corporate Credit Facility (PMCCF), the Secondary Market Corporate Credit Facility (SMCCF), the Repurchase Agreement Facility for Foreign and International Monetary Authorities (FIMA Repo Facility), the Paycheck Protection Program Liquidity Facility (PPPLF) and the Municipal Liquidity Facility (MLF). In broad terms, the intended goals of these measures are to support financial market functioning, encourage banks to lend, support corporations and businesses, support households and consumers, support state and municipal borrowing, and cushion United States money markets from international pressures.

At the end of the first quarter of 2020, the U.S. Congress approved four fiscal stimulus packages. The First included 8.3 billion USD for the Coronavirus Preparedness and Response Supplemental Appropriations Act (P.L. 116-123). The second package, 100 billion, comprised to "Families First Coronavirus Response Act (P.L. 116-127). Third, more than 2 trillion for the" Coronavirus Aid, Relief, and Economic Security (CARES) Act (P.L. 116-136). Fourth, 484 billion for the Paycheck Protection Program and Health Care Enhancement Act t (P.L. 116-139).

New legislation was also approved in April and June to improve the effectiveness of the programs at the course, as the FED provided up to 2.3 trillion USD in lending to support households, employers, financial markets, and state and local governments, Cheng et al. (2021). Lastly, the U.S. Congress approved 4.5 trillion destined to total aid spending. As a result, federal agencies have formally committed to using about 4 trillion and have accounted, to date, for 3.5 trillion in outlays, Rattner and Pramuk (2021).

This research aims to examine and estimate the impact of the exogenous Covid-19 shock on the U.S. real economic activity and, consequently, on credit availability. This research focuses on whether and to what scale the pandemic crisis affected real economic activity and credit availability. How did the U.S. financial sector recover after an increase in credit during the pandemic, and what were the effects of the increase in different types of credit on real economic activity? Furthermore, we study whether the VAR model is a good option to forecast the U.S. real economic activity.

In order to answer these questions, we estimate a Vector Auto Regression (VAR) model for U.S. weekly data on Covid-19 new confirmed cases (cases), Covid-19 new confirmed deaths (deaths), loans and leases in bank credit (LLBC), loans to commercial banks (LCB), Weekly economic index (WEI), and Federal Funds Effective Rate (FF), covering the period between March 4th, 2020 and March 9th, 2022. Our approach is generally more comparable to Brueckner and Vespignani (2021) but with minor differences in the methods. We opt for dropping the first two months of observations associated with the pandemic in the VAR. This choice is motivated by the works of Lenza and Primiceri (2020), Bobeica and Hartwig (2021), and Carriero et al. (2021), whose findings ensure more stable parameters when the model is estimated. Similar to Brueckner and Vespignani (2021), we decided to include in the model a dummy variable for the beginning of the vaccination process and an extra exogenous variable with the correspondent time series for the vaccination rate per hundred people. In addition, orthogonalized impulse response functions are computed, which enable us to make statements concerning the dynamic relationship between Covid-19 confirmed cases, real economic activity, and credit.

What first motivates this research is the lack of literature on the variables chosen. Few econometric studies have measured the impact of the pandemic using Covid-19 confirmed cases and VAR models, and the ones that do that, do not focus on the real economic activity and credit. This study fills this gap. Second, it will complement the studies on the effects of the pandemic on the economy and the effects of the increase in different types of credit on real economic activity. Third, the substantial support provided by the U.S. government and the conventional and unconventional monetary policies applied by the FED are also motives why we focus on the impact of the pandemic on credit. Fourth, the results of the relationships found in the model might be valuable to policymaking and taking appropriate measures toward a future recession of this type.

The main findings of the first part of this research illustrate that a one-standard deviation increase in the growth rate of Covid-19 confirmed cases and deaths decreases the WEI in the first two weeks after the initial shock, with an average effect of about 0.1%, whereas the effect on the aggregated credit growth rate and the Fed funds rate is very close to zero. In terms of effects that lasts more than three months, they are only significant for the model with the growth rate of Covid-19 deaths, with a negative effect over the real economic activity index lasting for fourteen weeks with an average effect of about 0.3%. Regarding the main findings of the second part of the research, the effects of both pandemic variables on real economic activity are robust to the ones from Part one. According to the analysis of which type of credit helps boost real economic activity the most in the short-run, we find that consumer and commercial, and industrial loans are the most effective, with an average positive maximum effect of about 0.9% and 0.7%. In terms of long-run effects, a shock in the consumer loans growth rate increases the weekly economic index on average by 0.15%. Considering the forecast ability, none of the VAR models is accurate for predicting future values of economic growth.

The remainder of this work organizes as follows. Section 2 reviews the theoretical and empirical literature. Section 3 describes the data and methodology. Then, in section 4, we present and analyze the results. Moreover, section 5 concludes.

2. Literature Review

Regarding the wide variety of existing studies about the effects of the pandemic and the variables of interest in our research, the literature review follows in two sections. First, it includes works on econometric models that study the Covid-19 impact, providing some details about the diversity of the existing literature. Next, it contains works focusing on the variables we choose for our model, enhancing acquaintance with them.

2.1. Covid-19 impact

Various authors have measured the effects of the pandemic using econometric models to estimate its shock on different economic variables of interest. However, the first empirical works had to take different approaches to measure Covid-19 shocks regarding the lack of data available at the time.

With Covid-19 starting at the end of 2019 in China and identified as a worldwide pandemic, uncertainty began to establish, and consumer confidence was hitting rock bottom. Pellegrino, Ravenna, and Züllig (2020) discuss the impact of Covid-19 uncertainty on the Euro area economy by estimating a VAR model with Industrial production (IP), inflation, and policy rate data. They conclude that uncertainty shocks significantly impacted the economy only during pessimistic times. One way to interpret high uncertainty can be the perceived idea of the probability of very adverse outcomes. The mystery behind the development of the pandemic raised uncertainty, and the U.S. government took several containment measures, such as lockdowns and curfews. Deb et al. (2021) estimated a negative impact of these measures of about 10% on economic activity over the first month of implementation.

A few months after the pandemic started, it became possible to estimate its impact on a macroeconomic variable by knowing the exact moment when there was an increase in the shock variance. However, with the inclusion of new observations in the model, the estimated coefficients became distorted since there was an immense variation in macroeconomic variables (e.g., real activity). Therefore, some authors such as Carriero et al. (2021), Bobeica and Hartwig (2021), and Lenza and Primiceri (2020) propose to tackle this problem by treating the extreme observations as outliers. As for the last ones, take a different approach by modeling the significant change in shock volatility.

One of the first impacts observed was in the financial markets. According to Altig et al. (2020) VAR model with stock market volatility and News-Based Uncertainty Measures data, there was high volatility, and colossal uncertainty jumps. Initially, there was a collapse, but the markets began to recover a few months later. Therefore, some authors have focused on financial and commodities market data. For example, Miescu and Rossi (2021) extract Covid-19 shocks with a VAR model using daily data (e.g., S&P500, volatility index) and find that while having contractionary effects on the economy, the Covid-19 shocks and structural uncertainty shocks have a high correlation (86%).

Adekoya and Oliyide (2020) estimate a VAR model with several financial and commodity market series and the Covid-19 proxies (the equity market volatility due to infectious diseases index and the U.S. Covid-19 new confirmed cases growth rate). Both examined how connectedness among the markets was influenced by this period, concluding that Covid-19 has been responsible for risk transmission across various commodity and financial markets.

Also, about the effects of the pandemic on the stock and commodities markets, Xu (2021) examined stock return responses to the pandemic in the U.S. and Canada, covering stock return and Covid-19 cases data between January 21th, 2020, and July 2nd, 2020. Moreover, it finds a symmetric relationship between the stock return responses and the increase and decrease of Covid-19 cases in the U.S. On the other hand, in Canada, the stock return responses are asymmetric to the increase and decrease of Covid-19 cases. Finally, Brueckner and Vespignani (2021) take similar conclusions in a VAR application for Australia, with Covid-19 infections having a significant positive effect on the performance of the Australian stock market between May 28th, 2019, and May 22nd, 2020, covering ASX-200 and Covid-19 infections data. Also, Chen and Hsu (2021), by estimating a regression model with Covid-19, economic news, stock indexes, and medical stocks data show that vaccination and treatment medicine developments directly and significantly affected the stock market movements.

Besides the pandemic influencing the stock market, it also affected significant macroeconomic aggregates, such as unemployment, GDP, I.P., consumer spending, and many more. For example, the unemployment rate in the U.S. spiked to its highest since the WWII era, registering 14.7% in the early 2020 months, according to FRED. Katris (2021) studied the relationship between Covid-19 cases and unemployment in 27 European Union (E.U.) countries between November 2019 and January 2021, using a VAR model, where he concludes that Covid-19 cases granger causes unemployment.

To estimate Covid-19 shocks, Ludvigson et al. (2020) quantify the impact of costly and deadly disasters that occurred in the U.S. by calibrating different shock profiles and translating the estimates into an analysis of the likely impact of Covid-19. This study concluded that Covid-19 could create a 12.75% drop in I.P., a loss in service employment of 17%, and reductions in air traffic. Altig et al. (2020) studied the pandemic uncertainty shocks and predicted drops in I.P. between 12% and 19%. Pellegrino, Ravenna, and Züllig (2020) on the effect of the pandemic shocks cover data between January 1999 to March 2020 for the Euro area, estimating a yearly loss of 15.41% on I.P., with the peak seven months after the shock occurs, recovering with a rebound to pre-crisis levels in June 2021. Furthermore, Baker et al. (2020) assess the macroeconomic effects of Covid-19 induced uncertainties using stock market volatility and newspaper-based economic uncertainty data and estimate a year-on-year contraction in U.S. real GDP of nearly 11% as of the last quarter of 2020.

In order to fight the downturn in the economy, policymakers quickly responded with monetary and fiscal stimulus. Feldkircher, Huber, and Pfarrhofer (2021) extract the results of a VAR model on U.S. monetary policy measures' effectiveness with I.P., unemployment, inflation, stock prices, and interest rate spreads data. They conclude that the monetary policy expansion caused higher output growth and stock market returns. Moreover, U.S. economic activity would have been significantly lower without such interventions. A similar study conducted by Trifonova and Kolev (2021) concluded that Fed's monetary policy influences the changes in the bond yields, the S&P 500 index, and the value of the U.S. dollar.

Regarding credit, no empirical frameworks using VAR models estimate the impact of Covid-19 confirmed cases in the U.S. Aforementioned, there is a study for China where Isaac Appiah-Otoo (2020) estimates the impact of Covid-19 cases and deaths in domestic credit, concluding that a rise in Covid-19 confirmed cases and deaths significantly increases domestic credit.

Also, policymakers have to consider the risks associated with long-term inflation targeting. Apergis and Apergis (2020), studying the effects of Covid-19 in the course of inflation expectations, using a GARCH model covering Covid-19 confirmed cases and deaths, VIX, and crude oil prices data between January 2019 and the end of July 2020, estimate that one standard deviation of Covid-19 deaths in the U.S. increases mean inflation by 0.84 (given that the mean inflation was 1.75). Accordingly, such results can affect real activity.

2.2. Variables of interest: Credit, Real economic activity, and Fed Funds Rate

This subsection presents several literature findings contributing to a better understanding of the variables we select for the study in our model.

Moreover, there are studies on how domestic credit to the private sector drives economic activity - a term typically used synonymously with total output, Lipschitz and Schadler (2019). For example, Basset et al. (2014), covering loans and net interest margin data between 1992 and 2011, find that bank credit supply shocks have significant macroeconomic effects. This research concludes that a negative credit supply shock substantially reduces businesses' and households' capacity to borrow from the financial sector and significantly declines real GDP. Similar research by Mésonnier and Stevanovic (2016) estimates a panel regression model using hundreds of U.S. large bank holding companies' data, concluding that shocks to large U.S. banks' capital explain a substantial share of the variance of bank credit to firms and real activity. Also, Meeks (2017) links aggregate bank capital and aggregate bank credit and evaluates the business cycle consequences of banking shocks in the U.K. The main conclusion was that increasing capital requirements lowered lending to firms and households, reduced aggregate expenditure, and raised credit spreads.

Meeks (2011), on how corporate credit shocks drive output during the great recession concludes that adverse credit shocks significantly increased bond spreads and drove down output. Also, Exogenous financial shocks are an independent driver of the U.S. business cycles. Finally, for Italy, Cipollini and Parla (2017), using a VAR model, estimate credit demand and supply shocks and their effects on real economic activity during the great recession finding that credit supply shocks play a more critical role than credit demand shocks.

Lopez-Salido and Zakrajsek (2015), through a forecast model with loans interest rate, loans growth rate, and employment to population ratio U.S. data between 1929 to 2015, conclude that elevated credit-market sentiment in the current year is associated with a decline in economic activity two and three years after. Investor sentiment in credit markets can be an essential driver of economic fluctuations. A similar study conducted by Ding Du (2017), but this time for the period between 1960 to 2015, finds robust evidence that U.S. credit-supply shocks influence real activities in economies the more economically or geographically integrated with the U.S.

More recent studies by Goaied and Gasmi (2020) measure the effects of firm credit on growth using a panel VAR with economic growth and credit data from 1995 to 2014. A sample of 142 countries confirms that firm credit expansion is essential to economic growth and that higher allocations of household credit are obstacles to this effect. Küçük, Özlü, and Yüncüler (2021) take similar conclusions in a VAR model for Turkey data covering the period between 2009 and 2018, credit expansions have statistically significant impacts on economic activity and investment, boosting it at least for the first six months. At the same time, household loans have a minor impact compared to business loans.

Therefore, several pieces of research also approach the credit-growth nexus; see Schularick and Taylor (2012); Jordà et al. (2012); Rousseau and Wachtel (2009); Levine et al. (1999); and King and Levine (1993).

Apart from the credit, monetary and fiscal, other shocks such as oil, energy, employment, unemployment, I.P., and many others also influence real economic activity. For more insights, a considerable amount of literature supports the hypothesis that shocks in volatility and uncertainty have a contractionary effect on real activity. For example, Urom et al. (2021) examined the interactions and causality between real economic activity and volatility shocks from stock and gold markets using a nonlinear cointegrating autoregressive distributed lag (NARDL) model. Results show that an increase in volatility shocks is harmful to economic activity. Additionally, Jurado et al. (2015) estimated a VAR model using hundreds of macroeconomic indicators and found a meaningful relationship between uncertainty and real economic activity. Uncertainty shocks account for up to 29% of United States I.P. variation at business cycle frequencies.

Also, Bloom (2009) estimates that uncertainty impact on macroeconomic aggregates has a negative impact in the short run, and the medium run induces an overshoot in output, employment, and productivity. For example, Bachmann et al. (2013) state that business uncertainty shocks led to declines in economic activity. The same conclusions for Basu and Bundick (2015) VAR model, estimating data from 1986 to 2014, uncertainty shocks cause significant declines in output, consumption, investment, and hours worked. Aforementioned, see also Leduc and Liu (2015), Baker et al. (2016), Piffer and Podstawski (2016), Ludvigson, et al. (2021), Alessandri and Mumtaz (2014), Mumtaz and Zanetti (2013), Jackson et al. (2019) and Fernández-Villaverde et al. (2015).

Some studies have also investigated how oil shocks can transmit to economic activity. For example, Jo (2012) estimates a VAR model and shows that an oil price uncertainty shock negatively affects the world I.P. Charles et al. (2020) took similar conclusions and showed that an increase in oil price uncertainty negatively affects output growth. Therefore, plenty of studies associate oil shocks, either in price, supply, or demand, with effects on economic activity. For example, De Michelis et al. (2020) demonstrate that a decrease in oil price diminishes consumption effects in oil-exporting economies worldwide. However, for the U.S., results are not linear. In the short run, there is a temporary decrease in GDP, but continuously consumption increases gradually, pushing GDP towards higher levels.

Similarly, Brown and Yücel (2012) link oil prices to aggregate economic activity and find that increasing oil prices stimulate GDP losses. Papapetrou (2001), using a VAR model for Greece's macroeconomic data, have suggestive results that oil price changes affect real economic activity and employment. He et al. (2010), utilizing Kilian economic index as a real activity proxy, find a cointegrating relationship between real future crude oil prices and the Kilian economic index. Finally, An et al. (2014) found that the negative impacts of higher oil prices are more significant than the positive effects of lower oil prices. For more insight, see also, ley (2021), Lyu (2021), Maghyereh et al. (2021), Atallah and Blazquez (2015), Darrat et al. (1996), Pinno and Serletis (2013).

Several authors aborded this topic regarding monetary policy shocks, with a general agreement that the FED employs its monetary policy by setting a target to the FF, Labonte (2020). Also, about how these shocks can affect credit availability and real economic activity, Gertler and Karadi (2015) show that monetary policy measures influence credit costs, consequently affecting economic activity. Feldkircher et al. (2021) studied the effectiveness of the policies to stimulate real economic activity taken by the FED between January 2011 and June 2020. The results extracted from a mixed frequency vector autoregressive (MF-VAR) model are clear, monetary expansion increases output growth and long-term financing conditions. The FED has successfully stimulated growth but must be cautious with

U.S. dollar depreciation and inflation in future outcomes. Finally, the authors support that monetary policy can mitigate uncertainty shocks but can no longer maintain its stabilization properties on a zero lower bound period. Azada, Serletis, and Xu (2021) investigate fiscal and monetary policy taken in Canada covering GDP income, government taxes and expenses, consumer price index (CPI), 3-Month Treasury bill rate, and output gap data between 1990 and 2020, finding that the positive effects on real GDP and real private consumption fade out with the end of the fiscal stimulus.

Canova and Gambetti (2008) cover a large U.S. period from 1967 to 2006 to study how the policy shocks affect output growth volatility. The researchers apply monetary policy restrictions from a DGSE model to an SVAR model. Results show that policy shocks explain a small fraction of the average output growth variability. Also, according to Kim's (2020) VAR model covering a very similar period, between 1974 and 1996, expansionary monetary policy shocks increase output temporarily and prices over time.

Bernanke (1990) contributed to the literature on how interest rates and spreads are good predictors of the state and the consequent course of the economy. An additional important conclusion of this work is that the effects of uncertainty shocks are statistically larger when the zero lower bound monetary policy is in action. Following the knowledge that interest rates and spreads have predictive power, Bomfim (1997) uses long-term interest rates to proxy the equilibrium funds rate. The VAR model, covering the period between 1968 and 1994, concluded that term structure spreads are useful for predicting economic activity. Also, a Fed Funds rate change can be considered a policy shock.

Our econometric research and model fall between the two points, 2.1. and 2.2., in the current section 2. It estimates the impact of the pandemic, using data from its progression, on the variables of interest referred to in subsection 2.2. Noticeably, no econometric literature concerning these variables' relationships using VAR models is available to date.

3. Data and Methodology

In this section, we present the data and explain the adopted methodology. Subsection 3.1. describes the chosen data and its transformations for the period under analysis. Subsection 3.2. shows the stationarity tests, and Subsection 3.3. presents the approach and methods used in our models.

3.1. Data

This econometric analysis is based on U.S. weekly data from March 4th, 2020, to March 9th, 2022. The time series is composed of T=106 observations, which is sufficient for constructing the econometric models and carrying out the necessary analysis. Also, it includes nine variables: new confirmed Covid-19 cases (cases), new confirmed Covid-19 deaths (deaths), loans and leases in bank credit (LLBC), loans to commercial banks (LCB), commercial and industrial loans (CIL), consumer loans (CL), other loans and leases (OLL), Weekly economic index (WEI), and Federal Funds Effective Rate (FF). The Covid-19 data is collected from the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU). The remaining data, such as LLBC, LCB, CIL, CL, OLL, WEI, and FF is obtained through the Federal Reserve Economic Data (FRED) website at the Federal Reserve of St. Louis. Table 1 in the Appendix displays the hyperlinks containing the data available for download. Table A.1 presents the descriptive statistics of the variables.

According to the literature presented in subsection 2.1., the magnitude of the pandemic can be defined based on changes in the number of confirmed Covid-19 cases and deaths. Therefore, this research selects the number of new confirmed Covid-19 cases and deaths in the U.S. to measure the epidemic effects and consequences in the chosen macroeconomic aggregates. Both variables are in daily frequency.

Furthermore, we choose the WEI as a proxy variable for real economic activity, which suffered a massive contraction. According to Lewis et al. (2020), the index can track in "real-time" the economic evolution in high frequency. The variable is not seasonally adjusted and has a weekly periodicity, ending every Saturday. It is also important to refer to how this index is created and interpreted. WEI is computed using ten weekly measures of real economic activity, the main ones being consumption, labor input, and production. This real economic activity index is scaled to match the mean and standard deviation of four-quarter GDP growth[1] and also has good predictability power for real economic activity.

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[1] Since the WEI is scaled to the four-quarter GDP growth, taking the quarterly average values for WEI provides a natural nowcast for the four-quarter GDP growth.

To represent credit in our model, we searched on the FRED website for the balance sheet of all commercial banks in the U.S. and selected on the asset side LLBC and LCB. LLBC represents all the loans and leases conceded by U.S. commercial banks, such as commercial and industrial loans (CIL), real estate loans (REL), consumer loans (CL), and other types of loans and leases (OLL)[2]. LCB represents the loans carried out between all commercial banks in the U.S. All variables are in billions of dollars, seasonally adjusted, and in a weekly frequency, ending every Wednesday.

Credit is also affected by interest rates, specifically, we choose the FF, as it is the short-term overnight nominal interest rate and a starting point rate for banks and financial institutions to charge their interest rates. In addition, the variable is not seasonally adjusted and has a weekly periodicity, ending every Wednesday. Our choice is also informed by theoretical models and empirical research on the credit-growth nexus. For example, Luintel and Khan (1999) suggest that variables such as interest rates are fundamental to measuring the relationship between loans and economic growth and are strongly linked with economic activity and GDP growth.

In order to achieve an equal length of the datasets, the Covid-19 data is daily and transformed to weekly observations by only keeping the records for Wednesdays. In addition, this study used interpolation methods to impute and fill missing values in the WEI data to ensure the validity and accuracy of the results. There was a mismatch in the data of two days between WEI and the other variables. WEI values are reported on Saturdays, while LCB, LLBC, and FF are reported on Wednesdays. In order to distinguish the two, we named "WeiInterp" to the transformation made in WEI[3], which now has the missing values for Wednesdays. Regarding more data transformations, we create a new variable, LCBLLBC, by summing LCB and LLBC, representing U.S. total credit in our model. Finally, the growth rate for cases, deaths, LCBLLBC, CIL, CL, and OLL were obtained for stationarity purposes, renaming them as casesgrowth, deathsgrowth, LCBLLBCgrowth, CILgrowth, CLgrowth, and OLLgrowth, respectively.

Figure A.1 and figure A.2 illustrate the U.S. new confirmed Covid-19 cases and deaths time series, respectively. Figure A.3 shows the total credit during the observed period. Figure A.4 is the WEI, and figure A.5 is the FF and so on. All of the time series are presented in the Appendix section A.

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[2]Other types of loans and leases (OLL) aggregate loans to non-depository financial institutions and all loans not elsewhere classified.

[3]The interpolation was computed using the following formula: $WeiInterp = WEI(current\ week) \times \left(\frac{3}{7}\right) + WEI(next\ week)\left(\frac{4}{7}\right)$.

3.2. Stationarity tests

Stationarity tests are performed using the data between March 4th, 2020, and March 9th, 2022 (T=106).

We start with the Augmented Dickey-Fuller (ADFc) test with a constant for the unit root for all variables, using a 1% significance level. Table C.1 shows that the null hypothesis was rejected for casesgrowth, deathsgrowth, LCBgrowth, LLBCgrowth, LCBLLBCgrowth, CILgrowth, and FF. In OLLgrowth, the null hypothesis of non-stationarity is rejected for a significance level of 10%. Therefore, these variables are stationary and can be included in a VAR model without taking the first differences or detrending the time series. For WeiInterp and CLgrowth, the results are different. Since the null hypothesis was not rejected, we conclude that we are in the presence of a non-stationary time series.

Once we have a non-stationary time series (p.e. WeiInterp and CLgrowth), the second step is to compute the Augmented Dickey-Fuller (ADFct) test with a constant and a trend for the unit root, to see whether the time series is a Difference-Stationary Process (DSP) or a Trend-Stationary Process (TSP). The WeiInterp results show that for a 10% significance level, the null hypothesis of a DSP is not rejected, concluding that the time series is stationary integrated of order one I(1) after applying the first differences. On the other hand, for CLgrowth, results show that for a 1% significance level, the null hypothesis of a DSP is rejected, concluding that the time series is stationary after removing the trend.

We take the first differences in WeiInterp to convert the series into a stationary one, and named it dWeiInterp. After taking the first differences, the ADFc test with constant is computed again to confirm that the series is stationary, as shown in Figure C.1. The same process is done for CLgrowth. The series' linear trend is removed in STATA, converting the series into a stationary one and confirming it through the ADFc test. The detrended series of CLgrowth is named CLgrowth_detrended.

3.3. Methodology

In this section, we present and explain the adopted methodology. Then, to analyze the interaction between the variables included in our data and answer the research questions, we estimate four Vector Auto Regression (VAR) models. The first part of the research focuses on the impact of Covid-19 cases and deaths in the U.S. real economy and the availability of credit, as it estimates a VAR model including Covid-19 cases shocks and another for Covid-19 deaths shocks. The second part of the research focuses on estimating credit growth's ability to boost economic activity during pandemic times, discriminating for different credit types. Again, a VAR model is estimated with new confirmed cases growth rate and another one with the new confirmed deaths growth rate. All econometric analysis is obtained in STATA version 14.

When starting to construct our models, concerning that the first months of the pandemic are associated with huge variability in different macroeconomic variables, we choose to drop the observations of the first months of the Covid-19 outbreak. This approach has the objective of parameter estimation and model stabilization, according to Lenza and Primiceri (2020), Bobeica and Hartwig (2021), and Carriero et al. (2021). Therefore, the dataset will start on March 4th, 2020, not January 22nd, 2020 (T=106).

3.3.1. VAR model

In order to achieve the objectives of this study, a VAR model proposed by Sims (1980) is adopted. This statistical model describes the evolution of a multivariate linear time series with K endogenous variables $Y_t = (y_{1t}, \dots, y_{kt}, \dots, y_{Kt})$ for $k = 1, \dots, K$. The evolution of these endogenous variables in the system is considered a linear function of their own history and a linear function of the p lagged values of all K variables, plus an error term v. A brief mathematical review of the reduced-form model follows.

The general reduced form of a K dimensional VAR(p) model with p lags and exogenous variables:

$$y_t = C + \varphi_1\, y_{t-1} + \cdots + \varphi_p\, y_{t-p} + \gamma_1 x_{t-1} + \cdots + \gamma_q x_{t-q} + v_t \qquad (1)$$

The general reduced form of a K dimensional VAR(p) model with p lags and exogenous variables in matrix notation:

$$\begin{pmatrix} y_{1t} \\ \cdots \\ y_{kt} \end{pmatrix} = \begin{pmatrix} c_1 \\ \cdots \\ c_k \end{pmatrix} + \begin{pmatrix} \varphi_{11}^{(1)} & \cdots & \varphi_{1k}^{(1)} \\ \cdots & \cdots & \cdots \\ \varphi_{k1}^{(1)} & \cdots & \varphi_{kk}^{(1)} \end{pmatrix} \begin{pmatrix} y_{1t-1} \\ \cdots \\ y_{kt-1} \end{pmatrix} + \cdots + \begin{pmatrix} \varphi_{11}^{(p)} & \cdots & \varphi_{1k}^{(p)} \\ \cdots & \cdots & \cdots \\ \varphi_{k1}^{(p)} & \cdots & \varphi_{kk}^{(p)} \end{pmatrix} \begin{pmatrix} y_{1t-p} \\ \cdots \\ y_{kt-p} \end{pmatrix} + \begin{pmatrix} \gamma_{11}^{(1)} & \cdots & \gamma_{1j}^{(1)} \\ \cdots & \cdots & \cdots \\ \gamma_{j1}^{(1)} & \cdots & \gamma_{jj}^{(1)} \end{pmatrix} \begin{pmatrix} x_{1t} \\ \cdots \\ x_{jt} \end{pmatrix} +$$

$$\cdots + \begin{pmatrix} \gamma_{11}^{(q)} & \cdots & \gamma_{1j}^{(q)} \\ \cdots & \cdots & \cdots \\ \gamma_{j1}^{(q)} & \cdots & \gamma_{jj}^{(q)} \end{pmatrix} \begin{pmatrix} x_{1t-q} \\ \cdots \\ x_{jt-q} \end{pmatrix} + \begin{pmatrix} v_{1t} \\ \cdots \\ v_{kt} \end{pmatrix} \qquad (2)$$

Y_t represents a vector of endogenous variables of length k, each φ_i is a matrix coefficient of size $K \times K$ for $i = 1, \dots p$, and C is a $K \times 1$ vector of intercepts. Each X represents a vector of exogenous variables of length $J \times 1$, and each γ_i is a matrix coefficient of size $J \times J$ for $i = 0, \dots q$. The vector of errors v has an expected value of zero, are white noise processes and are not autocorrelated. The variance-covariance matrix (Ω) is positive semidefinite: $v_t \sim WN_k$ such that $E(v_t) = 0_{k\times1}$, $E(v_t v'_t) = \Omega_{k\times k}$, $E(v_t v'_s) = 0_{k\times k}, t \neq s$.

Additional information about VAR models are in the Appendix.

3.3.2. Stationarity tests

The first thing to test before estimating a VAR is to check the stationarity of the variables. A standard unit root test was conducted on all-time series, more specifically the Augmented Dickey-Fuller (ADF), one of the most popular in the field. We select the optimal lag for each variable by running the command *varsoc* with a maximum lag length of 12[4]. Next, we performed the stationarity tests for a significance level of 1%, except for OLLgrowth.

For the ADF test, we first compute the version with constant (ADFc) to check the presence of a unit root. The null hypothesis is that the series we are testing is non-stationary and has at least one unit root.

In case of the null is not rejected, the next step is to perform the Augmented Dickey-Fuller (ADFct) test with a constant and a trend for the unit root to see whether the time series is a Difference-Stationary Process (DSP) or a Trend-Stationary Process (TSP). If the null hypothesis is not rejected, it is possible to conclude that the variable studied is a DSP.

More details about the Augmented Dickey–Fuller (ADF) test are in the Appendix.

3.3.3. Exogenous variables

It is known by the theory that exogenous or control variables may be added to VAR models to improve estimation. Our models include two exogenous variables to capture health measures taken into account to control the spread of the virus, "vac" represents the total number of people who received at least one vaccine dose per 100 people in the total population, and an instrumental variable named "dummy".

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[4]The number of lags considered to compute the ADF tests were the ones suggested by the information criteria

Since most of the endogenous variables are in growth rates, we computed the growth rates for "vac" and named the new variable "vacgrowth". Another fact taken into account is that "vac" has an upward trend having a permanent effect on the series, making it almost a deterministic variable, so we decide to consider "vacgrowth" since it captures the variation of the vaccination rate in the U.S.

The binary variable, "dummy", assumes a value of 0 between March 4th, 2020, and March 31st, 2021, and a value of 1 between April 7th, 2021, and March 9th, 2022; this was when the variable "vac" reached 33%, meaning that one-third of the total population in the U.S had received at least one dose of the Covid-19 prevention vaccine[5]. We believe the vaccine plays a significant role in containing pandemic development, so we test for that hypothesis in our model.

3.3.4. Identification scheme strategy

In order to correctly specify and identify the IRFs, restrictions were applied, more concretely, the Cholesky decomposition. This recursive identification scheme is the most common in the field when no economic theory is behind to support the model.

In this case, the reduced form innovations v_{it} depend on mutually uncorrelated structural orthogonal shocks ε_t:

$$\varepsilon_t \sim WN_k(0, I_k), i.e., v_t = B\varepsilon_t = LD^{\frac{1}{2}}\,\varepsilon_t \qquad (6)$$

In this case, B is assumed to be lower triangular. The covariance matrix of VAR residuals is orthogonalized with the variables ordered in a specific way. The order of the variables is crucial, as it plays a key role in defining which shocks have no contemporaneous effect on some system variables in a recursive way. The Covid-19 series are ordered first since a pandemic event is by nature seen as an exogenous one, followed by the economic activity indicator, credit measures, and the Fed Funds Rate. The subsequent order was decided through the decreasing exogeneity principle based on the results of the Granger causality tests between the variables.

After deciding on the ordering, we checked that results are robust, meaning that the results hold and are the same for different variable orderings. After it, the ordering of the macroeconomic series is irrelevant as tested. Completing, this is the identification restriction used in the estimated VAR models meaning that economic activity, credit, and interest rates can respond contemporaneously to Covid-19 shocks, but not the other way around.

The structural model with Cholesky decomposition that follows from the unrestricted one is represented in the Appendix section, as also the mathematical relationship between both models.

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[5] The time series for the exogenous variables are in the appendix section A- see Figure A.6, A.7 and A.8.

3.3.5. Stability condition and residual diagnostics

Stability and residual diagnostics are crucial before estimating the model. Such tests ensure that the model is well specified and that the forecasts will not explode.

More details about the Stability condition and residual diagnostics are described in the Appendix.

3.3.6. Optimal lag selection

The purpose of choosing the optimal lag is to eliminate the serial correlation of each error. The importance of an appropriate lag length is that if it is too small, the model can be miss specified, but if it is too large, degrees of freedom can be wasted, according to literature.

More details about the optimal lag selection are described in the Appendix.

3.3.7. Granger causality

When estimating VAR models, one important property of its interpretation is Granger causality since it allows one to assess the dynamic relationship between the variables in the system. The core of the test is to examine whether the lagged values of one variable help to predict or cause other variables in the model. This type of test can also be performed to analyze the exogeneity of a variable. If that variable is not affected by any other variables in the model, it can be assumed as exogenous.

3.3.8. Point forecast and forecast error

According to literature, VAR models are common in the field when forecasting variables' future values.

The restricted model with the Cholesky decomposition may be an added value to estimate the effect of the pandemic shocks, but another pertinent point is whether the VAR model is also a useful approach for forecasting. After including the pandemic data, it becomes more difficult to determine what works in forecasting. In this case, we firstly focus on an Ex-post analysis by looking at different error measurement criteria to judge the suitability of the VAR models and compare their forecast errors with the ones from an Autoregressive (AR(1)) model. Secondly, we generate the Ex-ante forecasts to see how the model predicts the data into the future.

3.3.8.1. Forecast error variance decomposition

The Forecast error variance decomposition (FEVD) displays the percentage of the error made forecasting a variable over time due to a specific shock; this is, how much of the variability in the dependent variable is explained by its own shocks versus the shocks in the other variables in the system. All variance decompositions start at lag zero, where there is no forecast error.

3.3.9. Orthogonalized impulse response functions

The impulse response functions (IRFs) allow us to trace the time path response (current and future values) of the variables in our model to a one unit increase impulse in the current value of one of the VAR errors. This means IRFs capture the effect of one-unit shock in y_{kt} on a different or the same y_{kt}, i.e., the dynamic marginal effect of each shock on all variables over time. After estimating the VAR models and the dynamic impulse response functions, they must converge to zero at a certain point in time, even though there is no limit on how far these IRFs can extend. If this effect is not visible, then the VAR model can be misspecified or unstable due to non-stationarity properties in some variable(s).

Also, functions like these are calculated based on identification assumptions that will originate unique conclusions according to the constraints applied to the model. This research will use the orthogonal impulse response functions (OIRF) instead of impulse response functions (IRF). The main difference is the fact that the variance-covariance matrix (Ω) is decomposed using the Cholesky approach. In our case, orthogonalizing the shocks in the model is important so that the shocks tracked by OIRFs are uncorrelated.

3.3.10. Cumulative orthogonalized impulse response functions

The cumulative orthogonalized impulse response functions (COIRFs) also are based on applying the Cholesky decomposition as the OIRFS. Recalling that the objective of the OIRFs is to track in our dynamic system how the endogenous variables will respond to a one-time exogenous shock, also called an impulse. The COIRFs interpretation has the same logic behind the process; the difference is that the cumulative case plots the impact of the shock on the variables in the model across time and not at a single point in time. In other words, the long-run effects are associated with the impulses since it is the cumulative sum of all OIRFs.

4. Empirical Results

This section presents the empirical results. It is worth noting that the models obtained generated a large amount of output. That said, only the most important results are shown to the reader, focusing exclusively on answering the research questions. Additional interpretable results are displayed in the Appendix.

PART I: Whether and to what scale does the pandemic crisis affect real economic activity and credit availability?

4.1. VAR model with new confirmed Covid-19 cases growth rate

The first VAR model measures the impact of the pandemic on the U.S real economy and the consequent availability of credit. The model contains four endogenous variables. These are casesgrowth, dWeiInterp, LCBLLBCgrowth, and FF. A similar version with deathsgrowth instead of casesgrowth is also estimated in section 4.2..

Given equation (2), our four-dimensional VAR(p) model has a vector of endogenous variables

$Y_t = \begin{pmatrix} casesgrowth \\ dWeiInterp \\ LCBLLBCgrowth \\ FF \end{pmatrix}$, and a vector of exogenous variables $X_t = \begin{pmatrix} vacgrowth \\ dummy \end{pmatrix}$.

4.1.1. Stability condition

Figure C.2 shows the stability results for the largest "p" allowed for the model. All the eigenvalues lie inside the unit circle, concluding that the VAR model satisfies the stability condition for a maximum of 15 lags[6].

4.1.2. Optimal lag selection

4.1.2.1. Minimum information criteria

We proceed to the optimal lag selection using the maximum correspondent number of lags (p) for which the model is stable. Figure C.3 shows that according to AIC, SBIC, and HQIC, the optimal lag is always one (p=1), independently of the maximum number of lags we test for[7].

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[6] The model is stable from (p=1) lags until (p=15) lags.

[7] The criteria were tested from (p=1) lags until (p=15) lags.

4.1.2.2. Wald lag-exclusion statistics test

The conclusions are very different when compared to the minimum information criteria results. Independently of the maximum number of lags we test for, the optimal lag (p) tends to be always the highest admitted in the selection. Figure C.4 shows the Wald lag-exclusion statistics test results.

After evaluating the results from the minimum information criteria and the Wald lag-exclusion statistic test, we are left with two main conclusions. First, either the optimal (p) lag is the highest allowed in the VAR according to the Wald lag-exclusion test, having into consideration the stability condition (p=15), or second, the optimal (p) lag is equal to one (p=1) according to the Minimum Information Criteria.

To make the final decision between (p=1) and (p=15), we test for serial correlation of the residuals for the optimal lag options taken into account. Next, we observe the difference in the significance of the exogenous variables in controlling the pandemic when changing p. To choose between the criteria already enunciated, the consequent relationships that the model retrieves are decisive and must make sense economically.

4.1.3. Residual diagnostics

Figure C.6 shows the Lagrange multiplier test for the serial correlation between residuals for p=1. When the p-value is greater than the significance level, we cannot reject the null hypothesis of no serial correlation of the residuals at a specific lag order. For a significance level of 1%, we conclude that there is autocorrelation in the first two lags. In this specific case, the optimal lag is p=1 according to minimum information criteria, which is wrongly assessed because the errors cannot be serially correlated for a VAR model to be well specified. After various tests, we concluded that the serial correlation of the residuals tends to decrease as the lag "p" increases. For this first specific model, autocorrelation problems stand when running the VAR model with optimal lag p=1, 2, or 15[8] lags. We are left to choose between p=3 and p=14.

Also, for p=1, for a 10% significance level, both variables “vacgrowth” and “dummy” are not significant to explain the new confirmed cases growth rate (casesgrowth). We also test the hypothesis for the dummy variable to assume different vaccination rates, such as 33%, 50%, and 66%. The conclusions are similar. Such results can be counterintuitive as we expect that the vaccine has statistical significance when explaining casesgrowth. When increasing the number of p lags, the exogenous variables tend to become more significant to explain casesgrowth, which may explain the

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[8] For p=15 lags, the errors are serially correlated at the 6^{th} lag, assuming a significance level of 1%.

fact that the vaccine does not have an immediate effect on controlling the pandemic. It takes a certain period for that effect to be felt in society (at least two weeks for an individual and much more for herd immunity). After that, we checked the Granger causality for the different p's and concluded that the model's relationships started to make economic sense as the number of lags increased. Aforementioned, there is no specific way to choose the optimal lag, so we focused on our own selection process. All tests indicate that the model is better specified when for larger p's. To finalize the support of our choice, we look at the literature which indicates that for higher data frequency a greater number of lags should be used. Following our decision process, the optimal lag for the VAR model will be p=14.

Figure C.7 shows the Lagrange multiplier test for the serial correlation between residuals for p=14. For a significance level of 1%, we conclude that there is no autocorrelation of the error terms at all lags. Also, now for p=14, the p-value for “vacgrowth” is smaller than 0.10, meaning that at a 10% significance level, the variable is significant in explaining the cases growth rate. “vacgrowth” has a negative coefficient of -0.0469772, meaning that cases growth rate decreases when the vaccination growth rate increases[9]. More residual diagnostics can be found in the Appendix (figure C.8, C.9, C.10).

4.1.4. Granger causality

When analyzing the results of figure C.11, it is possible to conclude that there is strong evidence for Granger causality among most variables. However, only casesgrowth does not help to predict FF[10]. The first row of results is not interpretable, this means that casesgrowth Granger causes (GC) the other variables but not vice versa. Also, it is common knowledge that at the beginning of the pandemic, interest rates had a sharp fall to stimulate the economy in the pandemic times, which could create expectations about how Covid-19 affected the FF. Therefore, according to the results, one way to interpret it could be that casesgrowth GC dWeiInterp, and dWeiInterp GC FF, in this case, FF is indirectly affected by the pandemic. Also, the FF in our data sample has very small variability, which may explain why casesgrowth does not GC FF in the model.

Orthogonalized impulse response functions

As stated in 3.3.9., we compute the OIRFs instead of the non-orthogonal IRFs because the decomposition of the variance-covariance matrix is through Cholesky factorization. Also, the ordering of the variables is already defined in the code when estimating the VAR.

[9] The vaccination rate assumed for the dummy variable was 33%.

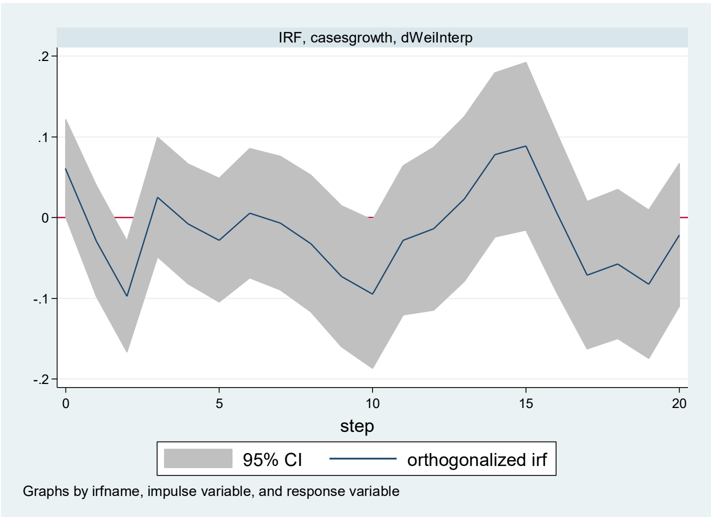
[10] The Granger causality tests are performed assuming a significance level of 10%.

Firstly, figure C.12 in the Appendix displays all results to compare the magnitude of the effects between OIRFs. Next, the analysis is done of each of the dynamic relationships that results from a shock in casesgrowth for a horizon of at most 20 weeks (five months)[11].

Response: dWeiInterp

```
. irf graph oirf, set(IRF) irf(IRF) impulse (casesgrowth) response (dWeiInterp) yline(0)
(file IRF.irf now active)

. irf table oirf, set(IRF) irf(IRF) impulse (casesgrowth) response (dWeiInterp)
(file IRF.irf now active)
```



Results from IRF

step	(1) oirf	(1) Lower	(1) Upper
0	.061066	.000689	.121443
1	-.029075	-.097617	.039466
2	-.097751	-.166322	-.029179
3	.02529	-.048739	.099318
4	-.007792	-.081969	.066385
5	-.027975	-.104769	.04882
6	.005574	-.074505	.085653
7	-.007031	-.089691	.075629
8	-.0323	-.116918	.052317
9	-.072852	-.160229	.014525
10	-.094945	-.186914	-.002977
11	-.028134	-.120357	.064089
12	-.013683	-.114652	.087286
13	.023017	-.078902	.124935
14	.077848	-.02377	.179467
15	.088396	-.015535	.192327
16	.006243	-.092491	.104978
17	-.071429	-.162781	.019924
18	-.05757	-.149785	.034646
19	-.082735	-.174498	.009029
20	-.021725	-.110081	.06663

95% lower and upper bounds reported
(1) irfname = IRF, impulse = casesgrowth, and response = dWeiInterp

Figure 1 – casesgrowth shock in dWeiInterp OIRFs for the model with optimal lag (p=14).

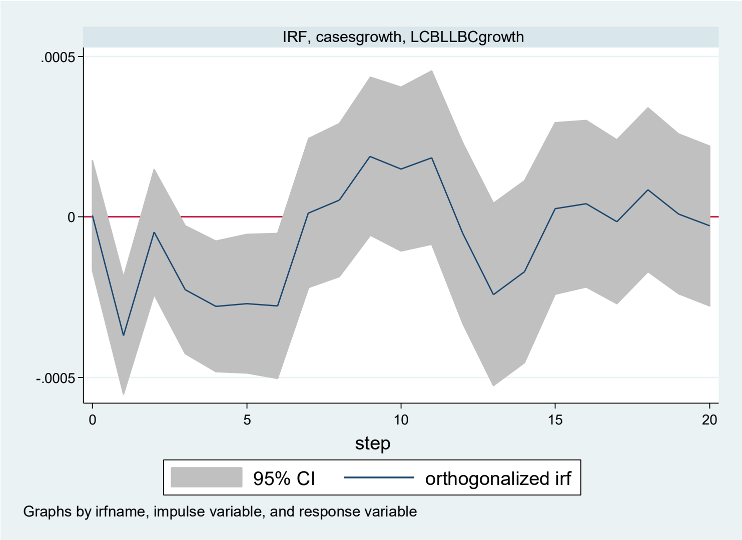
Figure 1 shows the effects of casesgrowth in dWeiInterp. First, we see that a one-standard deviation (0.126723%) shock in casesgrowth increases dWeiInterp in the current week by about 0.06%. Then, there is a decreasing effect in the following two weeks after the initial shock, with the peak occurring in the second week of between [-0.029179; -0.166322] percentage points. After the second week, the effect goes rapidly to zero, with the statistical significance of the effect disappearing.

Response: LCBLLBCgrowth

```
. irf graph oirf, set(IRF) irf(IRF) impulse (casesgrowth) response (LCBLLBCgrowth) yline(0)
(file IRF.irf now active)

. irf table oirf, set(IRF) irf(IRF) impulse (casesgrowth) response (LCBLLBCgrowth)
(file IRF.irf now active)
```

[11] Recalling, there is no Granger causality between casesgrowth and FF. Therefore, there is no need to compute the OIRF and COIRF for this specific case.



Results from IRF

step	(1) oirf	(1) Lower	(1) Upper
0	5.5e-06	-.000166	.000177
1	-.00037	-.000552	-.000187
2	-.000048	-.000242	.000147
3	-.000227	-.000426	-.000027
4	-.000279	-.000483	-.000075
5	-.00027	-.000486	-.000054
6	-.000277	-.000503	-.000051
7	.000012	-.00022	.000245
8	.000052	-.000187	.000291
9	.000189	-.000057	.000435
10	.00015	-.000105	.000405
11	.000185	-.000085	.000456
12	-.000051	-.000332	.000231
13	-.000242	-.000526	.000042
14	-.000171	-.000455	.000113
15	.000026	-.00024	.000293
16	.000041	-.000219	.000302
17	-.000015	-.000271	.000241
18	.000085	-.000171	.00034
19	9.6e-06	-.00024	.000259
20	-.000028	-.000277	.000221

95% lower and upper bounds reported
(1) irfname = IRF, impulse = casesgrowth, and response = LCBLLBCgrowth

Figure 2 – casesgrowth shock in LCBLLBCgrowth OIRF for the model with optimal lag (p=14).

Figure 2 shows the effects of new confirmed Covid-19 cases' growth rate on the model's total credit growth rate. We see that a one-standard-deviation (0.126723%) shock in casesgrowth has no immediate effect on LCBLLBCgrowth but decreases it between [-0.000187; -0.000552] at the first week and between the third and sixth weeks after the shock, with the lowest point happening four weeks following the shock [-0.000075; -0.000483]. After it, the response associated with the shock quickly dies out and has no more significance.

It is important to note that these results do not mean that credit has not been boosted by government aid, as seen in the introduction and literature review section, but the growth rate in Covid-19 cases decreased the credit growth rate in the American economy. This fact can be explained by the large increase in credit provided at the early stages of the pandemic, and throughout its development, available credit grew but less and less, having a negative effect. Even though the results mentioned are significant, the effect is very close to zero.

4.1.5. Cumulative orthogonalized impulse response functions

As stated in point 3.3.9. the COIRFs capture the accumulated effects of the shocks in the model.

Firstly, in figure C.23, we display all results to compare the magnitude of the effects between COIRFs. Next, the analysis is done of each of the dynamic relationships that results from a shock in casesgrowth.

Response: dWeiInterp

```
. irf table coirf, set(IRF) irf(IRF) impulse (casesgrowth) response (dWeiInterp)
(file IRF.irf now active)
```

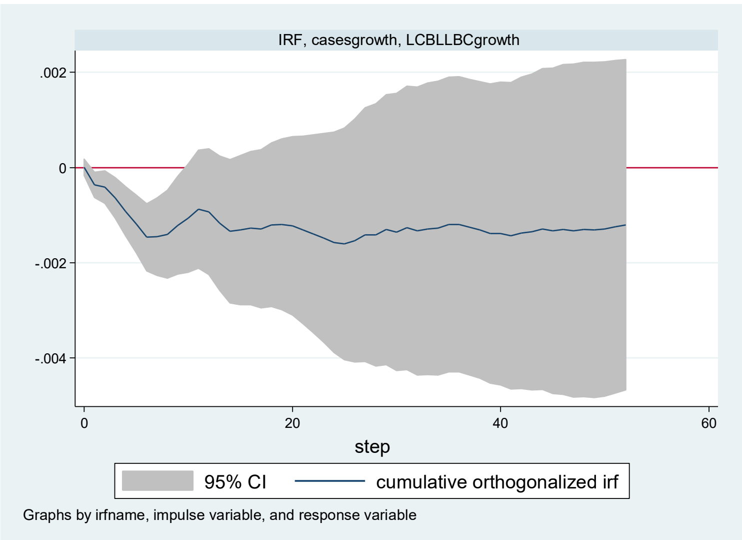
Figure 3 – casesgrowth shock in dWeiInterp COIRFs for the model with optimal lag (p=14).

Assessing figure 3, it is possible to conclude that casesgrowth has no significant cumulative effect in dWeiInterp.

Response: LCBLLBCgrowth

```
. irf graph coirf, set(IRF) irf(IRF) impulse (casesgrowth) response (LCBLLBCgrowth) yline(0)
(file IRF.irf now active)

. irf table coirf, set(IRF) irf(IRF) impulse (casesgrowth) response (LCBLLBCgrowth)
(file IRF.irf now active)
```



Results from IRF

step	(1) coirf	(1) Lower	(1) Upper
0	5.5e-06	-.000166	.000177
1	-.000364	-.000629	-.000099
2	-.000412	-.000755	-.000069
3	-.000638	-.001066	-.000211
4	-.000917	-.001431	-.000404
5	-.001187	-.001791	-.000584
6	-.001465	-.002171	-.000758
7	-.001452	-.002266	-.000639
8	-.0014	-.002321	-.000479
9	-.001211	-.002238	-.000184
10	-.001061	-.0022	.000078
11	-.000876	-.002114	.000362
12	-.000927	-.002244	.000391
13	-.001169	-.002581	.000243
14	-.001339	-.002842	.000164
15	-.001313	-.002879	.000253
16	-.001272	-.002881	.000338
17	-.001287	-.002948	.000375
18	-.001202	-.002922	.000518
19	-.001192	-.002984	.0006
20	-.00122	-.003095	.000655

95% lower and upper bounds reported
(1) irfname = IRF, impulse = casesgrowth, and response = LCBLLBCgrowth

Figure 4 - casesgrowth shock in LCBLLBCgrowth COIRFs for the model with optimal lag (p=14).

Figure 4 shows the effects of new confirmed Covid-19 cases' growth rate on the model's total credit growth rate. It is possible to see that a shock in casesgrowth has a decreasing long-run effect on

LCBLLBCgrowth. The effect peaks in the sixth week [-0.002171; -0.000758] and lasts for ten weeks after the initial shock. The results are expectable; as mentioned in the introduction, the FED provided large amounts of credit at the beginning of the pandemic, which means that as Covid-19 cases exponentially grew in the first stages, on the other hand, credit also continued to grow but not as at its initial rates.

4.1.6. Point forecast

In this section, we present the forecasts for dWeiInterp using our VAR model and compare them with the ones from a simple benchmark AR(1), based on the generated forecast errors. The analysis focus on the economic activity as it is the variable of greatest interest in our model regarding forecasting.

Ex-post Forecast

The Ex-post forecasts are generated using the rule of thumb method: the first 80% of the sample is used to train the model, and the rest 20% is used to predict the time series.

VAR(14) model:

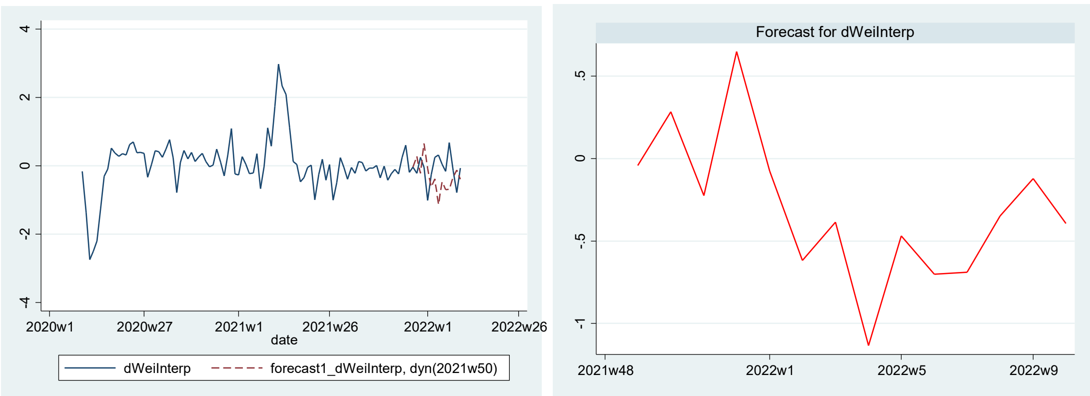


Figure 5 – dWeiInterp Ex-post forecast for VAR(14)

AR(1) Model:

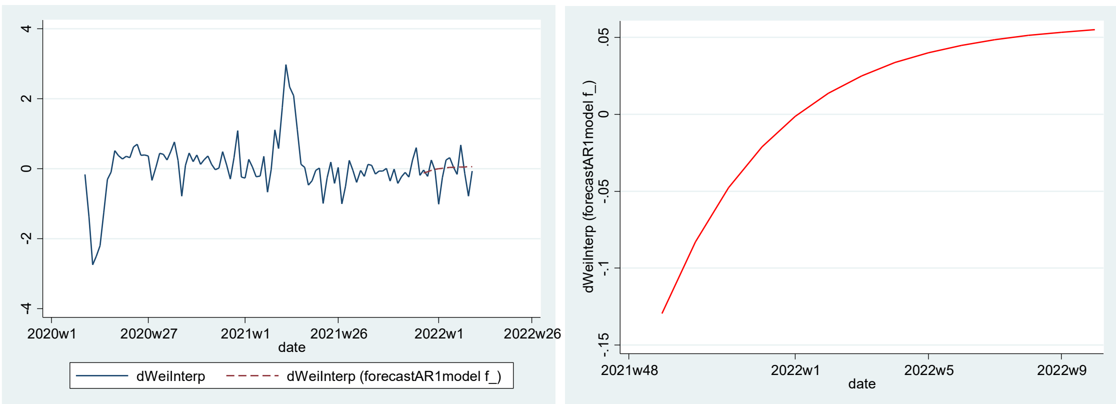


Figure 6 – dWeiInterp Ex-post forecast for AR(1)

Forecast error

This analysis answers whether our VAR(14) model is better for forecasting purposes of real economic activity or whether one should consider another approach since it could achieve more accurate results. The results are displayed in Table 2. To decide the model's forecasting accuracy, we compare the forecast errors measures.

VAR(14) VS. AR(1) Ex-post forecast errors for dWeiInterp		
Forecast error	**VAR(14)**	**AR(1)**
MAE	0.6200248	0.0413469
MAPE	3.6400895	0.1419424
MSE	0.53571891	0.0241532
RMSE	0.73192822	0.15541314

Table 2 - VAR(14) VS. AR(1) Ex-post forecast errors for dWeiInterp

The main conclusion from Table 2 is that the VAR(14) model is not the best approach for forecasting dWeiInterp. Clearly, the simple AR(1) model is more accurate when forecasting real economic activity index in first differences.

Ex-ante Forecast

The Ex-ante forecasts for the VAR(14) model are generated 16 weeks ahead, from 16th March 2022 to 29th June 2022. Regarding the values of exogenous variables "vacgrowth" and "dummy," the binary variable still assumes a value of 1 along the forecast period, while for "vacgrowth" the actual data was collected and entered into STATA once values for this date had already been published.

VAR(14) model:

```
. var casesgrowth dWeiInterp LCBLLBCgrowth FF, exog (dummy vacgrowth) lags(1/14)
. fcast compute forecast2_, step(16)
. twoway (line dWeiInterp date) (line forecast2_dWeiInterp date, lpattern(dash))
```

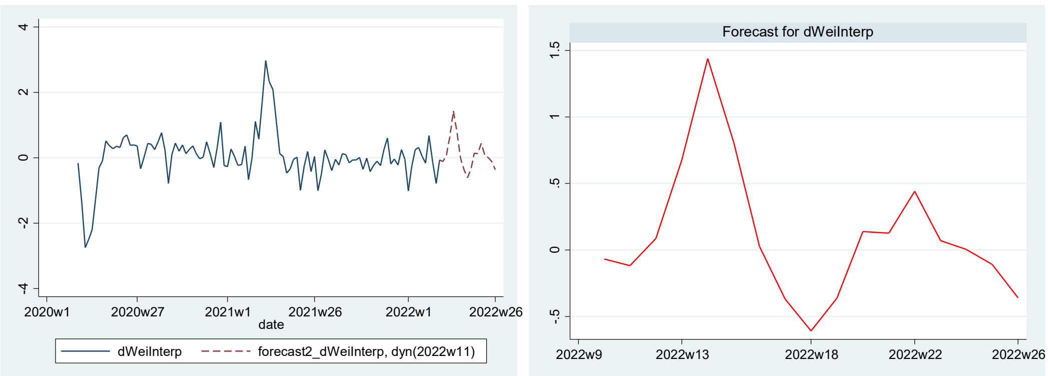


Figure 7 – dWeiInterp Ex-ante forecast for VAR(14)

Figure 7 shows dWeiInterp real values in blue and the forecasted values in red. Analyzing dWeiInterp behavior since 2020 is possible to verify that there has always been an oscillation between positive and negative values, with values above zero indicating a week of economic growth and values below zero indicating a week of economic recession. In this case, the forecast follows this pattern. Our forecast indicates that from March 23th (2022w11), to April 20th (2022w16) and from May 18th (2022w20), to June 15th (2022w24) will be periods of economic growth, while from April 27th (2022w17), to May 11th (2022w19), and June 22nd (2022w25), to June 29th (2022w26), will be periods of economic recession.

Forecast error variance decomposition

In the estimated VAR model, most of the variation associated with a variable in the first weeks is due to itself. For example, the variation associated with dWeiInterp shocks in the first week is of approximately 99%. Also, approximately 96% of the variation in the Federal Funds rate is due to shocks to the Federal Funds rate itself; the remaining 4% is from the other variables, and so on.

Part I of this thesis aims to see whether the pandemic affected real economic activity, where we focus this analysis. By looking at figure 8, it is possible to conclude that after sixteen weeks, around 33% of dWeiInterp uncertainty is explained by casesgrowth, 7% of dWeiInterp by LCBLLBCgrowth, 8% by FF, and the rest of the variability in dWeiInterp is associated to itself (around 52%).

```
. varbasic casesgrowth dWeiInterp LCBLLBCgrowth FF, lags(1/14) step (16) fevd

. irf table fevd, impulse(casesgrowth dWeiInterp LCBLLBCgrowth FF) response(dWeiInterp) noci std
```

Results from varbasic

step	(1) fevd	(1) S.E.	(2) fevd	(2) S.E.	(3) fevd	(3) S.E.	(4) fevd	(4) S.E.
0	0	0	0	0	0	0	0	0
1	.014372	.024773	.985628	.024773	0	0	0	0
2	.034645	.02747	.896507	.049022	.051265	.036262	.017582	.020174
3	.136012	.07077	.77206	.083241	.057008	.043379	.03492	.035637
4	.117704	.065658	.786007	.078512	.062855	.038619	.033435	.035767
5	.119783	.068898	.757305	.088097	.056268	.03406	.066645	.053448
6	.140104	.081732	.732479	.097664	.058173	.032585	.069244	.058981
7	.142087	.084667	.721572	.099164	.064856	.037272	.071485	.061903
8	.146146	.08615	.709554	.101365	.069075	.034743	.075225	.063589
9	.160728	.089995	.680948	.105331	.074698	.035146	.083626	.06437
10	.199604	.098706	.641971	.108324	.079273	.034942	.079151	.061287
11	.246002	.109982	.5998	.110505	.079266	.035074	.074932	.057072
12	.254015	.115811	.59318	.112584	.078098	.034688	.074707	.055931
13	.25277	.116991	.585998	.110851	.08224	.035302	.078993	.054996
14	.251778	.113506	.586665	.107788	.081193	.034697	.080363	.05476
15	.283508	.110334	.559063	.105006	.077443	.032329	.079986	.053039
16	.332862	.115224	.516136	.107095	.072102	.029591	.0789	.050871

(1) irfname = varbasic, impulse = casesgrowth, and response = dWeiInterp
(2) irfname = varbasic, impulse = dWeiInterp, and response = dWeiInterp
(3) irfname = varbasic, impulse = LCBLLBCgrowth, and response = dWeiInterp
(4) irfname = varbasic, impulse = FF, and response = dWeiInterp

Figure 8 - Forecast error variance decomposition for dWeiInterp

4.2. VAR model with new confirmed Covid-19 deaths growth rate

The second VAR model is estimated to measure the impact of the deaths caused by the pandemic on the U.S economy and the availability of credit. The model contains four endogenous variables: new confirmed deaths growth rate, LCBLLBC growth rate, dWeiInterp, and FF.

Given equation (2), our four-dimensional VAR(p) model has a vector of endogenous variables $Y_t = \begin{pmatrix} deathsgrowth \\ dWeiInterp \\ LCBLLBCgrowth \\ FF \end{pmatrix}$, and a vector of exogenous variables $X_t = \begin{pmatrix} vacgrowth \\ dummy \end{pmatrix}$.

4.2.1. Stability condition

Figure C.35 shows the stability results for the model's largest "p" allowed. Again, all the eigenvalues lie inside the unit circle, concluding that the VAR model satisfies the stability condition for a maximum of 14 lags[11].

4.2.2. Optimal lag selection

4.2.2.1. Minimum information criteria

As mentioned in subsection 3.3.1.4., we proceed to the optimal lag selection using the maximum correspondent number of lags (p) for which the model is stable.

According to AIC, SBIC, and HQIC, the optimal lag is always one (p=1), independently of the maximum number of lags we test for[12].

4.2.2.2. Wald lag-exclusion statistics test

The conclusions are very different when compared to the minimum information criteria results. Independently of the maximum number of lags we test for, the optimal lag (p) tends to be the highest admitted in the selection.

After evaluating the results from the minimum information criteria and the Wald lag-exclusion statistic test, we are left with two main conclusions. First, either the optimal (p) lag is the highest allowed in the VAR, having into consideration the stability condition (p=14), or second, the optimal (p) lag is equal to one (p=1) according to AIC, SBIC, and HQIC. Figure C.37 shows Wald lag-exclusion statistics test results[13].

---

[11] The model is stable from (p=1) lags until (p=14) lags.

[12] The criteria were tested from (p=1) lags until (p=14) lags.

[13] For an optimal lag of (p=14), all lags are jointly significant for a significance level of 10% except for (p=7).

To make the final choice between (p=1) and (p=14), we test for serial correlation of the residuals for the options considered. Next, we observe the difference in the significance of the exogenous variables in controlling the pandemic when changing "p". To choose between the criteria already enunciated, the consequent relationships that the model retrieves are decisive and must make sense economically.

4.2.3. Residual diagnostics

Figure C.38 shows the Lagrange multiplier test for the serial correlation between residuals for p=1.

When the p-value is greater than the significance level, we cannot reject the null hypothesis of no serial correlation of the residuals at a specific lag order. For a significance level of 1%, we conclude that there is autocorrelation in the first two lags. In this specific case, the optimal lag is p=1 according to minimum information criteria, which is wrongly assessed because the errors cannot be serially correlated for a VAR model to be well specified. After various tests, we concluded that the serial correlation of the residual tends to decrease as the lag "p" increases. For this first specific model, the autocorrelation problems stand when running the VAR model with optimal lag p=1 or 2. We are left to choose between p=3 and p=14.

Also, for p=1, for a 10% significance level, both control variables “vacgrowth” and “dummy” are not significant to explain the new confirmed deaths growth rate (deathsgrowth). We also test the hypothesis for the dummy variable to assume different vaccination rates, such as 33%, 50%, and 66%[14]. Such results can be counterintuitive as we expect that the vaccine has statistical significance when explaining deathsgrowth. When increasing the number of "p" lags, the exogenous variables tend to become more significant in explaining deathsgrowth. After that, we checked Granger causality for the different p's and concluded that the model's relationships started to make more economical sense as the number of lags increased. Following our decision process, the optimal lag for the VAR model will be p=14[15].

Figure C.39 shows the Lagrange multiplier test for the serial correlation between residuals for p=14. For a significance level of 1%, we conclude that there is no autocorrelation of the error terms at all lags.

[14] The vaccination rate assumed for the dummy variable was 33%.

[15] For an optimal lag of (p=14), all lags are jointly significant for a significance level of 1% except for (p=7).

4.2.4. Granger causality

When analyzing the results of figure C.43, it is possible to conclude that there is strong evidence for Granger causality among variables[16]. Again, the first row of results is not interpretable.

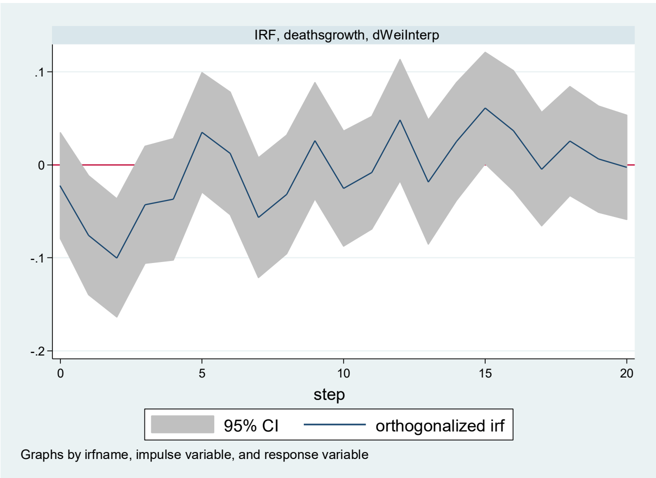
4.2.5. Orthogonalized impulse response functions

Firstly, in figure C.44, we display all results to compare the magnitude of the effects between OIRFs. Lastly, due to the identification scheme adopted, a singular analysis is done on each dynamic relationship that results from a shock in deathsgrowth for a horizon of at most 20 weeks (five months).

Response: dWeiInterp

```
. irf graph oirf, set(IRF) irf(IRF) impulse (deathsgrowth) response (dWeiInterp) yline(0)
(file IRF.irf now active)

. irf table oirf, set(IRF) irf(IRF) impulse (deathsgrowth) response (dWeiInterp)
(file IRF.irf now active)
```



Results from IRF

step	(1) oirf	(1) Lower	(1) Upper
0	-.022215	-.07916	.03473
1	-.07569	-.139592	-.011788
2	-.100097	-.163801	-.036393
3	-.042867	-.105985	.020251
4	-.03701	-.102233	.028213
5	.035007	-.029166	.099181
6	.012362	-.053536	.078259
7	-.056731	-.12117	.007708
8	-.031856	-.095662	.031949
9	.025931	-.036593	.088454
10	-.025452	-.087309	.036405
11	-.008251	-.06883	.052328
12	.048302	-.017034	.113638
13	-.018484	-.085344	.048377
14	.025298	-.03801	.088605
15	.061241	.001406	.121077
16	.036746	-.028015	.101508
17	-.004518	-.065667	.056631
18	.0258	-.032811	.084411
19	.006232	-.051073	.063537
20	-.002446	-.058487	.053594

95% lower and upper bounds reported
(1) irfname = IRF, impulse = deathsgrowth, and response = dWeiInterp

Figure 9 – deathsgrowth shock in dWeiInterp OIRF for the model with optimal lag (p=14).

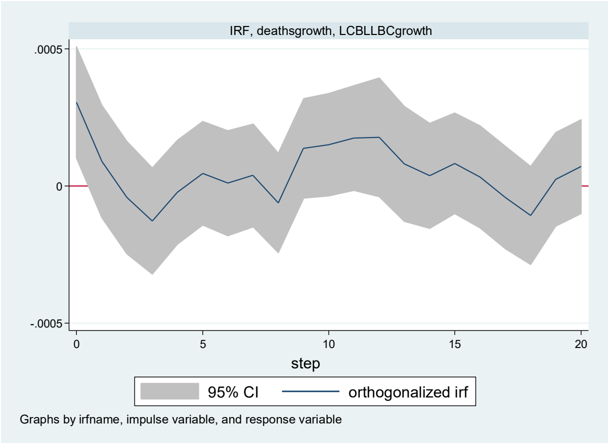
Figure 9 shows the effects of deathsgrowth shocks in dWeiInterp, which have an immediate negative impact of approximately 0.022 percentual points. We see that a one-standard deviation (0.15 percentage points) shock in deathsgrowth decreases dWeiInterp in the first two weeks by about 0.1 percentage points [-0.036393; -0.163801]. After the second week, the effect goes rapidly to zero, with the statistical significance of the effect disappearing. The effect caused by Covid-19 deaths growth rate is negative as expected; once deathsgrowth increases, it means individuals (p.e. human capital, consumers, producers) are being removed from the economic circle, ceasing their contribution to economic activity. The magnitude of the effects is very similar to the ones obtained in subsection 4.1.5.

[16] The Granger causality tests are performed assuming a significance level of 10%.

Response: LCBLLBCgrowth

```
. irf graph oirf, set(IRF) irf(IRF) impulse (deathsgrowth) response (LCBLLBCgrowth) yline(0)
(file IRF.irf now active)

. irf table oirf, set(IRF) irf(IRF) impulse (deathsgrowth) response (LCBLLBCgrowth)
(file IRF.irf now active)
```



Results from IRF

step	(1) oirf	(1) Lower	(1) Upper
0	.000305	.000102	.000507
1	.000089	-.000116	.000294
2	-.000043	-.000248	.000163
3	-.000128	-.000321	.000065
4	-.000023	-.000212	.000166
5	.000046	-.000143	.000235
6	.00001	-.000181	.000201
7	.000038	-.000149	.000226
8	-.000062	-.000244	.00012
9	.000136	-.000045	.000318
10	.00015	-.000037	.000337
11	.000175	-.000016	.000366
12	.000177	-.000039	.000394
13	.000081	-.000129	.00029
14	.000037	-.000155	.000229
15	.000082	-.000101	.000265
16	.000033	-.000153	.000218
17	-.000042	-.000228	.000144
18	-.000107	-.000286	.000071
19	.000024	-.000147	.000195
20	.000071	-.000101	.000242

95% lower and upper bounds reported
(1) irfname = IRF, impulse = deathsgrowth, and response = LCBLLBCgrowth

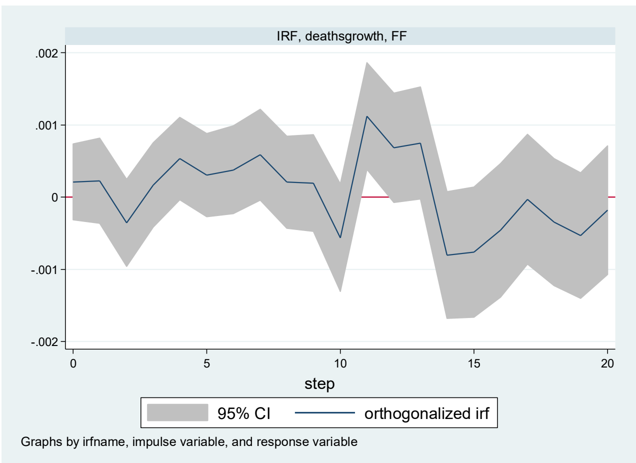
Figure 10 – deathsgrowth shock in LCBLLBCgrowth OIRF for the model with optimal lag (p=14).

Figure 10 shows the effects of new confirmed Covid-19 deaths' growth rate on the model's total credit growth rate. We see that a one-standard deviation (0.15 percentage points) shock in deathsgrowth immediately affects LCBLLBCgrowth by about 0.0003 percentual points. The rest of the effect is considered insignificant.

Response: FF

```
. irf graph oirf, set(IRF) irf(IRF) impulse (deathsgrowth) response (FF) yline(0)
(file IRF.irf now active)

. irf table oirf, set(IRF) irf(IRF) impulse (deathsgrowth) response (FF)
(file IRF.irf now active)
```



Results from IRF

step	(1) oirf	(1) Lower	(1) Upper
0	.00021	-.000315	.000735
1	.000227	-.000364	.000818
2	-.000358	-.000961	.000246
3	.000168	-.000416	.000753
4	.000533	-.000038	.001103
5	.000303	-.000273	.000878
6	.000377	-.000231	.000985
7	.000587	-.000044	.001218
8	.000207	-.00043	.000843
9	.000195	-.000473	.000863
10	-.000562	-.001306	.000181
11	.001122	.000383	.001861
12	.000685	-.000072	.001442
13	.00075	-.000024	.001524
14	-.000804	-.001681	.000073
15	-.000761	-.001662	.00014
16	-.00046	-.001384	.000464
17	-.000029	-.000926	.000869
18	-.000345	-.001225	.000536
19	-.000533	-.001402	.000335
20	-.000181	-.001072	.000711

95% lower and upper bounds reported
(1) irfname = IRF, impulse = deathsgrowth, and response = FF

Figure 11 – deathsgrowth shock in FF OIRF for the model with optimal lag (p=14).

The effects of deathsgrowth shocks in FF are almost insignificant. In this case, the output is significant only in the eleventh week, with an average effect of 0.001122 percentual points.

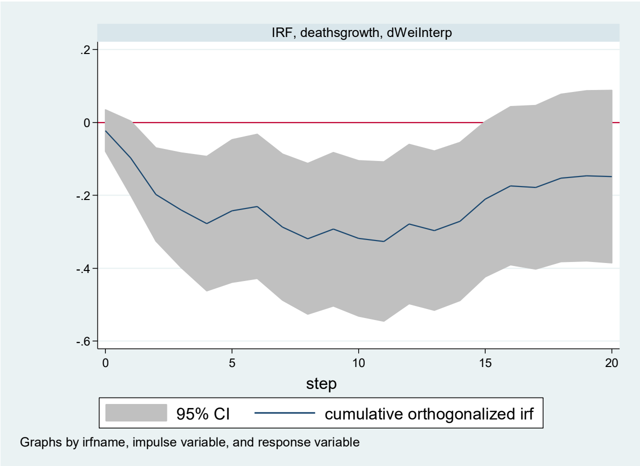
4.2.6. Cumulative orthogonalized impulse response functions

Firstly, in figure C.55, we display all results to compare the magnitude of effects between COIRFs. Lastly, a singular analysis for each relationship that results from a shock in deathsgrowth is done.

Response: dWeiInterp

```
. irf graph coirf, set(IRF) irf(IRF) impulse (deathsgrowth) response (dWeiInterp) yline(0)
(file IRF.irf now active)

. irf table coirf, set(IRF) irf(IRF) impulse (deathsgrowth) response (dWeiInterp)
(file IRF.irf now active)
```



Results from IRF

step	(1) coirf	(1) Lower	(1) Upper
0	-.022215	-.07916	.03473
1	-.097905	-.199517	.003707
2	-.198002	-.325896	-.070108
3	-.240869	-.398119	-.083619
4	-.277879	-.462601	-.093157
5	-.242871	-.438605	-.047138
6	-.23051	-.428442	-.032577
7	-.287241	-.487853	-.086629
8	-.319097	-.52624	-.111954
9	-.293166	-.503947	-.082385
10	-.318618	-.532121	-.105115
11	-.326869	-.545598	-.108139
12	-.278567	-.497398	-.059737
13	-.297051	-.516055	-.078046
14	-.271753	-.488903	-.054603
15	-.210512	-.424268	.003245
16	-.173765	-.39112	.04359
17	-.178283	-.402832	.046266
18	-.152483	-.38215	.077184
19	-.146251	-.380076	.087575
20	-.148697	-.385621	.088227

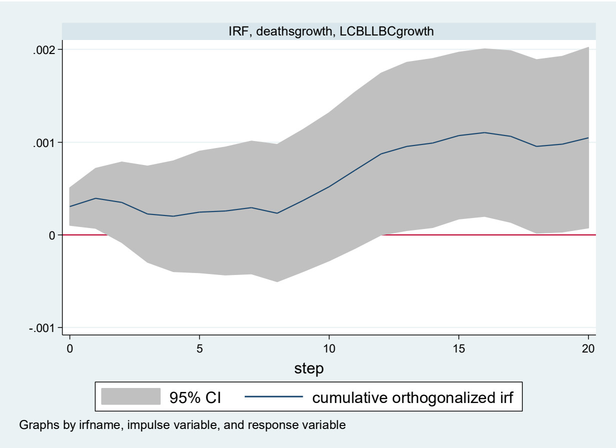
95% lower and upper bounds reported
(1) irfname = IRF, impulse = deathsgrowth, and response = dWeiInterp

Figure 12 – deathsgrowth shock in dWeiInterp COIRF for the model with optimal lag (p=14).

Assessing figure 12, it is possible to conclude that deathsgrowth has a significant long-run effect in dWeiInterp from the second to the fourteenth week, with the peak occurring at the eighth week [-0.52624;0.111954]. This negative effect could be explained by the fact that once economic agents are unexpectedly removed from the economy (focusing on individuals), it creates inefficiencies which translates into a decrease in economic activity. Although this fact also creates instability and uncertainty in companies as they lose workforce and consumers in one hit, the adaptation process to this new reality is not immediate.

Response: LCBLLBCgrowth

```
. irf graph coirf, set(IRF) irf(IRF) impulse (deathsgrowth) response (LCBLLBCgrowth) yline(0)
(file IRF.irf now active)
. irf table coirf, set(IRF) irf(IRF) impulse (deathsgrowth) response (LCBLLBCgrowth)
(file IRF.irf now active)
```



Results from IRF

step	(1) coirf	(1) Lower	(1) Upper
0	.000305	.000102	.000507
1	.000394	.000073	.000715
2	.000351	-.00008	.000783
3	.000224	-.000295	.000742
4	.0002	-.000394	.000795
5	.000246	-.000408	.0009
6	.000257	-.000432	.000945
7	.000295	-.000421	.001011
8	.000233	-.000506	.000972
9	.000369	-.000397	.001136
10	.000519	-.000277	.001316
11	.000694	-.000148	.001536
12	.000872	-5.2e-07	.001744
13	.000952	.000046	.001858
14	.000989	.000078	.0019
15	.001071	.000173	.001969
16	.001103	.0002	.002007
17	.001061	.000138	.001985
18	.000954	.000021	.001887
19	.000978	.000032	.001925
20	.001049	.000077	.00202

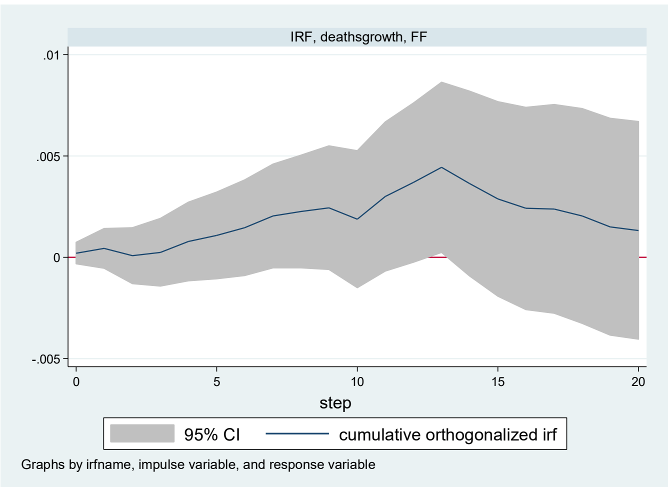
95% lower and upper bounds reported
(1) irfname = IRF, impulse = deathsgrowth, and response = LCBLLBCgrowth

Figure 13 – deathsgrowth shock in LCBLLBCgrowth COIRF for the model with optimal lag (p=14).

Figure 13 shows the effects of new confirmed Covid-19 deaths' growth rate on the model's total credit growth rate. It is possible to see that a shock in deathsgrowth has an increasing long-run effect on LCBLLBCgrowth. The effect peaks at the sixteenth week [0.0002;0.002007].

Response: FF

```
. irf graph coirf, set(IRF) irf(IRF) impulse (deathsgrowth) response (FF) yline(0)
(file IRF.irf now active)
. irf table coirf, set(IRF) irf(IRF) impulse (deathsgrowth) response (FF)
(file IRF.irf now active)
```



Results from IRF

step	(1) coirf	(1) Lower	(1) Upper
0	.00021	-.000315	.000735
1	.000437	-.000543	.001417
2	.000079	-.001296	.001455
3	.000248	-.001427	.001923
4	.000781	-.001156	.002717
5	.001083	-.001055	.003222
6	.00146	-.000893	.003813
7	.002047	-.00051	.004605
8	.002254	-.000528	.005036
9	.002449	-.000606	.005504
10	.001887	-.0015	.005273
11	.003009	-.000676	.006694
12	.003694	-.00024	.007627
13	.004444	.000234	.008653
14	.00364	-.000923	.008203
15	.002879	-.001919	.007677
16	.002419	-.00257	.007408
17	.00239	-.00277	.00755
18	.002046	-.003254	.007346
19	.001513	-.003846	.006871
20	.001332	-.004045	.006708

95% lower and upper bounds reported
(1) irfname = IRF, impulse = deathsgrowth, and response = FF

Figure 14 – deathsgrowth shock in FF COIRF for the model with optimal lag (p=14).

The effects of an impulse in deathsgrowth are only significant for the Fed Funds rate in the thirteenth week, though it is very small [0.000234;0.008203].

4.2.7. Point forecast

This section presents the forecasts for our VAR model, this time with deathsgrowth instead of casesgrowth. Again, the analysis will focus on the real economic activity, which is the variable of greatest interest when it comes to forecasting.

Ex-post Forecast

The Ex-post forecasts are generated using the rule of thumb method: The first 80% of the sample used to train, and the rest 20% is used to predict the time series.

VAR(14) model:

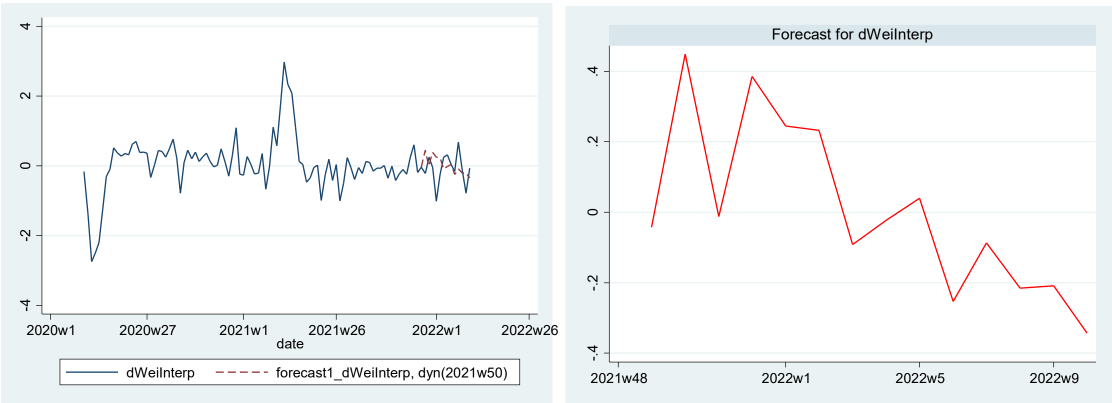


Figure 15 – dWeiInterp Ex-post forecast for VAR(14)

AR(1) Model:

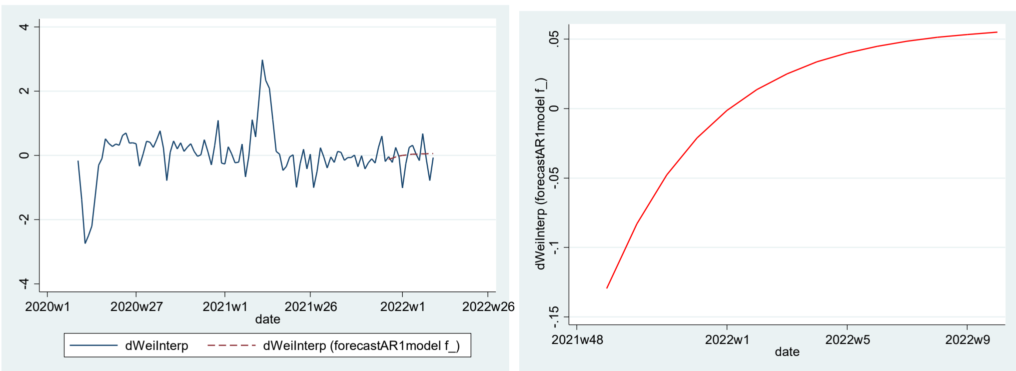


Figure 16 – dWeiInterp Ex-post forecast for AR(1)

Forecast error

This analysis answers whether our VAR(14) model is better for forecasting purposes of real economic activity or whether one should consider another approach since it could achieve more accurate results. The results are displayed in table 3. the model's forecasting accuracy, we compare the forecast errors.

VAR(14) VS. AR(1) forecast errors for dWeilnterp		
Forecast error	**VAR(14)**	**AR(1)**
MAE	0.39945128	0.0413469
MAPE	1.85737	0.1419424
MSE	0.2693513	0.0241532
RMSE	0.51899063	0.15541314

Table 3 – VAR(14) VS. AR(1) Ex-post forecast errors for dWeilnterp

The main conclusion from table 3 is the same as the first VAR(14) model using casesgrowth. Our VAR(14) model is not an accurate approach to forecast dWeilnterp.

Ex-ante Forecast

The Ex-ante forecasts for the VAR(14) model are generated 16 weeks ahead, from 16th March 2022 to 29th June 2022. Regarding the values of exogenous variables "vacgrowth" and "dummy," the binary variable still assumes a value of 1 along the forecast period, while for "vacgrowth" the actual data was collected and entered into STATA once values for this date had already been published.

```
. var deathsgrowth dWeiInterp LCBLLBCgrowth FF, exog (dummy vacgrowth) lags(1/14)
. fcast compute forecast2_, step(16)
. twoway (line dWeiInterp date) (line forecast2_dWeiInterp date, lpattern(dash))
```

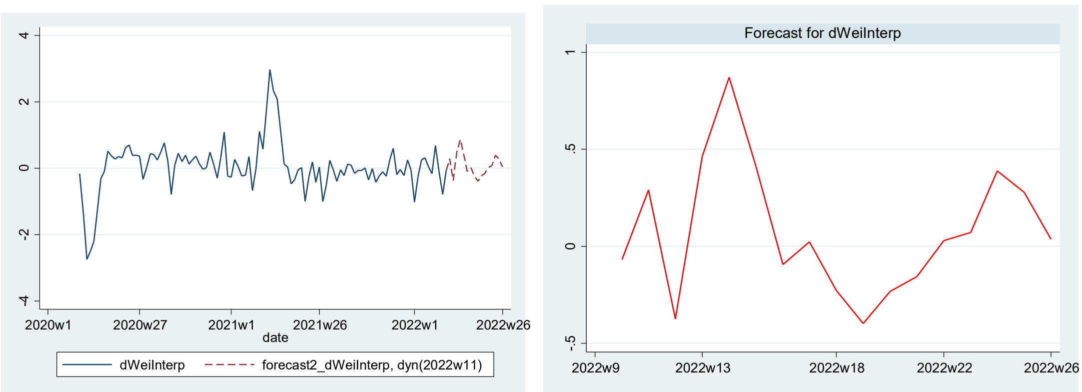


Figure 17– dWeilnterp Ex-ante forecast for VAR(14)

Figure 17 shows dWeilnterp real values in blue and the forecasted values in red. Analyzing our forecast, it indicates that from March 30th (2022w13) to April 13th (2022w15) and from June 1st (2022w22) to June 29th (2022w26) will be periods of economic growth, while from March 23rd (2022w12) and April 20th (2022w16) to May 25th (2022w21) will be periods of economic recession.

Forecast error variance decomposition

In the model estimated VAR model, most of the variation associated with a variable in the first weeks is due to itself. For example, the variation associated with dWeilnterp shocks in the first week is of approximately 98%.

Part I of this thesis aims to see whether the pandemic affected real economic activity, which is where we will focus this analysis. By looking at figure 18, it is possible to conclude that after sixteen weeks, around 23% of dWeiInterp uncertainty is explained by deathsgrowth, 19% of dWeiInterp by LCBLLBCgrowth, 18% by FF, and the rest of the variability in dWeiInterp is associated to itself (around 40%).

Results from varbasic

step	(1) fevd	(1) S.E.	(2) fevd	(2) S.E.	(3) fevd	(3) S.E.	(4) fevd	(4) S.E.
0	0	0	0	0	0	0	0	0
1	.017952	.027587	.982048	.027587	0	0	0	0
2	.083115	.059695	.783255	.073981	.023777	.026202	.109853	.051985
3	.185653	.085237	.675067	.090122	.026293	.031734	.112987	.058038
4	.207786	.092455	.647848	.095594	.034549	.028595	.109818	.058874
5	.199193	.091138	.547776	.099216	.060104	.040345	.192928	.080164
6	.184729	.087855	.510404	.101182	.095932	.061754	.208934	.089002
7	.172859	.084832	.482873	.102318	.149675	.084606	.194593	.084929
8	.193621	.086734	.456306	.102911	.165488	.093338	.184584	.082098
9	.207282	.08998	.445332	.102283	.168014	.095102	.179372	.081106
10	.207914	.091063	.445085	.102257	.167691	.094468	.17931	.08165
11	.213782	.092578	.435488	.098472	.174544	.092958	.176186	.080138
12	.215497	.093481	.432691	.097048	.176371	.093693	.175441	.078957
13	.212336	.09066	.422929	.094143	.192223	.095931	.172512	.077234
14	.211349	.090289	.422055	.093666	.195076	.097195	.17152	.076917
15	.213869	.088977	.414732	.092568	.19423	.095576	.177168	.076784
16	.230182	.089851	.401863	.092166	.18829	.091559	.179665	.077362

(1) irfname = varbasic, impulse = deathsgrowth, and response = dWeiInterp
(2) irfname = varbasic, impulse = dWeiInterp, and response = dWeiInterp
(3) irfname = varbasic, impulse = LCBLLBCgrowth, and response = dWeiInterp
(4) irfname = varbasic, impulse = FF, and response = dWeiInterp

Figure 18 – Forecast error variance decomposition for dWeiInterp

PART II: What are the effects of the increase in different types of credit in real economic activity?

4.3. VAR model with new confirmed Covid-19 cases growth rate

The third VAR model is estimated to measure the impact of different types of credit on U.S real economic activity. The model contains six variables: casesgrowth, dWeiInterp, CILgrowth, CLgrowth_detrended, OLLgrowth, and FF. A similar version with deathsgrowth instead of casesgrowth is also estimated in section 4.4..

Given equation (2), our six-dimensional VAR(p) model has a vector of endogenous variables

$$Y_t = \begin{pmatrix} casesgrowth \\ dWeiInterp \\ CILgrowth \\ CLgrowth\_detrended \\ OLLgrowth \\ FF \end{pmatrix}$$, and a vector of exogenous variables $X_t = \begin{pmatrix} vacgrowth \\ dummy \end{pmatrix}$.

4.3.1. Stability condition and residual diagnostics

Figure C.66 shows the stability results for the largest "p" allowed for the model. Again, all the eigenvalues lie inside the unit circle, concluding that the VAR model satisfies the stability condition for a maximum of 11 lags[17].

4.3.2. Optimal lag selection

Unlike Part I, the results for optimal lag selection were quite straightforward and according to the criteria, without having to make decisions supported by a specific rational process.

4.3.2.1. Minimum information criteria

Figure C.67 shows that according to AIC, the optimal lag is (p=11), and for SBIC and HQIC, (p=1).

4.3.2.2. Wald lag-exclusion statistics test

According to the Wald lag-exclusion statistics test results in figure C.68, it is possible to conclude that all lags are jointly significant, which is not conclusive for selecting an optimal lag.

We are left with two main results, either the optimal (p) lag is the highest allowed in the VAR (p=11), or the optimal (p) lag is equal to one (p=1). Therefore, we select the optimal lag (p=11). As will be shown in the next section, there is autocorrelation between the errors for an optimal lag (p=1), which does not happen for the other case (p=11).

4.3.3. Residual diagnostics

Figure C.69 shows the Lagrange multiplier test for the serial correlation between residuals for p=1.

When the p-value is greater than significance level, we cannot reject the null hypothesis of no serial correlation between residuals at a specific lag order. For a significance level of 1%, we conclude that there is autocorrelation between the error terms in the first lag. In this case, the optimal lag is p=1 according to minimum information criteria, which is wrongly assessed.

Figure C.70 shows the Lagrange multiplier test for the serial correlation of the residuals for p=11. Since the p-value is greater than the significance level, we cannot reject the null hypothesis of no serial correlation between residuals at a specific lag order. For a significance level of 1%, we conclude that there is no autocorrelation at all lags[18].

More residuals diagnostics can be found in the Appendix (figure C.71, C.72, C.73)

---

[17] The model is stable from (p=1) lags until (p=11) lags.

[18] The vaccination rate assumed for the dummy variable was 33%.

4.3.4. Granger causality

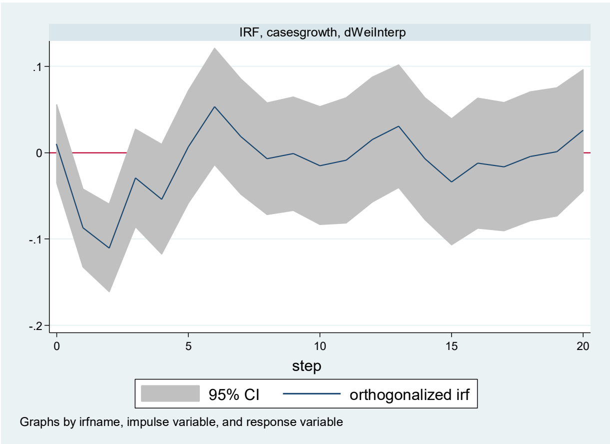
When analyzing the results of figure C.74, it is possible to evaluate the Granger causality among all variables. In this case, we decided to diminish the significance level from 10% to 1%. Again, casesgrowth can GC the other variables but not the other way around.

4.3.5. Orthogonalized impulse response functions

Response: dWeiInterp

```
. irf graph oirf, set(IRF) irf(IRF) impulse (casesgrowth) response (dWeiInterp) yline(0)
(file IRF.irf now active)

. irf table oirf, set(IRF) irf(IRF) impulse (casesgrowth) response (dWeiInterp)
(file IRF.irf now active)
```



Results from IRF

step	(1) oirf	(1) Lower	(1) Upper
0	.010259	-.035073	.05559
1	-.087162	-.132394	-.04193
2	-.110414	-.161258	-.059569
3	-.02925	-.08574	.027239
4	-.053997	-.117601	.009606
5	.006577	-.058475	.071629
6	.053557	-.01381	.120924
7	.018801	-.047983	.085584
8	-.006795	-.071395	.057805
9	-.001115	-.066765	.064535
10	-.014995	-.083325	.053335
11	-.008749	-.081236	.063738
12	.015274	-.056938	.087486
13	.030694	-.040436	.101825
14	-.006972	-.077517	.063573
15	-.033838	-.106891	.039215
16	-.012143	-.087366	.06308
17	-.016157	-.090238	.057924
18	-.00425	-.078942	.070441
19	.001051	-.073294	.075396
20	.026063	-.044078	.096203

95% lower and upper bounds reported
(1) irfname = IRF, impulse = casesgrowth, and response = dWeiInterp

Figure 19– casesgrowth shock in dWeiInterp OIRF for the model with optimal lag (p=11).

Figure 19 shows the effects of casesgrowth in dWeiInterp. We see that one standard-deviation shock in casesgrowth increases dWeiInterp in the current week by about 0.01%. Then, there is a decreasing effect in the first two weeks after the initial shock, with the peak occurring in the second week between [-0.059569; -0.161258] percentual points. After the second week, the effect goes rapidly to zero, with the statistical significance of the effect disappearing. Nevertheless, the results are robust with the ones obtained in the last models.

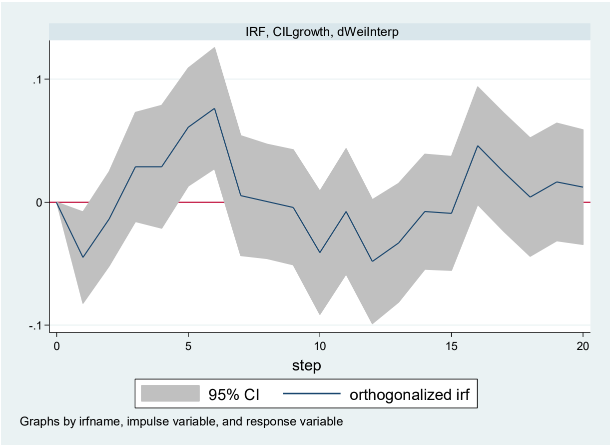
Impulse: CILgrowth

Response: dWeiInterp

```
. irf graph oirf, set(IRF) irf(IRF) impulse (CILgrowth) response (dWeiInterp) yline(0)
(file IRF.irf now active)

. irf table oirf, set(IRF) irf(IRF) impulse (CILgrowth) response (dWeiInterp)
(file IRF.irf now active)
```

Results from IRF



step	(1) oirf	(1) Lower	(1) Upper
0	0	0	0
1	-.04507	-.082303	-.007838
2	-.013627	-.051994	.024739
3	.028668	-.015622	.072957
4	.028798	-.021217	.078813
5	.061116	.013217	.109015
6	.076442	.027298	.125585
7	.005197	-.043529	.053923
8	.000619	-.045742	.04698
9	-.004231	-.050952	.042491
10	-.041099	-.091235	.009036
11	-.007518	-.058576	.043539
12	-.048347	-.098715	.00202
13	-.033092	-.081311	.015127
14	-.007747	-.054608	.039115
15	-.009174	-.055474	.037126
16	.04587	-.001951	.093691
17	.024261	-.023822	.072344
18	.004082	-.044152	.052316
19	.016462	-.031468	.064391
20	.012198	-.034325	.058721

95% lower and upper bounds reported
(1) irfname = IRF, impulse = CILgrowth, and response = dWeiInterp

Figure 20 – CILgrowth shock in dWeiInterp OIRF for the model with optimal lag (p=11).

Figure 20 shows the effects of the growth rate of commercial and industrial loans in the first differences of the weekly economic index. It is possible to see that a shock in CILgrowth has a small decreasing effect in dWeiInterp in the first week between [-0.082303; -0.007838] and an increasing effect from the fifth to the sixth week. The effect peaks in the sixth week [0.027298;0.125585]. Overall, the results are expectable; an increase in commercial and industrial loans contributes to generating economic activity. Also, the first decrease can seem as a point when companies or factories are investing the borrowed capital (p.e. companies can close a department or a factory having to upgrade by construction works).

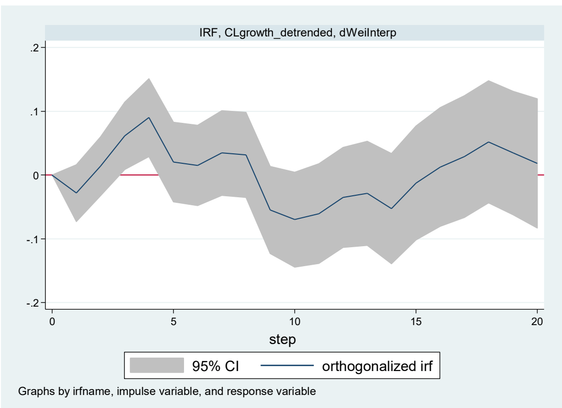
Impulse: CLgrowth_detrended

Response: dWeiInterp

```
. irf graph oirf, set(IRF) irf(IRF) impulse (CLgrowth_detrended) response (dWeiInterp) yline(0)
(file IRF.irf now active)

. irf table oirf, set(IRF) irf(IRF) impulse (CLgrowth_detrended) response (dWeiInterp)
(file IRF.irf now active)
```

Results from IRF



step	(1) oirf	(1) Lower	(1) Upper
0	0	0	0
1	-.028422	-.073119	.016276
2	.013817	-.03238	.060014
3	.061373	.008591	.114155
4	.090035	.028763	.151308
5	.020377	-.042119	.082872
6	.015032	-.047964	.078028
7	.034548	-.031739	.100834
8	.031561	-.035177	.098298
9	-.05485	-.123189	.013489
10	-.069999	-.144578	.00458
11	-.060621	-.138642	.017401
12	-.035036	-.113424	.043351
13	-.028815	-.110582	.052952
14	-.052856	-.139239	.033526
15	-.012488	-.101672	.076696
16	.012432	-.080706	.10557
17	.02877	-.066684	.124225
18	.052072	-.043909	.148053
19	.034635	-.062151	.131421
20	.01826	-.082971	.119491

95% lower and upper bounds reported
(1) irfname = IRF, impulse = CLgrowth_detrended, and response = dWeiInterp

Figure 31 – CLgrowth_detrended shock in dWeiInterp OIRF for the model with optimal lag (p=11).

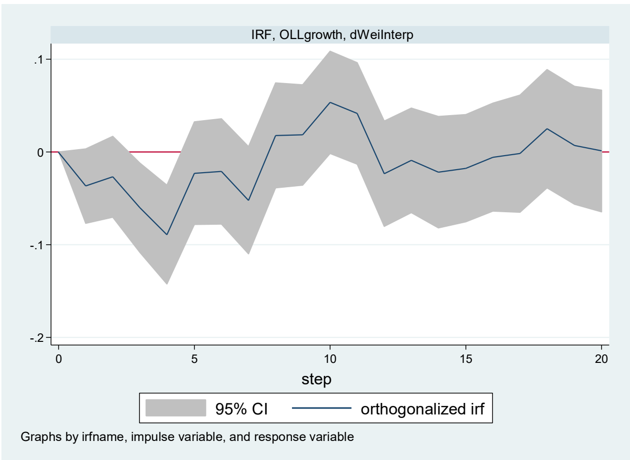
By observing figure 21, a shock in the growth rate of consumer loans increases dWeiInterp from the third to the fourth week after the initial shock, as expected once money is inserted into the economy to stimulate consumption. The peak is in the fourth week [0.028763; 0.151308]. After that, the effect is no longer significant.

Impulse: OLLgrowth

Response: dWeiInterp

```
. irf graph oirf, set(IRF) irf(IRF) impulse (OLLgrowth) response (dWeiInterp) yline(0)
(file IRF.irf now active)

. irf table oirf, set(IRF) irf(IRF) impulse (OLLgrowth) response (dWeiInterp)
(file IRF.irf now active)
```



Results from IRF

step	(1) oirf	(1) Lower	(1) Upper
0	0	0	0
1	-.036705	-.076861	.00345
2	-.026613	-.070181	.016955
3	-.060164	-.1082	-.012129
4	-.089213	-.142438	-.035987
5	-.02304	-.078366	.032286
6	-.021022	-.07789	.035846
7	-.052082	-.109884	.00572
8	.017829	-.038893	.07455
9	.018331	-.035754	.072416
10	.053406	-.001699	.108511
11	.041581	-.013274	.096437
12	-.023443	-.080233	.033348
13	-.009043	-.06548	.047393
14	-.021831	-.082011	.038349
15	-.017549	-.075495	.040398
16	-.0057	-.063918	.052518
17	-.001802	-.064827	.061223
18	.024956	-.03883	.088742
19	.007202	-.056465	.070868
20	.001021	-.064486	.066528

95% lower and upper bounds reported
(1) irfname = IRF, impulse = OLLgrowth, and response = dWeiInterp

Figure 24 – OLLgrowth shock in dWeiInterp OIRF for the model with optimal lag (p=11).

Assessing figure 22, it is possible to conclude that a shock in OLLgrowth has a significant negative effect on dWeiInterp from the third to the fourth week, with the peak occurring at the fourth week [-0.142438; -0.035987], the rest of the effect is insignificant. Although the shown result is not straightforward, as credit should help boost the economy in the short-run, this could support the fact that the governments should be extremely careful where to inject the credit and in which amount so as not to create inefficiencies in the economy.

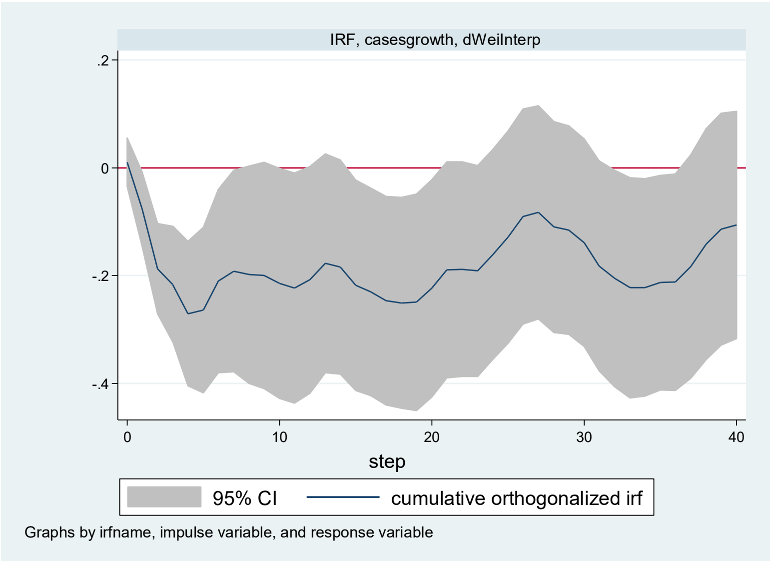
4.3.6. Cumulative orthogonalized impulse response functions

Firstly, in figure C.76, we display all results to compare the magnitude of effects between COIRFs. Lastly, a singular analysis is done of each long-run dynamic relationship.

Response: dWeiInterp

```
. irf graph coirf, set(IRF) irf(IRF) impulse (casesgrowth) response (dWeiInterp) yline(0)
(file IRF.irf now active)

. irf table coirf, set(IRF) irf(IRF) impulse (casesgrowth) response (dWeiInterp)
(file IRF.irf now active)
```



Results from IRF

step	(1) coirf	(1) Lower	(1) Upper
0	.010259	-.035073	.05559
1	-.076903	-.146094	-.007712
2	-.187316	-.270951	-.103681
3	-.216567	-.324199	-.108934
4	-.270564	-.404509	-.136618
5	-.263987	-.417453	-.110521
6	-.21043	-.380563	-.040297
7	-.191629	-.378959	-.0043
8	-.198424	-.400108	.00326
9	-.199539	-.409555	.010477
10	-.214534	-.427941	-.001128
11	-.223284	-.436535	-.010033
12	-.20801	-.41856	.002541
13	-.177315	-.380762	.026132
14	-.184287	-.382724	.014149
15	-.218125	-.413139	-.023111
16	-.230268	-.422738	-.037798
17	-.246425	-.439805	-.053046
18	-.250676	-.446192	-.055159
19	-.249625	-.450597	-.048653
20	-.223562	-.425248	-.021876
21	-.18922	-.389672	.011232
22	-.188195	-.387128	.010739
23	-.191369	-.387011	.004272
24	-.161226	-.35621	.033757
25	-.128672	-.325899	.068555
26	-.090675	-.290039	.108689
27	-.082834	-.280739	.11507
28	-.109846	-.305611	.085919
29	-.115844	-.309545	.077858
30	-.138955	-.331352	.053443
31	-.182169	-.377078	.012741
32	-.205373	-.406103	-.004644
33	-.222585	-.426919	-.018251
34	-.222183	-.423887	-.02048
35	-.213171	-.412207	-.014134
36	-.212221	-.413163	-.011279
37	-.18336	-.390946	.024226
38	-.141403	-.355814	.073007
39	-.113673	-.328778	.101433
40	-.105973	-.316932	.104987

95% lower and upper bounds reported
(1) irfname = IRF, impulse = casesgrowth, and response = dWeiInterp

Figure 53 – casesgrowth shock in dWeiInterp COIRF for the model with optimal lag (p=11).

Assessing figure 23, it is possible to conclude that casesgrowth has a significant long-run effect in dWeiInterp from the first to the seventh week, with the peak occurring at the fourth week [-0.404509; -0.136618], from the tenth to the eleventh week, with the new peak at the eleventh week [-0.436535; -0.010033], from the fifteenth to the twentieth week, with the peak at the eighteenth week [-0.446192; -0.055159], and from the thirty-second to the thirty-sixth week, with the peak at the thirty-fourth week [-0.423887; -0.02048][19].

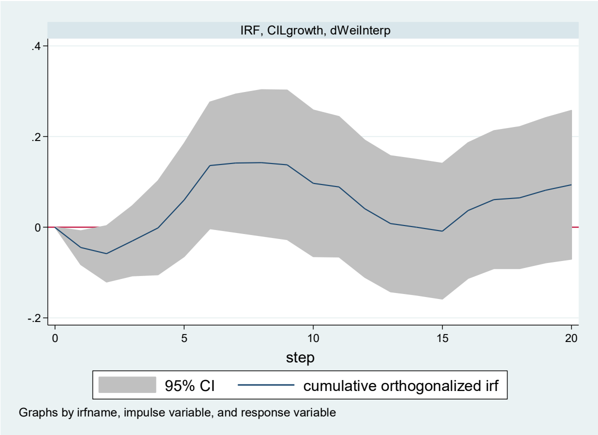
Impulse: CILgrowth

Response: dWeiInterp

```
. irf graph coirf, set(IRF) irf(IRF) impulse (CILgrowth) response (dWeiInterp) yline(0)
(file IRF.irf now active)

. irf table coirf, set(IRF) irf(IRF) impulse (CILgrowth) response (dWeiInterp)
(file IRF.irf now active)
```

[19] For this case, we generated the COIRFs 40 steps ahead due to the long-run response's significance.



Results from IRF

step	(1) coirf	(1) Lower	(1) Upper
0	0	0	0
1	-.04507	-.082303	-.007838
2	-.058698	-.120991	.003596
3	-.03003	-.106962	.046902
4	-.001232	-.105043	.102579
5	.059884	-.064969	.184737
6	.136326	-.003351	.276003
7	.141523	-.010881	.293927
8	.142142	-.01899	.303274
9	.137911	-.027068	.30289
10	.096812	-.064644	.258267
11	.089293	-.065528	.244115
12	.040946	-.110585	.192477
13	.007854	-.142031	.157739
14	.000107	-.149761	.149976
15	-.009067	-.158691	.140558
16	.036803	-.112642	.186248
17	.061064	-.091167	.213296
18	.065146	-.091089	.221382
19	.081608	-.078272	.241488
20	.093806	-.069994	.257606

95% lower and upper bounds reported
(1) irfname = IRF, impulse = CILgrowth, and response = dWeiInterp

Figure 64 – CILgrowth shock in dWeiInterp COIRF for the model with optimal lag (p=11).

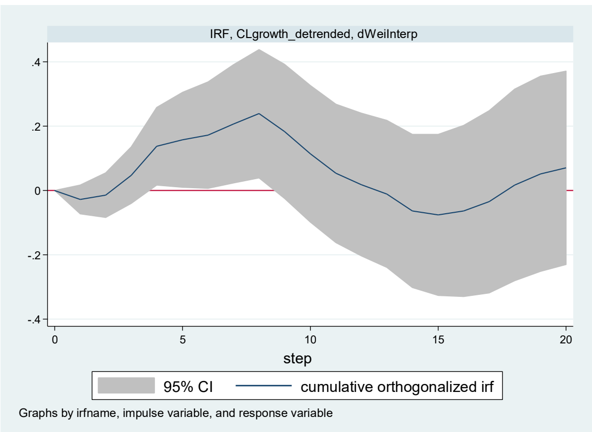
Figure 24 shows the long-run effects of the growth rate of commercial and industrial loans in the first differences of the weekly economic index. In this case, the negative effect occurs only in the first week and has a magnitude that is considered very close to zero.

Impulse: CLgrowth_detrended

Response: dWeiInterp

```
. irf graph coirf, set(IRF) irf(IRF) impulse (CLgrowth_detrended) response (dWeiInterp) yline(0)
(file IRF.irf now active)

. irf table coirf, set(IRF) irf(IRF) impulse (CLgrowth_detrended) response (dWeiInterp)
(file IRF.irf now active)
```



Results from IRF

step	(1) coirf	(1) Lower	(1) Upper
0	0	0	0
1	-.028422	-.073119	.016276
2	-.014605	-.083958	.054749
3	.046768	-.040899	.134435
4	.136803	.016413	.257193
5	.15718	.009741	.304619
6	.172212	.007005	.33742
7	.20676	.023172	.390348
8	.238321	.039389	.437253
9	.183471	-.025047	.391988
10	.113472	-.09897	.325914
11	.052851	-.162494	.268197
12	.017815	-.204037	.239667
13	-.011	-.239595	.217594
14	-.063856	-.301571	.173859
15	-.076344	-.326423	.173734
16	-.063912	-.329404	.201579
17	-.035142	-.318237	.247953
18	.01693	-.280677	.314537
19	.051565	-.251771	.354901
20	.069825	-.230778	.370428

95% lower and upper bounds reported
(1) irfname = IRF, impulse = CLgrowth_detrended, and response = dWeiInterp

Figure 75 – CLgrowth_detrended shock in dWeiInterp COIRF for the model with optimal lag (p=11).

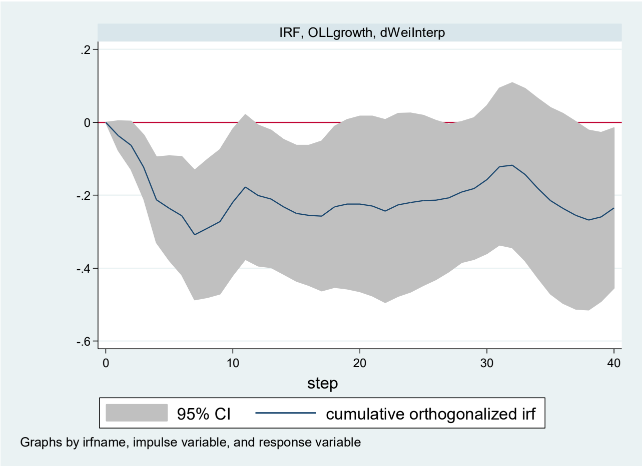
According to figure 25, a shock in the consumer loans growth rate increases dWeInterp from the fourth to the eighth week, peaking at the eighth week [0.039389; 0.437253].

Impulse: OLLgrowth

Response: dWeiInterp

```
. irf graph coirf, set(IRF) irf(IRF) impulse (OLLgrowth) response (dWeiInterp) yline(0)
(file IRF.irf now active)

. irf table coirf, set(IRF) irf(IRF) impulse (OLLgrowth) response (dWeiInterp)
(file IRF.irf now active)
```



Results from IRF

step	(1) coirf	(1) Lower	(1) Upper
0	0	0	0
1	-.036705	-.076861	.00345
2	-.063319	-.12976	.003122
3	-.123483	-.211267	-.035698
4	-.212696	-.329928	-.095463
5	-.235735	-.379368	-.092103
6	-.256757	-.418884	-.094631
7	-.30884	-.486436	-.131243
8	-.291011	-.48022	-.101802
9	-.27268	-.470555	-.074805
10	-.219274	-.419798	-.01875
11	-.177693	-.376382	.020997
12	-.201136	-.394527	-.007744
13	-.210179	-.398409	-.021949
14	-.23201	-.416881	-.047138
15	-.249558	-.436197	-.06292
16	-.255258	-.447584	-.062932
17	-.25706	-.462615	-.051505
18	-.232105	-.453209	-.011
19	-.224903	-.45683	.007024
20	-.223882	-.464828	.017064
21	-.22997	-.476459	.01652
22	-.243854	-.494893	.007185
23	-.226373	-.477468	.024723
24	-.220303	-.465691	.025085
25	-.214682	-.44777	.018405
26	-.213225	-.431236	.004787
27	-.207647	-.41006	-.005234
28	-.191186	-.384499	.002127
29	-.181881	-.375993	.012231
30	-.15727	-.359822	.045282
31	-.121563	-.336727	.093601
32	-.117696	-.343546	.108155
33	-.143642	-.379853	.092569
34	-.180538	-.426578	.065501
35	-.215089	-.470482	.040303
36	-.236122	-.496098	.023855
37	-.25572	-.512833	.001394
38	-.267825	-.514419	-.021231
39	-.260028	-.491647	-.028409
40	-.235133	-.454569	-.015696

95% lower and upper bounds reported
(1) irfname = IRF, impulse = OLLgrowth, and response = dWeiInterp

Figure 86 – OLLgrowth shock in dWeiInterp COIRF for the model with optimal lag (p=11).

By looking at figure 26, it is possible to conclude that a shock in OLLgrowth has a significant negative long-run effect on dWeiInterp from the third to the tenth week, with the peak occurring at the seventh week [-0.486436; -0.131243], the negative effect also holds from the twelfth until the eighteenth week, with the peak at the sixteenth week [-0.447584; -0.062932], and finally in the twenty-seventh week. The rest of the effect is insignificant[20].

4.4. VAR model with new confirmed Covid-19 deaths growth rate

The fourth VAR model is estimated to measure the impact of different types of credit on U.S real economic activity. The model contains six variables: deathsgrowth, dWeiInterp, CILgrowth, CLgrowth_detrended, OLLgrowth, and FF.

Given equation (2), our six-dimensional VAR(p) model has a vector of endogenous variables

$$Y_t = \begin{pmatrix} deathsgrowth \\ dWeiInterp \\ CILgrowth \\ CLgrowth\_detrended \\ OLLgrowth \\ FF \end{pmatrix}, \text{ and a vector of exogenous variables } X_t = \begin{pmatrix} vacgrowth \\ dummy \end{pmatrix}$$

[20] For this case, we generated the COIRFs 40 steps ahead due to the significance of the long-run response.

4.4.1. Stability condition and residual diagnostics

Figure C.77 shows the stability results for the model's largest "p" allowed. Again, all the eigenvalues lie inside the unit circle, concluding that the VAR model satisfies the stability condition for a maximum number of 10 lags[21].

4.4.2. Optimal lag selection

4.4.2.1. Minimum information criteria

As mentioned in subsection 3.3.1.5., we proceed to the optimal lag selection using the maximum correspondent number of lags (p) for which the model is stable.

According to AIC, SBIC, and HQIC, the optimal lag is always one (p=1), independently of the maximum number of lags we test for[22].

4.4.2.2. Wald lag-exclusion statistics test

According to the Wald lag-exclusion statistics test results in figure C.79, it is possible to conclude that all lags are jointly significant, which is not conclusive in selecting an optimal lag.

We are left with two main results, either the optimal (p) lag is the highest allowed in the VAR (p=10), or the optimal (p) lag is equal to one (p=1). Therefore, we select as optimal lag (p=10). Furthermore, as will be shown in the next section, there is autocorrelation between the errors for an optimal lag (p=1), which does not happen for the other case (p=10).

4.4.2.3. Residual diagnostics

According to the minimum information criteria results (SBIC and HQIC), the optimal lag is p=1. As so, we test for that possibility. Figure C.80 shows the Lagrange multiplier test for the serial correlation between residuals for p=1.

When the p-value is greater than the significance level, we cannot reject the null hypothesis of no serial correlation of the residuals at a specific lag order. For a significance level of 1%, we conclude that there is autocorrelation in the first lag. In this specific case, the optimal lag is p=1 according to minimum information criteria, which is wrongly assessed.

---

[21] The model is stable from (p=1) lags until (p=10) lags.

[22] The criteria were tested from (p=1) lags until (p=14) lags.

Figure C.81 shows the Lagrange multiplier test for the serial correlation of the residuals for p=11. Since the p-value is greater than the significance level, we cannot reject the null hypothesis of no serial correlation between residuals at a specific lag order. For a significance level of 1%, we conclude that there is no autocorrelation between the error terms at all lags[23].

More residuals diagnostics can be found in the Appendix (figure C.82, C.83, C.84)

4.4.2.4. Granger causality

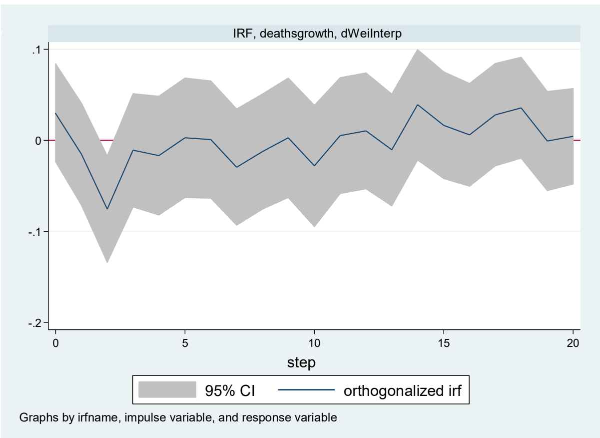
When analyzing the results of figure C.85, it is possible to evaluate that there is Granger causality among most variables. Therefore, we also decided to select 1% as the significance level in this case. Also, the first row of results is not interpretable since the identification scheme is based on the Cholesky decomposition; this means that deathsgrowth can affect the other variables but the other way around.[24]

4.4.2.5. Orthogonalized impulse response functions

Response: dWeiInterp

```
. irf graph oirf, set(IRF) irf(IRF) impulse (deathsgrowth) response (dWeiInterp) yline(0)
(file IRF.irf now active)

. irf table oirf, set(IRF) irf(IRF) impulse (deathsgrowth) response (dWeiInterp)
(file IRF.irf now active)
```



Results from IRF

step	(1) oirf	(1) Lower	(1) Upper
0	.030262	-.023458	.083981
1	-.015204	-.071222	.040815
2	-.075577	-.133884	-.01727
3	-.010797	-.073077	.051482
4	-.016676	-.081963	.048611
5	.002888	-.062853	.068629
6	.000983	-.063517	.065484
7	-.029464	-.093303	.034375
8	-.01226	-.07539	.05087
9	.002785	-.062895	.068465
10	-.028057	-.094727	.038613
11	.005354	-.058194	.068902
12	.01044	-.05319	.07407
13	-.010489	-.071955	.050976
14	.039194	-.021484	.099872
15	.01658	-.042093	.075252
16	.006051	-.050544	.062645
17	.028164	-.02797	.084299
18	.03574	-.019629	.091109
19	-.00085	-.055216	.053516
20	.004476	-.048063	.057015

95% lower and upper bounds reported
(1) irfname = IRF, impulse = deathsgrowth, and response = dWeiInterp

Figure 97 – deathsgrowth shock in dWeiInterp OIRFs for the model with optimal lag (p=10).

Figure 27 shows the effects of deathsgrowth shocks in dWeiInterp. We see that a one-standard-deviation shock in deathsgrowth decreases dWeiInterp in the second week between [- 0.01727; -0.133884] percentual points. After the second week, the effect goes rapidly to zero, with the statistical significance of the effect disappearing.[25]

---

[23] The vaccination rate assumed for the dummy variable was 33%.

[24]According to the Granger causality tests, there is no GC between CLgrowth_detrended and dWeiInterp for a significance level of 1%. In this way, the output will not be parsed.

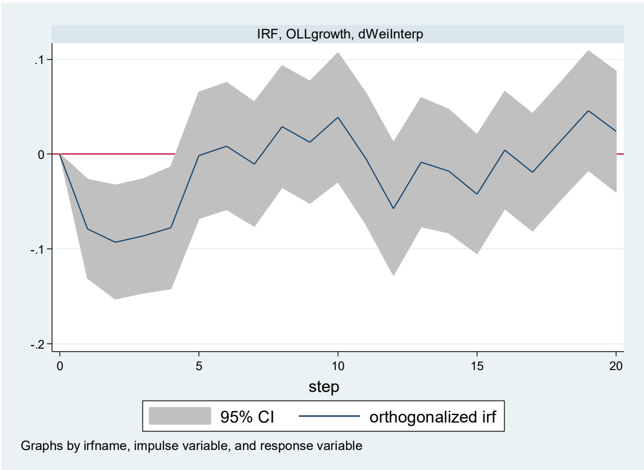
[25]Even though there is GC, a shock in CILgrowth does not have a significant response from dWeiInterp.

Impulse: OLLgrowth

Response: dWeiInterp

```
. irf graph oirf, set(IRF) irf(IRF) impulse (OLLgrowth) response (dWeiInterp) yline(0)
(file IRF.irf now active)

. irf table oirf, set(IRF) irf(IRF) impulse (OLLgrowth) response (dWeiInterp)
(file IRF.irf now active)
```



Results from IRF

step	(1) oirf	(1) Lower	(1) Upper
0	0	0	0
1	-.078768	-.130933	-.026602
2	-.09279	-.152773	-.032807
3	-.086232	-.146382	-.026082
4	-.077815	-.142087	-.013544
5	-.001353	-.067997	.065291
6	.008515	-.058322	.075352
7	-.010396	-.075885	.055093
8	.029031	-.035051	.093112
9	.012417	-.051862	.076696
10	.038868	-.029265	.107001
11	-.004512	-.07363	.064605
12	-.057643	-.127507	.012222
13	-.0086	-.076447	.059248
14	-.017898	-.082972	.047175
15	-.042169	-.104719	.020381
16	.004271	-.057354	.065896
17	-.019272	-.081178	.042633
18	.013445	-.048308	.075199
19	.045875	-.01701	.10876
20	.023857	-.03973	.087444

95% lower and upper bounds reported
(1) irfname = IRF, impulse = OLLgrowth, and response = dWeiInterp

Figure 108 – OLLgrowth shock in dWeiInterp OIRFs for the model with optimal lag (p=10).

Assessing figure 28, it is possible to conclude that a shock in OLLgrowth has a significant negative effect on dWeiInterp from the first to the fourth week, with the peak occurring at the second week [-0.152773; -0.032807], the rest of the effect is insignificant. However, results are robust with the third VAR in section 4.3..

4.4.2.6. Cumulative orthogonalized impulse response functions

OLLgrowth is the only variable with a significant accumulated effect in dWeiInterp.

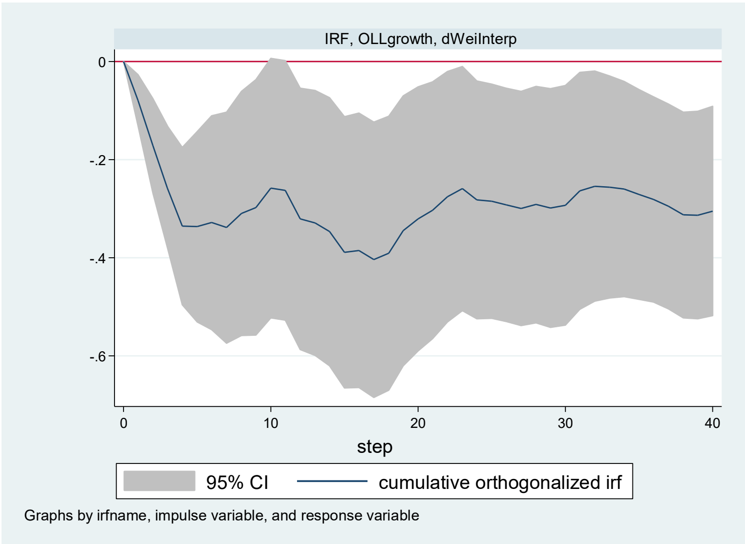
Impulse: OLLgrowth

Response: dWeiInterp

```
. irf graph coirf, set(IRF) irf(IRF) impulse (OLLgrowth) response (dWeiInterp) yline(0)
(file IRF.irf now active)

. irf table coirf, set(IRF) irf(IRF) impulse (OLLgrowth) response (dWeiInterp)
(file IRF.irf now active)
```

By looking at figure 29, it is possible to conclude that a shock in OLLgrowth has a significant negative long-run effect on dWeiInterp from the first to the ninth week, with the peak occurring at the fifth week [-0.530772; -0.143142], the negative effect also holds from the twelfth until the eighteenth week, with the peak at the sixteenth week [-0.447584; -0.062932], and finally in the twenty-seventh week. The rest of the effect is insignificant.



Results from IRF

step	(1) coirf	(1) Lower	(1) Upper
0	0	0	0
1	-.078768	-.130933	-.026602
2	-.171557	-.267868	-.075247
3	-.257789	-.382778	-.1328
4	-.335604	-.495923	-.175286
5	-.336957	-.530772	-.143142
6	-.328442	-.546415	-.11047
7	-.338838	-.574663	-.103014
8	-.309808	-.559091	-.060525
9	-.297391	-.558317	-.036465
10	-.258523	-.523324	.006278
11	-.263035	-.52771	.00164
12	-.320678	-.587126	-.054231
13	-.329278	-.599405	-.05915
14	-.347176	-.620366	-.073986
15	-.389345	-.666205	-.112485
16	-.385074	-.664749	-.105399
17	-.404346	-.685198	-.123495
18	-.390901	-.67027	-.111532
19	-.345026	-.620249	-.069802
20	-.321168	-.590522	-.051815
21	-.30321	-.564919	-.041501
22	-.275291	-.530741	-.019841
23	-.259032	-.508417	-.009647
24	-.28209	-.524854	-.039327
25	-.284776	-.523893	-.045658
26	-.29249	-.5307	-.054279
27	-.299798	-.538344	-.061253
28	-.291616	-.532752	-.05048
29	-.298665	-.542504	-.054825
30	-.293019	-.537218	-.04882
31	-.263855	-.505477	-.022233
32	-.254184	-.488667	-.019701
33	-.25591	-.482074	-.029746
34	-.259699	-.479176	-.040222
35	-.27108	-.484685	-.057475
36	-.280937	-.490304	-.07157
37	-.295529	-.504242	-.086815
38	-.312926	-.522739	-.103112
39	-.313075	-.524364	-.101786
40	-.305107	-.518611	-.091602

95% lower and upper bounds reported
(1) irfname = IRF, impulse = OLLgrowth, and response = dWeiInterp

Figure 119 – OLLgrowth shock in dWeiInterp COIRFs for the model with optimal lag (p=10).

5. Concluding Remarks

Based on weekly data over the last two and a half years and the registered number of cases and deaths related to the pandemic, we estimate for the U.S economy the impact of Covid-19 in some macroeconomic aggregates using the Cholesky decomposition as the identification scheme restriction in VAR models. This thesis contributes to recent literature on the effects of the Covid-19 pandemic on the economy and fills the gap of the lack of studies using the variables chosen. Also, it assesses the impacts of different types of credit on real economic activity, which can add value to the scope of policy making.

Our main empirical results point out that a one-standard deviation Covid-19 growth rate shock in cases and deaths can create an average drop in the following first weeks of between 0.16% and 0.3% in the changes of real economic activity index. Also, when analyzing different loan types' capability to boost the real U.S. economic activity, we conclude that the most effective ones in the short run are consumer, commercial and industrial loans, which create a positive effect of around 0.02% and 0.15%. These findings support the idea that the allocation of credit is important for financial development and real economic activity performance. Moreover, the effect of the pandemic on the variables of interest tends to have a short memory, but the constant increases in the growth rate of cases and deaths create a continuously lasting effect. Finally, as in recent Covid-19 literature, our VAR model is acceptable for parameter estimation but not an accurate model to forecast the future values of the economic aggregates.

The study of the pandemic effects is challenging and can have gaps as the new pandemic observations distort parameter estimation, and impulse response functions become explosive. To control these matters, we decided to drop the pandemic initial observations, as did the prior works related to this subject. Also, Covid-19 cases and deaths are used to define the pandemic series but are not economic series, which can complicate the models' estimation. Also, the frequency used in the model can overestimate or underestimate the effects. One way to improve this could be by implementing a time-varying parameter VAR (TVP- VAR) model, as it allows for the coefficients to vary over time. Moreover, this research may not have controlled for all the factors involved in the pandemic as several more instrumental variables could be taken into account, such as quarantines and lockdowns, the twelve-day period it takes for the protective effect of the vaccine to become active in an individual, and the exact time when was reached herd immunity, which is debatable.

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Appendix

Variable	Hyperlink
New confirmed Covid-19 cases (NCC) New confirmed Covid-19 deaths (NCD) Total vaccinations per hundred (vac)	https://github.com/owid/covid-19-data/tree/master/public/data
Balance sheet of Commercial Banks in the U.S.	https://fred.stlouisfed.org/release/tables?rid=22&eid=822916#snid=822918
Loans and leases in bank credit (LLBC) Commercial and industrial loans (CIL) consumer loans (CL) other loans and leases (OLL)	https://fred.stlouisfed.org/series/TOTLL Commercial and Industrial Loans, All Commercial Banks (TOTCI) | FRED | St. Louis Fed (stlouisfed.org) https://fred.stlouisfed.org/series/CLSACBW027SBOG https://fred.stlouisfed.org/series/AOLACBW027SBOG
Loans to commercial banks (LCB)	https://fred.stlouisfed.org/series/LCBACBW027SBOG
Weekly economic index (WEI)	https://fred.stlouisfed.org/series/WEI
Federal Funds Effective Rate (FF)	https://fred.stlouisfed.org/series/FF

Table 1 - hyperlinks containing the data available for download

A) Descriptive Statistics and time series plots

```
. summarize casesgrowth deathsgrowth dWeiInterp LCBLLBCgrowth FF CILgrowth CLgrowth OLLgrowth vacgrowth
```

Variable	Obs	Mean	Std. Dev.	Min	Max
casesgrowth	106	.2328356	1.222583	-.4722698	10.06061
deathsgrowth	106	.2103837	1.20475	-.6391673	11
dWeiInterp	105	.0357007	.763435	-2.747143	2.981429
LCBLLBCgro~h	106	.0007934	.0035675	-.0044155	.021382
FF	106	.109434	.180849	.04	1.51
CILgrowth	106	.0007793	.0114071	-.0153288	.063511
CLgrowth	106	.0005472	.0028078	-.0108415	.0054347
OLLgrowth	106	.0021378	.0061397	-.0086815	.0393018
vacgrowth	122	.642459	.9405338	0	3.91

Table A.1 – Descriptive statistics of the variables

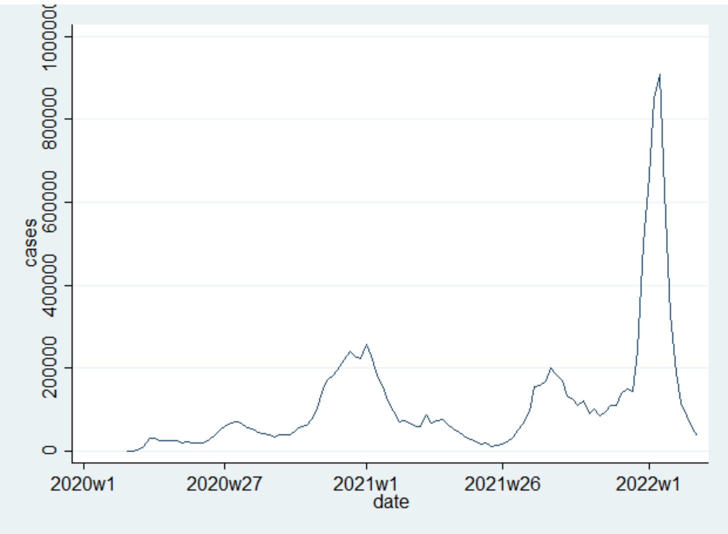


Figure A.1 - U.S new confirmed Covid-19 cases time series

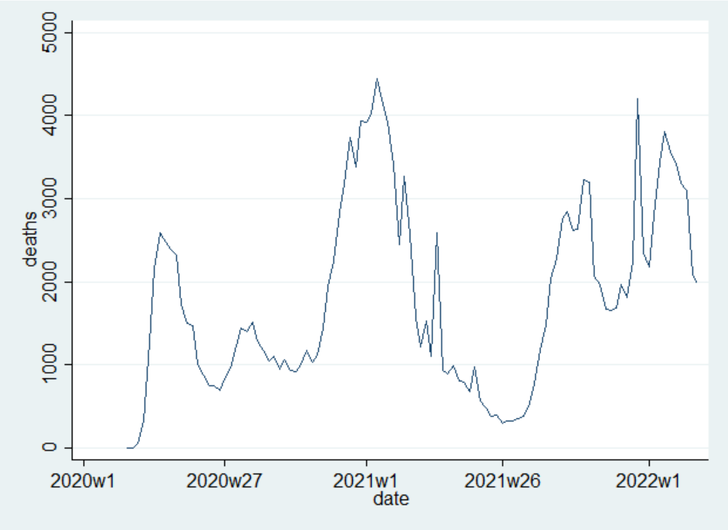


Figure A.2 - U.S new confirmed Covid-19 deaths time series

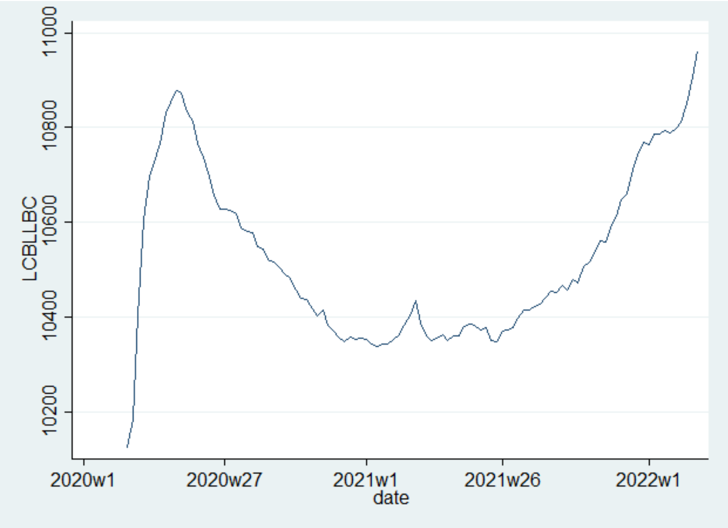


Figure A.3 - U.S total credit time series

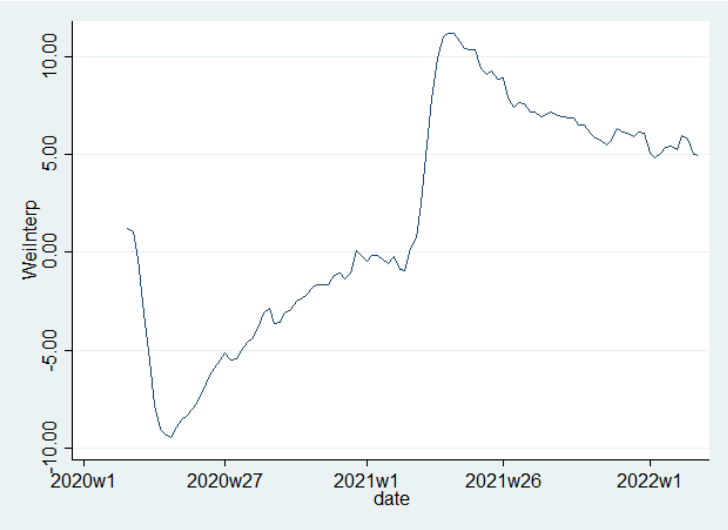


Figure A.4 - Weekly economic index time series

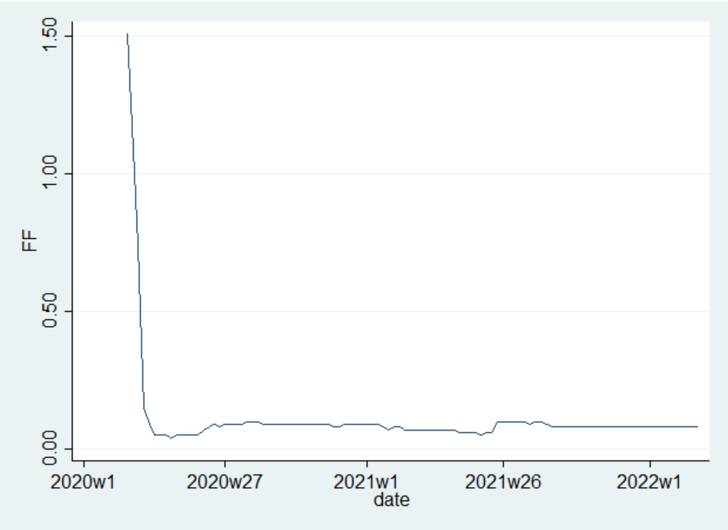


Figure A.5 - Fed funds effective rate time series

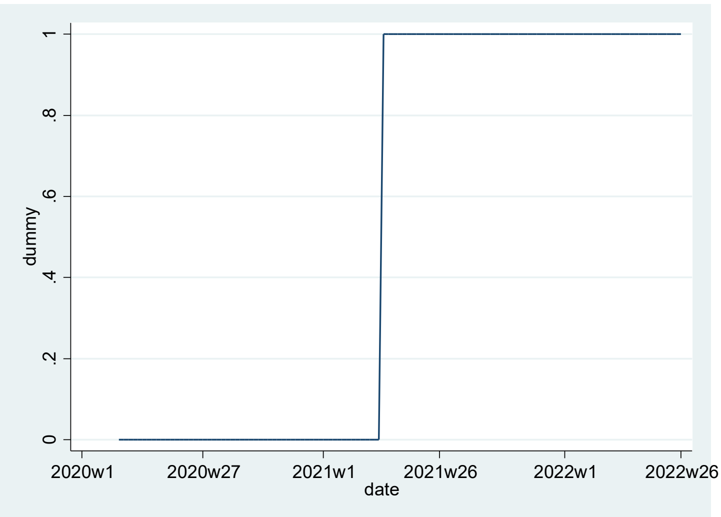


Figure A.6 - Dummy time series

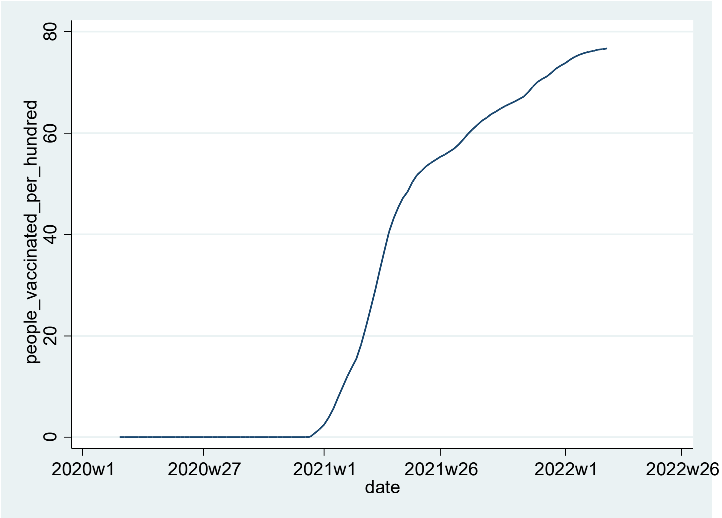


Figure A.7 - vac time series

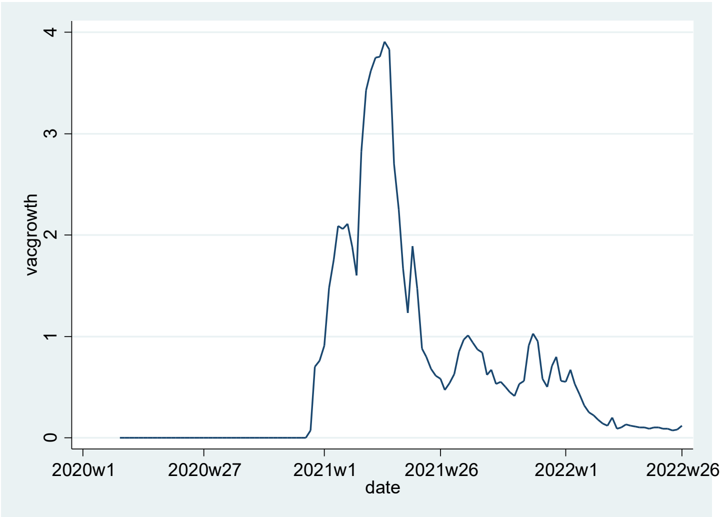


Figure A.8 - vacgrowth time series

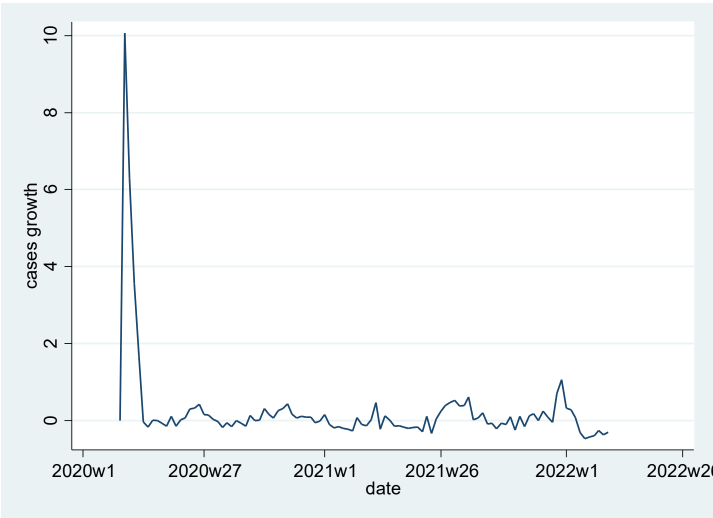


Figure A.9 - U.S new confirmed Covid-19 cases growth rate time series

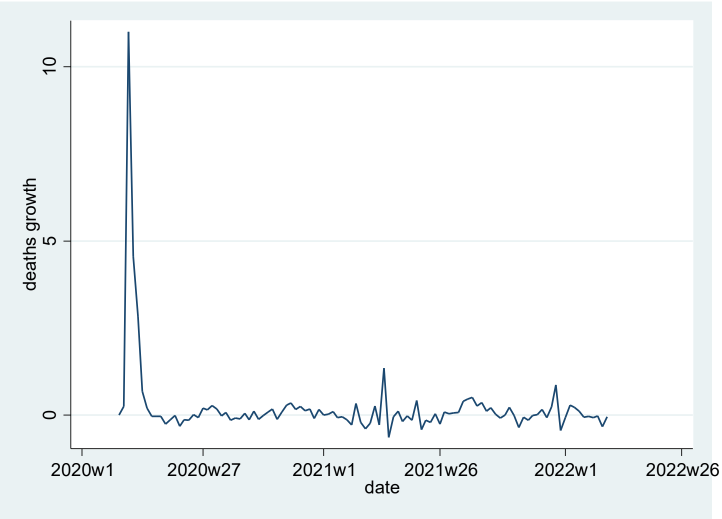


Figure A.10 - U.S new confirmed Covid-19 deaths growth rate time series

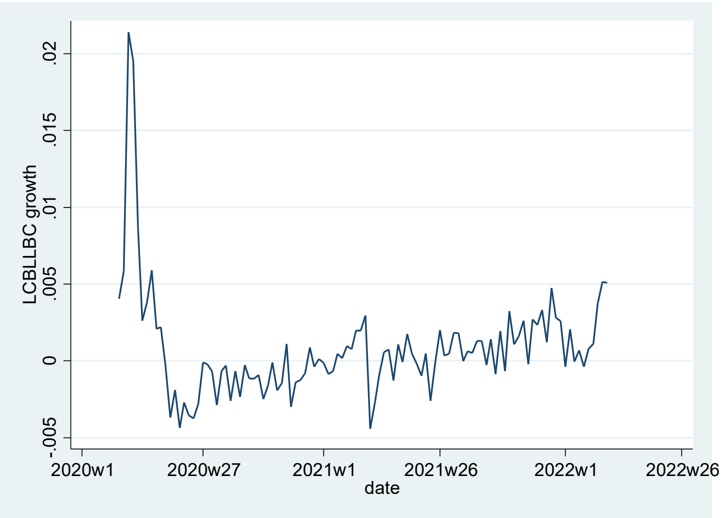


Figure A.11 - U.S total credit growth rate time series

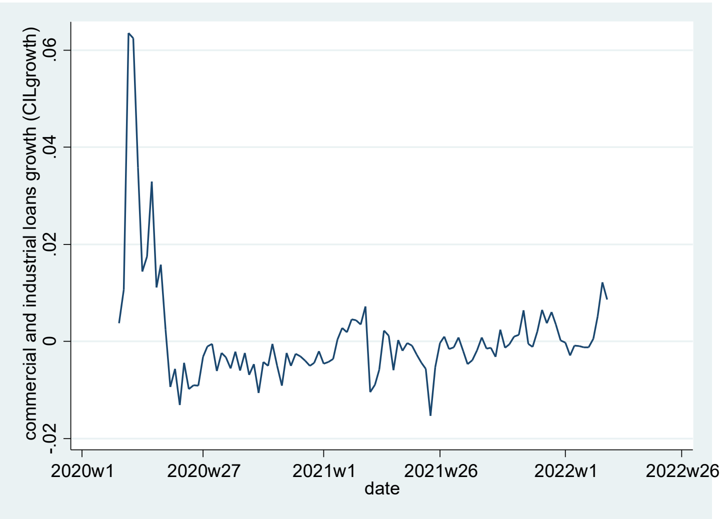


Figure A.12 - U.S Commercial and industrial loans growth rate time series

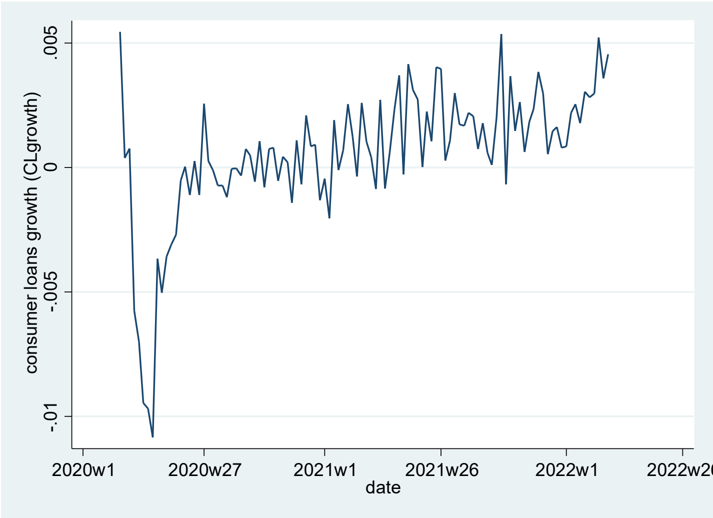


Figure A.13 - U.S consumer loans growth rate time series

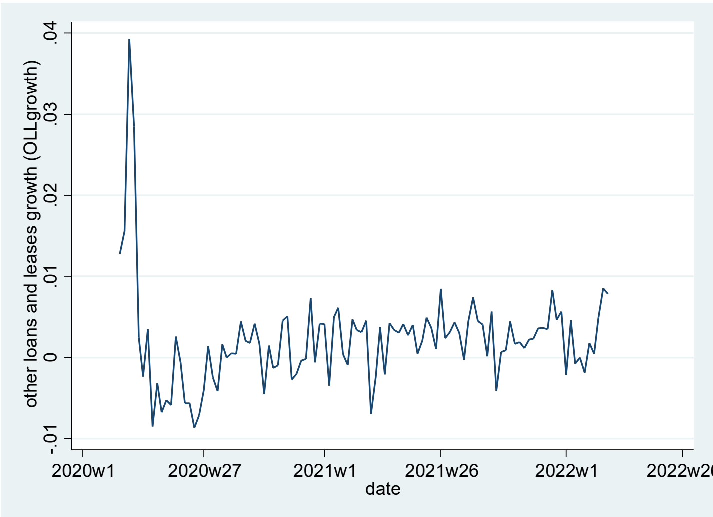


Figure A.14 - U.S Other loans and leases growth rate time series

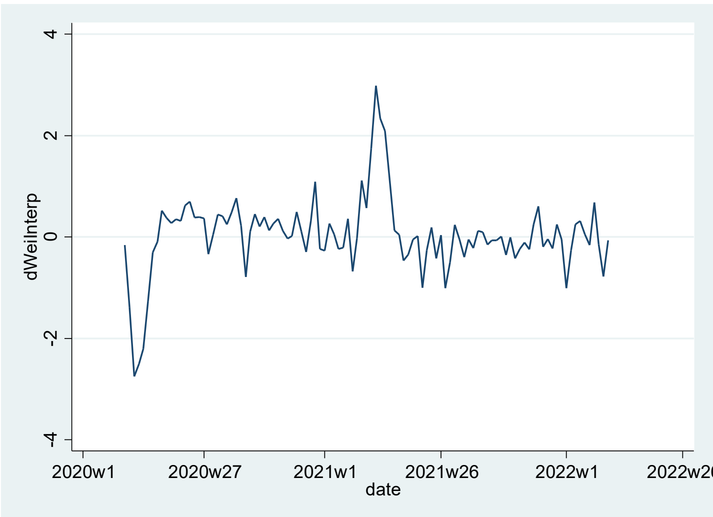


Figure A.15 – Interpolated weekly economic index in first differences time series

B) VAR model background

The general reduced form of a K dimensional VAR(p) model with p lags and exogenous variables:

$$Y_t = C + \phi_p Y_{t-p} + \Gamma_q X_{t-q} + V_t \qquad (3)$$

Where:

$$Y_t = \begin{pmatrix} y_{1t} \\ \cdots \\ y_{kt} \end{pmatrix};\ C = \begin{pmatrix} c_1 \\ \cdots \\ c_k \end{pmatrix};\ \phi_p = \begin{pmatrix} \varphi_{11}^{(p)} & \cdots & \varphi_{1k}^{(p)} \\ \cdots & \cdots & \cdots \\ \varphi_{k1}^{(p)} & \cdots & \varphi_{kk}^{(p)} \end{pmatrix};\ Y_{t-p} = \begin{pmatrix} y_{1t-p} \\ \cdots \\ y_{kt-p} \end{pmatrix};\ X_t = \begin{pmatrix} x_{1t} \\ \cdots \\ x_{kt} \end{pmatrix};\ \Gamma_q = \begin{pmatrix} \gamma_{11}^{(q)} & \cdots & \gamma_{1k}^{(q)} \\ \cdots & \cdots & \cdots \\ \gamma_{k1}^{(q)} & \cdots & \gamma_{kk}^{(q)} \end{pmatrix};$$

$$X_{t-q} = \begin{pmatrix} x_{1t-q} \\ \cdots \\ x_{kt-q} \end{pmatrix};\ V_t = \begin{pmatrix} v_{1t} \\ \cdots \\ v_{kt} \end{pmatrix};$$

Which can also be written as:

$$y_{it} = c_i + \varphi_{i1}^{(1)} y_{1t-1} + \cdots + \varphi_{ik}^{(1)} y_{kt-1} + \cdots + \varphi_{i1}^{(p)} y_{1t-1} + \cdots + \varphi_{ik}^{(p)} y_{kt-1} + \gamma_{i1}^{(1)} x_{1t-1} + \cdots + \gamma_{ik}^{(1)} x_{kt-1} + \cdots + \gamma_{i1}^{(p)} x_{1t-1} + \cdots + \gamma_{ik}^{(p)} x_{kt-1} + v_{it},\ \text{with i} = 1, \ldots, \text{k} \qquad (4)$$

Linkage between unrestricted and structural model with Cholesky decomposition:

The general structural form of a "k" dimensional VAR(p) model with "p" lags and exogenous variables using the Cholesky decomposition:

$$A_0 y_t = D + \alpha_1 y_{t-1} + \cdots + \alpha_p y_{t-p} + \rho_1 x_{t-1} + \cdots + \rho_p x_{t-p} + B\varepsilon_t,\ \text{with p} = 1, \ldots, \text{k} \qquad (8)$$

The general structural form of a "k" dimensional VAR(p) model with "p" lags and exogenous variables in matrix notation using the Cholesky decomposition:

$$(A_0)\begin{pmatrix} y_{1t} \\ \cdots \\ y_{kt} \end{pmatrix} = \begin{pmatrix} d_1 \\ \cdots \\ d_k \end{pmatrix} + \begin{pmatrix} \alpha_{11}^{(1)} & \cdots & \alpha_{1k}^{(1)} \\ \cdots & \cdots & \cdots \\ \alpha_{k1}^{(1)} & \cdots & \alpha_{kk}^{(1)} \end{pmatrix}\begin{pmatrix} y_{1t-1} \\ \cdots \\ y_{kt-1} \end{pmatrix} + \cdots + \begin{pmatrix} \alpha_{11}^{(p)} & \cdots & \alpha_{1k}^{(p)} \\ \cdots & \cdots & \cdots \\ \alpha_{k1}^{(p)} & \cdots & \alpha_{kk}^{(p)} \end{pmatrix}\begin{pmatrix} y_{1t-p} \\ \cdots \\ y_{kt-p} \end{pmatrix} +$$
$$\begin{pmatrix} \rho_{11}^{(1)} & \cdots & \rho_{1k}^{(1)} \\ \cdots & \cdots & \cdots \\ \rho_{k1}^{(1)} & \cdots & \rho_{kk}^{(1)} \end{pmatrix}\begin{pmatrix} x_{1t-1} \\ \cdots \\ x_{kt-1} \end{pmatrix} + \begin{pmatrix} \rho_{11}^{(q)} & \cdots & \rho_{1k}^{(q)} \\ \cdots & \cdots & \cdots \\ \rho_{k1}^{(q)} & \cdots & \rho_{kk}^{(q)} \end{pmatrix}\begin{pmatrix} x_{1t-q} \\ \cdots \\ x_{kt-q} \end{pmatrix} + B\begin{pmatrix} \varepsilon_{1t} \\ \cdots \\ \varepsilon_{kt} \end{pmatrix} \qquad (9)$$

Or:

$$A_0 Y_t = D + \mathrm{A}_p Y_{t-p} + \mathrm{P}_p X_{t-q} + BE_t \qquad (10)$$

Where, $Y_t = \begin{pmatrix} y_{1t} \\ \cdots \\ y_{kt} \end{pmatrix}; X_t = \begin{pmatrix} x_{1t} \\ \cdots \\ x_{kt} \end{pmatrix}; D = \begin{pmatrix} d_1 \\ \cdots \\ d_k \end{pmatrix}; \mathrm{A}_p = \begin{pmatrix} \alpha_{11}^{(p)} \dots \alpha_{1k}^{(p)} \\ \dots \quad \dots \quad \dots \\ \alpha_{k1}^{(p)} \dots \alpha_{kk}^{(p)} \end{pmatrix}; Y_{t-p} = \begin{pmatrix} y_{1t-p} \\ \cdots \\ y_{kt-p} \end{pmatrix}; X_{t-q} = \begin{pmatrix} x_{1t-q} \\ \cdots \\ x_{kt-q} \end{pmatrix}; \mathrm{P}_1 = \begin{pmatrix} \rho_{11}^{(q)} \dots \rho_{1k}^{(q)} \\ \dots \quad \dots \quad \dots \\ \rho_{k1}^{(q)} \dots \rho_{kk}^{(q)} \end{pmatrix}; \ V_t = B \begin{pmatrix} \varepsilon_{1t} \\ \cdots \\ \varepsilon_{kt} \end{pmatrix}; E_t = \begin{pmatrix} \varepsilon_{1t} \\ \cdots \\ \varepsilon_{kt} \end{pmatrix}$

Which can also be written as:

$$A_0 y_{it} = d_i + \alpha_{i1}^{(1)} y_{1t-1} + \cdots + \alpha_{ik}^{(1)} y_{kt-1} + \cdots + \alpha_{i1}^{(p)} y_{1t-1} + \cdots + \alpha_{ik}^{(p)} y_{kt-1} +$$
$$+ \rho_{i1}^{(1)} x_{1t-1} + \cdots + \rho_{ik}^{(1)} x_{kt-1} + \cdots + \rho_{i1}^{(q)} x_{1t-1} + \rho_{ik}^{(q)} x_{kt-1} + B\varepsilon_{it}, \text{ with } \mathrm{i} = 1, \dots, \mathrm{k} \quad (11)$$

Where each Y_i represents a vector of endogenous variables of length k, each A_p and P_i is a $K \times K$ matrix, D is an $K \times 1$ vector of intercepts, and X_i represents a vector of exogenous variables of length $K \times 1$. E_t represents a $K \times 1$ vector of uncorrelated structural orthogonal shocks ε_t.

Finally, in order to relate the unrestricted VAR(p) with the SVAR(p), we need to pre-multiply A_0^{-1} on the SVAR:

$$A_0 y_t = D + \alpha_1 y_{t-1} + \cdots + \alpha_p y_{t-p} + \rho_1 x_{t-1} + \cdots + \rho_p x_{t-q} + B\varepsilon_t$$

$$y_t = A_0^{-1} D + A_0^{-1} \alpha_1 y_{t-1} + \cdots + A_0^{-1} \alpha_p y_{t-p} + A_0^{-1} \rho_1 x_{t-1} + \cdots + A_0^{-1} \rho_p x_{t-q} + A_0^{-1} B\varepsilon_t$$

$$y_t = C + \varphi_1 y_{t-1} + \cdots + \varphi_p y_{t-p} + \gamma_1 x_{t-1} + \cdots + \gamma_p x_{t-q} + v_t \quad (12)$$

With:

$$C = A_0^{-1} D$$

$$\varphi_p = A_0^{-1} \mathrm{A}_p$$

$$\mathrm{v}_t = A_0^{-1} B\varepsilon_t$$

$$\Omega = A_0^{-1} B B' A'^{-1}_0$$

$$\omega_{ij,h} = \frac{\sigma_j^2 \sum_{s=0}^{h-1} c_{ij,s}^2}{\sum_{j=1}^{k} (\sigma_j^2 \sum_{s=0}^{h-1} c_{ij,s}^2)}$$

With $i = 1, 2, \dots, k$

Identification scheme strategy

The Cholesky decomposition implies that $A_0 = I_k$. Also, the variance-covariance matrix Ω is the identity matrix, meaning that diagonals are ones and off diagonals are zeros, which implies that $v_t =$

$B\varepsilon_t$. (v_t does not have to be pure white noise, the expectation is zero since it is unpredictable, but the variance is not necessarily equal to one).

Stability condition and residual diagnostics

To test for stability in our model, we use the command varstable, which calculates the eigenvalues of the companion matrix in modulus. If all modulus of each eigenvalue is less than one and lie outside the unit circle (i.e., are bigger than one in absolute value), then we have a stable VAR. This is, $|\phi_p - \lambda I_k| = 0$, where λ, represents the eigenvalues of the matrix ϕ_p.

The stability of a VAR model can also be tested by calculating if the $k \times p$ characteristic roots, z, of the lag polynomial equation $|\Pi(z)| = |I_k - \phi_1 z - \phi_2 z^2 - \cdots - \phi_p z^p| = 0$ are outside the unit circle.

The stability test is performed until we reach a "p" lag that turns the model into an unstable one. Then, the objective is to find the maximum "p" allowed for the model to compute the optimal lag selection tests.

Regarding the Lagrange multiplier test statistic (LM) for the serial correlation between residuals, the command varlmar is used. If the p-value is > significance level, we cannot reject the null hypothesis of no serial correlation between residuals at a specific lag order. Therefore, we will perform the Lagrange multiplier test for the serial correlation between residuals for a significance level of 1%. In the Appendix section, after choosing the optimal lag, we will also show the residuals of the variables, the covariance, and the correlation between variables for each model.

Optimal lag selection

The optimal lag selection is essential to improve model estimation. We focus on two methods to choose the optimal lag, the minimum information criteria and the Wald lag-exclusion statistics test. Sometimes it can happen that the criteria do not agree, so when choosing the optimal lag, it is mandatory to have some degree of judgment, logic, or reasoning when choosing between the recommendations. Furthermore, macroeconomic relationships held in the past must be assumed to be still valid.

Granger causality

To perform the test, we use the command *vargranger*. Stata uses an F-test to jointly test the significance of the lags in the explanatory variables by employing a Wald test. The null hypothesis is that the estimated coefficients on the lagged values of X are jointly zero. In other words, if the null hypothesis is not rejected, there is no Granger causality between variables. The GC test results of causal relationships are purely statistical.

The null hypothesis tested is the following:

$$\begin{cases} H_0: \phi_1 = \phi_2 = \cdots = \phi_k = 0 \\ H_1 \exists: \phi_j \neq 0 \end{cases} \quad (7)$$

The Granger causality tests will be performed for a significance level of 10%.

Point forecast and forecast error

The Forecast error is a measure that, according to each criterion, measures the difference between the observed and predicted values.

To verify the quality of each forecast, we analyze the forecast errors. Those we look for are the most common in the literature, more specifically, the Mean Absolute Error (MAE), Mean squared error (MSE), Root mean square error (RMSE), Mean absolute percentage error (MAPE), and Root mean square percentage error (RMSPE).

Forecast error variance decomposition

Usually, the shocks reflected on the series explain most of the error's variance, but the shocks also affect other variables in the system. Variance decomposition requires identifying restrictions, as in the OIRF, the variance decomposition applies the Cholesky decomposition for identification purposes. It is important to stress that, as in IRFs, the conclusions of variance decomposition can change according to the underlying assumptions. Since it also is connected to the identification scheme, the ordering of the variables may also play an important role.

The command *varbasic* is applied instead of *var* to achieve the output regarding the forecast error variance decomposition. In order to maintain the Cholesky decomposition as in the OIRFs, the command *fevd* is used after the number of steps ahead we desire to test.

The FEVDs are computed 16 weeks ahead, using the command *fevd*.

C) Empirical results

Stationarity tests

The ADF test hypothesis:

$$\begin{cases} H_0: A = \phi - 1 = 0 \\ H_1: A < 0 \end{cases} \quad (5)$$

Where testing for $A = 0$ is the same as testing for a presence of a unit root in y_t.

Augmented Dickey Fuller test with constant (ADFc) in levels						
Variable	Lags	t-Statistic	1% t-Statistic	p-value	Accepts H0/H1	Stationary/Non-Stationary

casesgrowth	1	-5.296	-2.580	0.0000	Accepts H1	Stationary
	5	-4.633	-2.580	0.0001	Accepts H1	Stationary
deathsgrowth	0	-6.556	-2.580	0.0000	Accepts H1	Stationary
WeiInterp	2	-1.628	-2.580	0.4683	Accepts H0	Non-Stationary
	5	-1.801	-2.580	0.3800	Accepts H0	Non-Stationary
LCBLLBCgrowth	2	-3.999	-2.580	0.0014	Accepts H1	Stationary
FF	1	-19.257	-2.580	0.0000	Accepts H1	Stationary
CILgrowth	1	-3.771	-2.580	0.0032	Accepts H1	Stationary
	6	-4.511	-2.580	0.0002	Accepts H1	Stationary
CLgrowth	4	-2.474	-2.580	0.1220	Accepts H0	Non-Stationary
OLLgrowth (10% statistic test)	1	-5.341	-2.580	0.0000	Accepts H1	Stationary
	12	-2.587	-2.582	0.0957	Accepts H1	Stationary
Augmented Dickey Fuller test with trend (ADFct) in levels						
Variables	**Lags**	**t-Statistic**	**10% t-Statistic**	**p-value**	**Accepts H0/H1**	**DSP/ TSP**
WeiInterp	1	-3.206	-3.149	0.0832	Accepts H1	TSP
	5	-1.417	-3.150	0.8560	Accepts H0	DSP
CLgrowth	4	-3.809	-3.150	0.0161	Accepts H1	TSP

Table C.1 - Stationarity tests results

```
. varsoc casesgrowth, maxlag(12)

   Selection-order criteria
   Sample:  2020w21 - 2022w10                     Number of obs      =        94

  +---------------------------------------------------------------------------+
  |lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
  |----+----------------------------------------------------------------------|
  |  0 | -7.07314                      .069522   .171769   .182698   .198825  |
  |  1 |  14.0363  42.219    1  0.000  .045322  -.256091  -.234233  -.201978* |
  |  2 |   15.441  2.8095    1  0.094  .044934  -.264702  -.231916  -.183533  |
  |  3 |  15.5074   .1328    1  0.716  .045837  -.244838  -.201123  -.136613  |
  |  4 |  17.6196  4.2245    1  0.040  .044767  -.268503  -.213859  -.133221  |
  |  5 |   20.571  5.9027    1  0.015   .04295   -.31002  -.244448* -.147682  |
  |  6 |  20.6119  .08191    1  0.775   .04384  -.289615  -.213114  -.100221  |
  |  7 |  21.9047  2.5856    1  0.108  .043573  -.295845  -.208414  -.079394  |
  |  8 |   22.298  .78664    1  0.375  .044147  -.282937  -.184578   -.03943  |
  |  9 |  22.5881  .58022    1  0.446  .044829  -.267832  -.158545   .002731  |
  | 10 |  22.9603  .74432    1  0.388  .045444  -.254474  -.134258   .043145  |
  | 11 |  28.8321  11.744*   1  0.001  .040983*  -.35813* -.226984  -.033454  |
  | 12 |  28.8889  .11366    1  0.736  .041829  -.338062  -.195988    .01367  |
  +---------------------------------------------------------------------------+
   Endogenous:  casesgrowth
    Exogenous:  _cons
```

```
. dfuller casesgrowth, regress lags(10)

Augmented Dickey-Fuller test for unit root         Number of obs   =        95

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -3.580            -3.517            -2.894            -2.582
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0062

------------------------------------------------------------------------------
D.           |
 casesgrowth |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 casesgrowth |
         L1. |  -.5741987   .1603868    -3.58   0.001    -.8932017   -.2551958
         LD. |   .0090504    .152657     0.06   0.953    -.2945781    .3126789
        L2D. |    .200641   .1387507     1.45   0.152    -.0753286    .4766107
        L3D. |    .385953   .1353265     2.85   0.005      .116794    .6551121
        L4D. |   .3273159   .1395103     2.35   0.021     .0498356    .6047962
        L5D. |   .0884037   .1403945     0.63   0.531    -.1908353    .3676426
        L6D. |   .0751342   .1205653     0.62   0.535    -.1646654    .3149338
        L7D. |   -.033992   .0843638    -0.40   0.688    -.2017883    .1338043
        L8D. |  -.0181382   .0671309    -0.27   0.788    -.1516588    .1153824
        L9D. |    .032654   .0589823     0.55   0.581    -.0846593    .1499673
       L10D. |   .0096311   .0247493     0.39   0.698    -.0395942    .0588565
             |
       _cons |   .0266139   .0234142     1.14   0.259     -.019956    .0731837
------------------------------------------------------------------------------


. dfuller casesgrowth, regress lags(0)

Dickey-Fuller test for unit root                   Number of obs   =       105

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -5.296            -3.508            -2.890            -2.580
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000

------------------------------------------------------------------------------
D.           |
 casesgrowth |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 casesgrowth |
         L1. |  -.4287439    .080962    -5.30   0.000    -.5893131   -.2681748
             |
       _cons |    .099143   .1007507     0.98   0.327    -.1006723    .2989583
------------------------------------------------------------------------------
```

```
. varsoc deathsgrowth, maxlag(12)

   Selection-order criteria
   Sample:  2020w21 - 2022w10                   Number of obs      =        94
  +---------------------------------------------------------------------------+
  |lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
  |----+----------------------------------------------------------------------|
  |  0 | -8.50204                      .071668*  .202171*    .2131*  .229227* |
  |  1 | -8.17576  .65256    1  0.419  .072704   .216506   .238363   .270618  |
  |  2 | -6.91983  2.5119    1  0.113   .07231    .21106   .243847   .292229  |
  |  3 | -6.17866  1.4823    1  0.223  .072711   .216567   .260282   .324792  |
  |  4 | -5.94654  .46424    1  0.496  .073913   .232905   .287549   .368187  |
  |  5 | -5.78134   .3304    1  0.565  .075243   .250667   .316239   .413005  |
  |  6 | -5.62005  .32257    1  0.570  .076605   .268512   .345013   .457906  |
  |  7 | -5.41871  .40268    1  0.526  .077929   .285505   .372935   .501955  |
  |  8 | -4.33293  2.1716    1  0.141    .0778   .283679   .382038   .527186  |
  |  9 | -4.29704  .07178    1  0.789   .07943   .304192    .41348   .574756  |
  | 10 | -4.23805  .11797    1  0.731  .081058   .324214    .44443   .621834  |
  | 11 | -2.76018  2.9557    1  0.086  .080264   .314046   .445192   .638722  |
  | 12 | -2.52106  .47824    1  0.489  .081606   .330235   .472309   .681968  |
  +---------------------------------------------------------------------------+
   Endogenous:  deathsgrowth
    Exogenous:  _cons
```

```
. dfuller deathsgrowth, regress lags(0)

Dickey-Fuller test for unit root                   Number of obs   =       105

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -6.556            -3.508            -2.890            -2.580
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000

------------------------------------------------------------------------------
D.           |
deathsgrowth |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
deathsgrowth |
         L1. |  -.5889423   .0898316    -6.56   0.000    -.7671022   -.4107825
             |
       _cons |   .1248953   .1098771     1.14   0.258      -.09302    .3428107
------------------------------------------------------------------------------


. varsoc LCBLLBCgrowth, maxlag(12)

   Selection-order criteria
   Sample:  2020w21 - 2022w10                  Number of obs      =        94
  +---------------------------------------------------------------------------+
  |lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
  |----+----------------------------------------------------------------------|
  |  0 |  453.086                      3.9e-06  -9.61885  -9.60792   -9.5918  |
  |  1 |  469.902  33.631    1  0.000  2.8e-06  -9.95535  -9.93349  -9.90124  |
  |  2 |  476.806  13.808*   1  0.000  2.5e-06*  -10.081* -10.0482*  -9.9998* |
  |  3 |  476.812  .01242    1  0.911  2.5e-06  -10.0598  -10.0161   -9.9516  |
  |  4 |  477.134  .64329    1  0.423  2.5e-06  -10.0454  -9.99075  -9.91011  |
  |  5 |  477.135  .00236    1  0.961  2.6e-06  -10.0241  -9.95857   -9.8618  |
  |  6 |  477.401  .53343    1  0.465  2.6e-06  -10.0085  -9.93204  -9.81915  |
  |  7 |   477.43   .0578    1  0.810  2.7e-06  -9.98788  -9.90045  -9.77143  |
  |  8 |  477.588  .31611    1  0.574  2.7e-06  -9.96997  -9.87161  -9.72646  |
  |  9 |  477.641  .10525    1  0.746  2.8e-06  -9.94981  -9.84052  -9.67925  |
  | 10 |  478.496  1.7096    1  0.191  2.8e-06  -9.94672   -9.8265   -9.6491  |
  | 11 |  478.603   .2141    1  0.644  2.9e-06  -9.92772  -9.79657  -9.60304  |
  | 12 |  479.334  1.4633    1  0.226  2.9e-06  -9.92201  -9.77994  -9.57028  |
  +---------------------------------------------------------------------------+
   Endogenous:  LCBLLBCgrowth
    Exogenous:  _cons
```

```
. dfuller LCBLLBCgrowth, regress lags(1)
```

Augmented Dickey-Fuller test for unit root   Number of obs   =   104

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-3.999	-3.509	-2.890	-2.580

MacKinnon approximate p-value for Z(t) = 0.0014

D. LCBLLBCgrowth	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
LCBLLBCgrowth						
L1.	-.3027937	.0757211	-4.00	0.000	-.453004	-.1525835
LD.	.0358035	.0993003	0.36	0.719	-.1611815	.2327885
_cons	.0002107	.0002535	0.83	0.408	-.0002923	.0007136

```
. varsoc WeiInterp, maxlag(12)
```

Selection-order criteria
Sample: 2020w21 - 2022w10   Number of obs   =   94

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-291.03				29.24	6.21341	6.22434	6.24047
1	-85.6367	410.79	1	0.000	.377849	1.86461	1.88647	1.91872
2	-63.423	44.427	1	0.000	.240605	1.41326	1.44604	1.49442*
3	-63.4072	.03157	1	0.859	.245704	1.4342	1.47791	1.54242
4	-60.8172	5.1799	1	0.023	.237542	1.40037	1.45501	1.53565
5	-57.5989	6.4367*	1	0.011	.226608*	1.35317*	1.41874*	1.51551
6	-57.5463	.10525	1	0.746	.231245	1.37332	1.44983	1.56272
7	-56.3893	2.314	1	0.128	.230506	1.36998	1.45741	1.58644
8	-55.2707	2.2372	1	0.135	.229965	1.36746	1.46582	1.61097
9	-55.2002	.14088	1	0.707	.23461	1.38724	1.49653	1.6578
10	-55.1996	.00131	1	0.971	.239716	1.4085	1.52872	1.70612
11	-54.8686	.66201	1	0.416	.243232	1.42274	1.55388	1.74741
12	-54.8225	.09219	1	0.761	.248314	1.44303	1.58511	1.79476

Endogenous: WeiInterp
Exogenous: _cons

```
. dfuller WeiInterp, regress lags(4)
```

Augmented Dickey-Fuller test for unit root   Number of obs   =   101

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-1.801	-3.510	-2.890	-2.580

MacKinnon approximate p-value for Z(t) = 0.3800

D.WeiInterp	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
WeiInterp						
L1.	-.014343	.0079643	-1.80	0.075	-.0301541	.0014682
LD.	.6821746	.0952788	7.16	0.000	.4930222	.871327
L2D.	-.1660475	.1132689	-1.47	0.146	-.3909146	.0588197
L3D.	.3734067	.112613	3.32	0.001	.1498416	.5969718
L4D.	-.2670382	.0893385	-2.99	0.004	-.4443976	-.0896788
_cons	.0786356	.0476807	1.65	0.102	-.0160226	.1732938

```
. dfuller WeiInterp, trend regress lags(4)

Augmented Dickey-Fuller test for unit root         Number of obs   =       101

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -1.417            -4.040            -3.450            -3.150
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.8560

------------------------------------------------------------------------------
D.WeiInterp  |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   WeiInterp |
         L1. |  -.0222637   .0157168    -1.42   0.160    -.0534698    .0089425
         LD. |   .6820024   .0956107     7.13   0.000     .4921651    .8718396
        L2D. |  -.1642909   .1137025    -1.44   0.152    -.3900498     .061468
        L3D. |   .3717938   .1130383     3.29   0.001     .1473536    .5962339
        L4D. |  -.2540934   .0923372    -2.75   0.007    -.4374311   -.0707558
      _trend |   .0018076   .0030884     0.59   0.560    -.0043246    .0079398
       _cons |  -.0067984   .1536125    -0.04   0.965    -.3117996    .2982027
------------------------------------------------------------------------------
```

```
. dfuller WeiInterp, regress lags(1)

Augmented Dickey-Fuller test for unit root         Number of obs   =       104

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -1.628            -3.509            -2.890            -2.580
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.4683

------------------------------------------------------------------------------
 D.WeiInterp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   WeiInterp |
         L1. |  -.0142191   .0087319    -1.63   0.107    -.0315408    .0031026
         LD. |   .7353835   .0675997    10.88   0.000      .601284    .8694831
             |
       _cons |   .0356086   .0536981     0.66   0.509    -.0709139    .1421311
------------------------------------------------------------------------------
```

```
. dfuller WeiInterp, trend regress lags(1)

Augmented Dickey-Fuller test for unit root         Number of obs   =       104

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -3.206            -4.039            -3.449            -3.149
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0832

------------------------------------------------------------------------------
D.WeiInterp  |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   WeiInterp |
         L1. |   -.048243   .0150482    -3.21   0.002    -.0780982   -.0183879
         LD. |   .7362122   .0655314    11.23   0.000     .6061999    .8662246
      _trend |   .0080922   .0029591     2.73   0.007     .0022214    .0139631
       _cons |  -.3375603   .1460507    -2.31   0.023    -.6273207   -.0477998
------------------------------------------------------------------------------
```

```
. varsoc FF, maxlag(12)

   Selection-order criteria
   Sample:  2020w21 - 2022w10                   Number of obs      =        94
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	283.807				.000143	-6.01717	-6.00625	-5.99012
1	346.367	125.12	1	0.000	.000039*	-7.32696*	-7.30511*	-7.27285*
2	346.581	.42755	1	0.513	.000039	-7.31023	-7.27745	-7.22907
3	347.335	1.5088	1	0.219	.000039	-7.30501	-7.26129	-7.19678
4	347.589	.50717	1	0.476	.00004	-7.28913	-7.23448	-7.15385
5	350.013	4.8481	1	0.028	.000039	-7.31943	-7.25385	-7.15709
6	350.607	1.1884	1	0.276	.000039	-7.31079	-7.23429	-7.1214
7	350.706	.19753	1	0.657	.00004	-7.29162	-7.20419	-7.07517
8	351.501	1.5898	1	0.207	.00004	-7.28725	-7.18889	-7.04375
9	352.326	1.6502	1	0.199	.00004	-7.28353	-7.17424	-7.01297
10	352.441	.23003	1	0.632	.000041	-7.2647	-7.14449	-6.96708
11	352.851	.81916	1	0.365	.000042	-7.25214	-7.121	-6.92746
12	355.231	4.7611*	1	0.029	.00004	-7.28151	-7.13944	-6.92978

```
   Endogenous:  FF
    Exogenous:  _cons


. dfuller FF, regress lags(0)

Dickey-Fuller test for unit root                   Number of obs   =       105
```

	Test Statistic	Interpolated Dickey-Fuller: 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-19.257	-3.508	-2.890	-2.580

```
MacKinnon approximate p-value for Z(t) = 0.0000
```

D.FF	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
FF						
L1.	-.3810071	.019785	-19.26	0.000	-.4202459	-.3417684
_cons	.0281829	.0041847	6.73	0.000	.0198836	.0364822

```
. varsoc dWeiInterp, maxlag(12)

   Selection-order criteria
   Sample:  2020w22 - 2022w10                   Number of obs      =        93
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-87.8524				.395711	1.91081	1.9218	1.93804
1	-65.1784	45.348	1	0.000	.248286	1.4447	1.46669	1.49916*
2	-65.1508	.05512	1	0.814	.253537	1.46561	1.4986	1.54731
3	-62.7644	4.7729	1	0.029	.246097	1.43579	1.47978	1.54472
4	-59.3538	6.8211*	1	0.009	.233676*	1.38395*	1.43893*	1.52011
5	-59.2787	.15037	1	0.698	.238388	1.40384	1.46982	1.56724
6	-57.7862	2.9849	1	0.084	.235902	1.39325	1.47022	1.58388
7	-57.0945	1.3833	1	0.240	.237505	1.39988	1.48785	1.61774
8	-57.0943	.00045	1	0.983	.24271	1.42138	1.52034	1.66647
9	-57.0115	.16571	1	0.684	.247601	1.44111	1.55106	1.71343
10	-56.4726	1.0778	1	0.299	.250138	1.45102	1.57197	1.75058
11	-56.3632	.21866	1	0.640	.255061	1.47018	1.60212	1.79696
12	-56.2915	.14337	1	0.705	.260307	1.49014	1.63308	1.84416

```
   Endogenous:  dWeiInterp
    Exogenous:  _cons
```

```
. dfuller dWeiInterp, regress lags(3)

Augmented Dickey-Fuller test for unit root         Number of obs   =       101

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -5.403            -3.510            -2.890            -2.580
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000

------------------------------------------------------------------------------
D.dWeiInterp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  dWeiInterp |
         L1. |  -.4044438   .0748562    -5.40   0.000    -.5530322   -.2558554
         LD. |    .108201   .0963994     1.12   0.264    -.0831503    .2995522
        L2D. |  -.0729314   .0900719    -0.81   0.420    -.2517227      .10586
        L3D. |   .2956015   .0889406     3.32   0.001     .1190558    .4721473
             |
       _cons |   .0529143   .0460198     1.15   0.253    -.0384343    .1442629
------------------------------------------------------------------------------


. dfuller dWeiInterp, regress lags(0)

Dickey-Fuller test for unit root                   Number of obs   =       104

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -4.017            -3.509            -2.890            -2.580
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0013

------------------------------------------------------------------------------
D.dWeiInterp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  dWeiInterp |
         L1. |  -.2729602   .0679488    -4.02   0.000    -.4077362   -.1381841
             |
       _cons |   .0109251   .0519297     0.21   0.834    -.0920771    .1139274
------------------------------------------------------------------------------


. varsoc CLgrowth, maxlag(12)

   Selection-order criteria
   Sample:  2020w21 - 2022w10                    Number of obs      =        94
  +---------------------------------------------------------------------------+
  |lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
  |----+----------------------------------------------------------------------|
  |  0 |  468.655                      2.8e-06   -9.9501  -9.93917  -9.92304  |
  |  1 |  474.963  12.616    1  0.000  2.5e-06   -10.063  -10.0412  -10.0089  |
  |  2 |  482.363    14.8    1  0.000  2.2e-06  -10.1992  -10.1664   -10.118  |
  |  3 |  484.431  4.1364    1  0.042  2.1e-06  -10.2219  -10.1782  -10.1137  |
  |  4 |  487.081  5.2993*   1  0.021  2.1e-06*  -10.257* -10.2024* -10.1218* |
  |  5 |  487.513  .86555    1  0.352  2.1e-06   -10.245  -10.1794  -10.0826  |
  |  6 |  488.841  2.6551    1  0.103  2.1e-06  -10.2519  -10.1754  -10.0625  |
  |  7 |  489.012  .34279    1  0.558  2.1e-06  -10.2343  -10.1469  -10.0179  |
  |  8 |  489.042   .0595    1  0.807  2.1e-06  -10.2137  -10.1153  -9.97015  |
  |  9 |  489.062   .0404    1  0.841  2.2e-06  -10.1928  -10.0835  -9.92225  |
  | 10 |  489.642  1.1592    1  0.282  2.2e-06  -10.1839  -10.0637  -9.88625  |
  | 11 |  490.213  1.1416    1  0.285  2.2e-06  -10.1747  -10.0436  -9.85006  |
  | 12 |  490.792  1.1576    1  0.282  2.3e-06  -10.1658  -10.0237  -9.81405  |
  +---------------------------------------------------------------------------+
   Endogenous:  CLgrowth
    Exogenous:  _cons
```

```
. dfuller CLgrowth, regress lags(3)

Augmented Dickey-Fuller test for unit root         Number of obs   =       102

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -2.474            -3.509            -2.890            -2.580
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.1220

------------------------------------------------------------------------------
  D.CLgrowth |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    CLgrowth |
         L1. |  -.1788476   .0722939    -2.47   0.015    -.3223311   -.0353642
         LD. |  -.3547824   .1043793    -3.40   0.001    -.5619464   -.1476183
        L2D. |   .0427017    .107732     0.40   0.693    -.1711166    .2565199
        L3D. |   .0639984   .0934803     0.68   0.495     -.121534    .2495309
             |
       _cons |   .0001926   .0001743     1.10   0.272    -.0001534    .0005386
------------------------------------------------------------------------------


. dfuller CLgrowth, trend regress lags(3)

Augmented Dickey-Fuller test for unit root         Number of obs   =       102

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -3.809            -4.039            -3.450            -3.150
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0161

------------------------------------------------------------------------------
D.CLgrowth   |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    CLgrowth |
         L1. |  -.3999318   .1049857    -3.81   0.000    -.6083267    -.191537
         LD. |  -.2248061   .1108611    -2.03   0.045    -.4448637   -.0047484
        L2D. |   .1252886   .1081079     1.16   0.249    -.0893039     .339881
        L3D. |   .1105923   .0917984     1.20   0.231    -.0716262    .2928107
      _trend |    .000024   8.51e-06     2.82   0.006     7.11e-06    .0000409
       _cons |  -.0010197   .0004617    -2.21   0.030    -.0019361   -.0001033
------------------------------------------------------------------------------


. varsoc CLgrowth_detrended, maxlag(12)

   Selection-order criteria
   Sample:  2020w21 - 2022w10                   Number of obs      =        94
  +---------------------------------------------------------------------------+
  |lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
  |----+----------------------------------------------------------------------|
  |  0 |  484.877                      2.0e-06  -10.2953  -10.2843* -10.2682* |
  |  1 |  485.194  .63473    1  0.426  2.0e-06  -10.2807  -10.2589  -10.2266  |
  |  2 |    487.5  4.6102    1  0.032  2.0e-06  -10.3085  -10.2757  -10.2273  |
  |  3 |  487.996  .99201    1  0.319  2.0e-06  -10.2978  -10.2541  -10.1896  |
  |  4 |  489.143  2.2943    1  0.130  2.0e-06  -10.3009  -10.2463  -10.1656  |
  |  5 |  490.581  2.8771    1  0.090  1.9e-06* -10.3102* -10.2447  -10.1479  |
  |  6 |  490.989  .81627    1  0.366  2.0e-06  -10.2976  -10.2211  -10.1083  |
  |  7 |  491.932  1.8849    1  0.170  2.0e-06  -10.2964   -10.209    -10.08   |
  |  8 |  492.109  .35331    1  0.552  2.0e-06  -10.2789  -10.1805  -10.0354  |
  |  9 |  492.375  .53376    1  0.465  2.0e-06  -10.2633   -10.154  -9.99274  |
  | 10 |  492.383  .01544    1  0.901  2.1e-06  -10.2422   -10.122  -9.94458  |
  | 11 |  494.649  4.5318*   1  0.033  2.0e-06  -10.2691   -10.138  -9.94445  |
  | 12 |  494.649  8.3e-05   1  0.993  2.1e-06  -10.2479  -10.1058  -9.89612  |
  +---------------------------------------------------------------------------+
   Endogenous:  CLgrowth_detrended
    Exogenous:  _cons
```

```
. dfuller CLgrowth_detrended, regress lags(0)

Dickey-Fuller test for unit root                   Number of obs   =       105

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -6.563            -3.508            -2.890            -2.580
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000

------------------------------------------------------------------------------------
D.                 |
CLgrowth_detrended |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------------+----------------------------------------------------------------
CLgrowth_detrended |
               L1. |   -.521639   .0794836    -6.56   0.000     -.679276   -.364002
                   |
             _cons |  -.0000702    .000175    -0.40   0.689    -.0004172   .0002768
------------------------------------------------------------------------------------
```

```
. dfuller CLgrowth_detrended, regress lags(4)

Augmented Dickey-Fuller test for unit root         Number of obs   =       101

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -4.926            -3.510            -2.890            -2.580
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000

------------------------------------------------------------------------------------
D.                 |
CLgrowth_detrended |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------------+----------------------------------------------------------------
CLgrowth_detrended |
               L1. |  -.4990022    .101309    -4.93   0.000    -.7001259   -.2978785
               LD. |  -.2362009   .1094704    -2.16   0.033    -.4535272   -.0188746
              L2D. |   .1047248   .1021587     1.03   0.308     -.098086    .3075355
              L3D. |   .2332254   .0983679     2.37   0.020     .0379405    .4285104
              L4D. |   .3323693   .0833923     3.99   0.000     .1668148    .4979239
                   |
             _cons |   .0000469   .0001507     0.31   0.756    -.0002522    .0003459
------------------------------------------------------------------------------------
```

```
. varsoc CILgrowth, maxlag(12)

   Selection-order criteria
   Sample:  2020w21 - 2022w10                   Number of obs      =        94
  +---------------------------------------------------------------------------+
  |lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
  |----+----------------------------------------------------------------------|
  |  0 |  372.746                      .000022   -7.9095  -7.89857  -7.88244  |
  |  1 |  392.251  39.009    1  0.000  .000015  -8.30321  -8.28135* -8.24909* |
  |  2 |  393.284  2.0675    1  0.150  .000014  -8.30392  -8.27114  -8.22275  |
  |  3 |  393.877  1.1853    1  0.276  .000015  -8.29526  -8.25154  -8.18703  |
  |  4 |  394.229  .70376    1  0.402  .000015  -8.28147  -8.22682  -8.14619  |
  |  5 |  394.352  .24523    1  0.620  .000015   -8.2628  -8.19723  -8.10046  |
  |  6 |  399.213  9.7235*   1  0.002  .000014* -8.34496* -8.26846  -8.15557  |
  |  7 |  399.471  .51567    1  0.473  .000014  -8.32917  -8.24174  -8.11272  |
  |  8 |  399.756  .57059    1  0.450  .000014  -8.31397  -8.21561  -8.07046  |
  |  9 |  399.983  .45266    1  0.501  .000015  -8.29751  -8.18822  -8.02694  |
  | 10 |  400.149  .33275    1  0.564  .000015  -8.27977  -8.15955  -7.98215  |
  | 11 |  400.889  1.4794    1  0.224  .000015  -8.27423  -8.14309  -7.94956  |
  | 12 |  401.273  .76781    1  0.381  .000015  -8.26112  -8.11905  -7.90939  |
  +---------------------------------------------------------------------------+
   Endogenous:  CILgrowth
    Exogenous:  _cons
```

```
. dfuller CILgrowth, regress lags(0)

Dickey-Fuller test for unit root                   Number of obs   =       105

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -3.771            -3.508            -2.890            -2.580
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0032

------------------------------------------------------------------------------
D.CILgrowth |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
------------+----------------------------------------------------------------
  CILgrowth |
        L1. |  -.2446362   .0648673    -3.77   0.000    -.3732851   -.1159872
            |
      _cons |   .0002192   .0007397     0.30   0.768    -.0012477    .0016862
------------------------------------------------------------------------------


. dfuller CILgrowth, regress lags(5)

Augmented Dickey-Fuller test for unit root         Number of obs   =       100

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -4.511            -3.510            -2.890            -2.580
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0002

------------------------------------------------------------------------------
D.CILgrowth |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
------------+----------------------------------------------------------------
  CILgrowth |
        L1. |  -.3115926   .0690677    -4.51   0.000    -.4487474   -.1744378
        LD. |  -.2111487   .0842731    -2.51   0.014    -.3784985    -.043799
       L2D. |   .0234132   .0814977     0.29   0.775     -.138425    .1852515
       L3D. |  -.0061682    .076674    -0.08   0.936    -.1584275    .1460911
       L4D. |    .012313   .0599225     0.21   0.838    -.1066811    .1313072
       L5D. |   .2549136   .0592978     4.30   0.000       .13716    .3726672
            |
      _cons |  -.0004016   .0004391    -0.91   0.363    -.0012736    .0004704
------------------------------------------------------------------------------


. varsoc OLLgrowth, maxlag(12)

   Selection-order criteria
   Sample:  2020w21 - 2022w10                  Number of obs      =        94
  +---------------------------------------------------------------------------+
  |lag |    LL      LR      df    p      FPE       AIC       HQIC      SBIC    |
  |----+----------------------------------------------------------------------|
  |  0 |  396.103                      .000013  -8.40644  -8.39551  -8.37938  |
  |  1 |  401.458   10.71    1  0.001  .000012   -8.4991  -8.47724* -8.44499* |
  |  2 |  402.628  2.3399    1  0.126  .000012  -8.50272  -8.46993  -8.42155  |
  |  3 |  404.044  2.8335    1  0.092  .000012  -8.51158  -8.46787  -8.40336  |
  |  4 |  404.045  .00139    1  0.970  .000012  -8.49032  -8.43568  -8.35504  |
  |  5 |  404.046   .0016    1  0.968  .000012  -8.46906  -8.40349  -8.30672  |
  |  6 |  407.366  6.6408    1  0.010  .000012  -8.51843  -8.44193  -8.32904  |
  |  7 |  408.238  1.7436    1  0.187  .000012   -8.5157  -8.42827  -8.29925  |
  |  8 |   408.26  .04458    1  0.833  .000012   -8.4949  -8.39654   -8.2514  |
  |  9 |  408.921  1.3206    1  0.250  .000012  -8.48767  -8.37839  -8.21711  |
  | 10 |  408.965  .08952    1  0.765  .000012  -8.46735  -8.34713  -8.16973  |
  | 11 |  409.024  .11674    1  0.733  .000013  -8.44732  -8.31617  -8.12264  |
  | 12 |  413.443   8.839*   1  0.003  .000012* -8.52007*    -8.378  -8.16834  |
  +---------------------------------------------------------------------------+
   Endogenous:  OLLgrowth
    Exogenous:  _cons
```

```
. dfuller OLLgrowth, regress lags(0)

Dickey-Fuller test for unit root                   Number of obs   =       105

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -5.341            -3.508            -2.890            -2.580
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000

------------------------------------------------------------------------------
D.OLLgrowth |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
------------+-----------------------------------------------------------------
  OLLgrowth |
        L1. |  -.4231701   .0792271    -5.34   0.000    -.5802984   -.2660418
            |
      _cons |   .0008347   .0005117     1.63   0.106    -.0001803    .0018496
------------------------------------------------------------------------------

. dfuller OLLgrowth, regress lags(11)

Augmented Dickey-Fuller test for unit root         Number of obs   =        94

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -2.587            -3.518            -2.895            -2.582
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0957

------------------------------------------------------------------------------
D.OLLgrowth |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
------------+-----------------------------------------------------------------
  OLLgrowth |
        L1. |   -.415528   .1606286    -2.59   0.011    -.7351285   -.0959276
        LD. |  -.3651675   .1721789    -2.12   0.037    -.7077494   -.0225855
       L2D. |  -.2324717   .1758632    -1.32   0.190    -.5823843    .1174408
       L3D. |  -.1003069   .1705559    -0.59   0.558    -.4396596    .2390459
       L4D. |  -.1934926   .1594669    -1.21   0.229    -.5107817    .1237966
       L5D. |  -.2757929   .1484608    -1.86   0.067    -.5711833    .0195976
       L6D. |  -.0387217   .1432288    -0.27   0.788    -.3237021    .2462587
       L7D. |   .0376899   .1181159     0.32   0.750    -.1973237    .2727034
       L8D. |  -.0263859   .0863409    -0.31   0.761    -.1981773    .1454055
       L9D. |   .0714429   .0797371     0.90   0.373     -.087209    .2300947
      L10D. |   .0912745    .072004     1.27   0.209    -.0519909    .2345398
      L11D. |   .1915823   .0677931     2.83   0.006     .0566953    .3264693
            |
      _cons |   .0009223   .0004035     2.29   0.025     .0001194    .0017252
------------------------------------------------------------------------------
```

Figure C.1 – Stationarity tests

Part I: Whether and to what scale does the pandemic crisis affect real economic activity and credit availability?

VAR model with new confirmed Covid-19 cases growth rate

Stability condition

```
. varstable
```

Eigenvalue stability condition

Eigenvalue	Modulus
.9398761 + .3203728*i*	.992978
.9398761 − .3203728*i*	.992978
−.04436982 + .9839686*i*	.984968
−.04436982 − .9839686*i*	.984968
.5392229 + .8185221*i*	.980173
.5392229 − .8185221*i*	.980173
−.9256341 + .2858066*i*	.968754
−.9256341 − .2858066*i*	.968754
−.7543267 + .6015147*i*	.964795
−.7543267 − .6015147*i*	.964795
.1147892 + .9567887*i*	.96365
.1147892 − .9567887*i*	.96365
−.821195 + .4997583*i*	.961311
−.821195 − .4997583*i*	.961311
−.9513971 + .1345327*i*	.960862
−.9513971 − .1345327*i*	.960862
.9569314 + .08484342*i*	.960685
.9569314 − .08484342*i*	.960685
.6633717 + .6937504*i*	.959871
.6633717 − .6937504*i*	.959871
−.575673 + .7666658*i*	.958737
−.575673 − .7666658*i*	.958737
.8705642 + .3877477*i*	.953011
.8705642 − .3877477*i*	.953011
−.3369501 + .8913707*i*	.952931
−.3369501 − .8913707*i*	.952931
.7646329 + .5518713*i*	.942988
.7646329 − .5518713*i*	.942988
.3274316 + .8791296*i*	.938126
.3274316 − .8791296*i*	.938126
.9039888 + .2453505*i*	.936692
.9039888 − .2453505*i*	.936692
.04586036 + .9347059*i*	.93583
.04586036 − .9347059*i*	.93583
−.3147861 + .8797815*i*	.934401
−.3147861 − .8797815*i*	.934401
−.6538693 + .6624181*i*	.930775
−.6538693 − .6624181*i*	.930775
−.4962076 + .7789427*i*	.923566
−.4962076 − .7789427*i*	.923566
.370829 + .8422984*i*	.920316
.370829 − .8422984*i*	.920316
.7986654 + .4466547*i*	.915077
.7986654 − .4466547*i*	.915077
−.9019447	.901945
−.102631 + .8899321*i*	.89583
−.102631 − .8899321*i*	.89583
.6127064 + .6054492*i*	.861381
.6127064 − .6054492*i*	.861381
−.8241651 + .2241376*i*	.854099
−.8241651 − .2241376*i*	.854099
−.3782147 + .6834437*i*	.781116
−.3782147 − .6834437*i*	.781116
.1699194 + .717961*i*	.737794
.1699194 − .717961*i*	.737794
.5954707 + .2164559*i*	.633592
.5954707 − .2164559*i*	.633592
−.4037766 + .2034842*i*	.452152
−.4037766 − .2034842*i*	.452152
.129304	.129304

All the eigenvalues lie inside the unit ci
VAR satisfies stability condition.

Figure C.2 – Stability test for the first VAR model

Optimal lag selection

Minimum information criteria

```
. varsoc casesgrowth dWeiInterp LCBLLBCgrowth FF, exog (dummy vacgrowth) maxlag(15)

   Selection-order criteria
   Sample:  2020w25 - 2022w10                   Number of obs      =        90
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	688.685				3.5e-12	-15.0375	-14.903	-14.7041
1	765.352	153.33	16	0.000	9.0e-13*	-16.3856*	-16.072*	-15.6079*
2	773.395	16.086	16	0.447	1.1e-12	-16.2088	-15.7159	-14.9866
3	786.23	25.671	16	0.059	1.2e-12	-16.1385	-15.4664	-14.4719
4	797.957	23.454	16	0.102	1.3e-12	-16.0435	-15.1922	-13.9325
5	814.071	32.227	16	0.009	1.3e-12	-16.046	-15.0155	-13.4907
6	821.377	14.613	16	0.553	1.7e-12	-15.8528	-14.6431	-12.8531
7	836.883	31.013	16	0.013	1.7e-12	-15.8419	-14.453	-12.3977
8	844.762	15.757	16	0.470	2.2e-12	-15.6614	-14.0933	-11.7728
9	867.89	46.256	16	0.000	2.0e-12	-15.8198	-14.0724	-11.4868
10	882.225	28.671	16	0.026	2.3e-12	-15.7828	-13.8562	-11.0054
11	890.463	16.475	16	0.420	3.1e-12	-15.6103	-13.5045	-10.3885
12	922.086	63.247	16	0.000	2.5e-12	-15.9575	-13.6725	-10.2912
13	935.78	27.388	16	0.037	3.2e-12	-15.9062	-13.4421	-9.79558
14	954.896	38.231	16	0.001	3.8e-12	-15.9755	-13.3321	-9.4204
15	971.881	33.971*	16	0.005	5.1e-12	-15.9974	-13.1748	-8.99789

```
   Endogenous:  casesgrowth dWeiInterp LCBLLBCgrowth FF
    Exogenous:  dummy vacgrowth  _cons
```

Figure C.3 – First Var model optimal lag criteria selection

Wald lag-exclusion statistics test

```
. varwle
```

Equation: casesgrowth

lag	chi2	df	Prob > chi2
1	34.07038	4	0.000
2	24.62343	4	0.000
3	11.61123	4	0.020
4	7.848711	4	0.097
5	15.88355	4	0.003
6	7.699674	4	0.103
7	24.27116	4	0.000
8	14.61755	4	0.006
9	14.10358	4	0.007
10	2.910552	4	0.573
11	6.760428	4	0.149
12	19.44731	4	0.001
13	8.731119	4	0.068
14	13.53048	4	0.009
15	15.50118	4	0.004

Equation: dWeiInterp

lag	chi2	df	Prob > chi2
1	36.75929	4	0.000
2	20.35426	4	0.000
3	15.49236	4	0.004
4	11.59234	4	0.021
5	5.473361	4	0.242
6	15.98405	4	0.003
7	9.44866	4	0.051
8	3.459215	4	0.484
9	14.38772	4	0.006
10	5.792705	4	0.215
11	21.11747	4	0.000
12	8.186612	4	0.085
13	11.06437	4	0.026
14	3.018352	4	0.555
15	12.74382	4	0.013

Equation: FF

lag	chi2	df	Prob > chi2
1	18.76071	4	0.001
2	2.409013	4	0.661
3	3.198841	4	0.525
4	6.629992	4	0.157
5	9.423967	4	0.051
6	4.374884	4	0.358
7	9.74846	4	0.045
8	8.764457	4	0.067
9	14.34407	4	0.006
10	3.692279	4	0.449
11	7.953094	4	0.093
12	11.06679	4	0.026
13	9.677893	4	0.046
14	11.89055	4	0.018
15	8.785632	4	0.067

Equation: LCBLLBCgrowth

lag	chi2	df	Prob > chi2
1	28.58639	4	0.000
2	17.87488	4	0.001
3	11.88289	4	0.018
4	6.599222	4	0.159
5	19.0808	4	0.001
6	10.51292	4	0.033
7	11.01123	4	0.026
8	15.45494	4	0.004
9	5.117583	4	0.275
10	14.68316	4	0.005
11	16.86668	4	0.002
12	25.01679	4	0.000
13	4.671412	4	0.323
14	11.06463	4	0.026
15	.5419744	4	0.969

Equation: All

lag	chi2	df	Prob > chi2
1	122.9348	16	0.000
2	74.1881	16	0.000
3	42.94994	16	0.000
4	34.05005	16	0.005
5	53.05685	16	0.000
6	49.47095	16	0.000
7	54.0257	16	0.000
8	46.1357	16	0.000
9	45.01073	16	0.000
10	25.36526	16	0.064
11	48.8688	16	0.000
12	60.22613	16	0.000
13	36.6005	16	0.002
14	42.90712	16	0.000
15	37.30957	16	0.002

Figure C.4 - Wald lag-exclusion statistics test for p=15.

Residual diagnostics

```
. varlmar, mlag(4)

   Lagrange-multiplier test

  lag        chi2    df   Prob > chi2

    1      56.1369    16     0.00000
    2      29.1886    16     0.02270
    3      19.9266    16     0.22355
    4      13.8472    16     0.61009

   H0: no autocorrelation at lag order
```

Figure C.5 – Lagrange multiplier test for the serial correlation between residuals for the model with optimal lag, p=1.

```
. var casesgrowth dWeiInterp LCBLLBCgrowth FF, exog (dummy vacgrowth) lags (1/14)

Vector autoregression

Sample:  2020w24 - 2022w10                     Number of obs     =         91
Log likelihood =   964.5256                    AIC               =  -16.01155
FPE            =   3.53e-12                    HQIC              =   -13.3845
Det(Sigma_ml)  =   7.31e-15                    SBIC              =  -9.499873

Equation           Parms      RMSE     R-sq      chi2     P>chi2

casesgrowth          59     .213698   0.7703   305.2204   0.0000
dWeiInterp           59     .500876   0.7754   314.2484   0.0000
LCBLLBCgrowth        59     .001406   0.8053   376.3447   0.0000
FF                   59     .004872   0.9304   1216.871   0.0000


              |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]

casesgrowth   |
  casesgrowth |
          L1. |   .5111743   .1022146     5.00   0.000     .3108373    .7115113
          L2. |  -.2489897   .1195853    -2.08   0.037    -.4833726   -.0146068
          L3. |    .171739   .1215326     1.41   0.158    -.0664604    .4099385
          L4. |  -.0252937   .1278714    -0.20   0.843     -.275917    .2253296
          L5. |  -.3402594   .1257305    -2.71   0.007    -.5866867   -.0938322
          L6. |   .1717798   .1158675     1.48   0.138    -.0553163     .398876
          L7. |  -.3234173    .124126    -2.61   0.009    -.5666999   -.0801348
          L8. |   .2704722   .1242784     2.18   0.030     .0268911    .5140534
          L9. |  -.1898271   .1163341    -1.63   0.103    -.4178377    .0381836
         L10. |  -.1722591    .117216    -1.47   0.142    -.4019982      .05748
         L11. |  -.0078782   .1240627    -0.06   0.949    -.2510366    .2352802
         L12. |  -.2627135   .1148645    -2.29   0.022    -.4878439   -.0375832
         L13. |  -.0671935   .1137675    -0.59   0.555    -.2901738    .1557868
         L14. |   .0142191   .0951542     0.15   0.881    -.1722797    .2007178
              |
   dWeiInterp |
          L1. |  -.0930834   .0462178    -2.01   0.044    -.1836688   -.0024981
          L2. |   .1206856   .0502583     2.40   0.016     .0221812      .21919
          L3. |  -.1078178   .0555166    -1.94   0.052    -.2166284    .0009927
          L4. |   .0204219   .0577517     0.35   0.724    -.0927694    .1336132
          L5. |  -.0934398   .0590111    -1.58   0.113    -.2090994    .0222197
          L6. |   .1244929   .0620318     2.01   0.045     .0029128     .246073
          L7. |  -.1472096   .0650299    -2.26   0.024    -.2746659   -.0197533
          L8. |   .0381748   .0636959     0.60   0.549    -.0866669    .1630165
          L9. |  -.0897225   .0650733    -1.38   0.168    -.2172638    .0378188
         L10. |  -.0508874   .0691395    -0.74   0.462    -.1863982    .0846235
         L11. |   .0245995   .0635976     0.39   0.699    -.1000494    .1492485
         L12. |  -.0534954   .0639264    -0.84   0.403    -.1787889     .071798
         L13. |   .0367168   .0633809     0.58   0.562    -.0875074    .1609411
         L14. |  -.1215514   .0540209    -2.25   0.024    -.2274303   -.0156724
              |
LCBLLBCgrowth |
          L1. |  -28.52754   15.19979    -1.88   0.061    -58.31858    1.263504
          L2. |   37.31666   15.38398     2.43   0.015     7.164622     67.4687
          L3. |  -11.25864   14.93762    -0.75   0.451    -40.53583    18.01856
          L4. |   23.24349   14.73237     1.58   0.115    -5.631424    52.11841
          L5. |   6.239784   14.50064     0.43   0.667    -22.18095    34.66052
          L6. |  -22.37985     15.088    -1.48   0.138    -51.95178    7.192089
          L7. |  -1.283318   14.87042    -0.09   0.931     -30.4288    27.86217
          L8. |  -9.419737   13.88725    -0.68   0.498    -36.63825    17.79878
          L9. |   -11.5149   14.68818    -0.78   0.433    -40.30321    17.27341
         L10. |  -18.05987   14.78389    -1.22   0.222    -47.03576    10.91602
         L11. |   10.67206   14.26758     0.75   0.454    -17.29187      38.636
         L12. |  -32.61791   13.50988    -2.41   0.016    -59.09678   -6.139033
         L13. |   .6989867    12.7428     0.05   0.956    -24.27645    25.67442
         L14. |  -17.33065   11.74409    -1.48   0.140    -40.34864    5.687337
              |
           FF |
          L1. |   1.020976   3.929295     0.26   0.795    -6.680302    8.722254
          L2. |   4.505434   4.303723     1.05   0.295    -3.929708    12.94058
          L3. |  -2.580565   4.228235    -0.61   0.542    -10.86775    5.706624
          L4. |  -4.298927   4.190515    -1.03   0.305    -12.51219     3.91433
          L5. |  -2.337116    4.04373    -0.58   0.563    -10.26268    5.588449
          L6. |  -.4359642   4.126737    -0.11   0.916     -8.52422    7.652292
          L7. |   4.191484   4.063014     1.03   0.302    -3.771877    12.15484
          L8. |   -6.55859   4.103406    -1.60   0.110    -14.60112    1.483939
          L9. |   1.285653   3.971965     0.32   0.746    -6.499256    9.070562
         L10. |   4.653785   3.688383     1.26   0.207    -2.575313    11.88288
         L11. |  -9.141766   3.590451    -2.55   0.011    -16.17892   -2.104612
         L12. |   6.746347   2.813052     2.40   0.016     1.232867    12.25983
         L13. |   .8956173   1.021248     0.88   0.380    -1.105992    2.897226
         L14. |   1.035236   .8582006     1.21   0.228    -.6468064    2.717278
              |
        dummy |   .0672896   .0595877     1.13   0.259    -.0495002    .1840794
    vacgrowth |  -.0469772   .0263904    -1.78   0.075    -.0987015     .004747
        _cons |   .2116638   .5450171     0.39   0.698      -.85655    1.279878
```

dWeiInterp						
casesgrowth						
L1.	-.4545112	.2395757	-1.90	0.058	-.9240709	.0150485
L2.	-.5039812	.2802899	-1.80	0.072	-1.053339	.0453769
L3.	.4196083	.284854	1.47	0.141	-.1386952	.9779118
L4.	-.3665184	.2997112	-1.22	0.221	-.9539416	.2209047
L5.	.4566697	.2946933	1.55	0.121	-.1209185	1.034258
L6.	-.3191428	.271576	-1.18	0.240	-.8514219	.2131363
L7.	.1693874	.2909326	0.58	0.560	-.40083	.7396049
L8.	-.3934693	.2912897	-1.35	0.177	-.9643868	.1774481
L9.	-.0428154	.2726696	-0.16	0.875	-.577238	.4916071
L10.	-.4504166	.2747365	-1.64	0.101	-.9888903	.0880572
L11.	.2538266	.2907842	0.87	0.383	-.3161	.8237532
L12.	-.3264683	.2692251	-1.21	0.225	-.8541398	.2012032
L13.	-.1624456	.2666539	-0.61	0.542	-.6850777	.3601864
L14.	.0380138	.223027	0.17	0.865	-.399111	.4751386
dWeiInterp						
L1.	.4484146	.1083277	4.14	0.000	.2360963	.6607329
L2.	-.353137	.1177978	-3.00	0.003	-.5840164	-.1222576
L3.	.5233898	.1301225	4.02	0.000	.2683544	.7784253
L4.	-.1806109	.1353613	-1.33	0.182	-.4459143	.0846924
L5.	.1080129	.138313	0.78	0.435	-.1630757	.3791014
L6.	-.2693884	.1453931	-1.85	0.064	-.5543536	.0155769
L7.	-.0690496	.1524203	-0.45	0.651	-.3677879	.2296887
L8.	.0325095	.1492936	0.22	0.828	-.2601006	.3251195
L9.	-.2854922	.1525219	-1.87	0.061	-.5844296	.0134453
L10.	.2081818	.1620524	1.28	0.199	-.1094351	.5257987
L11.	-.4825353	.1490631	-3.24	0.001	-.7746936	-.190377
L12.	.4027256	.1498338	2.69	0.007	.1090568	.6963945
L13.	-.2639714	.1485553	-1.78	0.076	-.5551343	.0271916
L14.	.1193076	.1266168	0.94	0.346	-.1288567	.367472
LCBLLBCgrowth						
L1.	-91.4321	35.62601	-2.57	0.010	-161.2578	-21.6064
L2.	-13.59899	36.05772	-0.38	0.706	-84.27082	57.07283
L3.	46.33987	35.01152	1.32	0.186	-22.28145	114.9612
L4.	68.80635	34.53045	1.99	0.046	1.12791	136.4848
L5.	41.75381	33.98731	1.23	0.219	-24.8601	108.3677
L6.	81.66099	35.36399	2.31	0.021	12.34884	150.9731
L7.	-105.1183	34.85401	-3.02	0.003	-173.4309	-36.80567
L8.	-25.94222	32.54962	-0.80	0.425	-89.7383	37.85386
L9.	-106.2408	34.42688	-3.09	0.002	-173.7162	-38.7653
L10.	20.74696	34.6512	0.60	0.549	-47.16814	88.66207
L11.	19.7226	33.44104	0.59	0.555	-45.82063	85.26584
L12.	38.95517	31.66511	1.23	0.219	-23.1073	101.0177
L13.	10.34155	29.8672	0.35	0.729	-48.1971	68.88019
L14.	26.34177	27.52636	0.96	0.339	-27.60891	80.29245
FF						
L1.	-11.78433	9.209675	-1.28	0.201	-29.83496	6.266297
L2.	8.597082	10.08728	0.85	0.394	-11.17361	28.36778
L3.	2.579503	9.910343	0.26	0.795	-16.84441	22.00342
L4.	-19.72247	9.821933	-2.01	0.045	-38.9731	-.4718354
L5.	23.13573	9.477891	2.44	0.015	4.559401	41.71205
L6.	-23.27997	9.672448	-2.41	0.016	-42.23762	-4.322323
L7.	7.919995	9.523089	0.83	0.406	-10.74492	26.58491
L8.	-2.488548	9.617764	-0.26	0.796	-21.33902	16.36192
L9.	12.20941	9.309687	1.31	0.190	-6.037241	30.45606
L10.	-2.536893	8.645012	-0.29	0.769	-19.48081	14.40702
L11.	10.09329	8.415474	1.20	0.230	-6.400737	26.58732
L12.	-11.64798	6.593369	-1.77	0.077	-24.57075	1.274783
L13.	1.019978	2.393651	0.43	0.670	-3.671491	5.711447
L14.	.8022721	2.011493	0.40	0.690	-3.140181	4.744725
dummy	-.3292341	.1396647	-2.36	0.018	-.6029718	-.0554964
vacgrowth	.0865341	.0618551	1.40	0.162	-.0346997	.2077679
_cons	.7683554	1.277438	0.60	0.548	-1.735376	3.272087
LCBLLBCgrowth						
casesgrowth						
L1.	-.0025825	.0006725	-3.84	0.000	-.0039006	-.0012644
L2.	.0010395	.0007868	1.32	0.186	-.0005026	.0025815
L3.	-.0027193	.0007996	-3.40	0.001	-.0042865	-.0011521
L4.	-.0014626	.0008413	-1.74	0.082	-.0031115	.0001864
L5.	-.0023264	.0008272	-2.81	0.005	-.0039478	-.0007051
L6.	-.0012703	.0007623	-1.67	0.096	-.0027645	.0002238
L7.	.0014173	.0008167	1.74	0.083	-.0001833	.003018
L8.	-.0005609	.0008177	-0.69	0.493	-.0021635	.0010417
L9.	.0015711	.0007654	2.05	0.040	.0000709	.0030713
L10.	-.0012105	.0007712	-1.57	0.117	-.002722	.0003011
L11.	-.0007099	.0008163	-0.87	0.384	-.0023097	.0008899
L12.	-.0012494	.0007557	-1.65	0.098	-.0027307	.0002318
L13.	-.0019347	.0007485	-2.58	0.010	-.0034018	-.0004676
L14.	-.001607	.0006261	-2.57	0.010	-.0028341	-.00038

dWeiInterp						
L1.	-.0005318	.0003041	-1.75	0.080	-.0011278	.0000642
L2.	-.0010819	.0003307	-3.27	0.001	-.00173	-.0004338
L3.	-.0001525	.0003653	-0.42	0.676	-.0008684	.0005634
L4.	-.0004728	.00038	-1.24	0.213	-.0012175	.0002719
L5.	.0007984	.0003883	2.06	0.040	.0000375	.0015594
L6.	-.0005843	.0004081	-1.43	0.152	-.0013842	.0002156
L7.	.0006949	.0004279	1.62	0.104	-.0001437	.0015335
L8.	-.0017926	.0004191	-4.28	0.000	-.002614	-.0009712
L9.	.0003484	.0004281	0.81	0.416	-.0004908	.0011875
L10.	-.0015993	.0004549	-3.52	0.000	-.0024909	-.0007078
L11.	.001433	.0004184	3.42	0.001	.0006129	.0022531
L12.	-.0020748	.0004206	-4.93	0.000	-.0028991	-.0012504
L13.	-.000071	.000417	-0.17	0.865	-.0008883	.0007463
L14.	-.0010216	.0003554	-2.87	0.004	-.0017182	-.0003249
LCBLLBCgrowth						
L1.	.0497371	.1000049	0.50	0.619	-.1462689	.2457432
L2.	-.1657497	.1012168	-1.64	0.102	-.3641309	.0326315
L3.	.0210445	.09828	0.21	0.830	-.1715808	.2136697
L4.	-.1196938	.0969296	-1.23	0.217	-.3096724	.0702847
L5.	.203923	.095405	2.14	0.033	.0169327	.3909133
L6.	.1212369	.0992694	1.22	0.222	-.0733276	.3158014
L7.	.1839257	.0978379	1.88	0.060	-.007833	.3756844
L8.	.0674703	.0913693	0.74	0.460	-.1116102	.2465508
L9.	.0453624	.0966389	0.47	0.639	-.1440463	.2347712
L10.	-.1664917	.0972686	-1.71	0.087	-.3571346	.0241512
L11.	-.1537956	.0938716	-1.64	0.101	-.3377805	.0301892
L12.	-.0739327	.0888864	-0.83	0.406	-.2481469	.1002814
L13.	.0394271	.0838395	0.47	0.638	-.1248953	.2037495
L14.	-.0989225	.0772686	-1.28	0.200	-.2503662	.0525212
FF						
L1.	.0735685	.0258523	2.85	0.004	.022899	.124238
L2.	-.0770953	.0283158	-2.72	0.006	-.1325931	-.0215974
L3.	-.0041839	.0278191	-0.15	0.880	-.0587083	.0503405
L4.	.0181824	.0275709	0.66	0.510	-.0358556	.0722204
L5.	-.071989	.0266052	-2.71	0.007	-.1241341	-.0198438
L6.	.0458475	.0271513	1.69	0.091	-.0073681	.099063
L7.	-.0049195	.026732	-0.18	0.854	-.0573134	.0474743
L8.	.002178	.0269978	0.08	0.936	-.0507367	.0550927
L9.	-.0339463	.026133	-1.30	0.194	-.0851661	.0172734
L10.	-.0316961	.0242672	-1.31	0.192	-.079259	.0158667
L11.	.0139396	.0236229	0.59	0.555	-.0323603	.0602396
L12.	.0096585	.0185081	0.52	0.602	-.0266167	.0459337
L13.	.0098244	.0067192	1.46	0.144	-.0033449	.0229937
L14.	.01247	.0056464	2.21	0.027	.0014032	.0235368
dummy	.0005041	.000392	1.29	0.199	-.0002643	.0012725
vacgrowth	-.0001706	.0001736	-0.98	0.326	-.0005109	.0001697
_cons	.0049329	.0035859	1.38	0.169	-.0020952	.0119611
FF						
casesgrowth						
L1.	.0037355	.0023306	1.60	0.109	-.0008323	.0083033
L2.	-.004683	.0027266	-1.72	0.086	-.0100271	.0006611
L3.	.0051522	.002771	1.86	0.063	-.0002789	.0105833
L4.	.0000841	.0029156	0.03	0.977	-.0056303	.0057985
L5.	.0062547	.0028667	2.18	0.029	.000636	.0118734
L6.	-.0013341	.0026419	-0.50	0.614	-.0065121	.0038438
L7.	-.0007094	.0028302	-0.25	0.802	-.0062564	.0048376
L8.	.0012481	.0028336	0.44	0.660	-.0043058	.0068019
L9.	-.0007631	.0026525	-0.29	0.774	-.0059619	.0044357
L10.	.0029891	.0026726	1.12	0.263	-.0022491	.0082273
L11.	.0015224	.0028287	0.54	0.590	-.0040218	.0070665
L12.	-.0042001	.002619	-1.60	0.109	-.0093333	.000933
L13.	.0046485	.002594	1.79	0.073	-.0004356	.0097326
L14.	.0028143	.0021696	1.30	0.195	-.001438	.0070666
dWeiInterp						
L1.	.0003748	.0010538	0.36	0.722	-.0016906	.0024402
L2.	.0015618	.0011459	1.36	0.173	-.0006842	.0038078
L3.	-.0021524	.0012658	-1.70	0.089	-.0046333	.0003286
L4.	.0034164	.0013168	2.59	0.009	.0008355	.0059972
L5.	-.0045746	.0013455	-3.40	0.001	-.0072117	-.0019375
L6.	.0016271	.0014144	1.15	0.250	-.001145	.0043992
L7.	-.0050544	.0014827	-3.41	0.001	-.0079605	-.0021483
L8.	.0024735	.0014523	1.70	0.089	-.000373	.00532
L9.	-.0042852	.0014837	-2.89	0.004	-.0071933	-.0013772
L10.	-.0023377	.0015764	-1.48	0.138	-.0054274	.000752
L11.	-.0003785	.0014501	-0.26	0.794	-.0032206	.0024636
L12.	.0020796	.0014576	1.43	0.154	-.0007772	.0049364
L13.	-.000557	.0014451	-0.39	0.700	-.0033894	.0022754
L14.	.0018354	.0012317	1.49	0.136	-.0005787	.0042495

```
LCBLLBCgrowth |
          L1. | -.4650675  .3465658  -1.34  0.180  -1.144324   .2141889
          L2. |  .2126599  .3507653   0.61  0.544  -.4748275   .9001473
          L3. |  -.237715  .3405881  -0.70  0.485  -.9052553   .4298253
          L4. |  .4747495  .3359083   1.41  0.158  -.1836186   1.133118
          L5. | -.5123402  .3306246  -1.55  0.121  -1.160353   .1356723
          L6. | -.1246083  .3440168  -0.36  0.717   -.798869   .5496523
          L7. | -.3444904  .3390558  -1.02  0.310  -1.009028   .3200468
          L8. | -.8458641   .316639  -2.67  0.008  -1.466465  -.2252631
          L9. |  -.909504  .3349008  -2.72  0.007  -1.565897  -.2531105
         L10. |   .202034  .3370829   0.60  0.549  -.4586364   .8627043
         L11. |  .4674791  .3253106   1.44  0.151   -.170118   1.105076
         L12. | -.3105014  .3080346  -1.01  0.313  -.9142381   .2932352
         L13. |  .2838773  .2905447   0.98  0.329  -.2855799   .8533345
         L14. | -1.041879  .2677733  -3.89  0.000  -1.566705  -.5170531
              |
           FF |
          L1. |  .4431085  .0895907   4.95  0.000   .2675141    .618703
          L2. | -.0254121  .0981279  -0.26  0.796  -.2177392   .1669149
          L3. | -.0751015  .0964067  -0.78  0.436  -.2640552   .1138521
          L4. |  .0812713  .0955466   0.85  0.395  -.1059966   .2685393
          L5. |  -.076682  .0921998  -0.83  0.406  -.2573904   .1040263
          L6. | -.0561524  .0940925  -0.60  0.551  -.2405702   .1282654
          L7. | -.0002993  .0926395  -0.00  0.997  -.1818694   .1812708
          L8. |  .0152656  .0935605   0.16  0.870  -.1681096   .1986409
          L9. |  .0309715  .0905636   0.34  0.732  -.1465298   .2084728
         L10. | -.1120254  .0840977  -1.33  0.183  -.2768538    .052803
         L11. | -.2247623  .0818648  -2.75  0.006  -.3852142  -.0643103
         L12. |  .2296318  .0641395   3.58  0.000   .1039206   .3553429
         L13. | -.0704505  .0232852  -3.03  0.002  -.1160885  -.0248124
         L14. | -.0114756  .0195676  -0.59  0.558  -.0498273   .0268761
              |
        dummy |   .000605  .0013586   0.45  0.656  -.0020579   .0032679
    vacgrowth | -.0029539  .0006017  -4.91  0.000  -.0041333  -.0017746
        _cons |  .0723307  .0124268   5.82  0.000   .0479747   .0966867
------------------------------------------------------------------------

. varlmar, mlag(16)

   Lagrange-multiplier test
```

lag	chi2	df	Prob > chi2
1	12.5094	16	0.70823
2	13.9232	16	0.60444
3	16.7453	16	0.40226
4	15.0559	16	0.52054
5	15.9348	16	0.45752
6	26.2836	16	0.05017
7	8.9078	16	0.91716
8	28.4369	16	0.02802
9	12.0965	16	0.73731
10	9.6393	16	0.88477
11	10.4930	16	0.83965
12	19.3062	16	0.25311
13	10.6789	16	0.82886
14	10.8531	16	0.81846
15	26.0824	16	0.05288
16	15.9088	16	0.45934

H0: no autocorrelation at lag order

Figure C.6 – VAR(14) model estimation and Lagrange multiplier test for the serial correlation between residuals for a model with optimal lag, p=14.

```
. summarize rescasesgrowth resdWeiInterp resLCBLLBCgrowth resFF
```

Variable	Obs	Mean	Std. Dev.	Min	Max
rescasesgr~h	91	-9.62e-11	.1274248	-.400363	.631493
resdWeiInt~p	91	1.79e-11	.2986645	-1.060426	.9575102
resLCBLLBC~h	91	5.64e-12	.0008384	-.0029537	.001772
resFF	91	-4.00e-12	.0029054	-.0100899	.0091451

Figure C.7 – Residuals of the variables for the model with optimal lag (p=14).

```
. corr rescasesgrowth resdWeiInterp resLCBLLBCgrowth resFF, cov
(obs=91)

             | rescas~h resdWe~p resLCB~h    resFF
-------------+------------------------------------
rescasesgr~h |  .016237
resdWeiInt~p |  .007824  .089201
resLCBLLBC~h |  7.0e-07 -.000048  7.0e-07
       resFF | -.000018 -.000075  4.2e-07  8.4e-06
```

Figure C.8 – Covariance between residuals for the model with optimal lag (p=14).

```
. corr rescasesgrowth resdWeiInterp resLCBLLBCgrowth resFF
(obs=91)

             | rescas~h resdWe~p resLCB~h    resFF
-------------+------------------------------------
rescasesgr~h |   1.0000
resdWeiInt~p |   0.2056   1.0000
resLCBLLBC~h |   0.0066  -0.1934   1.0000
       resFF |  -0.0482  -0.0859   0.1710   1.0000
```

Figure C.9 – Correlation between residuals for the model with optimal lag (p=14).

Granger causality

. vargranger

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
casesgrowth	dWeiInterp	26.093	14	0.025
casesgrowth	LCBLLBCgrowth	24.784	14	0.037
casesgrowth	FF	19.776	14	0.137
casesgrowth	ALL	77.35	42	0.001
dWeiInterp	casesgrowth	26.637	14	0.021
dWeiInterp	LCBLLBCgrowth	41.226	14	0.000
dWeiInterp	FF	21.537	14	0.089
dWeiInterp	ALL	72.408	42	0.002
LCBLLBCgrowth	casesgrowth	75.002	14	0.000
LCBLLBCgrowth	dWeiInterp	62.932	14	0.000
LCBLLBCgrowth	FF	33.068	14	0.003
LCBLLBCgrowth	ALL	151.33	42	0.000
FF	casesgrowth	18.613	14	0.180
FF	dWeiInterp	113.59	14	0.000
FF	LCBLLBCgrowth	46.805	14	0.000
FF	ALL	214.07	42	0.000

Figure C.10 - Granger causality between variables for the model with optimal lag (p=14)

Orthogonalized impulse response functions

```
. irf create IRF, set(IRF, replace) step (20) order(casesgrowth dWeiInterp LCBLLBCgrowth FF)
(file IRF.irf created)
(file IRF.irf now active)
(file IRF.irf updated)
```

In Stata, we start by creating an IRF entry in a file called *IRF* to hold the results of the VAR(14) and run the IRF effect horizon out over 20 weeks (five months). Next, the order of the variables is listed again in the IRFs command[26].

The final step to attaining the output is to plot the orthogonal impulse response functions and table their values. To get the OIRFs case, it is necessary to run *oirf* instead of *irf*.

```
. irf graph oirf, set(IRF) irf(IRF) impulse (casesgrowth dWeiInterp LCBLLBCgrowth FF) response(casesgrowth dWeiInterp LCBLLBCgrowth
>  FF) yline(0)
(file IRF.irf now active)
```

This command will provide all OIRFs[27] results in the same graphic, which can make interpretation of some values difficult regarding the different scales of effects caused. If the output containing the table with the values is desired, the same command is applied, replacing *graph* with *table*.

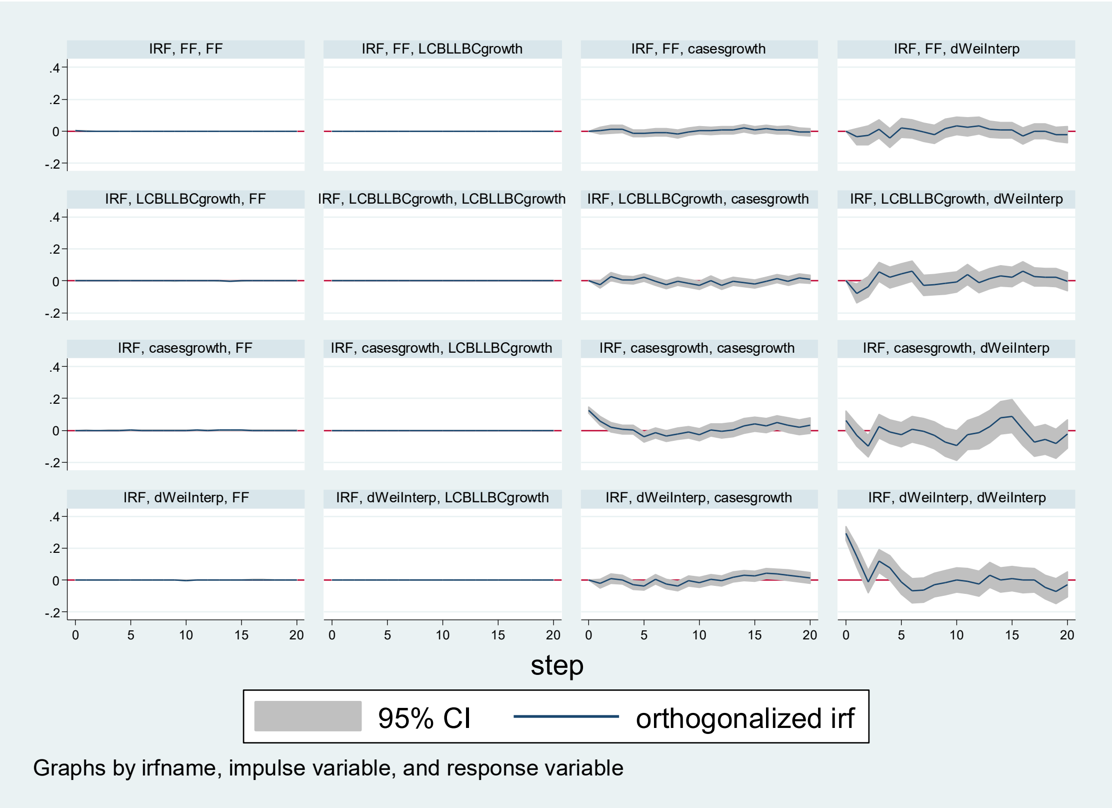


Figure C.11 – All OIRF'S for the model with optimal lag (p=14).

---

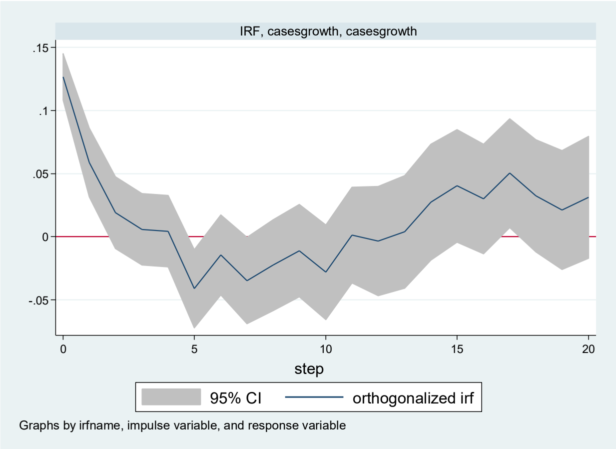
[26] This particular step is unnecessary once the order is already defined in the *var* command.

[27] The shaded area in the OIRFs represents the confidence interval bands of our VAR model.

Impulse: casesgrowth

Response: casesgrowth

```
. irf graph oirf, set(IRF) irf(IRF) impulse (casesgrowth) response (casesgrowth) yline(0)
(file IRF.irf now active)
. irf table oirf, set(IRF) irf(IRF) impulse (casesgrowth) response (casesgrowth)
(file IRF.irf now active)
```



Results from IRF

step	(1) oirf	(1) Lower	(1) Upper
0	.126723	.108312	.145133
1	.058795	.031553	.086037
2	.019143	-.009285	.047571
3	.005799	-.022464	.034062
4	.004359	-.024047	.032765
5	-.041198	-.072222	-.010175
6	-.01441	-.046243	.017423
7	-.034745	-.069025	-.000465
8	-.02253	-.058479	.013418
9	-.011059	-.04757	.025451
10	-.028164	-.065684	.009356
11	.001257	-.03676	.039274
12	-.003583	-.046884	.039718
13	.003804	-.040787	.048396
14	.027416	-.018538	.07337
15	.040274	-.004472	.08502
16	.029921	-.013486	.073328
17	.050362	.007189	.093534
18	.032456	-.012003	.076914
19	.021037	-.026055	.068129
20	.031279	-.017105	.079663

95% lower and upper bounds reported
(1) irfname = IRF, impulse = casesgrowth, and response = casesgrowth

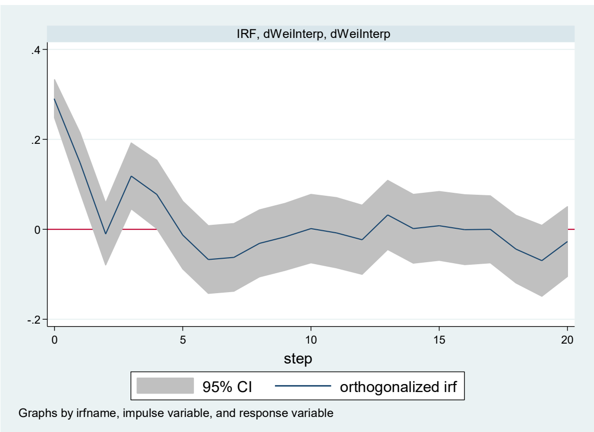
Figure C.12 – casesgrowth shock on itself OIRF for the model with optimal lag (p=14).

Figure C.13 shows the effects of a shock in the growth rate of new Covid-19 confirmed cases on future values of its own growth. In both cases, a one-standard-deviation shock to casesgrowth is just over 0.12 percent (0.126723%).

Impulse: dWeiInterp

Response: dWeiInterp

```
. irf graph oirf, set(IRF) irf(IRF) impulse (dWeiInterp) response (dWeiInterp) yline(0)
(file IRF.irf now active)
. irf table oirf, set(IRF) irf(IRF) impulse (dWeiInterp) response (dWeiInterp)
(file IRF.irf now active)
```



Results from IRF

step	(1) oirf	(1) Lower	(1) Upper
0	.290674	.248444	.332904
1	.148158	.082153	.214163
2	-.010257	-.079151	.058637
3	.118641	.045495	.191787
4	.077661	.001318	.154003
5	-.012838	-.087961	.062285
6	-.067229	-.142212	.007754
7	-.062368	-.137878	.013142
8	-.031141	-.105465	.043182
9	-.016467	-.090828	.057895
10	.001924	-.074232	.07808
11	-.007527	-.085619	.070566
12	-.023306	-.100167	.053556
13	.031813	-.045063	.108689
14	.00134	-.074895	.077575
15	.007793	-.068842	.084428
16	-.00065	-.078191	.076891
17	-.000085	-.074435	.074264
18	-.043996	-.119302	.03131
19	-.069816	-.148447	.008815
20	-.027337	-.104901	.050228

95% lower and upper bounds reported
(1) irfname = IRF, impulse = dWeiInterp, and response = dWeiInterp

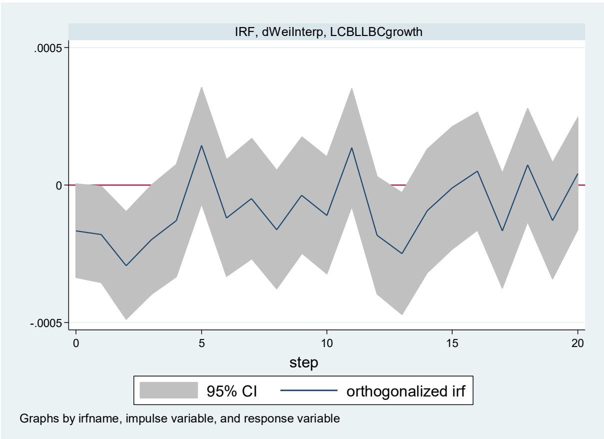
Figure C.13 – dWeiInterp shock on itself OIRF for the model with optimal lag (p=14).

Figure C.14 shows the effects of shocks to the first differences of the economic activity index on future values of its own. In this case, a one-standard deviation shock to dWeiInterp is about 0.3 percent.

Response: LCBLLBCgrowth

```
. irf graph oirf, set(IRF) irf(IRF) impulse (dWeiInterp) response (LCBLLBCgrowth) yline(0)
(file IRF.irf now active)

. irf table oirf, set(IRF) irf(IRF) impulse (dWeiInterp) response (LCBLLBCgrowth)
(file IRF.irf now active)
```



Results from IRF

step	(1) oirf	(1) Lower	(1) Upper
0	-.000166	-.000336	3.7e-06
1	-.000179	-.000355	-3.5e-06
2	-.000293	-.000488	-.000097
3	-.000199	-.000397	1.7e-07
4	-.000129	-.000333	.000075
5	.000144	-.000067	.000356
6	-.00012	-.000332	.000092
7	-.000049	-.000267	.000169
8	-.000162	-.000377	.000053
9	-.000037	-.000248	.000175
10	-.00011	-.000323	.000102
11	.000137	-.000077	.00035
12	-.000182	-.000396	.000031
13	-.000249	-.00047	-.000028
14	-.000094	-.000319	.000132
15	-.00001	-.000233	.000213
16	.000051	-.000164	.000265
17	-.000166	-.000375	.000043
18	.000073	-.000133	.000279
19	-.00013	-.000341	.000082
20	.000042	-.000162	.000246

95% lower and upper bounds reported
(1) irfname = IRF, impulse = dWeiInterp, and response = LCBLLBCgrowth

Figure C.14 – dWeiInterp shock in LCBLLBCgrowth OIRF for the model with optimal lag (p=14).

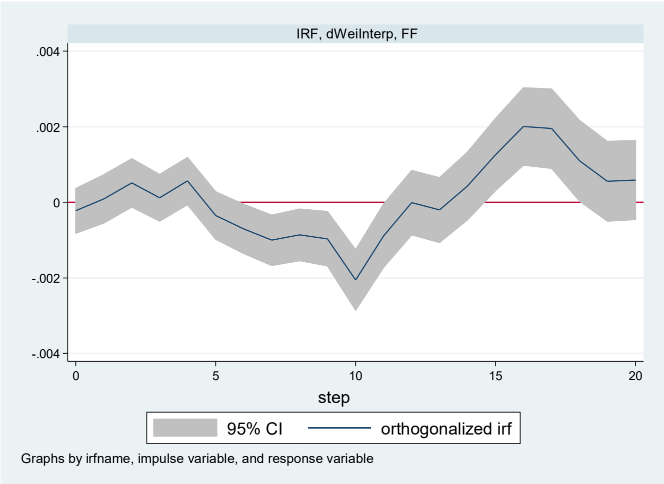
The first thing to notice is the immediate negative effect that a shock on dWeiInterp has on LCBLLBCgrowth, on average -0.000166%. The negative effect of the shock remains during the first two weeks. The peak occurs in the second week [-0.000097; -0.000488]. Even though the results mentioned are significant, the effect is very close to zero.

A positive shock in the first differences in real economic activity can be viewed as economic growth. Once there is economic growth, the government's stimulus to credit can gradually decrease, generating a negative effect, as shown in the chart above.

Response: FF

```
. irf graph oirf, set(IRF) irf(IRF) impulse (dWeiInterp) response (FF) yline(0)
(file IRF.irf now active)

. irf table oirf, set(IRF) irf(IRF) impulse (dWeiInterp) response (FF)
(file IRF.irf now active)
```



Results from IRF

step	(1) oirf	(1) Lower	(1) Upper
0	-.000224	-.000816	.000368
1	.000087	-.000551	.000724
2	.000518	-.000122	.001157
3	.000118	-.000503	.000739
4	.000566	-.000059	.001191
5	-.000354	-.000982	.000274
6	-.000704	-.001352	-.000056
7	-.001007	-.001677	-.000337
8	-.000862	-.001546	-.000178
9	-.000968	-.001689	-.000247
10	-.002057	-.002854	-.00126
11	-.000892	-.001733	-.000052
12	-.00001	-.000866	.000845
13	-.000206	-.001063	.000652
14	.000428	-.000466	.001322
15	.001264	.000311	.002217
16	.002005	.000982	.003028
17	.00195	.0009	.003
18	.001099	.00003	.002168
19	.000556	-.000505	.001617
20	.000588	-.000463	.001638

95% lower and upper bounds reported
(1) irfname = IRF, impulse = dWeiInterp, and response = FF

Figure C.15 – dWeiInterp shock in FF OIRF for the model with optimal lag (p=14).

Figure C.16 shows the effects of dWeiInterp in FF. We see that one-standard deviation (0.3 percentage points) shock in dWeiInterp has no instantaneous effect on the Fed Funds rate. The shock only starts being significant five weeks ahead of its occurrence. From the fifth to the tenth week, the response is negative, with the lowest point in the tenth week reaching percentual values of [-0.00126; -0.002854]. After the response starts being positive from the thirteenth week, the twenty-second, with the peak in the sixteenth week, registering values between [0.000982;0.003028].

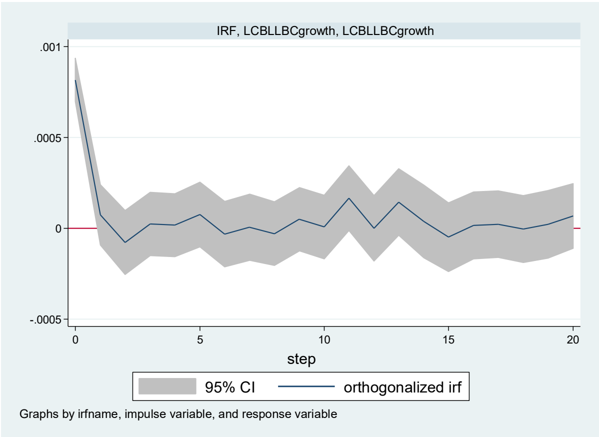
This dynamic between variables could be supported by the fact that the FED implemented easing monetary policy to boost real economic activity, p.e. lowering interest rates. By analyzing the results from a short-term political perspective, the output becomes more interesting as it is possible to see. After the initial positive shock in real economic activity, the Fed funds interest rates decreased, intending to continue to stimulate the economy. Then, more a less three months later, the interest rates increased proportionally to what had decreased to control the initial downfall and future inflation.

Impulse: LCBLLBCgrowth

Response: LCBLLBCgrowth

```
. irf graph oirf, set(IRF) irf(IRF) impulse (LCBLLBCgrowth) response (LCBLLBCgrowth) yline(0)
(file IRF.irf now active)

. irf table oirf, set(IRF) irf(IRF) impulse (LCBLLBCgrowth) response (LCBLLBCgrowth)
(file IRF.irf now active)
```



Results from IRF

step	(1) oirf	(1) Lower	(1) Upper
0	.000817	.000698	.000936
1	.000074	-.000091	.00024
2	-.000079	-.000255	.000098
3	.000023	-.000151	.000197
4	.000017	-.000156	.000191
5	.000076	-.000101	.000254
6	-.000032	-.000212	.000148
7	6.9e-06	-.000175	.000189
8	-.000029	-.000205	.000146
9	.00005	-.000123	.000224
10	7.9e-06	-.000167	.000183
11	.000166	-.000011	.000344
12	-1.2e-07	-.000181	.000181
13	.000145	-.000039	.000329
14	.000038	-.000162	.000238
15	-.000049	-.000238	.000141
16	.000016	-.000168	.0002
17	.000023	-.000161	.000207
18	-4.4e-06	-.000189	.00018
19	.000021	-.000165	.000208
20	.000068	-.000111	.000246

95% lower and upper bounds reported
(1) irfname = IRF, impulse = LCBLLBCgrowth, and response = LCBLLBCgrowth

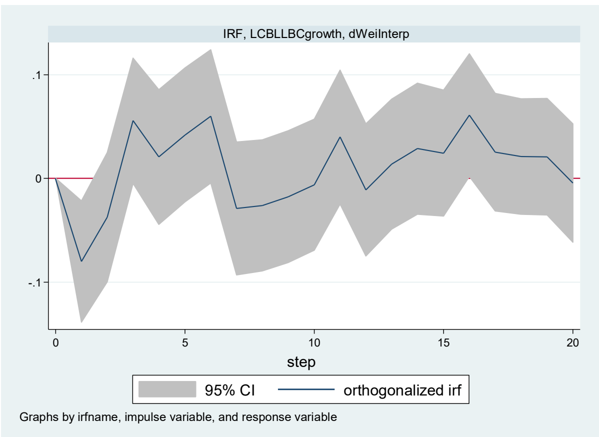
Figure C.16– LCBLLBCgrowth shock on itself OIRF for the model with optimal lag (p=14).

Figure C.17 shows the effects of shocks to the growth rate of total credit in the US on future values of its own growth. In this case, a one-standard deviation shock to LCBLLBCgrowth is just 0.000817 percent.

Response: dWeiInterp

```
. irf graph oirf, set(IRF) irf(IRF) impulse (LCBLLBCgrowth) response (dWeiInterp) yline(0)
(file IRF.irf now active)
. irf table oirf, set(IRF) irf(IRF) impulse (LCBLLBCgrowth) response (dWeiInterp)
(file IRF.irf now active)
```

Results from IRF



step	(1) oirf	(1) Lower	(1) Upper
0	0	0	0
1	-.080121	-.138613	-.021629
2	-.037436	-.099897	.025026
3	.05566	-.00489	.116211
4	.020663	-.04438	.085705
5	.041882	-.02267	.106434
6	.059831	-.00434	.124002
7	-.02886	-.092939	.03522
8	-.026089	-.089235	.037057
9	-.017647	-.081351	.046056
10	-.006092	-.069399	.057216
11	.039864	-.024761	.10449
12	-.011204	-.074882	.052473
13	.013685	-.048945	.076316
14	.028665	-.034666	.091996
15	.024409	-.036336	.085153
16	.061007	.001844	.120169
17	.02549	-.031263	.082243
18	.021016	-.034714	.076746
19	.020808	-.035371	.076987
20	-.004444	-.061614	.052727

95% lower and upper bounds reported
(1) irfname = IRF, impulse = LCBLLBCgrowth, and response = dWeiInterp

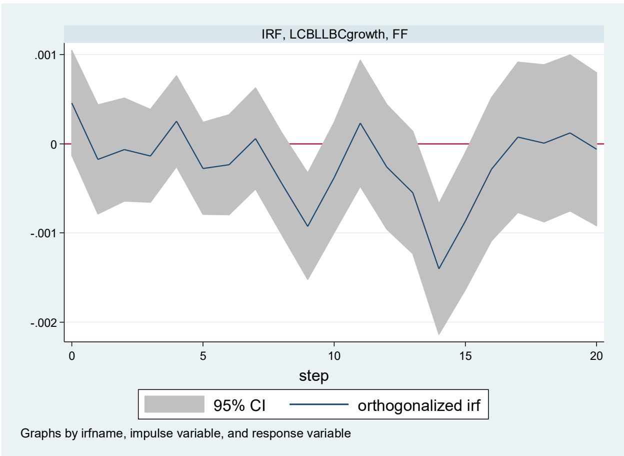
Figure C.17 – LCBLLBCgrowth shock in dWeiInterp OIRF for the model with optimal lag (p=14).

Figure C.18 shows the effects of the growth rate of total credit in the first differences in the real economic activity index. We see that a one-standard deviation (0.000817 percentage points) shock in

LCBLLBCgrowth has no immediate effect in dWeiInterp. The first week after the shock dWeiInterp has an adverse response between [-0.021629; -0.138613]. After it, the impulse associated with shock quickly dies out and has no more significance.

Response: FF

```
. irf graph oirf, set(IRF) irf(IRF) impulse (LCBLLBCgrowth) response (FF) yline(0)
(file IRF.irf now active)
. irf table oirf, set(IRF) irf(IRF) impulse (LCBLLBCgrowth) response (FF)
(file IRF.irf now active)
```



Results from IRF

step	(1) oirf	(1) Lower	(1) Upper
0	.00046	-.000128	.001047
1	-.000176	-.000788	.000435
2	-.000066	-.000643	.000511
3	-.000136	-.000656	.000383
4	.000254	-.000255	.000764
5	-.000276	-.000793	.00024
6	-.000235	-.000796	.000325
7	.00006	-.000506	.000626
8	-.000444	-.001015	.000127
9	-.000925	-.001524	-.000327
10	-.000378	-.000996	.000241
11	.000231	-.000475	.000937
12	-.000258	-.000958	.000441
13	-.000547	-.001234	.00014
14	-.001404	-.002137	-.00067
15	-.000867	-.001636	-.000099
16	-.000285	-.001088	.000518
17	.000073	-.000771	.000918
18	5.7e-06	-.000875	.000886
19	.000122	-.000755	.000999
20	-.000059	-.000916	.000798

95% lower and upper bounds reported
(1) irfname = IRF, impulse = LCBLLBCgrowth, and response = FF

Figure C.18– LCBLLBCgrowth shock in FF OIRF for the model with optimal lag (p=14).

Looking at figure 35, the first thing to analyse in the initial effect that a shock on LCBLLBCgrowth has in the FF.

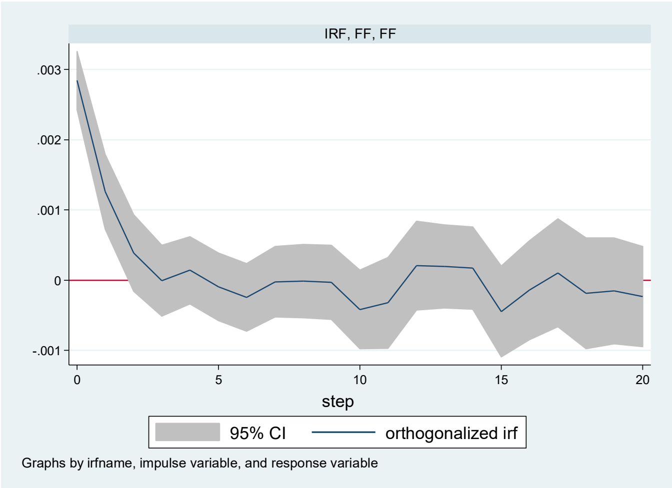
Looking at figure C.19, the first thing to analyze is the initial effect that a shock on LCBLLBCgrowth has on the FF. The first thing to notice is the immediate effect that a shock on LCBLLBCgrowth has on FF. A one-standard deviation shock in LCBLLBCgrowth (0.000817 percent) changes FF in the current week between [-0.000128;0.001047] percentual points. The short-term response is negative in the ninth week between [-0.000327; -0.001524] and the fourteenth week between [-0.00067; -0.002137]. This result reflects the monetary policy taken by the Fed in the period of analysis, a boost (shock) in credit followed by a reduction in the Fed funds rate.

Impulse: FF

Response: FF

```
. irf table oirf, set(IRF) irf(IRF) impulse (FF) response (FF)
(file IRF.irf now active)

. irf graph oirf, set(IRF) irf(IRF) impulse (FF) response (FF) yline(0)
(file IRF.irf now active)
```



Results from IRF

step	(1) oirf	(1) Lower	(1) Upper
0	.00284	.002428	.003253
1	.001259	.000727	.00179
2	.000387	-.000157	.000931
3	-8.4e-06	-.000515	.000498
4	.00014	-.000337	.000618
5	-.000095	-.000575	.000384
6	-.000245	-.000727	.000236
7	-.000022	-.000523	.000478
8	-.000013	-.000535	.000509
9	-.000033	-.000561	.000495
10	-.000418	-.000977	.000141
11	-.000323	-.000968	.000322
12	.000206	-.000427	.000839
13	.000193	-.000398	.000784
14	.00017	-.000416	.000756
15	-.000446	-.001092	.0002
16	-.000144	-.000847	.000559
17	.000105	-.000662	.000872
18	-.000189	-.000978	.000601
19	-.000152	-.000906	.000602
20	-.000233	-.000946	.000481

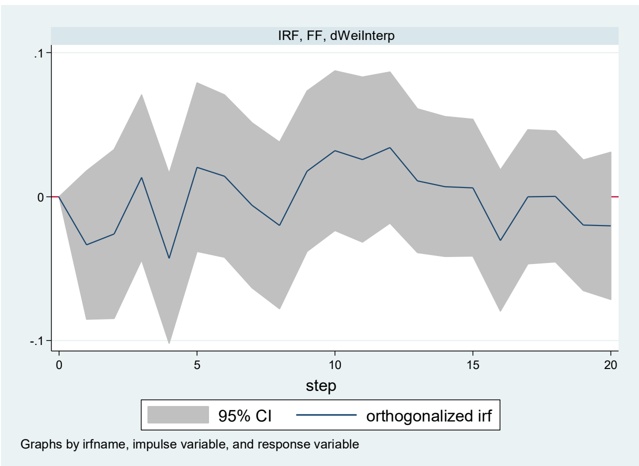
95% lower and upper bounds reported
(1) irfname = IRF, impulse = FF, and response = FF

Figure C.19 – FF shock on itself OIRF for the model with optimal lag (p=14).

Figure C.20 show the effects of shocks to the FF on future values of its own. In this case, a one-standard deviation shock to FF is between [0.002428;0.003253] percent.

Response: dWeiInterp

```
. irf graph oirf, set(IRF) irf(IRF) impulse (FF) response (dWeiInterp) yline(0)
(file IRF.irf now active)
. irf table oirf, set(IRF) irf(IRF) impulse (FF) response (dWeiInterp)
(file IRF.irf now active)
```



Results from IRF

step	(1) oirf	(1) Lower	(1) Upper
0	0	0	0
1	-.033472	-.084972	.018029
2	-.025846	-.084467	.032775
3	.0134	-.04403	.07083
4	-.042864	-.101767	.016039
5	.020486	-.03798	.078952
6	.014254	-.04211	.070618
7	-.005915	-.063159	.051328
8	-.019996	-.077869	.037878
9	.017688	-.038107	.073484
10	.032041	-.023423	.087505
11	.025877	-.031405	.083158
12	.03419	-.018289	.086669
13	.011035	-.038894	.060964
14	.007084	-.041618	.055786
15	.006215	-.041289	.053718
16	-.030347	-.079311	.018616
17	-.000048	-.046681	.046584
18	.000302	-.045138	.045742
19	-.01971	-.065056	.025636
20	-.020194	-.07131	.030922

95% lower and upper bounds reported
(1) irfname = IRF, impulse = FF, and response = dWeiInterp

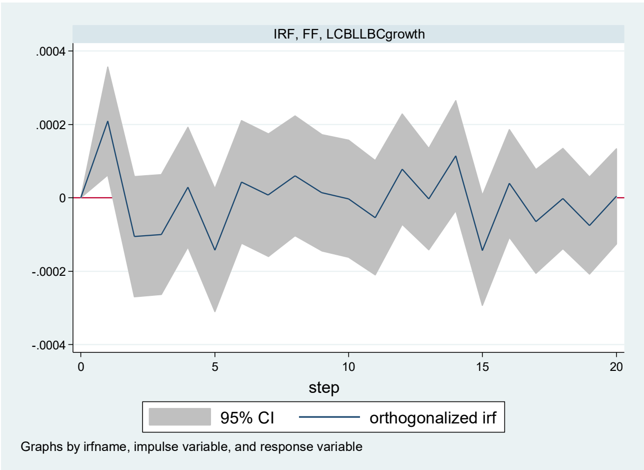
Figure C.20 – FF shock in dWeiInterp OIRF for the model with optimal lag (p=14).

As it is possible to observe, a shock on FF will not stimulate a significant response on dWeiInterp for the analysis period.

Response: LCBLLBCgrowth

```
. irf graph oirf, set(IRF) irf(IRF) impulse (FF) response (LCBLLBCgrowth) yline(0)
(file IRF.irf now active)

. irf table oirf, set(IRF) irf(IRF) impulse (FF) response (LCBLLBCgrowth)
(file IRF.irf now active)
```



Results from IRF

step	(1) oirf	(1) Lower	(1) Upper
0	0	0	0
1	.000209	.000062	.000356
2	-.000106	-.000269	.000058
3	-.0001	-.000263	.000063
4	.000029	-.000135	.000192
5	-.000143	-.00031	.000024
6	.000043	-.000123	.00021
7	7.4e-06	-.00016	.000174
8	.00006	-.000104	.000223
9	.000014	-.000145	.000172
10	-2.8e-06	-.000162	.000157
11	-.000054	-.00021	.000102
12	.000078	-.000073	.000228
13	-3.4e-06	-.000141	.000134
14	.000115	-.000035	.000265
15	-.000144	-.000294	6.4e-06
16	.000039	-.000108	.000186
17	-.000065	-.000206	.000077
18	-2.1e-06	-.000139	.000135
19	-.000076	-.000208	.000056
20	3.9e-06	-.000126	.000133

95% lower and upper bounds reported
(1) irfname = IRF, impulse = FF, and response = LCBLLBCgrowth

Figure C.21 – FF shock in LCBLLBCgrowth OIRF for the model with optimal lag (p=14).

When there is a one standard deviation shock in FF, there is no immediate response in the current week by LCBLLBCgrowth. However, only one week ahead of the initial shock, there is a positive response between [0.000062;0.000356] percent.

Cumulative orthogonalized impulse response functions

Again in Stata, we create an IRF entry in a file called *IRF* to hold the results of the VAR(14) and run the IRF effect horizon out over 52 weeks (one year). Next, the order of the variables is listed again in the IRFs command.

```
. irf create IRF, set(IRF, replace) step (52) order(casesgrowth dWeiInterp LCBLLBCgrowth FF)
(file IRF.irf created)
(file IRF.irf now active)
(file IRF.irf updated)
```

The final step to attaining the output is to plot the orthogonal impulse response functions and table their values. To obtain the COIRFs case, it is necessary to run *coirf* instead of *irf* or *oirf*.

```
. irf graph coirf, set(IRF) irf(IRF) impulse (casesgrowth dWeiInterp LCBLLBCgrowth FF) response(casesgrowth dWeiInterp LCBLLBCgrowt
> h FF) yline(0)
(file IRF.irf now active)
```

This command will provide all COIRFs results in the same graphic, which can make interpretation of some values difficult regarding the different scales of effects caused. If the output containing the table with the values is desired, the same command is applied, replacing *graph* with *table*.

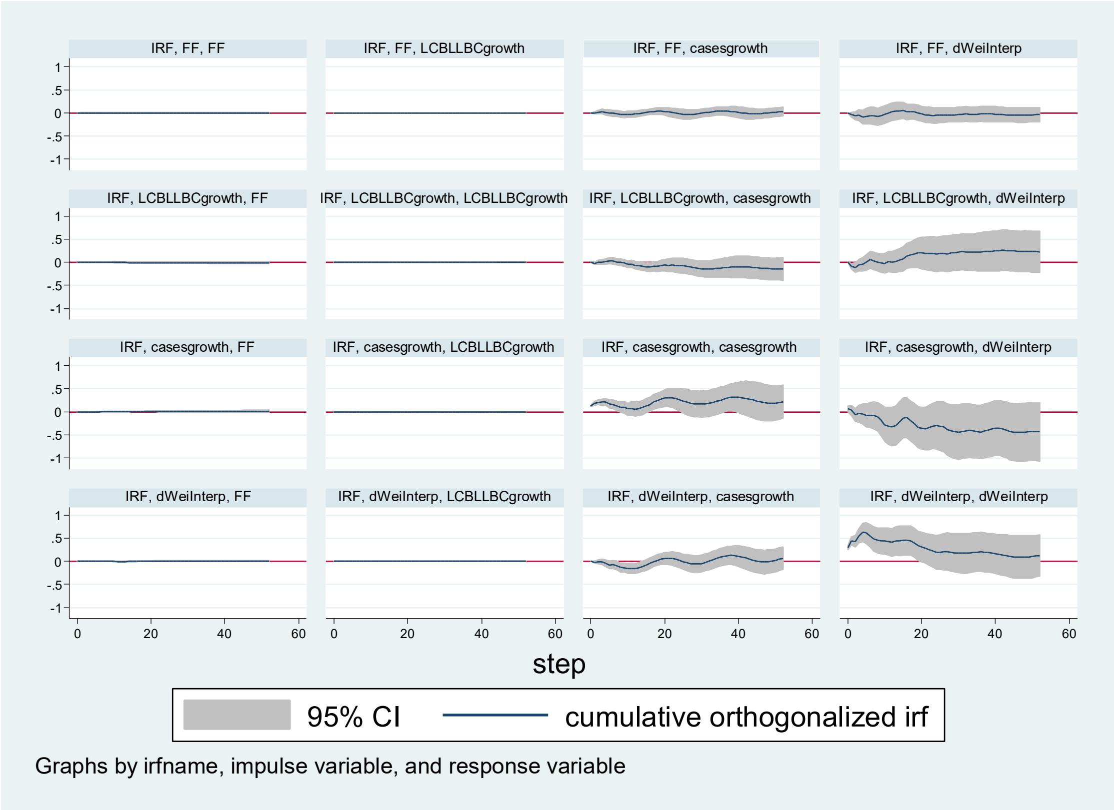
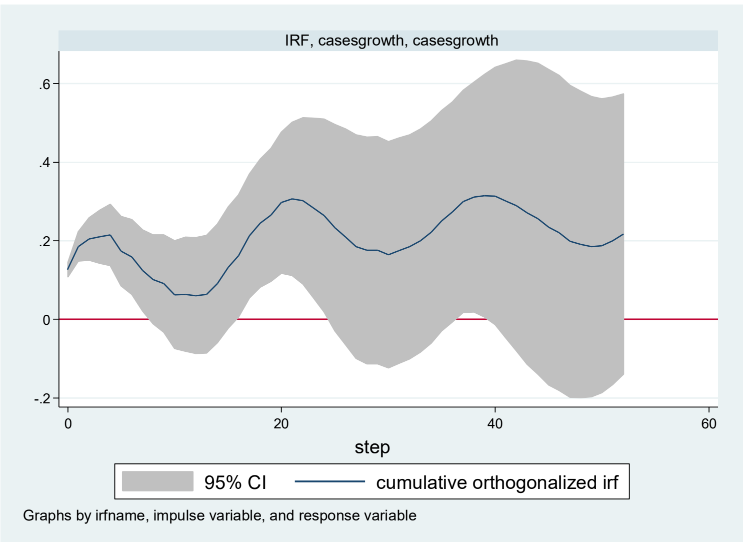


Figure C.22 – All COIRF'S for the model with optimal lag (p=14).

Impulse: casesgrowth

Response: casesgrowth

```
. irf graph coirf, set(IRF) irf(IRF) impulse (casesgrowth) response (casesgrowth) yline(0)
(file IRF.irf now active)
. irf table coirf, set(IRF) irf(IRF) impulse (casesgrowth) response (casesgrowth)
(file IRF.irf now active)
```



Results from IRF

step	(1) coirf	(1) Lower	(1) Upper
0	.126723	.108312	.145133
1	.185518	.14816	.222875
2	.204661	.150862	.25846
3	.21046	.143004	.277916
4	.214819	.136774	.292865
5	.173621	.085519	.261723
6	.159211	.064052	.254369
7	.124466	.021137	.227795
8	.101935	-.011262	.215132
9	.090876	-.033228	.21498
10	.062712	-.074193	.199616
11	.063969	-.080805	.208743
12	.060386	-.087043	.207814
13	.06419	-.084899	.213279
14	.091606	-.059097	.242309
15	.131881	-.021891	.285652
16	.161802	.006422	.317181
17	.212163	.054541	.369786
18	.244619	.082164	.407074
19	.265656	.096648	.434663
20	.296935	.117109	.47676
21	.306696	.112252	.501139
22	.301437	.089919	.512955
23	.284111	.056012	.51221
24	.263941	.018517	.509365
25	.233404	-.02888	.495687
26	.20958	-.065309	.484468
27	.185	-.098912	.468912
28	.175477	-.112929	.463883
29	.175628	-.113267	.464523
30	.164466	-.123621	.452553
31	.174907	-.111361	.461174
32	.184787	-.099896	.469469
33	.200332	-.083408	.484071
34	.222165	-.060208	.504537
35	.250617	-.029546	.530781
36	.273034	-.006545	.552613
37	.299964	.017223	.582704
38	.310903	.018709	.603098
39	.314452	.006315	.622588
40	.31401	-.013419	.641438
41	.301216	-.047636	.650068
42	.289918	-.079447	.659282
43	.271592	-.1136	.656783
44	.256317	-.139474	.652108
45	.234661	-.166319	.635642
46	.220068	-.180275	.620411
47	.198741	-.197613	.595094
48	.190897	-.198654	.580447
49	.184989	-.196797	.566776
50	.187087	-.186824	.560998
51	.199872	-.165487	.565231
52	.217388	-.138832	.573608

95% lower and upper bounds reported
(1) irfname = IRF, impulse = casesgrowth, and response = casesgrowth

Figure C.23 – casesgrowth shock on itself COIRFs for the model with optimal lag (p=14).

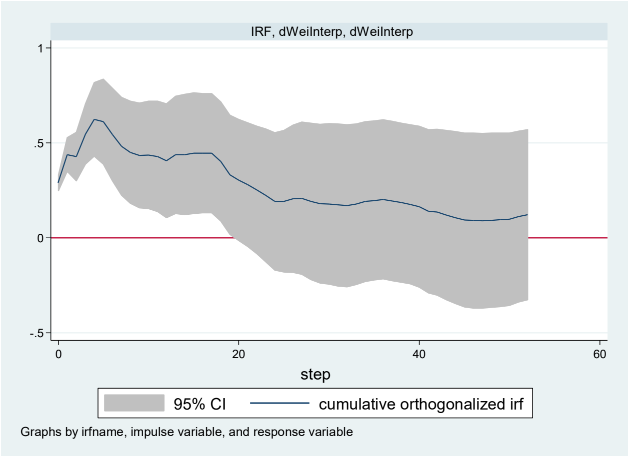
Figure C.24 shows the cumulative effects of shocks to the growth rate of new Covid-19 confirmed cases on future values of its own growth. There is a positive cyclical effect as it is possible to notice in the COIRF. This fact can be explained since an increase in the growth rate of Covid-19 cases is related to a rise in the number of infected people, increasing the probability of spreading the virus to the entire population.

Impulse: dWeiInterp

Response: dWeiInterp

```
. irf graph coirf, set(IRF) irf(IRF) impulse (dWeiInterp) response (dWeiInterp) yline(0)
(file IRF.irf now active)

. irf table coirf, set(IRF) irf(IRF) impulse (dWeiInterp) response (dWeiInterp)
(file IRF.irf now active)
```



Results from IRF

step	(1) coirf	(1) Lower	(1) Upper
0	.290674	.248444	.332904
1	.438832	.349624	.528039
2	.428575	.301041	.556109
3	.547215	.388728	.705702
4	.624876	.43094	.818811
5	.612038	.387586	.83649
6	.544809	.300269	.78935
7	.482442	.223762	.741121
8	.4513	.181725	.720876
9	.434833	.158669	.710998
10	.436758	.1533	.720215
11	.429231	.137361	.721101
12	.405925	.105933	.705918
13	.437738	.12809	.747386
14	.439078	.122015	.756141
15	.446871	.128944	.764799
16	.446222	.131741	.760702
17	.446136	.132376	.759896
18	.40214	.088528	.715752
19	.332324	.018852	.645796
20	.304987	-.013598	.623573

95% lower and upper bounds reported
(1) irfname = IRF, impulse = dWeiInterp, and response = dWeiInterp

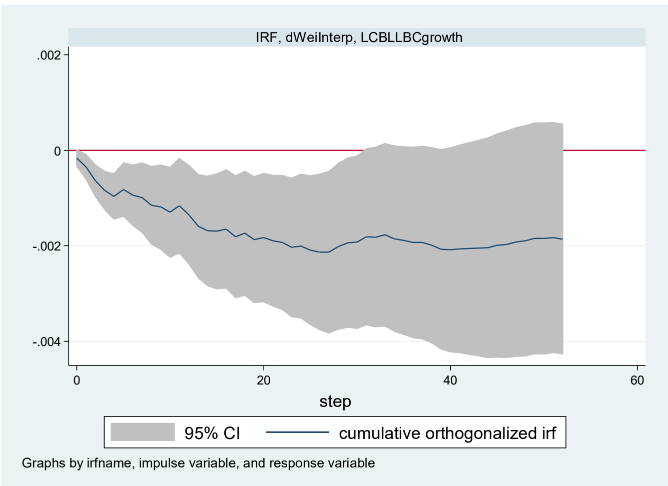
Figure C.24 - dWeiInterp shock on itself COIRF for the model with optimal lag (p=14).

Figure C.25 shows the long-run effects of shocks on the first differences of the real economic activity index on future values of its own. In this case, the cumulative effect is positive, meaning that a weekly increase in real economic activity measures will increase the variable itself, with the peak occurring in the fourth week with a total cumulative effect of 0.62. The effect completely dies out after twenty weeks. This result can be explained by the fact that an increase in real economic activity contributes to a country's wealth/GDP. These results suggest wealth is created and replaced in the economy, generating more real economic activity again, in this case sensibly five months ahead.

Response: LCBLLBCgrowth

```
. irf graph coirf, set(IRF) irf(IRF) impulse (dWeiInterp) response (LCBLLBCgrowth) yline(0)
(file IRF.irf now active)

. irf table coirf, set(IRF) irf(IRF) impulse (dWeiInterp) response (LCBLLBCgrowth)
(file IRF.irf now active)
```



Results from IRF

step	(1) coirf	(1) Lower	(1) Upper
0	-.000166	-.000336	3.7e-06
1	-.000345	-.000602	-.000088
2	-.000638	-.000968	-.000309
3	-.000837	-.001234	-.00044
4	-.000966	-.001441	-.00049
5	-.000822	-.001378	-.000265
6	-.000942	-.001577	-.000307
7	-.000991	-.00172	-.000262
8	-.001153	-.001966	-.00034
9	-.00119	-.002075	-.000304
10	-.0013	-.002244	-.000355
11	-.001163	-.002155	-.000171
12	-.001345	-.002372	-.000319
13	-.001595	-.002676	-.000513
14	-.001688	-.002835	-.000541
15	-.001698	-.002903	-.000494
16	-.001648	-.00289	-.000405
17	-.001814	-.003089	-.000539
18	-.001741	-.003041	-.00044
19	-.00187	-.003189	-.000552
20	-.001828	-.003172	-.000484
21	-.001899	-.003272	-.000527
22	-.001931	-.003337	-.000525
23	-.002034	-.003486	-.000583
24	-.002008	-.003511	-.000504
25	-.002092	-.003652	-.000532
26	-.002131	-.003758	-.000505
27	-.002133	-.003825	-.000441
28	-.002014	-.003752	-.000277
29	-.001937	-.003711	-.000162
30	-.001926	-.003734	-.000117
31	-.001814	-.00366	.000031

95% lower and upper bounds reported
(1) irfname = IRF, impulse = dWeiInterp, and response = LCBLLBCgrowth

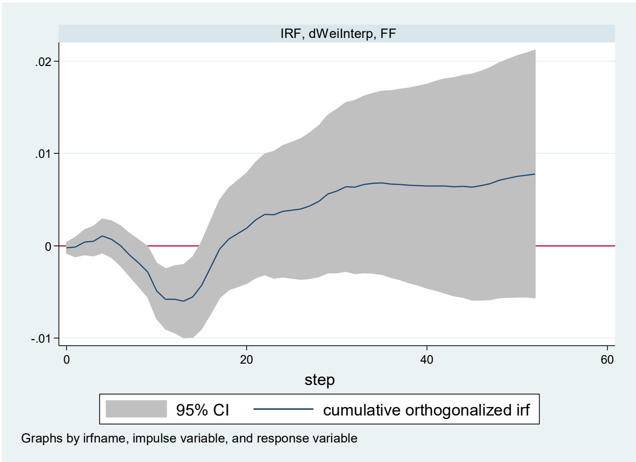
Figure C.25 – dWeiInterp shock in LCBLLBCgrowth COIRF for the model with optimal lag (p=14).

Interpreting the output from figure C.26, it is possible to conclude that the long-run effect of real economic activity on the total credit growth rate is negative for thirty weeks, with a peak effect of 0.002%. In this case, increases in real economic activity discourage credit growth once it is not necessary for the government to increase credit incentives continuously. Even though the results mentioned are significant, the effect is very close to zero.

Response: FF

```
. irf graph coirf, set(IRF) irf(IRF) impulse (dWeiInterp) response (FF) yline(0)
(file IRF.irf now active)

. irf table coirf, set(IRF) irf(IRF) impulse (dWeiInterp) response (FF)
(file IRF.irf now active)
```



Results from IRF

step	(1) coirf	(1) Lower	(1) Upper
0	-.000224	-.000816	.000368
1	-.000138	-.001163	.000888
2	.00038	-.000989	.001749
3	.000498	-.001103	.002098
4	.001064	-.000754	.002882
5	.00071	-.001282	.002702
6	6.1e-06	-.002139	.002151
7	-.001001	-.003318	.001317
8	-.001863	-.004379	.000653
9	-.002831	-.005564	-.000098
10	-.004888	-.007886	-.00189
11	-.00578	-.00906	-.0025
12	-.00579	-.009403	-.002178
13	-.005996	-.00995	-.002043
14	-.005568	-.009904	-.001232
15	-.004304	-.008998	.000389
16	-.002299	-.007319	.00272
17	-.00035	-.005633	.004934
18	.000749	-.004776	.006274
19	.001306	-.004438	.007049
20	.001893	-.004075	.007862

95% lower and upper bounds reported
(1) irfname = IRF, impulse = dWeiInterp, and response = FF

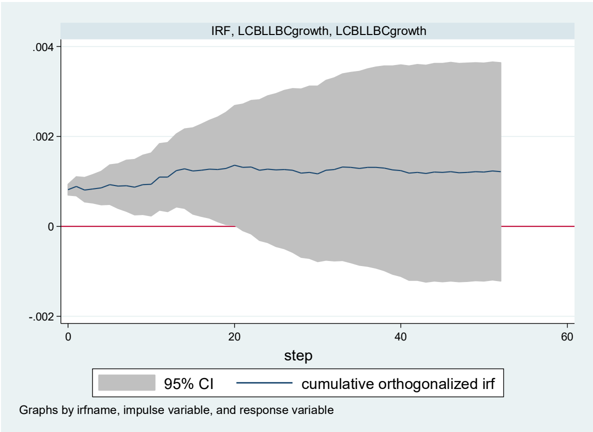
Figure C.26 – dWeiInterp shock in FF COIRF for the model with optimal lag (p=14).

Figure C.27 shows the long-run effects of dWeiInterp in FF. The shock only starts being significant eight weeks after its occurrence, with the peak in the fourteenth week, registering values between [-0.002043; -0.00995]. Also, the effect lasts for two months. Usually, in a normal economic environment, the inverse relationship is expected. However, regarding the specificity of the period and the variability of the variables themselves, such a relationship is understandable, reinforcing, even more, the politic measures adopted by the FED for the analysis period.

Impulse: LCBLLBCgrowth

Response: LCBLLBCgrowth

```
. irf graph coirf, set(IRF) irf(IRF) impulse (LCBLLBCgrowth) response (LCBLLBCgrowth) yline(0)
(file IRF.irf now active)
. irf table coirf, set(IRF) irf(IRF) impulse (LCBLLBCgrowth) response (LCBLLBCgrowth)
(file IRF.irf now active)
```



Results from IRF

step	(1) coirf	(1) Lower	(1) Upper
0	.000817	.000698	.000936
1	.000892	.000681	.001102
2	.000813	.000541	.001085
3	.000836	.000523	.001149
4	.000854	.00048	.001228
5	.00093	.000489	.001371
6	.000898	.000402	.001394
7	.000905	.00034	.001469
8	.000876	.000259	.001492
9	.000926	.000263	.001589
10	.000934	.000232	.001635
11	.0011	.000359	.001841
12	.0011	.000331	.001868
13	.001245	.000434	.002056
14	.001283	.000398	.002168
15	.001234	.000276	.002193
16	.00125	.000227	.002274
17	.001273	.000187	.00236
18	.001269	.000102	.002436
19	.00129	.000043	.002538
20	.001358	.000027	.00269

95% lower and upper bounds reported
(1) irfname = IRF, impulse = LCBLLBCgrowth, and response = LCBLLBCgrowth

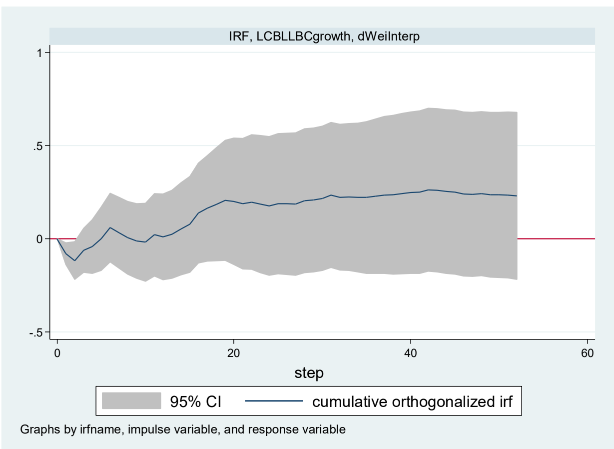
Figure C.27 – LCBLLBCgrowth shock on itself COIRF for the model with optimal lag (p=14).

Figure C.28 shows the long-run effects of shocks to the growth rate of total credit in the US on future values of its own growth. In this case, a shock in LCBLLBCgrowth is significant twenty weeks after the initial shock, with an average accumulated effect of around 0.0015.

The result can be explained by the fact that the period under analysis is a period of incentive to credit by the state. In this type of condition, a positive shock in the credit growth rate is expected to generate a positive long-term effect.

Response: dWeiInterp

```
. irf graph coirf, set(IRF) irf(IRF) impulse (LCBLLBCgrowth) response (dWeiInterp) yline(0)
(file IRF.irf now active)
. irf table coirf, set(IRF) irf(IRF) impulse (LCBLLBCgrowth) response (dWeiInterp)
(file IRF.irf now active)
```



Results from IRF

step	(1) coirf	(1) Lower	(1) Upper
0	0	0	0
1	-.080121	-.138613	-.021629
2	-.117556	-.218589	-.016524
3	-.061896	-.179428	.055636
4	-.041233	-.185635	.103169
5	.000649	-.16904	.170337
6	.06048	-.123074	.244034
7	.03162	-.158818	.222058
8	.005532	-.189351	.200414
9	-.012116	-.212592	.18836
10	-.018207	-.227537	.191122
11	.021657	-.199659	.242973
12	.010452	-.219972	.240877
13	.024138	-.212833	.261108
14	.052803	-.19369	.299295
15	.077211	-.179814	.334237
16	.138218	-.129406	.405843
17	.163708	-.119717	.447134
18	.184725	-.11831	.487759
19	.205533	-.116708	.527774
20	.201089	-.137906	.540084

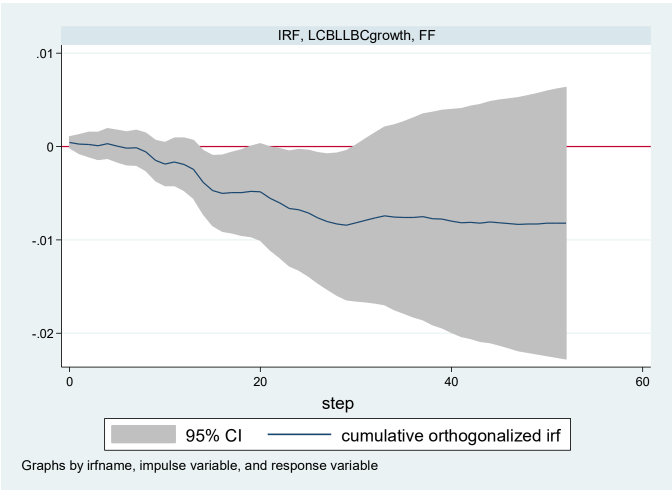
95% lower and upper bounds reported
(1) irfname = IRF, impulse = LCBLLBCgrowth, and response = dWeiInterp

Figure C.28 – LCBLLBCgrowth shock in dWeiInterp COIRF for the model with optimal lag (p=14).

Assessing figure C.29, it is possible to conclude that LCBLLBCgrowth has no significant long-run effect on dWeiInterp. The effect is very short and small-sized to consider.

Response: FF

```
. irf graph coirf, set(IRF) irf(IRF) impulse (LCBLLBCgrowth) response (FF) yline(0)
(file IRF.irf now active)
. irf table coirf, set(IRF) irf(IRF) impulse (LCBLLBCgrowth) response (FF)
(file IRF.irf now active)
```



Results from IRF

step	(1) coirf	(1) Lower	(1) Upper
0	.00046	-.000128	.001047
1	.000283	-.000725	.001292
2	.000217	-.001087	.001522
3	.000081	-.001369	.001531
4	.000335	-.001259	.00193
5	.000059	-.001631	.00175
6	-.000176	-.001953	.0016
7	-.000116	-.001987	.001754
8	-.00056	-.002562	.001442
9	-.001486	-.003639	.000668
10	-.001863	-.004187	.000461
11	-.001632	-.004192	.000928
12	-.00189	-.004726	.000945
13	-.002437	-.005519	.000645
14	-.003841	-.007236	-.000446
15	-.004708	-.008451	-.000965
16	-.004993	-.009073	-.000912
17	-.004919	-.009253	-.000585
18	-.004914	-.009494	-.000334
19	-.004791	-.009657	.000074
20	-.004851	-.010028	.000326
21	-.005552	-.01106	-.000044
22	-.006028	-.011848	-.000209
23	-.00664	-.012796	-.000485
24	-.00675	-.013214	-.000285
25	-.007124	-.01386	-.000389
26	-.007635	-.014612	-.000658
27	-.008023	-.015289	-.000757
28	-.008295	-.015913	-.000678
29	-.008418	-.016413	-.000423
30	-.00817	-.016544	.000205

95% lower and upper bounds reported
(1) irfname = IRF, impulse = LCBLLBCgrowth, and response = FF

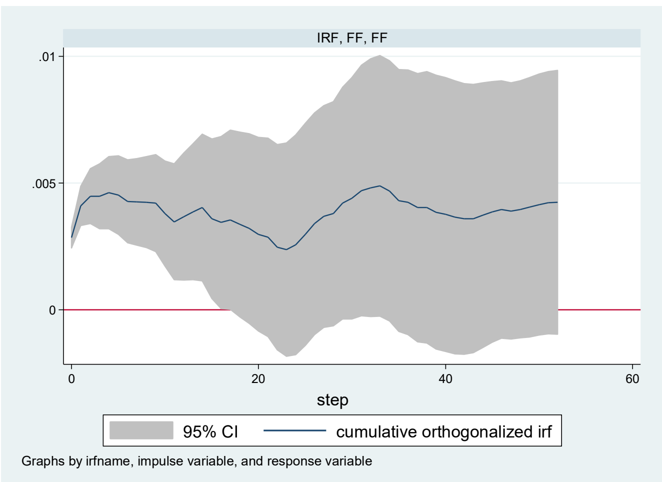
Figure C.29 – LCBLLBCgrowth shock in FF COIRF for the model with optimal lag (p=14).

The accumulated response is significant and negative from the fourteenth week until the eighteenth week, with the peak occurring at the sixteenth week [-0.000912;-0.009073] and between the twenty-first and twenty-ninth with the magnitude of the effect holding.

Impulse: FF

Response: FF

```
. irf graph coirf, set(IRF) irf(IRF) impulse (FF) response (FF) yline(0)
(file IRF.irf now active)
. irf table coirf, set(IRF) irf(IRF) impulse (FF) response (FF)
(file IRF.irf now active)
```



Results from IRF

step	(1) coirf	(1) Lower	(1) Upper
0	.00284	.002428	.003253
1	.004099	.003322	.004876
2	.004486	.003408	.005563
3	.004477	.003199	.005755
4	.004618	.003188	.006047
5	.004522	.002973	.006072
6	.004277	.002642	.005912
7	.004254	.002545	.005964
8	.004241	.002442	.006041
9	.004208	.002287	.006129
10	.00379	.001714	.005866
11	.003467	.001176	.005758
12	.003673	.001161	.006186
13	.003866	.001178	.006555
14	.004036	.001136	.006936
15	.00359	.000436	.006744
16	.003446	.000051	.006841
17	.003551	.000012	.007089
18	.003362	-.000289	.007013
19	.00321	-.000535	.006955
20	.002977	-.000845	.0068

95% lower and upper bounds reported
(1) irfname = IRF, impulse = FF, and response = FF

Figure C.30 – FF shock on itself COIRF for the model with optimal lag (p=14).

Response: dWeiInterp

```
. irf graph coirf, set(IRF) irf(IRF) impulse (FF) response (dWeiInterp) yline(0)
(file IRF.irf now active)

. irf table coirf, set(IRF) irf(IRF) impulse (FF) response (dWeiInterp)
(file IRF.irf now active)
```

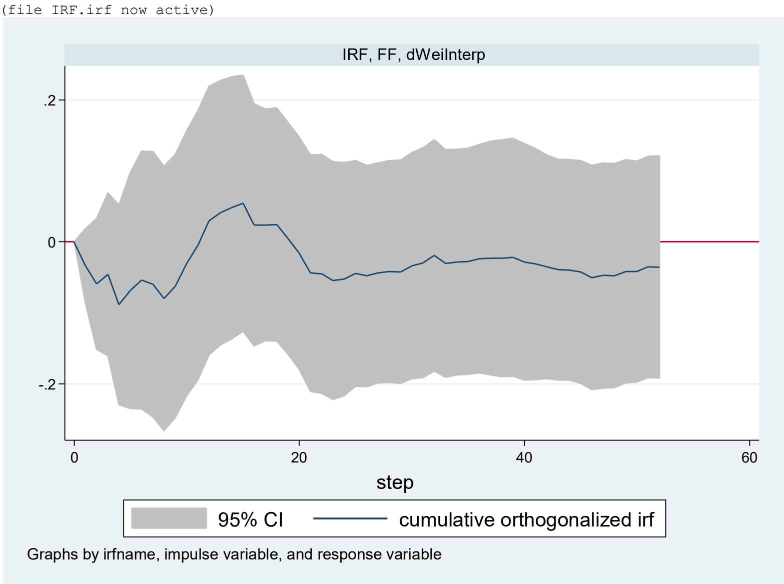


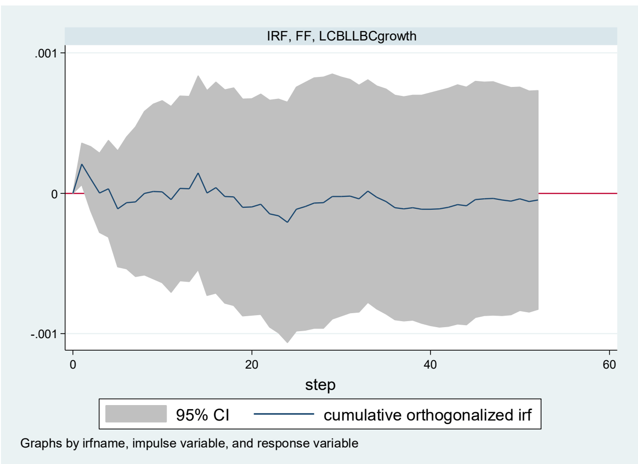
Figure C.31 – FF shock in dWeiInterp COIRF for the model with optimal lag (p=14).

Assessing figure C.32, it is possible to conclude that FF has no significant long-run effect in dWeiInterp.

Response: LCBLLBCgrowth

```
. irf graph coirf, set(IRF) irf(IRF) impulse (FF) response (LCBLLBCgrowth) yline(0)
(file IRF.irf now active)

. irf table coirf, set(IRF) irf(IRF) impulse (FF) response (LCBLLBCgrowth)
(file IRF.irf now active)
```



Results from IRF

step	(1) coirf	(1) Lower	(1) Upper
0	0	0	0
1	.000209	.000062	.000356
2	.000103	-.000125	.000332
3	3.0e-06	-.00028	.000286
4	.000032	-.000312	.000376
5	-.000111	-.000523	.000301
6	-.000068	-.000536	.000401
7	-.00006	-.000593	.000472
8	-5.2e-07	-.000582	.000581
9	.000013	-.000608	.000634
10	.00001	-.000638	.000658
11	-.000044	-.000707	.000619
12	.000034	-.000624	.000692
13	.000031	-.000628	.00069
14	.000145	-.000544	.000835
15	1.8e-06	-.000728	.000732
16	.000041	-.000711	.000793
17	-.000024	-.000783	.000736
18	-.000026	-.0008	.000749
19	-.000101	-.000872	.00067
20	-.000097	-.000868	.000673

95% lower and upper bounds reported
(1) irfname = IRF, impulse = FF, and response = LCBLLBCgrowth

Figure C.32 – FF shock in LCBLLBCgrowth COIRF for the model with optimal lag (p=14).

Assessing figure C.33, it is possible to conclude that FF has no significant long-run effect in LCBLLBCgrowth.

One explanation for FF not affecting the long-term credit growth rate may be that debtors (consumers, households, and banks) are sensitive to interest rate changes, implying only a cause-and-effect reaction on the short term.

Point Forecast

VAR(14) model:

```
. var casesgrowth dWeiInterp LCBLLBCgrowth FF if t<100, exog(dummy vacgrowth) lags(1/14)

. fcast compute forecast1_, step(13)

. fcast graph forecast1_dWeiInterp

. twoway (line dWeiInterp date) (line forecast1_dWeiInterp date, lpattern(dash))
```

AR(1) Model:

```
. regress dWeiInterp l.dWeiInterp if t<100

. estimates store forecastAR1

. forecast create forecastAR1model, replace
  Forecast model forecastAR1model started.

. forecast estimates forecastAR1
  Added estimation results from regress.
  Forecast model forecastAR1model now contains 1 endogenous variable.

. forecast solve, begin(w(2021w49)) end(w(2022w10))
```

VAR model with new confirmed Covid-19 deaths growth rate

Stability condition

```
. varstable

  Eigenvalue stability condition
```

Eigenvalue	Modulus
.9197474 + .312096*i*	.971256
.9197474 - .312096*i*	.971256
-.9324089 + .26495999*i*	.969325
-.9324089 - .26495999*i*	.969325
.1240302 + .960813*i*	.968785
.1240302 - .960813*i*	.968785
-.643287 + .7202757*i*	.96572
-.643287 - .7202757*i*	.96572
.8620716 + .4025971*i*	.951447
.8620716 - .4025971*i*	.951447
-.08972162 + .9463021*i*	.950546
-.08972162 - .9463021*i*	.950546
.721836 + .6147818*i*	.948158
.721836 - .6147818*i*	.948158
.02128091 + .9463581*i*	.946597
.02128091 - .9463581*i*	.946597
.9389527 + .1110162*i*	.945493
.9389527 - .1110162*i*	.945493
.2180204 + .9167773*i*	.942345
.2180204 - .9167773*i*	.942345
-.7995091 + .4901189*i*	.93778
-.7995091 - .4901189*i*	.93778
-.9340273 + .08276311*i*	.937687
-.9340273 - .08276311*i*	.937687
-.871098 + .3442518*i*	.936654
-.871098 - .3442518*i*	.936654
-.2546953 + .9011661*i*	.936467
-.2546953 - .9011661*i*	.936467
-.7322316 + .5771531*i*	.932346
-.7322316 - .5771531*i*	.932346
-.339719 + .8670852*i*	.93126
-.339719 - .8670852*i*	.93126
.3588295 + .8560127*i*	.928179
.3588295 - .8560127*i*	.928179
.5018411 + .7781391*i*	.925929
.5018411 - .7781391*i*	.925929
.6270138 + .6726593*i*	.919574
.6270138 - .6726593*i*	.919574
-.3788227 + .8361773*i*	.917986
-.3788227 - .8361773*i*	.917986
.8736452 + .27404*i*	.915617
.8736452 - .27404*i*	.915617
-.8998026	.899803
.7725336 + .4612927*i*	.899777
.7725336 - .4612927*i*	.899777
-.5011411 + .7407537*i*	.894348
-.5011411 - .7407537*i*	.894348
.4910805 + .7175815*i*	.86953
.4910805 - .7175815*i*	.86953
.6688588 + .1794027*i*	.692501
.6688588 - .1794027*i*	.692501
-.4700667 + .3598186*i*	.591973
-.4700667 - .3598186*i*	.591973
-.3936496	.39365
-.00382299 + .1902201*i*	.190258
-.00382299 - .1902201*i*	.190258

```
  All the eigenvalues lie inside the unit circle.
  VAR satisfies stability condition.
```

Figure C.33 – Stability test for the second VAR model

Optimal lag selection

Minimum information criteria

```
. varsoc deathsgrowth dWeiInterp LCBLLBCgrowth FF, exog (dummy vacgrowth) maxla
```

Selection-order criteria
Sample: 2020w24 - 2022w10 Number of obs = 91

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	691.155				3.9e-12	-14.9265	-14.7929	-14.5954
1	752.026	121.74	16	0.000	1.4e-12*	-15.9127*	-15.601*	-15.1401*
2	761.776	19.5	16	0.244	1.7e-12	-15.7753	-15.2855	-14.5613
3	769.449	15.347	16	0.499	2.0e-12	-15.5923	-14.9244	-13.9368
4	781.066	23.234	16	0.108	2.2e-12	-15.496	-14.65	-13.399
5	793.249	24.366	16	0.082	2.5e-12	-15.4121	-14.388	-12.8736
6	804.897	23.295	16	0.106	2.8e-12	-15.3164	-14.1142	-12.3365
7	811.275	12.757	16	0.690	3.6e-12	-15.105	-13.7246	-11.6836
8	825.824	29.096	16	0.023	3.9e-12	-15.073	-13.5146	-11.2102
9	847.231	42.815	16	0.000	3.8e-12	-15.1919	-13.4554	-10.8876
10	870.733	47.005	16	0.000	3.5e-12	-15.3568	-13.4421	-10.611
11	893.067	44.667	16	0.000	3.4e-12	-15.496	-13.4032	-10.3087
12	913.595	41.056	16	0.001	3.6e-12	-15.5955	-13.3246	-9.96675
13	938.059	48.928*	16	0.000	3.5e-12	-15.7815	-13.3326	-9.7113
14	950.123	24.129	16	0.087	4.8e-12	-15.695	-13.068	-9.18334

Endogenous: deathsgrowth dWeiInterp LCBLLBCgrowth FF
Exogenous: dummy vacgrowth _cons

Figure C.34 - Second Var model optimal lag criteria selection

Wald lag-exclusion statistics test

```
. varwle
```

Equation: deathsgrowth

lag	chi2	df	Prob > chi2
1	29.57739	4	0.000
2	15.04886	4	0.005
3	14.32863	4	0.006
4	15.29004	4	0.004
5	9.156561	4	0.057
6	11.23394	4	0.024
7	4.904247	4	0.297
8	17.90567	4	0.001
9	19.95797	4	0.001
10	2.965852	4	0.564
11	11.02595	4	0.026
12	2.409449	4	0.661
13	11.7023	4	0.020
14	8.976806	4	0.062

Equation: dWeiInterp

lag	chi2	df	Prob > chi2
1	42.28355	4	0.000
2	29.46696	4	0.000
3	17.98891	4	0.001
4	8.863475	4	0.065
5	7.934845	4	0.094
6	8.754484	4	0.068
7	5.609064	4	0.230
8	2.13725	4	0.711
9	17.22457	4	0.002
10	3.051276	4	0.549
11	15.85883	4	0.003
12	7.260018	4	0.123
13	17.92837	4	0.001
14	3.710974	4	0.447

Equation: FF

lag	chi2	df	Prob > chi2
1	38.95103	4	0.000
2	2.253733	4	0.689
3	11.50531	4	0.021
4	12.1372	4	0.016
5	9.374783	4	0.052
6	3.867526	4	0.424
7	1.486378	4	0.829
8	6.032907	4	0.197
9	3.865457	4	0.425
10	22.79108	4	0.000
11	21.82078	4	0.000
12	16.31716	4	0.003
13	.56981	4	0.966
14	4.243447	4	0.374

Equation: LCBLLBCgrowth

lag	chi2	df	Prob > chi2
1	12.01598	4	0.017
2	8.148957	4	0.086
3	4.427291	4	0.351
4	5.822943	4	0.213
5	15.24545	4	0.004
6	11.70208	4	0.020
7	3.617126	4	0.460
8	12.46033	4	0.014
9	5.196907	4	0.268
10	2.257145	4	0.689
11	12.5497	4	0.014
12	19.23733	4	0.001
13	1.299365	4	0.861
14	5.30138	4	0.258

Equation: All

lag	chi2	df	Prob > chi2
1	137.367	16	0.000
2	64.98958	16	0.000
3	50.16347	16	0.000
4	49.98748	16	0.000
5	51.72329	16	0.000
6	40.44381	16	0.001
7	15.99089	16	0.454
8	41.54888	16	0.000
9	51.37972	16	0.000
10	31.43887	16	0.012
11	76.90214	16	0.000
12	50.69937	16	0.000
13	34.20273	16	0.005
14	25.56125	16	0.061

Figure C.35 - Wald lag-exclusion statistics test for p=14.

Residual diagnostics

```
. varlmar, mlag(4)

  Lagrange-multiplier test
```

lag	chi2	df	Prob > chi2
1	72.6522	16	0.00000
2	24.2012	16	0.08520
3	15.5408	16	0.48544
4	17.6151	16	0.34691

```
  H0: no autocorrelation at lag order
```

Figure C.36 - Lagrange multiplier test for the serial correlation between residuals for a model with optimal lag, p=1.

```
. var deathsgrowth dWeiInterp LCBLLBCgrowth FF, exog (dummy vacgrowth) lags (1/14)

Vector autoregression

Sample:  2020w24 - 2022w10                      Number of obs     =         91
Log likelihood =   950.1234                     AIC               =  -15.69502
FPE            =   4.84e-12                     HQIC              =  -13.06796
Det(Sigma_ml)  =   1.00e-14                     SBIC              =   -9.18334

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
deathsgrowth         59     .257234   0.6711   185.6605   0.0000
dWeiInterp           59     .468135   0.8038   372.9157   0.0000
LCBLLBCgrowth        59     .001702   0.7147    228.009   0.0000
FF                   59     .004315   0.9454   1576.392   0.0000
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
deathsgrowth |
 deathsgrowth |
         L1. |   -.241301   .1031254    -2.34   0.019     -.443423   -.0391789
         L2. |   .0199754   .0991144     0.20   0.840    -.1742853    .2142361
         L3. |  -.2853116   .1003657    -2.84   0.004    -.4820248   -.0885985
         L4. |  -.0945555   .1043286    -0.91   0.365    -.2990359    .1099248
         L5. |  -.1521778   .0922388    -1.65   0.099    -.3329626    .0286069
         L6. |  -.1063177   .0904651    -1.18   0.240     -.283626    .0709906
         L7. |   -.004961   .0973203    -0.05   0.959    -.1957052    .1857833
         L8. |  -.3442065   .0942425    -3.65   0.000    -.5289185   -.1594945
         L9. |  -.1717691   .1008004    -1.70   0.088    -.3693342     .025796
        L10. |  -.1588834   .0969234    -1.64   0.101    -.3488498    .0310831
        L11. |   -.262339   .1086994    -2.41   0.016    -.4753859   -.0492921
        L12. |  -.1087319   .1457463    -0.75   0.456    -.3943895    .1769257
        L13. |  -.2801219   .0915555    -3.06   0.002    -.4595674   -.1006764
        L14. |  -.0890423   .0864546    -1.03   0.303    -.2584902    .0804057
             |
  dWeiInterp |
         L1. |  -.1450371   .0578634    -2.51   0.012    -.2584472   -.0316269
         L2. |  -.0174104   .0599356    -0.29   0.771    -.1348821    .1000613
         L3. |   .0324366   .0649668     0.50   0.618    -.0948961    .1597693
         L4. |  -.1159225   .0693085    -1.67   0.094    -.2517647    .0199197
         L5. |   .0585263   .0728079     0.80   0.421    -.0841745    .2012272
         L6. |  -.1214828   .0694588    -1.75   0.080    -.2576196     .014654
         L7. |  -.0999807    .075391    -1.33   0.185    -.2477443    .0477829
         L8. |    .111434   .0751418     1.48   0.138    -.0358412    .2587093
         L9. |  -.2036909   .0785161    -2.59   0.009    -.3575797   -.0498022
        L10. |  -.0164212    .080432    -0.20   0.838     -.174065    .1412225
        L11. |  -.1504284   .0714586    -2.11   0.035    -.2904848   -.0103721
        L12. |   .0657614   .0773342     0.85   0.395    -.0858109    .2173338
        L13. |  -.0578922   .0728138    -0.80   0.427    -.2006046    .0848203
        L14. |  -.1710257   .0592599    -2.89   0.004    -.2871729   -.0548785
             |
LCBLLBCgrowth |
         L1. |  -50.67729   16.47434    -3.08   0.002     -82.9664   -18.38819
         L2. |  -42.85536   18.85941    -2.27   0.023    -79.81912   -5.891595
         L3. |  -26.74212   17.16023    -1.56   0.119    -60.37556    6.891323
         L4. |   46.85296   16.56332     2.83   0.005     14.38945    79.31647
         L5. |  -10.07597   17.44379    -0.58   0.564    -44.26517    24.11322
         L6. |  -38.65586   17.51778    -2.21   0.027    -72.99008   -4.321643
         L7. |   27.50746   17.16707     1.60   0.109    -6.139377    61.15429
         L8. |  -13.49799   16.87782    -0.80   0.424    -46.57791    19.58194
         L9. |  -45.08044   17.50397    -2.58   0.010    -79.38759   -10.77329
        L10. |   2.894026    17.8996     0.16   0.872    -32.18855     37.9766
        L11. |  -20.52459   17.58909    -1.17   0.243    -54.99857    13.94939
        L12. |   10.51282   16.46004     0.64   0.523    -21.74827     42.7739
        L13. |  -10.97113    16.0521    -0.68   0.494    -42.43268    20.49041
        L14. |   -4.10095   14.70202    -0.28   0.780    -32.91639    24.71449
             |
          FF |
         L1. |  -11.90425   6.289114    -1.89   0.058    -24.23069    .4221859
         L2. |   19.37507   8.376747     2.31   0.021     2.956953     35.7932
         L3. |  -10.04576   7.785732    -1.29   0.197    -25.30551    5.213993
         L4. |  -12.05162   6.714554    -1.79   0.073    -25.21191    1.108661
         L5. |   12.66982   5.212874     2.43   0.015     2.452774    22.88686
         L6. |  -5.568194   6.066154    -0.92   0.359    -17.45764    6.321249
         L7. |   1.850973   5.732649     0.32   0.747    -9.384812    13.08676
         L8. |   4.157218   5.012831     0.83   0.407    -5.667752    13.98219
         L9. |  -4.351991   4.526838    -0.96   0.336    -13.22443    4.520448
        L10. |   1.567359   4.347939     0.36   0.718    -6.954445    10.08916
        L11. |   1.091005   4.399086     0.25   0.804    -7.531045    9.713056
        L12. |  -1.723533   3.583785    -0.48   0.631    -8.747622    5.300556
        L13. |   1.809406   3.003928     0.60   0.547    -4.078184    7.696995
        L14. |   3.002076   1.602939     1.87   0.061    -.1396275    6.143779
             |
       dummy |   .2469299   .0764796     3.23   0.001     .0970327    .3968271
   vacgrowth |   .0165034    .032706     0.50   0.614    -.0475991    .0806059
       _cons |   .1441682   .6863711     0.21   0.834    -1.201094    1.489431
------------------------------------------------------------------------------
```

dWeiInterp						
deathsgrowth						
L1.	-.2151404	.1876761	-1.15	0.252	-.5829789	.152698
L2.	-.4960973	.1803766	-2.75	0.006	-.8496289	-.1425656
L3.	-.3905979	.1826538	-2.14	0.032	-.7485927	-.0326031
L4.	-.2561172	.1898658	-1.35	0.177	-.6282474	.116013
L5.	.1625246	.1678638	0.97	0.333	-.1664825	.4915316
L6.	-.233354	.1646358	-1.42	0.156	-.5560343	.0893263
L7.	-.2322442	.1771115	-1.31	0.190	-.5793764	.114888
L8.	-.2308107	.1715104	-1.35	0.178	-.5669649	.1053434
L9.	-.1297528	.1834449	-0.71	0.479	-.4892981	.2297926
L10.	-.2455107	.1763893	-1.39	0.164	-.5912274	.1002059
L11.	-.4197107	.1978201	-2.12	0.034	-.807431	-.0319903
L12.	.3319524	.2652412	1.25	0.211	-.1879109	.8518156
L13.	-.6275469	.1666203	-3.77	0.000	-.9541167	-.3009771
L14.	-.2339489	.1573373	-1.49	0.137	-.5423243	.0744266
dWeiInterp						
L1.	.417718	.1053045	3.97	0.000	.211325	.6241111
L2.	-.3593245	.1090758	-3.29	0.001	-.5731092	-.1455399
L3.	.3709468	.118232	3.14	0.002	.1392163	.6026773
L4.	-.2480622	.1261334	-1.97	0.049	-.4952791	-.0008454
L5.	.0839868	.1325018	0.63	0.526	-.1757119	.3436856
L6.	-.2522578	.1264069	-2.00	0.046	-.5000109	-.0045048
L7.	-.147406	.1372027	-1.07	0.283	-.4163184	.1215064
L8.	.0710982	.1367493	0.52	0.603	-.1969255	.3391218
L9.	-.328463	.1428901	-2.30	0.022	-.6085225	-.0484036
L10.	.0765912	.1463767	0.52	0.601	-.2103019	.3634843
L11.	-.4167183	.1300464	-3.20	0.001	-.6716045	-.1618321
L12.	.2178004	.1407393	1.55	0.122	-.0580435	.4936443
L13.	-.2452725	.1325126	-1.85	0.064	-.5049925	.0144475
L14.	-.0126769	.107846	-0.12	0.906	-.2240513	.1986974
LCBLLBCgrowth						
L1.	-86.88871	29.98136	-2.90	0.004	-145.6511	-28.12632
L2.	-16.07765	34.32191	-0.47	0.639	-83.34736	51.19206
L3.	-4.884243	31.22961	-0.16	0.876	-66.09316	56.32467
L4.	9.862006	30.1433	0.33	0.744	-49.21777	68.94178
L5.	15.88046	31.74565	0.50	0.617	-46.33987	78.10079
L6.	21.50996	31.88031	0.67	0.500	-40.97429	83.99421
L7.	-34.71267	31.24205	-1.11	0.267	-95.94595	26.52062
L8.	-1.946067	30.71566	-0.06	0.949	-62.14765	58.25551
L9.	-85.77108	31.85517	-2.69	0.007	-148.2061	-23.33609
L10.	-17.92477	32.57517	-0.55	0.582	-81.77094	45.9214
L11.	33.48003	32.01008	1.05	0.296	-29.25858	96.21863
L12.	-34.06388	29.95534	-1.14	0.255	-92.77527	24.64751
L13.	25.06708	29.21294	0.86	0.391	-32.18924	82.3234
L14.	40.28658	26.75596	1.51	0.132	-12.15413	92.72729
FF						
L1.	-33.90304	11.44545	-2.96	0.003	-56.33571	-11.47037
L2.	40.30682	15.2447	2.64	0.008	10.42777	70.18588
L3.	-27.29465	14.16912	-1.93	0.054	-55.06561	.4763158
L4.	-18.6171	12.2197	-1.52	0.128	-42.56727	5.333071
L5.	22.59157	9.486819	2.38	0.017	3.997752	41.1854
L6.	-18.24915	11.03969	-1.65	0.098	-39.88654	3.388241
L7.	6.705573	10.43275	0.64	0.520	-13.74224	27.15338
L8.	-1.179303	9.122765	-0.13	0.897	-19.05959	16.70099
L9.	14.6402	8.238314	1.78	0.076	-1.506596	30.787
L10.	-2.565523	7.912738	-0.32	0.746	-18.0742	12.94316
L11.	-1.569969	8.005821	-0.20	0.845	-17.26109	14.12115
L12.	-8.176116	6.522068	-1.25	0.210	-20.95913	4.606902
L13.	4.773392	5.466796	0.87	0.383	-5.94133	15.48811
L14.	3.051503	2.917161	1.05	0.296	-2.666028	8.769033
dummy	-.2412246	.1391839	-1.73	0.083	-.5140199	.0315707
vacgrowth	.126633	.059521	2.13	0.033	.0099739	.2432921
_cons	2.054722	1.249115	1.64	0.100	-.3934982	4.502942
LCBLLBCgrowth						
deathsgrowth						
L1.	-.0001029	.0006822	-0.15	0.880	-.0014401	.0012343
L2.	-.0011002	.0006557	-1.68	0.093	-.0023854	.000185
L3.	-.0012298	.000664	-1.85	0.064	-.0025312	.0000716
L4.	-.0007607	.0006902	-1.10	0.270	-.0021135	.000592
L5.	.0001177	.0006102	0.19	0.847	-.0010783	.0013138
L6.	.0010762	.0005985	1.80	0.072	-.0000968	.0022492
L7.	.0001049	.0006438	0.16	0.871	-.001157	.0013668
L8.	-.0012025	.0006235	-1.93	0.054	-.0024245	.0000195
L9.	.0005338	.0006669	0.80	0.423	-.0007732	.0018408
L10.	.0001477	.0006412	0.23	0.818	-.0011091	.0014044
L11.	.0011379	.0007191	1.58	0.114	-.0002715	.0025474
L12.	.0002361	.0009642	0.24	0.807	-.0016537	.0021259
L13.	-.0000434	.0006057	-0.07	0.943	-.0012305	.0011438
L14.	-.0003011	.000572	-0.53	0.599	-.0014221	.00082

dWeiInterp						
L1.	-.0005559	.0003828	-1.45	0.146	-.0013062	.0001943
L2.	-.0000921	.0003965	-0.23	0.816	-.0008693	.000685
L3.	.0002519	.0004298	0.59	0.558	-.0005905	.0010943
L4.	.0001586	.0004585	0.35	0.729	-.0007401	.0010573
L5.	.000595	.0004817	1.24	0.217	-.0003491	.001539
L6.	-.0010503	.0004595	-2.29	0.022	-.001951	-.0001497
L7.	.0007879	.0004988	1.58	0.114	-.0001897	.0017654
L8.	-.0013944	.0004971	-2.80	0.005	-.0023687	-.0004201
L9.	.0009373	.0005194	1.80	0.071	-.0000808	.0019554
L10.	-.0007275	.0005321	-1.37	0.172	-.0017704	.0003154
L11.	.0014466	.0004727	3.06	0.002	.00052	.0023731
L12.	-.0017879	.0005116	-3.49	0.000	-.0027907	-.0007852
L13.	.0002716	.0004817	0.56	0.573	-.0006725	.0012157
L14.	-.0002954	.000392	-0.75	0.451	-.0010638	.000473
LCBLLBCgrowth						
L1.	.2500157	.1089887	2.29	0.022	.0364016	.4636297
L2.	.1741946	.1247676	1.40	0.163	-.0703454	.4187346
L3.	-.0310535	.1135264	-0.27	0.784	-.2535611	.1914542
L4.	.0433722	.1095774	0.40	0.692	-.1713956	.25814
L5.	-.023436	.1154023	-0.20	0.839	-.2496204	.2027484
L6.	-.1290737	.1158918	-1.11	0.265	-.3562175	.0980701
L7.	.0779889	.1135716	0.69	0.492	-.1446074	.3005852
L8.	.0321842	.1116581	0.29	0.773	-.1866616	.25103
L9.	.085606	.1158004	0.74	0.460	-.1413587	.3125707
L10.	-.0762507	.1184178	-0.64	0.520	-.3083454	.1558439
L11.	.0385239	.1163636	0.33	0.741	-.1895445	.2665923
L12.	.0970781	.1088942	0.89	0.373	-.1163505	.3105067
L13.	.0435418	.1061954	0.41	0.682	-.1645974	.2516809
L14.	-.1401421	.0972637	-1.44	0.150	-.3307755	.0504913
FF						
L1.	.0784468	.0416067	1.89	0.059	-.0031008	.1599945
L2.	-.0823459	.0554178	-1.49	0.137	-.1909628	.0262709
L3.	-.0070245	.0515078	-0.14	0.892	-.1079779	.093929
L4.	.0707443	.0444213	1.59	0.111	-.0163198	.1578084
L5.	-.1190681	.0344866	-3.45	0.001	-.1866607	-.0514756
L6.	.0555637	.0401317	1.38	0.166	-.0230929	.1342204
L7.	.0345041	.0379253	0.91	0.363	-.0398281	.1088364
L8.	-.0206592	.0331632	-0.62	0.533	-.0856579	.0443396
L9.	.0202407	.0299481	0.68	0.499	-.0384564	.0789378
L10.	-.0118771	.0287645	-0.41	0.680	-.0682545	.0445003
L11.	-.011484	.0291029	-0.39	0.693	-.0685246	.0455566
L12.	.0109226	.0237091	0.46	0.645	-.0355464	.0573916
L13.	-.0144559	.019873	-0.73	0.467	-.0534063	.0244944
L14.	-.0018379	.0106045	-0.17	0.862	-.0226224	.0189465
dummy	.0009394	.000506	1.86	0.063	-.0000523	.001931
vacgrowth	.0000722	.0002164	0.33	0.739	-.0003519	.0004963
_cons	-.0001998	.0045408	-0.04	0.965	-.0090996	.0087
FF						
deathsgrowth						
L1.	.0015079	.00173	0.87	0.383	-.0018829	.0048987
L2.	-.0014014	.0016627	-0.84	0.399	-.0046603	.0018574
L3.	.0029435	.0016837	1.75	0.080	-.0003566	.0062435
L4.	.0031474	.0017502	1.80	0.072	-.000283	.0065777
L5.	-.0000608	.0015474	-0.04	0.969	-.0030936	.002972
L6.	.0023342	.0015176	1.54	0.124	-.0006403	.0053087
L7.	.0010276	.0016326	0.63	0.529	-.0021723	.0042275
L8.	-.0004574	.001581	-0.29	0.772	-.0035561	.0026413
L9.	-.0001106	.001691	-0.07	0.948	-.0034249	.0032038
L10.	-.0070053	.001626	-4.31	0.000	-.0101921	-.0038184
L11.	.0060271	.0018235	3.31	0.001	.002453	.0096011
L12.	.002699	.002445	1.10	0.270	-.0020931	.0074912
L13.	-.0003206	.0015359	-0.21	0.835	-.003331	.0026897
L14.	.0008466	.0014503	0.58	0.559	-.001996	.0036893
dWeiInterp						
L1.	.0009168	.0009707	0.94	0.345	-.0009858	.0028193
L2.	.00048	.0010055	0.48	0.633	-.0014907	.0024507
L3.	-.0026789	.0010899	-2.46	0.014	-.004815	-.0005428
L4.	.0024592	.0011627	2.12	0.034	.0001803	.0047381
L5.	-.0022559	.0012214	-1.85	0.065	-.0046498	.000138
L6.	-.0012197	.0011652	-1.05	0.295	-.0035035	.0010641
L7.	-.0009787	.0012647	-0.77	0.439	-.0034576	.0015002
L8.	-.0007378	.0012606	-0.59	0.558	-.0032085	.0017328
L9.	-.0022729	.0013172	-1.73	0.084	-.0048545	.0003087
L10.	-.0026911	.0013493	-1.99	0.046	-.0053357	-.0000465
L11.	.0006168	.0011988	0.51	0.607	-.0017328	.0029663
L12.	.0012974	.0012973	1.00	0.317	-.0012454	.0038401
L13.	.0001976	.0012215	0.16	0.871	-.0021965	.0025917
L14.	.0003175	.0009941	0.32	0.749	-.001631	.0022659

LCBLLBCgrowth						
L1.	-.3429004	.2763709	-1.24	0.215	-.8845773	.1987766
L2.	-.2839872	.3163825	-0.90	0.369	-.9040855	.3361111
L3.	-.1733083	.2878774	-0.60	0.547	-.7375376	.390921
L4.	.2203743	.2778636	0.79	0.428	-.3242284	.764977
L5.	-.5389458	.2926343	-1.84	0.066	-1.112498	.0346068
L6.	.1275342	.2938755	0.43	0.664	-.4484513	.7035196
L7.	.0319583	.287992	0.11	0.912	-.5324956	.5964123
L8.	-.654532	.2831397	-2.31	0.021	-1.209476	-.0995884
L9.	-.2539487	.2936438	-0.86	0.387	-.82948	.3215826
L10.	-.0519593	.3002809	-0.17	0.863	-.640499	.5365805
L11.	-.0100554	.2950718	-0.03	0.973	-.5883855	.5682746
L12.	-.2917885	.276131	-1.06	0.291	-.8329954	.2494183
L13.	.0580941	.2692876	0.22	0.829	-.4696998	.585888
L14.	-.4547366	.2466388	-1.84	0.065	-.9381398	.0286666
FF						
L1.	.5784957	.1055052	5.48	0.000	.3717094	.7852821
L2.	-.0004214	.140527	-0.00	0.998	-.2758492	.2750064
L3.	-.141855	.1306122	-1.09	0.277	-.3978502	.1141402
L4.	.184438	.1126423	1.64	0.102	-.0363369	.4052128
L5.	-.1305556	.0874503	-1.49	0.135	-.3019551	.0408439
L6.	.0124366	.1017648	0.12	0.903	-.1870188	.211892
L7.	-.0696714	.09617	-0.72	0.469	-.2581612	.1188183
L8.	.0207321	.0840945	0.25	0.805	-.14409	.1855542
L9.	-.0152207	.0759415	-0.20	0.841	-.1640633	.1336219
L10.	-.1058807	.0729403	-1.45	0.147	-.2488412	.0370797
L11.	-.1999647	.0737984	-2.71	0.007	-.3446068	-.0553225
L12.	.2308453	.060121	3.84	0.000	.1130103	.3486804
L13.	-.0224835	.0503934	-0.45	0.655	-.1212527	.0762858
L14.	-.0193103	.0268907	-0.72	0.473	-.072015	.0333944
dummy	.0001106	.001283	0.09	0.931	-.0024041	.0026252
vacgrowth	-.0025182	.0005487	-4.59	0.000	-.0035936	-.0014428
_cons	.0584699	.0115145	5.08	0.000	.0359019	.0810378

```
. varlmar, mlag(16)
```

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	18.2690	16	0.30838
2	11.9663	16	0.74629
3	9.0241	16	0.91242
4	15.5786	16	0.48274
5	14.9920	16	0.52523
6	15.4472	16	0.49216
7	16.6080	16	0.41139
8	19.5178	16	0.24273
9	8.6547	16	0.92695
10	10.1990	16	0.85603
11	17.8451	16	0.33304
12	17.3421	16	0.36380
13	13.7462	16	0.61761
14	16.5677	16	0.41409
15	26.9970	16	0.04152
16	15.7042	16	0.47379

H0: no autocorrelation at lag order

Figure C.37 - VAR(14) model estimation and Lagrange multiplier test for the serial correlation between residuals for a model with optimal lag, p=14.

```
. summarize resdeathsgrowth resLCBLLBCgrowth resdWeiInterp resFF

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
resdeathsg~h |         91    6.27e-11    .1533845   -.392263   .5941305
resLCBLLBC~h |         91   -2.25e-12    .0010147  -.0029245   .0026849
resdWeiInt~p |         91    3.99e-10    .2791417  -.8279798   .8723417
       resFF |         91   -2.71e-12    .0025732  -.0094762   .0058853
```

Figure C.38 – Residuals of the variables for the model with optimal lag (p=14).

```
. corr resdeathsgrowth resdWeiInterp resLCBLLBCgrowth resFF, cov
(obs=91)

             | resdea~h resdWe~p resLCB~h    resFF
-------------+------------------------------------
resdeathsg~h |  .023527
resdWeiInt~p | -.003426   .07792
resLCBLLBC~h |  .000047 -.000055  1.0e-06
       resFF |  .000032  .000038 -3.9e-07  6.6e-06
```

Figure C.39 – Covariance between residuals for the model with optimal lag (p=14).

```
. corr resdeathsgrowth resdWeiInterp resLCBLLBCgrowth resFF
(obs=91)

             | resdea~h resdWe~p resLCB~h    resFF
-------------+------------------------------------
resdeathsg~h |   1.0000
resdWeiInt~p |  -0.0800   1.0000
resLCBLLBC~h |   0.3018  -0.1931   1.0000
       resFF |   0.0821   0.0523  -0.1499   1.0000
```

Figure C.40 – Correlation between residuals for the model with optimal lag (p=14).

Granger causality

```
. vargranger

  Granger causality Wald tests
```

Equation	Excluded	chi2	df	Prob > chi2
deathsgrowth	dWeiInterp	53.179	14	0.000
deathsgrowth	LCBLLBCgrowth	52.203	14	0.000
deathsgrowth	FF	35.916	14	0.001
deathsgrowth	ALL	143.87	42	0.000
dWeiInterp	deathsgrowth	43.667	14	0.000
dWeiInterp	LCBLLBCgrowth	28.341	14	0.013
dWeiInterp	FF	38.066	14	0.001
dWeiInterp	ALL	96.064	42	0.000
LCBLLBCgrowth	deathsgrowth	22.313	14	0.072
LCBLLBCgrowth	dWeiInterp	29.636	14	0.009
LCBLLBCgrowth	FF	26.182	14	0.025
LCBLLBCgrowth	ALL	74.414	42	0.002
FF	deathsgrowth	48.745	14	0.000
FF	dWeiInterp	85.138	14	0.000
FF	LCBLLBCgrowth	28.173	14	0.013
FF	ALL	297.93	42	0.000

Figure C.41 – Granger causality between variables for the model with optimal lag (p=14).

Orthogonalized impulse response functions

As stated in 3.3.9., we compute the OIRFs instead of the non-orthogonal IRFs because the decomposition of the variance-covariance matrix is through Cholesky factorization. Also, the ordering of the variables is already defined in the code when estimating the VAR.

In Stata, we start by creating an IRF entry in a file called *IRF* to hold the results of the VAR(14), and run the IRF effect horizon out over 20 week. Next, the order of the variables is listed again in the IRFs command[28].

```
. irf create IRF, set(IRF, replace) step (20) order(deathsgrowth dWeiInterp LCBLLBCgrowth FF)
(file IRF.irf created)
(file IRF.irf now active)
```

The final step to attaining the output is to plot the orthogonal impulse response functions and table their values. To obtain the OIRFs case, it is necessary to run *oirf* instead of *irf*.

```
. irf graph oirf, set(IRF) irf(IRF) impulse (deathsgrowth dWeiInterp LCBLLBCgrowth FF) response(deathsgrowth dWeiInterp LCBLLBCgro
> wth FF) yline(0)
(file IRF.irf now active)
```

This command will provide all OIRFs[29] results in the same graphic, which can make interpretation of some values difficult regarding the different scales of effects caused. If the output containing the table with the values is desired, the same command is applied, replacing *graph* with *table*.

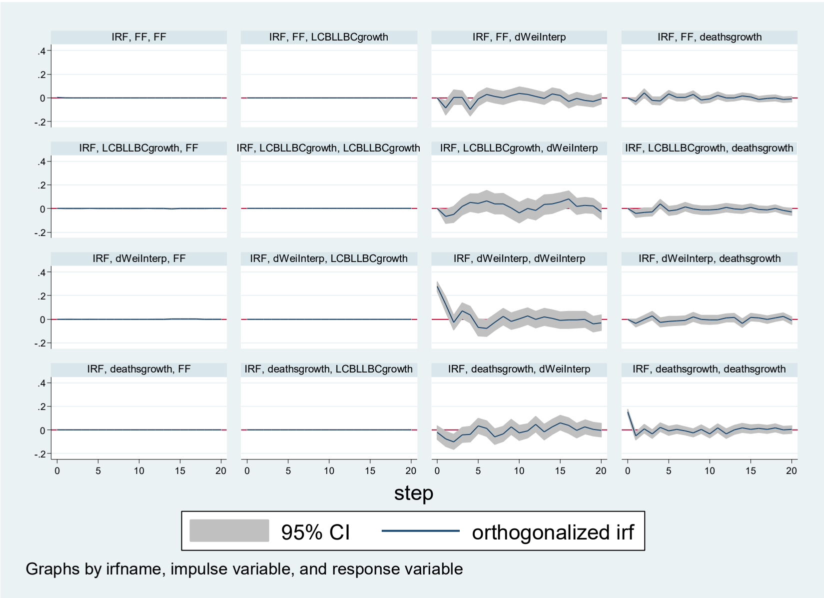


Figure C.42 – All OIRF’S for the model with optimal lag (p=14).

---

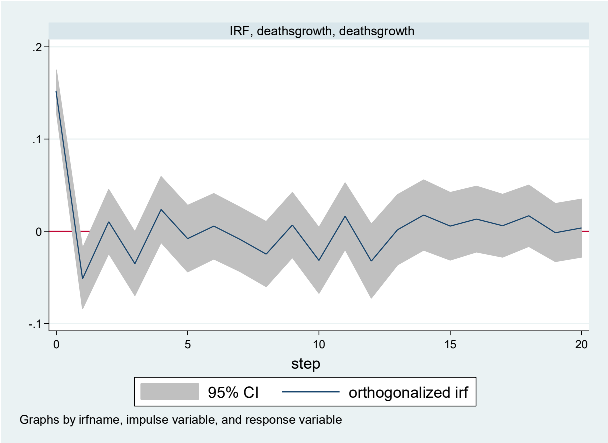
[28] This particular step is unnecessary once the order is already defined in the *var* command.

[29] The shaded area of the OIRFs represents the confidence bands of our VAR model.

Impulse: deathsgrowth

Response: deathsgrowth

```
. irf graph oirf, set(IRF) irf(IRF) impulse (deathsgrowth) response (deathsgrowth) yline(0)
(file IRF.irf now active)
. irf table oirf, set(IRF) irf(IRF) impulse (deathsgrowth) response (deathsgrowth)
(file IRF.irf now active)
```



Results from IRF

step	(1) oirf	(1) Lower	(1) Upper
0	.152539	.130378	.174701
1	-.051525	-.084144	-.018906
2	.010638	-.023932	.045208
3	-.035281	-.069623	-.000939
4	.023518	-.012108	.059144
5	-.008069	-.044101	.027962
6	.005602	-.029794	.040998
7	-.008759	-.043733	.026214
8	-.024685	-.059947	.010577
9	.006798	-.028537	.042133
10	-.031508	-.067108	.004092
11	.016509	-.019385	.052403
12	-.032242	-.072278	.007793
13	.001736	-.036297	.039769
14	.017583	-.020332	.055499
15	.005542	-.031145	.042229
16	.013256	-.022448	.04896
17	.00614	-.027862	.040142
18	.016828	-.01622	.049875
19	-.001478	-.032813	.029857
20	.003459	-.027979	.034896

95% lower and upper bounds reported
(1) irfname = IRF, impulse = deathsgrowth, and response = deathsgrowth

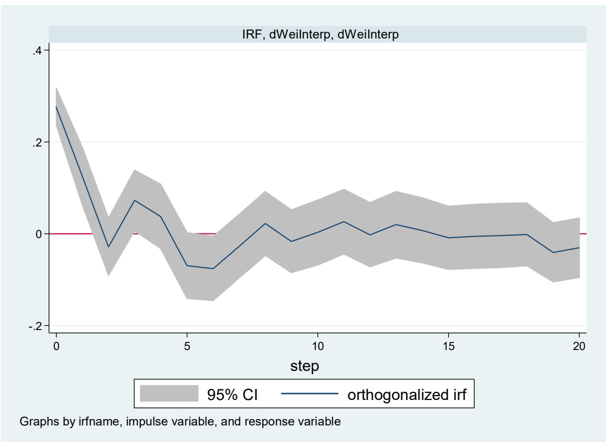
Figure C.43 – casesgrowth shock on itself OIRF for the model with optimal lag (p=14).

C.45 shows the effects of shocks to the growth rate of new Covid-19 confirmed deaths on future values of its growth. In this case, a one-standard-deviation shock to deathsgrowth is just over 0.1 percent (0.152539%). As expected, there is no long-run effect once deaths associated with Covid-19 should not contribute to more future deaths.

Impulse: dWeiInterp

Response: dWeiInterp

```
. irf graph oirf, set(IRF) irf(IRF) impulse (dWeiInterp) response (dWeiInterp) yline(0)
(file IRF.irf now active)
. irf table oirf, set(IRF) irf(IRF) impulse (dWeiInterp) response (dWeiInterp)
(file IRF.irf now active)
```



Results from IRF

step	(1) oirf	(1) Lower	(1) Upper
0	.276713	.236512	.316915
1	.125323	.062804	.187843
2	-.028584	-.090727	.033559
3	.072593	.006561	.138625
4	.037922	-.03232	.108164
5	-.069356	-.140893	.002181
6	-.075634	-.145663	-.005606
7	-.027094	-.096311	.042123
8	.02249	-.047065	.092046
9	-.016606	-.084911	.051698
10	.002951	-.068011	.073912
11	.026585	-.043739	.096908
12	-.00211	-.072029	.06781
13	.019765	-.052477	.092007
14	.007596	-.063565	.078756
15	-.008545	-.077462	.060371
16	-.005584	-.075459	.06429
17	-.003554	-.073879	.066771
18	-.001168	-.069944	.067608
19	-.040677	-.105158	.023805
20	-.030231	-.095175	.034714

95% lower and upper bounds reported
(1) irfname = IRF, impulse = dWeiInterp, and response = dWeiInterp

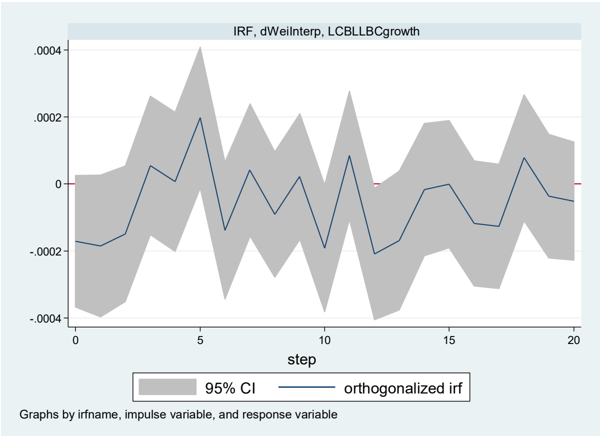
Figure C.44 – dWeiInterp shock on itself OIRF for the model with optimal lag (p=14)

Figure C.46 show the effects of shocks to the first differences of the economic activity index on future values of its own. In this case, a one-standard deviation shock to dWeiInterp is about 0.27 percent.

Response: LCBLLBCgrowth

```
. irf graph oirf, set(IRF) irf(IRF) impulse (dWeiInterp) response (LCBLLBCgrowth) yline(0)
(file IRF.irf now active)

. irf table oirf, set(IRF) irf(IRF) impulse (dWeiInterp) response (LCBLLBCgrowth)
(file IRF.irf now active)
```



Results from IRF

step	(1) oirf	(1) Lower	(1) Upper
0	-.000171	-.000367	.000025
1	-.000185	-.000396	.000027
2	-.000149	-.000351	.000053
3	.000055	-.000152	.000262
4	6.6e-06	-.000201	.000214
5	.000198	-.000012	.000408
6	-.000139	-.000343	.000065
7	.000042	-.000156	.00024
8	-.000091	-.000278	.000096
9	.000022	-.000166	.00021
10	-.000192	-.000381	-2.5e-06
11	.000085	-.000106	.000277
12	-.000209	-.000405	-.000012
13	-.000169	-.000377	.000039
14	-.000017	-.000215	.000181
15	-2.9e-07	-.00019	.00019
16	-.000118	-.000305	.000069
17	-.000127	-.000312	.000059
18	.000078	-.00011	.000266
19	-.000037	-.000221	.000148
20	-.000051	-.000227	.000125

95% lower and upper bounds reported
(1) irfname = IRF, impulse = dWeiInterp, and response = LCBLLBCgrowth

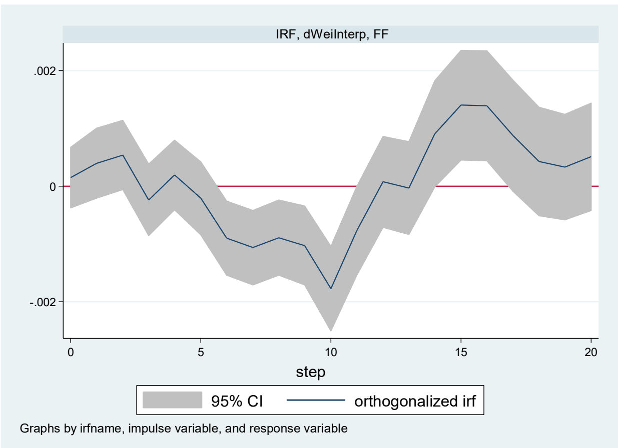
Figure C.45 – dWeiInterp shock in LCBLLBCgrowth OIRF for the model with optimal lag (p=14).

A shock in dWeiInterp has no significant effect on LCBLLBCgrowth.

Response: FF

```
. irf graph oirf, set(IRF) irf(IRF) impulse (dWeiInterp) response (FF) yline(0)
(file IRF.irf now active)

. irf table oirf, set(IRF) irf(IRF) impulse (dWeiInterp) response (FF)
(file IRF.irf now active)
```



Results from IRF

step	(1) oirf	(1) Lower	(1) Upper
0	.000151	-.000372	.000675
1	.0004	-.000207	.001007
2	.000541	-.000058	.001139
3	-.000237	-.000854	.000381
4	.000197	-.000404	.000798
5	-.000208	-.000842	.000426
6	-.000898	-.001538	-.000257
7	-.001063	-.001708	-.000418
8	-.00089	-.00154	-.000241
9	-.001027	-.001712	-.000342
10	-.001773	-.002505	-.001041
11	-.000771	-.001538	-4.1e-06
12	.000077	-.000712	.000865
13	-.00003	-.000834	.000774
14	.000908	-.000013	.001829
15	.001404	.000457	.00235
16	.001394	.000443	.002345
17	.000873	-.000088	.001834
18	.000429	-.000511	.001369
19	.000333	-.000581	.001247
20	.000512	-.000417	.00144

95% lower and upper bounds reported
(1) irfname = IRF, impulse = dWeiInterp, and response = FF

Figure C.46 – dWeiInterp shock in FF OIRF for the model with optimal lag (p=14).

Figure C.48 shows the effects of dWeiInterp in FF. We see that a one-standard deviation (0.27 percentage points) shock in dWeiInterp has no instantaneous effect on the Fed Funds rate. The shock only starts being significant six weeks ahead of its occurrence. The response is negative from the sixth to the tenth week, with the lowest point in the eleventh week reaching percentual values of [-

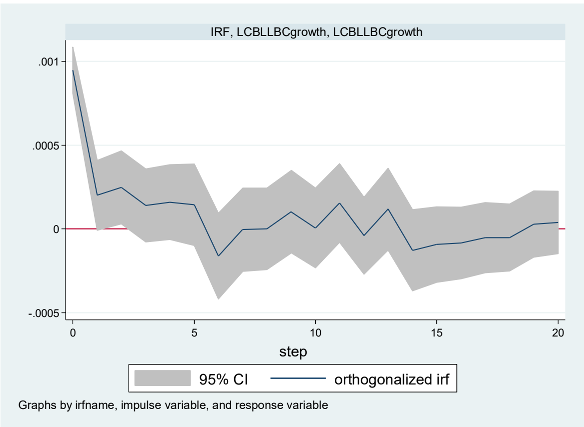
0.000004.1; -0.001538]. After the response starts being positive from the twelfth week, the twentieth, with the peak in the sixteenth week, registering values between [0.000457;0.00235].

Impulse: LCBLLBCgrowth

Response: LCBLLBCgrowth

```
. irf graph oirf, set(IRF) irf(IRF) impulse (LCBLLBCgrowth) response (LCBLLBCgrowth) yline(0)
(file IRF.irf now active)

. irf table oirf, set(IRF) irf(IRF) impulse (LCBLLBCgrowth) response (LCBLLBCgrowth)
(file IRF.irf now active)
```



Results from IRF

step	(1) oirf	(1) Lower	(1) Upper
0	.000947	.000809	.001084
1	.000201	-6.7e-06	.00041
2	.000248	.00003	.000466
3	.00014	-.000077	.000357
4	.00016	-.000063	.000382
5	.000145	-.000098	.000388
6	-.000161	-.000417	.000094
7	-4.2e-06	-.000253	.000244
8	1.0e-06	-.000243	.000245
9	.000103	-.000143	.000349
10	5.2e-06	-.000233	.000243
11	.000155	-.00008	.00039
12	-.00004	-.00027	.00019
13	.000119	-.000125	.000363
14	-.000128	-.000369	.000114
15	-.000093	-.000318	.000132
16	-.000084	-.000297	.000129
17	-.000052	-.000262	.000157
18	-.000051	-.000251	.000148
19	.000029	-.000168	.000226
20	.000038	-.000148	.000224

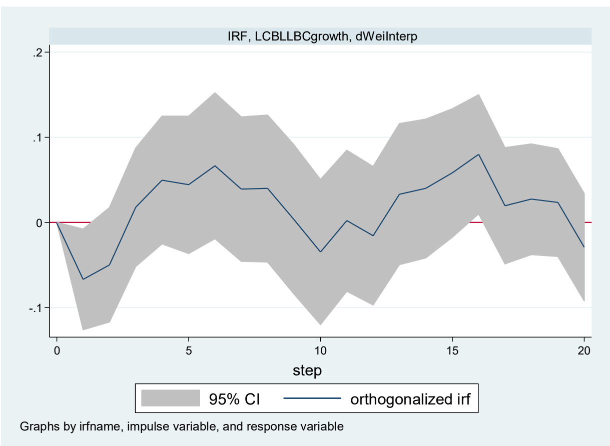
95% lower and upper bounds reported
(1) irfname = IRF, impulse = LCBLLBCgrowth, and response = LCBLLBCgrowth

Figure C.47 – LCBLLBCgrowth shock on itself OIRF for the model with optimal lag (p=14).

Figure C.49 shows the effects of shocks to the growth rate of total credit in the US on future values of its own growth. In this case, a one-standard deviation shock to LCBLLBCgrowth is just 0.000947 percent.

Response: dWeiInterp

```
. irf graph oirf, set(IRF) irf(IRF) impulse (LCBLLBCgrowth) response (dWeiInterp) yline(0)
(file IRF.irf now active)
. irf table oirf, set(IRF) irf(IRF) impulse (LCBLLBCgrowth) response (dWeiInterp)
(file IRF.irf now active)
```



Results from IRF

step	(1) oirf	(1) Lower	(1) Upper
0	0	0	0
1	-.067036	-.12611	-.007961
2	-.049845	-.117007	.017316
3	.017872	-.051715	.087459
4	.049803	-.025221	.124828
5	.044223	-.036561	.125007
6	.066703	-.018944	.152349
7	.03925	-.045507	.124007
8	.039898	-.046366	.126161
9	.003646	-.083918	.091209
10	-.034929	-.120162	.050304
11	.002085	-.080832	.085002
12	-.015678	-.097012	.065657
13	.033283	-.049658	.116224
14	.039854	-.041531	.121239
15	.058118	-.017386	.133622
16	.080095	.010055	.150135
17	.019548	-.048664	.087759
18	.027364	-.037724	.092452
19	.023465	-.039859	.086788
20	-.029017	-.092002	.033968

95% lower and upper bounds reported
(1) irfname = IRF, impulse = LCBLLBCgrowth, and response = dWeiInterp

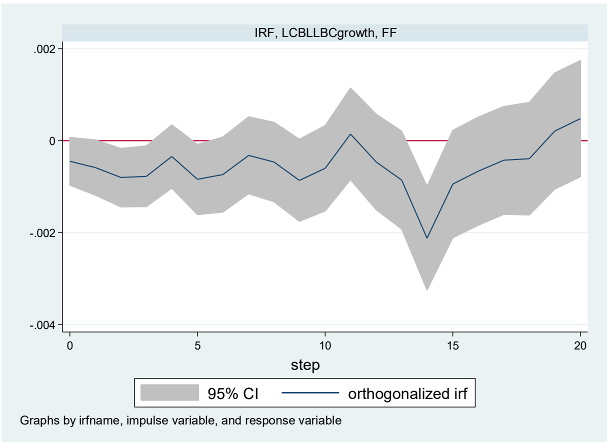
Figure C.48 – LCBLLBCgrowth shock in dWeiInterp OIRF for the model with optimal lag (p=14).

Figure C.50 shows the effects of the growth rate of total credit in dWeiInterp. We see that a one-standard deviation (0.000947 percentage points) shock in LCBLLBCgrowth has no immediate effect in dWeiInterp. However, the first week after the shock dWeiInterp has an adverse response between [-0.12611; -0.007961] and the sixteenth week, an increasing response of [0.010055; 0.150135]. After it, the impulse associated with shock quickly dies out and has no more significance.

Response: FF

```
. irf graph oirf, set(IRF) irf(IRF) impulse (LCBLLBCgrowth) response (FF) yline(0)
(file IRF.irf now active)

. irf table oirf, set(IRF) irf(IRF) impulse (LCBLLBCgrowth) response (FF)
(file IRF.irf now active)
```



Results from IRF

step	(1) oirf	(1) Lower	(1) Upper
0	-.000449	-.000968	.00007
1	-.000584	-.001183	.000014
2	-.000802	-.001437	-.000167
3	-.000773	-.001433	-.000113
4	-.000342	-.001031	.000346
5	-.000843	-.001605	-.00008
6	-.000734	-.001551	.000084
7	-.000316	-.001152	.00052
8	-.00046	-.001326	.000405
9	-.00086	-.001754	.000034
10	-.000598	-.001524	.000327
11	.000149	-.000845	.001144
12	-.000461	-.0015	.000578
13	-.000854	-.00192	.000211
14	-.002119	-.003249	-.00099
15	-.000942	-.002108	.000225
16	-.000665	-.00184	.00051
17	-.000425	-.001596	.000745
18	-.00039	-.001616	.000836
19	.000213	-.001051	.001477
20	.000481	-.000787	.001749

95% lower and upper bounds reported
(1) irfname = IRF, impulse = LCBLLBCgrowth, and response = FF

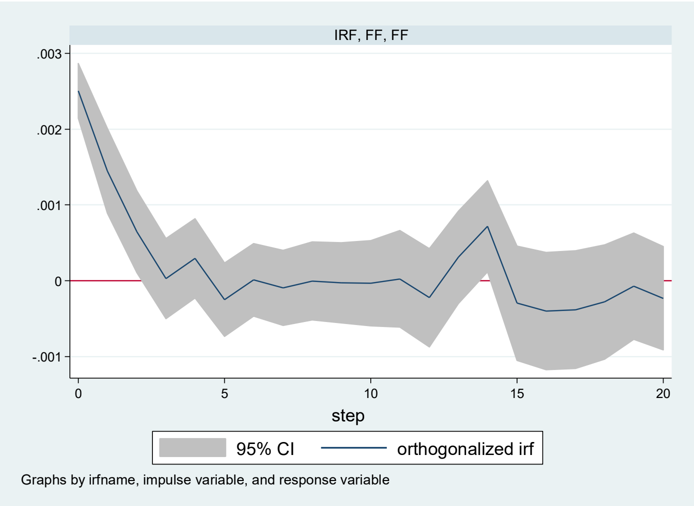
Figure C.49 – LCBLLBCgrowth shock in FF OIRF for the model with optimal lag (p=14).

Looking at figure C.51, the first thing to notice is that there is no immediate effect. The short-term response is negative from the second until the third week in an average of -0.0008 percentual points and also in the fifth week. The effect is also negative in the fourteenth week at about [-0.003249; -0.00099].

Impulse: FF

Response: FF

```
. irf table oirf, set(IRF) irf(IRF) impulse (FF) response (FF)
(file IRF.irf now active)
. irf graph oirf, set(IRF) irf(IRF) impulse (FF) response (FF) yline(0)
(file IRF.irf now active)
```



Results from IRF

step	(1) oirf	(1) Lower	(1) Upper
0	.002506	.002142	.00287
1	.00145	.00089	.002009
2	.000647	.000109	.001186
3	.000028	-.000499	.000555
4	.000295	-.000228	.000819
5	-.000251	-.000736	.000234
6	.000013	-.000467	.000492
7	-.000093	-.000587	.0004
8	-2.8e-06	-.00052	.000514
9	-.000028	-.000556	.0005
10	-.000035	-.000597	.000527
11	.000025	-.000612	.000661
12	-.000224	-.000873	.000424
13	.000311	-.000298	.000921
14	.000719	.000117	.001321
15	-.000296	-.001051	.000459
16	-.000399	-.001174	.000376
17	-.000381	-.00116	.000398
18	-.000279	-.001033	.000475
19	-.000071	-.000772	.000631
20	-.000231	-.000912	.000451

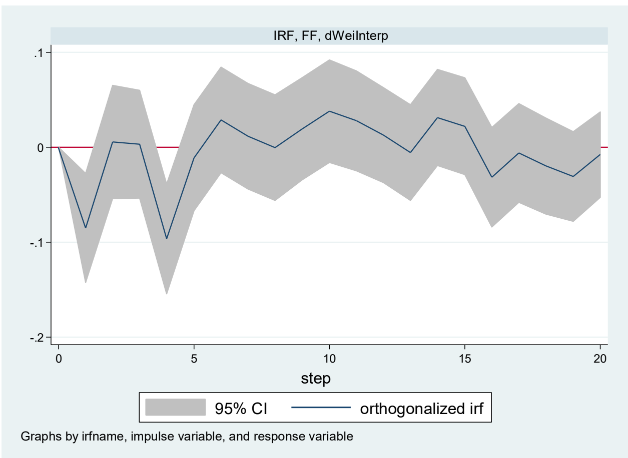
95% lower and upper bounds reported
(1) irfname = IRF, impulse = FF, and response = FF

Figure C.50 – FF shock on itself OIRF for the model with optimal lag (p=14).

Figure C.52 shows the effects of shocks to the FF on future values of its own. In this case, a one-standard deviation shock to FF is between [0.002142; 0.00287] percent.

Response: dWeiInterp

```
. irf graph oirf, set(IRF) irf(IRF) impulse (FF) response (dWeiInterp) yline(0)
(file IRF.irf now active)
. irf table oirf, set(IRF) irf(IRF) impulse (FF) response (dWeiInterp)
(file IRF.irf now active)
```



Results from IRF

step	(1) oirf	(1) Lower	(1) Upper
0	0	0	0
1	-.084958	-.142512	-.027405
2	.005706	-.053847	.065259
3	.003256	-.053749	.060261
4	-.09647	-.154276	-.038664
5	-.010951	-.066626	.044724
6	.02893	-.026822	.084682
7	.011708	-.044054	.06747
8	-.000355	-.055876	.055166
9	.019322	-.034473	.073118
10	.038186	-.01583	.092203
11	.027971	-.024622	.080564
12	.012895	-.036989	.062778
13	-.005476	-.055754	.044801
14	.03133	-.019283	.081943
15	.022245	-.028788	.073278
16	-.031576	-.08412	.020967
17	-.005864	-.057778	.046049
18	-.019725	-.070441	.030991
19	-.030769	-.077908	.016369
20	-.007685	-.052565	.037194

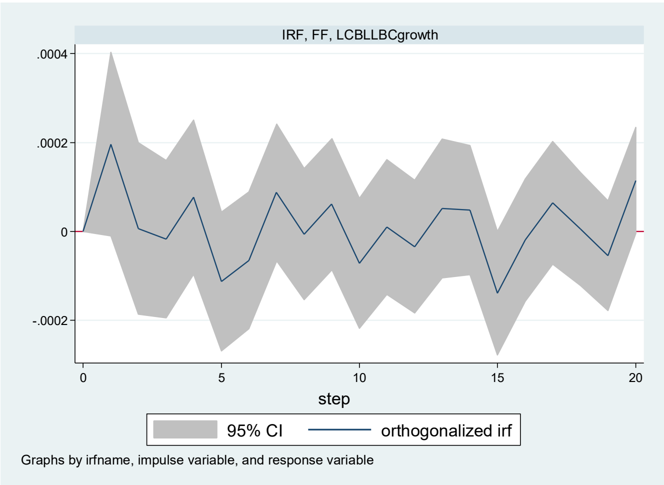
95% lower and upper bounds reported
(1) irfname = IRF, impulse = FF, and response = dWeiInterp

Figure C.51 – FF shock in dWeiInterp OIRF for the model with optimal lag (p=14).

As it is possible to observe, a shock on FF will create a negative response in dWeiInterp of [-0.027405; -0.142512] in the first week and [-0.038664; -0.154276] in the fourth week.

Response: LCBLLBCgrowth

```
. irf graph oirf, set(IRF) irf(IRF) impulse (FF) response (LCBLLBCgrowth) yline(0)
(file IRF.irf now active)
. irf table oirf, set(IRF) irf(IRF) impulse (FF) response (LCBLLBCgrowth)
(file IRF.irf now active)
```



Results from IRF

step	(1) oirf	(1) Lower	(1) Upper
0	0	0	0
1	.000197	-9.8e-06	.000403
2	6.8e-06	-.000186	.0002
3	-.000017	-.000194	.00016
4	.000077	-.000096	.000251
5	-.000113	-.000269	.000043
6	-.000065	-.000219	.000089
7	.000088	-.000066	.000241
8	-5.8e-06	-.000153	.000141
9	.000061	-.000086	.000209
10	-.000072	-.000218	.000075
11	.00001	-.000141	.000162
12	-.000034	-.000183	.000115
13	.000052	-.000104	.000208
14	.000048	-.000097	.000193
15	-.000139	-.000278	-3.8e-07
16	-.000019	-.000157	.000118
17	.000064	-.000074	.000202
18	5.5e-06	-.000121	.000132
19	-.000054	-.000178	.000069
20	.000115	-4.9e-06	.000234

95% lower and upper bounds reported
(1) irfname = IRF, impulse = FF, and response = LCBLLBCgrowth

Figure C.52 – FF shock in LCBLLBCgrowth OIRF for the model with optimal lag (p=14).

When there is a one standard deviation shock in FF, there is no significant response by LCBLLBCgrowth.

Cumulative orthogonalized impulse response functions

Again in Stata, we start by creating an IRF entry in a file called *IRF* to hold the results of the VAR(14) and run the IRF effect horizon out over 20 weeks. Next, the order of the variables is listed again in the IRFs command.

```
. irf create IRF, set(IRF, replace) step (20) order(deathsgrowth dWeiInterp LCBLLBCgrowth FF)
(file IRF.irf created)
(file IRF.irf now active)
```

The final step to attaining the output is to plot the orthogonal impulse response functions and table their values. In order to obtain the COIRFs case, it is just necessary to run *coirf* instead of *irf* or *oirf*.

```
. irf graph coirf, set(IRF) irf(IRF) impulse (casesgrowth dWeiInterp LCBLLBCgrowth FF) response(casesgrowth dWeiInterp LCBLLBCgrowt
> h FF) yline(0)
(file IRF.irf now active)
```

This command will provide all COIRFs results in the same graphic, which can make the interpretation of some values difficult regarding the different scales of effects caused. If the output containing the table with the values is desired, the same command is applied, replacing *graph* with *table*.

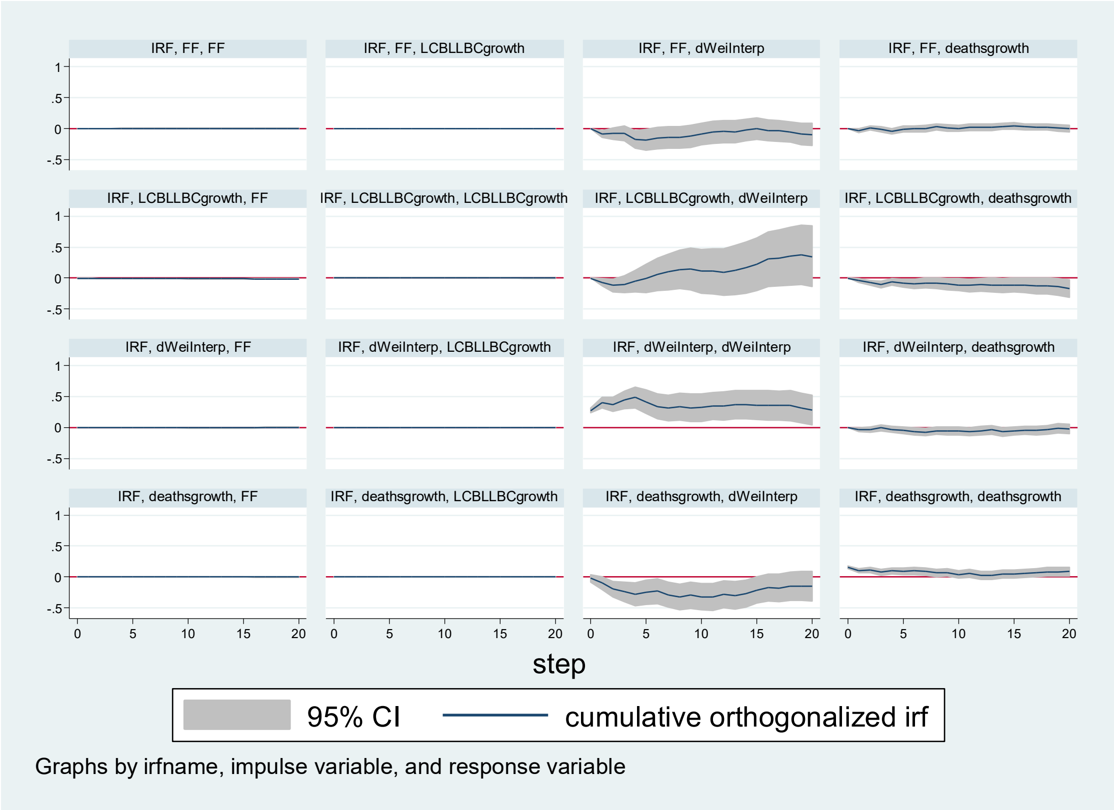
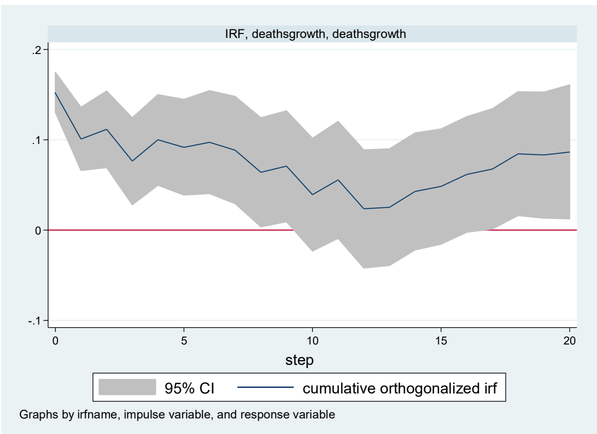


Figure C.53 – All COIRF for the model with optimal lag (p=14).

Impulse: deathsgrowth

Response: deathsgrowth



Results from IRF

step	(1) coirf	(1) Lower	(1) Upper
0	.152539	.130378	.174701
1	.101015	.066038	.135991
2	.111653	.06925	.154056
3	.076372	.028233	.12451
4	.09989	.049525	.150255
5	.09182	.038788	.144853
6	.097422	.040284	.154561
7	.088663	.029078	.148248
8	.063978	.003454	.124502
9	.070776	.009413	.13214
10	.039268	-.023219	.101756
11	.055778	-.009098	.120654
12	.023535	-.041842	.088912
13	.025271	-.039367	.089909
14	.042854	-.022082	.107791
15	.048396	-.015378	.112171
16	.061652	-.002445	.125749
17	.067792	.001189	.134395
18	.08462	.0161	.153139
19	.083141	.01333	.152952
20	.0866	.012443	.160756

95% lower and upper bounds reported
(1) irfname = IRF, impulse = deathsgrowth, and response = deathsgrowth

Figure C.54 – deathsgrowth shock on itself COIRF for the model with optimal lag (p=14).

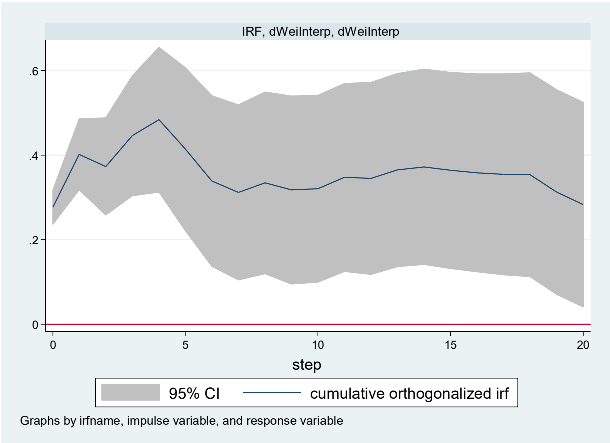
Figure C.56 shows the cumulative effects of shocks to the growth rate of new Covid-19 confirmed deaths on future values of its growth. In addition, there is a small long-run effect ending at the twentieth week, as it is possible to notice in the COIRF.

Impulse: dWeiInterp

Response: dWeiInterp

```
. irf graph coirf, set(IRF) irf(IRF) impulse (dWeiInterp) response (dWeiInterp) yline(0)
(file IRF.irf now active)

. irf table coirf, set(IRF) irf(IRF) impulse (dWeiInterp) response (dWeiInterp)
(file IRF.irf now active)
```



Results from IRF

step	(1) coirf	(1) Lower	(1) Upper
0	.276713	.236512	.316915
1	.402037	.318438	.485636
2	.373453	.25867	.488236
3	.446046	.30397	.588122
4	.483968	.312903	.655034
5	.414612	.222244	.606981
6	.338978	.136978	.540978
7	.311884	.105243	.518525
8	.334374	.119312	.549436
9	.317768	.095449	.540087
10	.320719	.099343	.542095
11	.347303	.124743	.569864
12	.345194	.118323	.572064
13	.364959	.13665	.593268
14	.372554	.141351	.603757
15	.364009	.131784	.596234
16	.358424	.124078	.592771
17	.354871	.117244	.592498
18	.353703	.112567	.594838
19	.313026	.071138	.554914
20	.282796	.040824	.524767

95% lower and upper bounds reported
(1) irfname = IRF, impulse = dWeiInterp, and response = dWeiInterp

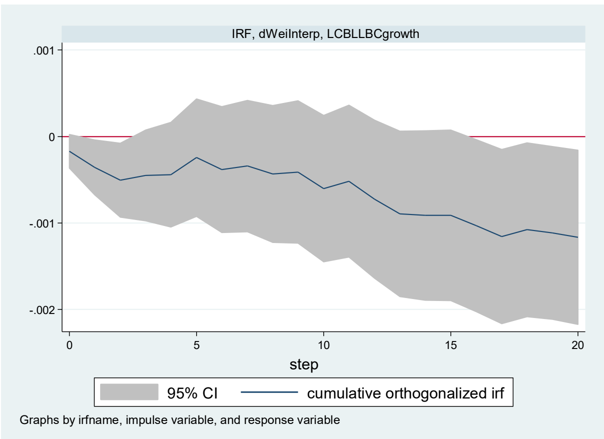
Figure C.55 – dWeiInterp shock on itself COIRF for the model with optimal lag (p=14).

Figure C.57 shows the long-run effects of shocks on the first differences of the real economic activity index on future values of its own. In this case, the cumulative effect is positive and very similar to the one obtained in the first VAR model using casesgrowth instead. The peak occurred in the fourth week with a cumulative effect of [0.312903;0.655034].

Response: LCBLLBCgrowth

```
. irf graph coirf, set(IRF) irf(IRF) impulse (dWeiInterp) response (LCBLLBCgrowth) yline(0)
(file IRF.irf now active)

. irf table coirf, set(IRF) irf(IRF) impulse (dWeiInterp) response (LCBLLBCgrowth)
(file IRF.irf now active)
```



Results from IRF

step	(1) coirf	(1) Lower	(1) Upper
0	-.000171	-.000367	.000025
1	-.000356	-.000673	-.000038
2	-.000505	-.000933	-.000076
3	-.00045	-.000973	.000074
4	-.000443	-.001047	.000161
5	-.000245	-.000925	.000435
6	-.000384	-.001111	.000344
7	-.000342	-.001101	.000417
8	-.000433	-.001223	.000357
9	-.000411	-.001234	.000411
10	-.000603	-.001449	.000243
11	-.000518	-.001396	.000361
12	-.000726	-.001641	.000188
13	-.000895	-.00185	.00006
14	-.000912	-.001892	.000068
15	-.000913	-.001898	.000073
16	-.00103	-.002024	-.000037
17	-.001157	-.002163	-.000151
18	-.001079	-.002085	-.000072
19	-.001115	-.002114	-.000117
20	-.001167	-.002173	-.00016

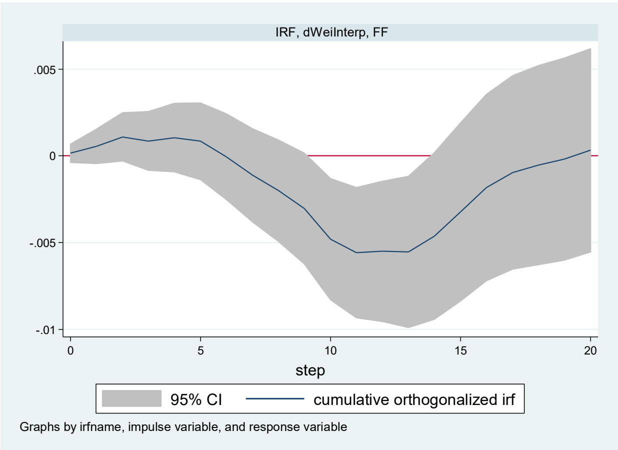
95% lower and upper bounds reported
(1) irfname = IRF, impulse = dWeiInterp, and response = LCBLLBCgrowth

Figure C.56 – dWeiInterp shock in LCBLLBCgrowth COIRF for the model with optimal lag (p=14).

Interpreting the output from figure C.58, a shock in real economic activity decreases credit growth even though the results are very close to zero. The shock ends and has no more significance after the twenty-first week.

Response: FF

```
. irf graph coirf, set(IRF) irf(IRF) impulse (dWeiInterp) response (FF) yline(0)
(file IRF.irf now active)
. irf table coirf, set(IRF) irf(IRF) impulse (dWeiInterp) response (FF)
(file IRF.irf now active)
```



Results from IRF

step	(1) coirf	(1) Lower	(1) Upper
0	.000151	-.000372	.000675
1	.000551	-.000436	.001538
2	.001092	-.000295	.002478
3	.000855	-.000844	.002554
4	.001052	-.000915	.003019
5	.000844	-.001365	.003053
6	-.000054	-.002522	.002414
7	-.001117	-.003802	.001568
8	-.002008	-.004923	.000907
9	-.003034	-.006221	.000152
10	-.004807	-.0083	-.001314
11	-.005578	-.009339	-.001817
12	-.005502	-.009545	-.001459
13	-.005532	-.009885	-.001178
14	-.004623	-.00942	.000173
15	-.00322	-.008353	.001913
16	-.001826	-.007195	.003543
17	-.000953	-.00652	.004614
18	-.000524	-.00626	.005212
19	-.000191	-.006021	.005639
20	.000321	-.005528	.00617

95% lower and upper bounds reported
(1) irfname = IRF, impulse = dWeiInterp, and response = FF

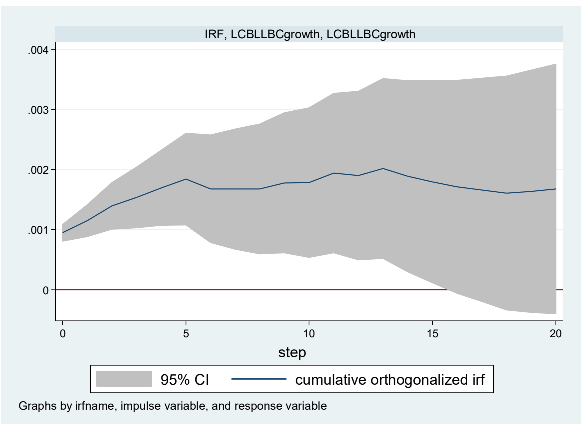
Figure C.57 – dWeiInterp shock in FF COIRF for the model with optimal lag (p=14).

Figure C.59 shows the long-run effects of dWeiInterp in FF. The shock is only significant from the tenth to the thirteenth week, with the peak at the eleventh week [-0.009339; -0.001817]. Results are similar to the ones obtained in the VAR model with the covid-19 new confirmed cases growth rate.

Impulse: LCBLLBCgrowth

Response: LCBLLBCgrowth

```
. irf graph coirf, set(IRF) irf(IRF) impulse (LCBLLBCgrowth) response (LCBLLBCgrowth) yline(0)
(file IRF.irf now active)
. irf table coirf, set(IRF) irf(IRF) impulse (LCBLLBCgrowth) response (LCBLLBCgrowth)
(file IRF.irf now active)
```



Results from IRF

step	(1) coirf	(1) Lower	(1) Upper
0	.000947	.000809	.001084
1	.001148	.000883	.001413
2	.001396	.001009	.001783
3	.001537	.001031	.002042
4	.001696	.001071	.002322
5	.001841	.001077	.002605
6	.00168	.000784	.002575
7	.001675	.000675	.002676
8	.001676	.000595	.002758
9	.001779	.000615	.002943
10	.001784	.000539	.00303
11	.001939	.000613	.003266
12	.001899	.000497	.003301
13	.002017	.000521	.003514
14	.00189	.000299	.00348
15	.001797	.000114	.00348
16	.001713	-.000058	.003484
17	.001661	-.000199	.00352
18	.001609	-.000334	.003553
19	.001639	-.000376	.003653
20	.001677	-.000402	.003755

95% lower and upper bounds reported
(1) irfname = IRF, impulse = LCBLLBCgrowth, and response = LCBLLBCgrowth

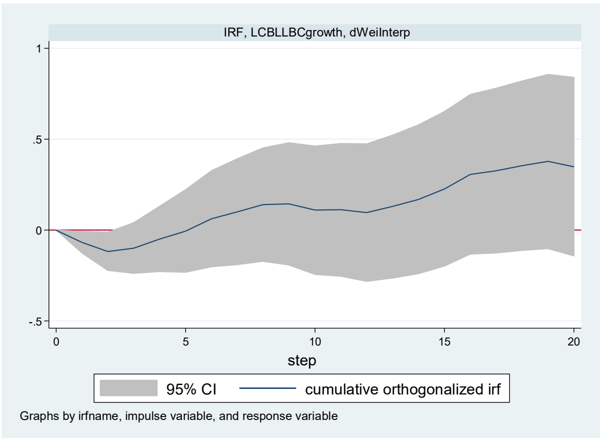
Figure C.58 – LCBLLBCgrowth shock on itself COIRF for the model with optimal lag (p=14).

Figure C.60 shows the long-run effects of shocks to the growth rate of total credit in the US on future values of its own growth. In this case, a shock in LCBLLBCgrowth is significant for sixteen weeks after the initial shock, with an average accumulated effect of around 0.002.

Response: dWeiInterp

```
. irf graph coirf, set(IRF) irf(IRF) impulse (LCBLLBCgrowth) response (dWeiInterp) yline(0)
(file IRF.irf now active)

. irf table coirf, set(IRF) irf(IRF) impulse (LCBLLBCgrowth) response (dWeiInterp)
(file IRF.irf now active)
```



Results from IRF

step	(1) coirf	(1) Lower	(1) Upper
0	0	0	0
1	-.067036	-.12611	-.007961
2	-.116881	-.221763	-.011999
3	-.099009	-.237413	.039394
4	-.049206	-.228872	.13046
5	-.004984	-.231314	.221347
6	.061719	-.202767	.326205
7	.100969	-.189805	.391743
8	.140866	-.17139	.453123
9	.144512	-.190952	.479976
10	.109583	-.243023	.462189
11	.111668	-.253007	.476343
12	.09599	-.282191	.474172
13	.129273	-.264757	.523303
14	.169127	-.240607	.578861
15	.227245	-.197549	.652039
16	.307341	-.131965	.746646
17	.326888	-.126781	.780558
18	.354253	-.11215	.820655
19	.377717	-.101645	.857079
20	.3487	-.142158	.839559

95% lower and upper bounds reported
(1) irfname = IRF, impulse = LCBLLBCgrowth, and response = dWeiInterp

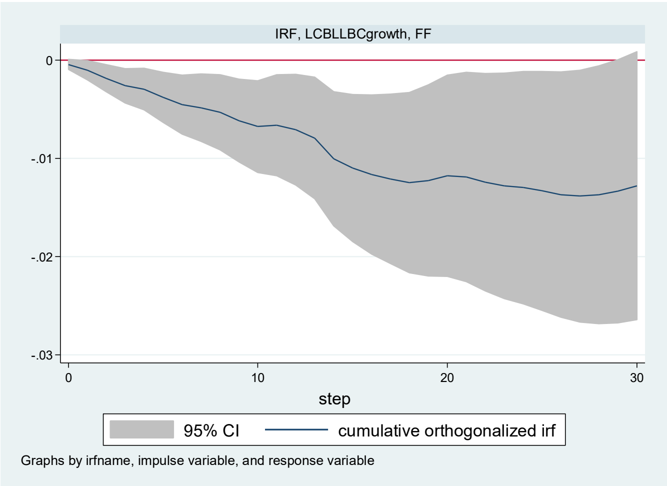
Figure C.59– LCBLLBCgrowth shock in dWeiInterp OIRF for the model with optimal lag (p=14).

Assessing figure C.61, it is possible to conclude that LCBLLBCgrowth has no significant long-run effect on dWeiInterp. The effect is very short and small-sized to consider.

Response: FF

```
. irf graph coirf, set(IRF) irf(IRF) impulse (LCBLLBCgrowth) response (FF) yline(0)
(file IRF.irf now active)

. irf table coirf, set(IRF) irf(IRF) impulse (LCBLLBCgrowth) response (FF)
(file IRF.irf now active)
```



Results from IRF

step	(1) coirf	(1) Lower	(1) Upper
0	-.000449	-.000968	.00007
1	-.001034	-.002006	-.000061
2	-.001835	-.003221	-.00045
3	-.002609	-.00436	-.000857
4	-.002951	-.005082	-.00082
5	-.003794	-.006336	-.001251
6	-.004527	-.007533	-.001521
7	-.004843	-.008277	-.00141
8	-.005304	-.009121	-.001486
9	-.006164	-.010381	-.001947
10	-.006762	-.011426	-.002098
11	-.006613	-.011757	-.001469
12	-.007073	-.01272	-.001427
13	-.007928	-.014125	-.001731
14	-.010047	-.016891	-.003203
15	-.010989	-.018482	-.003495
16	-.011654	-.019745	-.003563
17	-.012079	-.020698	-.003461
18	-.01247	-.021637	-.003302
19	-.012257	-.021992	-.002522
20	-.011776	-.022018	-.001533
21	-.011884	-.02255	-.001218
22	-.012413	-.02348	-.001346
23	-.012804	-.024269	-.001339
24	-.012975	-.024809	-.001141
25	-.013314	-.025479	-.001149
26	-.013693	-.026175	-.001211
27	-.013842	-.02667	-.001014
28	-.013704	-.026848	-.00056
29	-.013355	-.026762	.000052
30	-.012786	-.026421	.000849

95% lower and upper bounds reported
(1) irfname = IRF, impulse = LCBLLBCgrowth, and response = FF

Figure C.60– LCBLLBCgrowth shock in FF COIRF for the model with optimal lag (p=14).

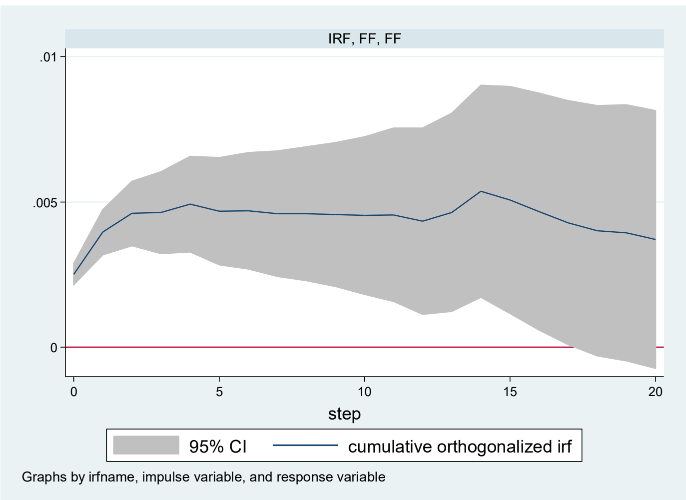
The long-term response is significant and negative from the first to the twenty-eighth week. The peak happens in the sixteenth week [-0.19745; -0.003563]. This specific COIRF has generated thirty steps ahead, so one can see the complete effect.

Impulse: FF

Response: FF

```
. irf graph coirf, set(IRF) irf(IRF) impulse (FF) response (FF) yline(0)
(file IRF.irf now active)

. irf table coirf, set(IRF) irf(IRF) impulse (FF) response (FF)
(file IRF.irf now active)
```



Results from IRF

step	(1) coirf	(1) Lower	(1) Upper
0	.002506	.002142	.00287
1	.003956	.003182	.004729
2	.004603	.003494	.005712
3	.004631	.003225	.006036
4	.004926	.003279	.006574
5	.004675	.002833	.006518
6	.004688	.002684	.006692
7	.004595	.002435	.006755
8	.004592	.002287	.006897
9	.004564	.002086	.007042
10	.004529	.001818	.00724
11	.004554	.001571	.007537
12	.004329	.001124	.007535
13	.004641	.001222	.00806
14	.00536	.001708	.009011
15	.005064	.001157	.008971
16	.004665	.000588	.008742
17	.004284	.000081	.008488
18	.004005	-.000311	.008321
19	.003935	-.000476	.008345
20	.003704	-.000733	.00814

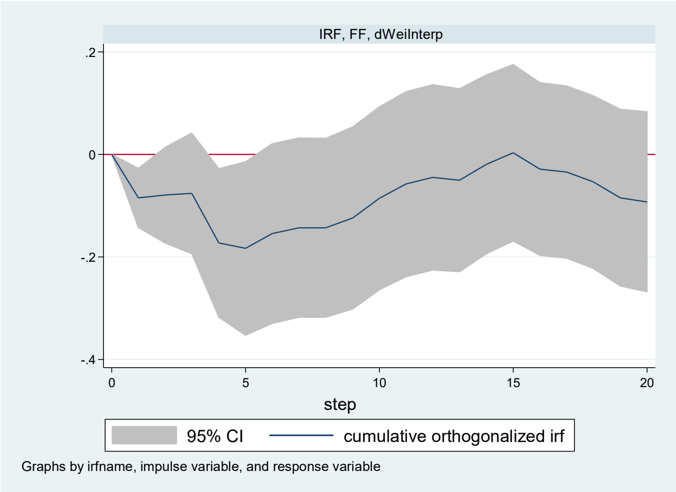
95% lower and upper bounds reported
(1) irfname = IRF, impulse = FF, and response = FF

Figure C.61 – FF shock on itself COIRF for the model with optimal lag (p=14).

Response: dWeiInterp

```
. irf graph coirf, set(IRF) irf(IRF) impulse (FF) response (dWeiInterp) yline(0)
(file IRF.irf now active)

. irf table coirf, set(IRF) irf(IRF) impulse (FF) response (dWeiInterp)
(file IRF.irf now active)
```



Results from IRF

step	(1) coirf	(1) Lower	(1) Upper
0	0	0	0
1	-.084958	-.142512	-.027405
2	-.079252	-.172508	.014004
3	-.075996	-.193459	.041467
4	-.172466	-.317385	-.027547
5	-.183417	-.352733	-.014101
6	-.154487	-.329961	.020987
7	-.142779	-.317756	.032198
8	-.143134	-.317942	.031674
9	-.123812	-.301779	.054156
10	-.085625	-.2642	.092949
11	-.057654	-.238011	.122703
12	-.044759	-.225651	.136132
13	-.050236	-.228477	.128006
14	-.018906	-.193586	.155774
15	.00334	-.168457	.175136
16	-.028237	-.196734	.140261
17	-.034101	-.201958	.133756
18	-.053826	-.222014	.114362
19	-.084595	-.257093	.087903
20	-.09228	-.267693	.083132

95% lower and upper bounds reported
(1) irfname = IRF, impulse = FF, and response = dWeiInterp

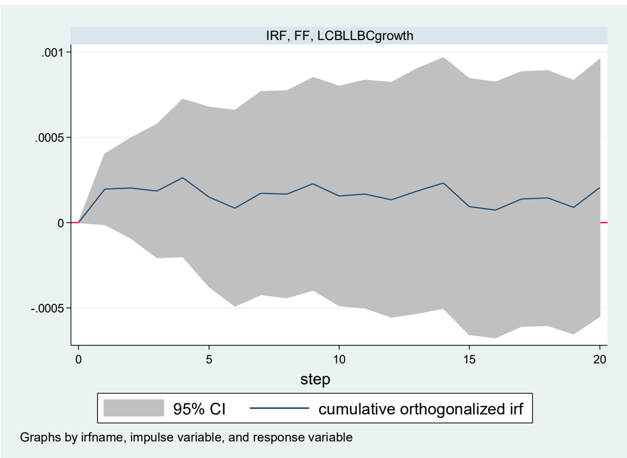
Figure C.62 – FF shock in dWeiInterp COIRF for the model with optimal lag (p=14).

Assessing figure C.64, it is possible to conclude that FF has a decreasing effect in dWeiInterp in the first week of about [-0.142512; -0.027405] and also from the fourth to the fifth week, with the peak at the fourth week [-0.352733; -0.014101].

Response: LCBLLBCgrowth

```
. irf graph coirf, set(IRF) irf(IRF) impulse (FF) response (LCBLLBCgrowth) yline(0)
(file IRF.irf now active)

. irf table coirf, set(IRF) irf(IRF) impulse (FF) response (LCBLLBCgrowth)
(file IRF.irf now active)
```



Results from IRF

step	(1) coirf	(1) Lower	(1) Upper
0	0	0	0
1	.000197	-9.8e-06	.000403
2	.000203	-.000089	.000496
3	.000186	-.000204	.000577
4	.000264	-.000197	.000724
5	.000151	-.000374	.000676
6	.000086	-.000488	.000659
7	.000174	-.000422	.000769
8	.000168	-.000438	.000773
9	.000229	-.000394	.000852
10	.000158	-.000486	.000801
11	.000168	-.000499	.000835
12	.000134	-.000553	.000821
13	.000186	-.000531	.000902
14	.000234	-.000501	.000968
15	.000095	-.000655	.000844
16	.000075	-.000673	.000824
17	.00014	-.000605	.000885
18	.000145	-.000601	.000891
19	.000091	-.000651	.000833
20	.000205	-.000548	.000958

95% lower and upper bounds reported
(1) irfname = IRF, impulse = FF, and response = LCBLLBCgrowth

Figure C.63 – FF shock in LCBLLBCgrowth COIRF for the model with optimal lag (p=14).

Assessing figure C.65, it is possible to conclude that FF has no significant long-run effect on LCBLLBCgrowth.

Point Forecast

VAR(14) model:

```
. var deathsgrowth dWeiInterp LCBLLBCgrowth FF if t<100, exog(dummy vacgrowth) lags(1/14)

. fcast compute forecast1_, step(13)

. fcast graph forecast1_dWeiInterp, observed

. twoway (line dWeiInterp date) (line forecast1_dWeiInterp date, lpattern(dash))
```

AR(1) Model:

```
. regress dWeiInterp l.dWeiInterp if t<100

. estimates store forecastAR1

. forecast create forecastAR1model, replace
  Forecast model forecastAR1model started.

. forecast estimates forecastAR1
  Added estimation results from regress.
  Forecast model forecastAR1model now contains 1 endogenous variable.

. forecast solve, begin(w(2021w49)) end(w(2022w10))
```

Part II: What are the effects of the increase in different types of credit in real economic activity?

VAR model with new confirmed Covid-19 cases growth rate

Stability condition

```
. varstable

  Eigenvalue stability condition
```

Eigenvalue	Modulus
.1039134 + .9906914i	.996126
.1039134 − .9906914i	.996126
.9289544 + .3348038i	.987446
.9289544 − .3348038i	.987446
.8584103 + .4856865i	.986286
.8584103 − .4856865i	.986286
.864212 + .4617125i	.979817
.864212 − .4617125i	.979817
−.3663571 + .9030222i	.974508
−.3663571 − .9030222i	.974508
.5684672 + .7903907i	.973587
.5684672 − .7903907i	.973587
−.0482573 + .9695302i	.97073
−.0482573 − .9695302i	.97073
.4720493 + .8478929i	.97044
.4720493 − .8478929i	.97044
−.9677115	.967712
−.7190398 + .6393045i	.962148
−.7190398 − .6393045i	.962148
−.602024 + .7492895i	.96118
−.602024 − .7492895i	.96118
−.8104721 + .509146i	.957128
−.8104721 − .509146i	.957128
−.5380338 + .7867851i	.953158
−.5380338 − .7867851i	.953158
.07397776 + .948366i	.951247
.07397776 − .948366i	.951247
.6270817 + .7113395i	.94828
.6270817 − .7113395i	.94828
−.9236994 + .2080446i	.946839
−.9236994 − .2080446i	.946839
−.9048904 + .2777823i	.946567
−.9048904 − .2777823i	.946567
−.3666145 + .8622436i	.936947
−.3666145 − .8622436i	.936947
.2935848 + .8843075i	.931768
.2935848 − .8843075i	.931768
−.2199423 + .9006589i	.927125
−.2199423 − .9006589i	.927125
−.6109955 + .6846912i	.91767
−.6109955 − .6846912i	.91767
−.8937353 + .190036i	.913716
−.8937353 − .190036i	.913716
−.07934466 + .906206i	.909673
−.07934466 − .906206i	.909673
−.7782665 + .4708655i	.909622
−.7782665 − .4708655i	.909622
.8996357 + .1239739i	.908138
.8996357 − .1239739i	.908138
.8417755 + .315754i	.899048
.8417755 − .315754i	.899048
.8763165 + .1991623i	.898664
.8763165 − .1991623i	.898664
.6972944 + .5287127i	.875075
.6972944 − .5287127i	.875075
−.8663585	.866358
.3234161 + .7704295i	.835559
.3234161 − .7704295i	.835559
.5567788 + .5817293i	.80524
.5567788 − .5817293i	.80524
.7816916	.781692
−.5141377	.514138
.2895217 + .3735676i	.472626
.2895217 − .3735676i	.472626
−.02955449 + .28198i	.283525
−.02955449 − .28198i	.283525

```
  All the eigenvalues lie inside the unit circle.
  VAR satisfies stability condition.
```

Figure C.64 – Stability test for the third VAR model

Optimal lag selection
Minimum information criteria

```
. varsoc casesgrowth dWeiInterp CILgrowth CLgrowth_detrended OLLgrowth FF, exog (dummy vacgrowth) maxlag(11)
```

Selection-order criteria
Sample: 2020w21 - 2022w10   Number of obs   =   94

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	1518.06				5.5e-22	-31.9162	-31.7194	-31.4291
1	1636.15	236.17	36	0.000	9.7e-23*	-33.6627	-33.0725*	-32.2016*
2	1656.69	41.087	36	0.257	1.4e-22	-33.3338	-32.3502	-30.8987
3	1690.9	68.417	36	0.001	1.5e-22	-33.2957	-31.9187	-29.8866
4	1722.29	62.788	36	0.004	1.7e-22	-33.1977	-31.4272	-28.8146
5	1747.93	51.269	36	0.047	2.3e-22	-32.9771	-30.8132	-27.62
6	1786.63	77.405	36	0.000	2.5e-22	-33.0346	-30.4773	-26.7035
7	1818.41	63.568	36	0.003	3.3e-22	-32.9449	-29.9942	-25.6397
8	1847.48	58.141	36	0.011	5.0e-22	-32.7975	-29.4533	-24.5183
9	1901.52	108.08	36	0.000	5.0e-22	-33.1813	-29.4437	-23.9281
10	1967.66	132.28	36	0.000	4.5e-22	-33.8226	-29.6915	-23.5953
11	2076.79	218.26*	36	0.000	2.0e-22	-35.3786*	-30.8541	-24.1773

Endogenous: casesgrowth dWeiInterp CILgrowth CLgrowth_detrended OLLgrowth FF
Exogenous: dummy vacgrowth _cons

Figure C.65 – Third Var model optimal lag criteria selection

Wald lag-exclusion statistics test

```
. varwle
```

Equation: casesgrowth

lag	chi2	df	Prob > chi2
1	16.71545	6	0.010
2	44.39235	6	0.000
3	16.37731	6	0.012
4	37.02847	6	0.000
5	30.9092	6	0.000
6	33.72483	6	0.000
7	13.18007	6	0.040
8	17.20126	6	0.009
9	19.571	6	0.003
10	52.29982	6	0.000
11	45.38219	6	0.000

Equation: OLLgrowth

lag	chi2	df	Prob > chi2
1	57.45363	6	0.000
2	38.5757	6	0.000
3	29.23537	6	0.000
4	42.49929	6	0.000
5	56.15312	6	0.000
6	15.96329	6	0.014
7	30.18278	6	0.000
8	57.74433	6	0.000
9	29.25543	6	0.000
10	21.813	6	0.001
11	81.0962	6	0.000

Equation: dWeiInterp

lag	chi2	df	Prob > chi2
1	46.66174	6	0.000
2	53.26962	6	0.000
3	72.13161	6	0.000
4	40.84882	6	0.000
5	23.52846	6	0.001
6	49.66327	6	0.000
7	18.94124	6	0.004
8	13.09153	6	0.042
9	21.96051	6	0.001
10	2.013338	6	0.918
11	44.83746	6	0.000

Equation: FF

lag	chi2	df	Prob > chi2
1	91.50482	6	0.000
2	24.1719	6	0.000
3	6.690848	6	0.350
4	12.15284	6	0.059
5	43.61762	6	0.000
6	30.24528	6	0.000
7	21.39094	6	0.002
8	21.98711	6	0.001
9	42.38944	6	0.000
10	60.39116	6	0.000
11	25.32005	6	0.000

Equation: CILgrowth

lag	chi2	df	Prob > chi2
1	46.20201	6	0.000
2	45.56899	6	0.000
3	49.79151	6	0.000
4	43.67677	6	0.000
5	77.99157	6	0.000
6	87.86517	6	0.000
7	58.93849	6	0.000
8	92.29621	6	0.000
9	54.29237	6	0.000
10	123.5598	6	0.000
11	88.10601	6	0.000

Equation: All

lag	chi2	df	Prob > chi2
1	282.4725	36	0.000
2	295.7026	36	0.000
3	243.0791	36	0.000
4	184.2671	36	0.000
5	233.6021	36	0.000
6	280.1847	36	0.000
7	157.8396	36	0.000
8	179.762	36	0.000
9	188.1185	36	0.000
10	337.5637	36	0.000
11	312.2305	36	0.000

Equation: CLgrowth_detrended

lag	chi2	df	Prob > chi2
1	21.97037	6	0.001
2	24.31583	6	0.000
3	20.55655	6	0.002
4	14.15702	6	0.028
5	10.9488	6	0.090
6	49.02252	6	0.000
7	25.09999	6	0.000
8	6.439956	6	0.376
9	22.44042	6	0.001
10	36.70742	6	0.000
11	16.06468	6	0.013

Figure C.66 - Wald lag-exclusion statistics test for p=11.

Residual diagnostics

```
. varlmar, mlag(4)
```

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	91.6431	36	0.00000
2	51.7844	36	0.04289
3	38.2684	36	0.36686
4	45.3490	36	0.13659

H0: no autocorrelation at lag order

Figure C.67 - Lagrange multiplier test for the serial correlation between residuals for a model with optimal lag, p=1.

```
. var casesgrowth dWeiInterp CILgrowth CLgrowth_detrended OLLgrowth FF, exog (dummy vacgrowth) lags (1/11)

Vector autoregression

Sample:  2020w21 - 2022w10                     Number of obs     =         94
Log likelihood =   2076.794                    AIC               =   -35.3786
FPE            =   2.00e-22                    HQIC              =  -30.85408
Det(Sigma_ml)  =   2.60e-27                    SBIC              =  -24.17728

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
casesgrowth          69     .196028   0.8498   531.9864   0.0000
dWeiInterp           69     .435048   0.8688   622.4447   0.0000
CILgrowth            69     .002678   0.9094    943.098   0.0000
CLgrowth_detre~d     69     .001164   0.8138   410.8458   0.0000
OLLgrowth            69     .002653   0.8538   548.9779   0.0000
FF                   69     .004841   0.9554   2012.396   0.0000
----------------------------------------------------------------

------------------------------------------------------------------------------------
                   |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------+----------------------------------------------------------------
casesgrowth        |
       casesgrowth |
               L1. |   .2600948   .0947189     2.75   0.006     .0744492    .4457405
               L2. |  -.2022504   .1049355    -1.93   0.054    -.4079202    .0034194
               L3. |   .0368908   .1063734     0.35   0.729    -.1715972    .2453787
               L4. |   .1944582   .0979832     1.98   0.047     .0024146    .3865017
               L5. |   -.299189   .0994451    -3.01   0.003    -.4940978   -.1042803
               L6. |   .2020682   .0976456     2.07   0.039     .0106863      .39345
               L7. |  -.0850116   .1055398    -0.81   0.421    -.2918659    .1218426
               L8. |   .2406652   .1006828     2.39   0.017     .0433306    .4379998
               L9. |  -.1348039   .0882558    -1.53   0.127    -.3077821    .0381742
              L10. |  -.3863354   .0894251    -4.32   0.000    -.5616054   -.2110654
              L11. |  -.0375749   .0963088    -0.39   0.696    -.2263367    .1511868
                   |
        dWeiInterp |
               L1. |  -.1716958   .0510458    -3.36   0.001    -.2717437    -.071648
               L2. |   .2073725   .0485032     4.28   0.000      .112308     .302437
               L3. |  -.0517796   .0555192    -0.93   0.351    -.1605953    .0570361
               L4. |   .1178656   .0593345     1.99   0.047      .001572    .2341592
               L5. |   .0670929   .0612512     1.10   0.273    -.0529572     .187143
               L6. |   .0725094   .0556479     1.30   0.193    -.0365585    .1815773
               L7. |  -.0167848   .0577011    -0.29   0.771    -.1298768    .0963073
               L8. |    -.04892   .0570914    -0.86   0.392     -.160817     .062977
               L9. |  -.1928621   .0524727    -3.68   0.000    -.2957067   -.0900175
              L10. |  -.1921183   .0507522    -3.79   0.000    -.2915907   -.0926459
              L11. |  -.0086761   .0516136    -0.17   0.867     -.109837    .0924847
                   |
         CILgrowth |
               L1. |  -1.405931   5.996229    -0.23   0.815    -13.15832    10.34646
               L2. |   13.90887   5.794161     2.40   0.016     2.552524    25.26522
               L3. |  -1.256834   5.819556    -0.22   0.829    -12.66296    10.14929
               L4. |   12.81326    6.11188     2.10   0.036     .8341913    24.79232
               L5. |    4.64764   6.288353     0.74   0.460    -7.677305    16.97259
               L6. |  -4.258053   6.133022    -0.69   0.488    -16.27855    7.762448
               L7. |   8.080273    6.31697     1.28   0.201    -4.300762    20.46131
               L8. |  -8.914591   6.442088    -1.38   0.166    -21.54085     3.71167
               L9. |  -7.342538   5.915521    -1.24   0.215    -18.93675    4.251671
              L10. |  -17.36916   5.452454    -3.19   0.001    -28.05578    -6.68255
              L11. |  -7.542287   4.806237    -1.57   0.117    -16.96234    1.877763
                   |
CLgrowth_detrended |
               L1. |   8.780351    16.8298     0.52   0.602    -24.20545    41.76616
               L2. |  -.1321468   15.83693    -0.01   0.993    -31.17197    30.90768
               L3. |   55.55026   16.39456     3.39   0.001     23.41751    87.68301
               L4. |    97.0076   20.34178     4.77   0.000     57.13844    136.8768
               L5. |   40.50009    20.8173     1.95   0.052    -.3010749    81.30126
               L6. |   17.22794    19.3841     0.89   0.374    -20.76419    55.22008
               L7. |  -4.962602    18.4076    -0.27   0.787    -41.04084    31.11564
               L8. |  -46.83455   17.46728    -2.68   0.007     -81.0698   -12.59931
               L9. |   4.144116   14.96238     0.28   0.782    -25.18162    33.46985
              L10. |  -27.92511   13.01211    -2.15   0.032    -53.42838    -2.42184
              L11. |  -38.27818   13.81705    -2.77   0.006    -65.35909   -11.19727
                   |
         OLLgrowth |
               L1. |  -19.17137   7.535948    -2.54   0.011    -33.94156   -4.401183
               L2. |   19.60076   7.488952     2.62   0.009     4.922678    34.27883
               L3. |   9.390238   7.428356     1.26   0.206    -5.169073    23.94955
               L4. |   13.68932   6.817854     2.01   0.045     .3265676    27.05206
               L5. |   29.55822   6.988342     4.23   0.000     15.86132    43.25512
               L6. |   28.16209   6.563099     4.29   0.000     15.29865    41.02552
               L7. |   20.60739   7.352722     2.80   0.005     6.196316    35.01846
               L8. |   2.994451   6.753782     0.44   0.657    -10.24272    16.23162
               L9. |  -16.28662   6.141585    -2.65   0.008     -28.3239   -4.249333
              L10. |  -24.43258   5.893841    -4.15   0.000     -35.9843   -12.88087
              L11. |   2.200254   5.306215     0.41   0.678    -8.199737    12.60024
                   |
                FF |
               L1. |  -3.950823   3.536068    -1.12   0.264    -10.88139    2.979742
               L2. |   12.97873     4.1476     3.13   0.002     4.849581    21.10788
               L3. |  -12.91281   4.698363    -2.75   0.006    -22.12143   -3.704186
               L4. |  -2.021383   4.199555    -0.48   0.630    -10.25236    6.209593
               L5. |   2.297131    3.96157     0.58   0.562    -5.467403    10.06167
               L6. |  -7.726388    3.92535    -1.97   0.049    -15.41993   -.0328432
               L7. |   1.385783   3.997532     0.35   0.729    -6.449234    9.220801
               L8. |   .9400011    4.04178     0.23   0.816    -6.981743    8.861745
               L9. |  -7.450755   3.357321    -2.22   0.026    -14.03098   -.8705275
              L10. |   .3386066   1.044281     0.32   0.746    -1.708147    2.385361
              L11. |   5.721829    1.07964     5.30   0.000     3.605775    7.837884
                   |
             dummy |  -.0638506   .0586901    -1.09   0.277     -.178881    .0511798
         vacgrowth |  -.1583854   .0310452    -5.10   0.000    -.2192328    -.097538
             _cons |   .9621792   .4135767     2.33   0.020     .1515837    1.772775
------------------------------------------------------------------------------------
```

dWeiInterp						
casesgrowth						
L1.	-.8617192	.2102114	-4.10	0.000	-1.273726	-.4497125
L2.	-.835772	.2328852	-3.59	0.000	-1.292219	-.3793253
L3.	.2562655	.2360763	1.09	0.278	-.2064355	.7189665
L4.	.0148183	.2174559	0.07	0.946	-.4113874	.4410239
L5.	.4254135	.2207002	1.93	0.054	-.0071509	.8579779
L6.	-.2820116	.2167066	-1.30	0.193	-.7067487	.1427254
L7.	-.0138194	.2342264	-0.06	0.953	-.4728947	.4452559
L8.	-.0196065	.2234471	-0.09	0.930	-.4575547	.4183417
L9.	.2254237	.1958677	1.15	0.250	-.1584698	.6093173
L10.	.0330457	.1984627	0.17	0.868	-.3559341	.4220256
L11.	-.6373769	.2137398	-2.98	0.003	-1.056299	-.2184546
dWeiInterp						
L1.	.0999609	.1132868	0.88	0.378	-.1220771	.3219988
L2.	-.4008565	.1076439	-3.72	0.000	-.6118347	-.1898783
L3.	.4173951	.1232148	3.39	0.001	.1758984	.6588917
L4.	-.2700711	.1316822	-2.05	0.040	-.5281634	-.0119787
L5.	.0909404	.1359358	0.67	0.503	-.1754888	.3573697
L6.	-.08332	.1235004	-0.67	0.500	-.3253763	.1587364
L7.	-.0584677	.128057	-0.46	0.648	-.3094549	.1925194
L8.	.3160198	.1267039	2.49	0.013	.0676848	.5643549
L9.	-.4000543	.1164536	-3.44	0.001	-.6282991	-.1718095
L10.	.0070225	.1126352	0.06	0.950	-.2137384	.2277834
L11.	-.7071384	.1145471	-6.17	0.000	-.9316465	-.4826302
CILgrowth						
L1.	-28.86568	13.30754	-2.17	0.030	-54.94797	-2.783383
L2.	-1.985581	12.85908	-0.15	0.877	-27.18892	23.21776
L3.	51.09721	12.91544	3.96	0.000	25.78341	76.41102
L4.	51.89427	13.5642	3.83	0.000	25.30892	78.47962
L5.	31.31085	13.95585	2.24	0.025	3.957878	58.66382
L6.	59.73544	13.61112	4.39	0.000	33.05813	86.41276
L7.	-6.15433	14.01936	-0.44	0.661	-33.63178	21.32312
L8.	33.4077	14.29704	2.34	0.019	5.386017	61.42938
L9.	10.33424	13.12842	0.79	0.431	-15.397	36.06547
L10.	.4160089	12.10073	0.03	0.973	-23.30098	24.133
L11.	-1.113677	10.66657	-0.10	0.917	-22.01976	19.79241
CLgrowth_detrended						
L1.	-43.66989	37.35068	-1.17	0.242	-116.8759	29.53609
L2.	57.4226	35.14719	1.63	0.102	-11.46463	126.3098
L3.	111.3817	36.38474	3.06	0.002	40.06889	182.6945
L4.	214.5512	45.14488	4.75	0.000	126.0689	303.0335
L5.	162.5415	46.20021	3.52	0.000	71.99074	253.0922
L6.	104.1589	43.01947	2.42	0.015	19.84226	188.4755
L7.	139.7398	40.85232	3.42	0.001	59.67073	219.8089
L8.	91.1832	38.76545	2.35	0.019	15.20431	167.1621
L9.	36.01993	33.20628	1.08	0.278	-29.06319	101.1031
L10.	17.03974	28.87801	0.59	0.555	-39.56013	73.6396
L11.	29.94239	30.66441	0.98	0.329	-30.15876	90.04354
OLLgrowth						
L1.	-28.17473	16.72466	-1.68	0.092	-60.95446	4.605013
L2.	-25.27017	16.62036	-1.52	0.128	-57.84549	7.305143
L3.	-48.49446	16.48588	-2.94	0.003	-80.80619	-16.18272
L4.	-31.174	15.13098	-2.06	0.039	-60.83018	-1.517815
L5.	-8.683178	15.50935	-0.56	0.576	-39.08095	21.71459
L6.	60.8198	14.5656	4.18	0.000	32.27174	89.36785
L7.	30.96252	16.31803	1.90	0.058	-1.020226	62.94526
L8.	29.43186	14.98879	1.96	0.050	.0543779	58.80934
L9.	-20.86964	13.63013	-1.53	0.126	-47.5842	5.844915
L10.	7.499777	13.0803	0.57	0.566	-18.13715	33.1367
L11.	13.74611	11.77618	1.17	0.243	-9.33477	36.827
FF						
L1.	-17.19602	7.847657	-2.19	0.028	-32.57715	-1.814897
L2.	9.695253	9.204843	1.05	0.292	-8.345908	27.73641
L3.	9.03969	10.42716	0.87	0.386	-11.39717	29.47655
L4.	-17.73031	9.320146	-1.90	0.057	-35.99746	.5368453
L5.	17.58321	8.791982	2.00	0.046	.3512429	34.81518
L6.	-15.44773	8.711599	-1.77	0.076	-32.52215	1.626689
L7.	-5.934644	8.871792	-0.67	0.504	-23.32304	11.45375
L8.	-4.816438	8.969994	-0.54	0.591	-22.3973	12.76443
L9.	3.349727	7.450961	0.45	0.653	-11.25389	17.95334
L10.	1.951684	2.317592	0.84	0.400	-2.590714	6.494081
L11.	-.2501211	2.396063	-0.10	0.917	-4.946319	4.446077
dummy	-.5791757	.1302519	-4.45	0.000	-.8344647	-.3238867
vacgrowth	-.0290665	.0688991	-0.42	0.673	-.1641062	.1059732
_cons	2.58251	.9178582	2.81	0.005	.7835411	4.381479

CILgrowth						
casesgrowth						
L1.	-.0013008	.0012942	-1.01	0.315	-.0038373	.0012357
L2.	.0063434	.0014337	4.42	0.000	.0035334	.0091535
L3.	-.0004703	.0014534	-0.32	0.746	-.0033189	.0023783
L4.	-.0029186	.0013388	-2.18	0.029	-.0055425	-.0002947
L5.	-.0012513	.0013587	-0.92	0.357	-.0039144	.0014117
L6.	-.0006411	.0013341	-0.48	0.631	-.003256	.0019737
L7.	.0010356	.001442	0.72	0.473	-.0017907	.0038618
L8.	-.0003685	.0013756	-0.27	0.789	-.0030647	.0023277
L9.	-.0001331	.0012058	-0.11	0.912	-.0024965	.0022303
L10.	-.004614	.0012218	-3.78	0.000	-.0070088	-.0022193
L11.	-.0007302	.0013159	-0.55	0.579	-.0033092	.0018489
dWeiInterp						
L1.	.0020825	.0006974	2.99	0.003	.0007156	.0034495
L2.	.0000997	.0006627	0.15	0.880	-.0011992	.0013985
L3.	.0014648	.0007586	1.93	0.053	-.000022	.0029515
L4.	-.0002582	.0008107	-0.32	0.750	-.0018471	.0013307
L5.	-.0011978	.0008369	-1.43	0.152	-.002838	.0004425
L6.	-.0016601	.0007603	-2.18	0.029	-.0031503	-.0001699
L7.	.0013046	.0007884	1.65	0.098	-.0002406	.0028498
L8.	-.0042497	.00078	-5.45	0.000	-.0057785	-.0027208
L9.	.0025476	.0007169	3.55	0.000	.0011424	.0039527
L10.	-.0002108	.0006934	-0.30	0.761	-.0015699	.0011483
L11.	.0042214	.0007052	5.99	0.000	.0028393	.0056036
CILgrowth						
L1.	.3315385	.0819269	4.05	0.000	.1709646	.4921123
L2.	.1778158	.079166	2.25	0.025	.0226532	.3329784
L3.	-.4349086	.079513	-5.47	0.000	-.5907512	-.2790659
L4.	-.015759	.0835071	-0.19	0.850	-.1794298	.1479119
L5.	-.011096	.0859182	-0.13	0.897	-.1794926	.1573007
L6.	-.574039	.0837959	-6.85	0.000	-.7382759	-.409802
L7.	-.056469	.0863092	-0.65	0.513	-.225632	.1126939
L8.	-.0574755	.0880187	-0.65	0.514	-.229989	.115038
L9.	-.3324828	.0808242	-4.11	0.000	-.4908953	-.1740703
L10.	-.2493518	.0744973	-3.35	0.001	-.3953638	-.1033398
L11.	.3714609	.065668	5.66	0.000	.2427541	.5001678
CLgrowth_detrended						
L1.	.6664946	.2299468	2.90	0.004	.2158071	1.117182
L2.	-.2215995	.2163812	-1.02	0.306	-.6456989	.2024998
L3.	-.5894738	.2240001	-2.63	0.008	-1.028506	-.1504417
L4.	-1.578807	.2779312	-5.68	0.000	-2.123542	-1.034072
L5.	-1.928816	.2844283	-6.78	0.000	-2.486286	-1.371347
L6.	-.8634135	.2648463	-3.26	0.001	-1.382503	-.3443242
L7.	-1.784286	.2515044	-7.09	0.000	-2.277226	-1.291346
L8.	-.6423758	.2386568	-2.69	0.007	-1.110134	-.1746172
L9.	.1367304	.2044321	0.67	0.504	-.2639492	.5374101
L10.	-.0454086	.1777854	-0.26	0.798	-.3938617	.3030445
L11.	-.3466668	.1887833	-1.84	0.066	-.7166752	.0233417
OLLgrowth						
L1.	.2943814	.1029642	2.86	0.004	.0925753	.4961876
L2.	.2419364	.1023221	2.36	0.018	.0413887	.442484
L3.	.0805945	.1014942	0.79	0.427	-.1183304	.2795195
L4.	.1203081	.0931528	1.29	0.197	-.0622681	.3028843
L5.	.0633621	.0954822	0.66	0.507	-.1237796	.2505039
L6.	-.4897278	.0896721	-5.46	0.000	-.6654819	-.3139737
L7.	-.2010783	.1004608	-2.00	0.045	-.3979778	-.0041788
L8.	-.675011	.0922774	-7.32	0.000	-.8558714	-.4941506
L9.	-.1559845	.0839129	-1.86	0.063	-.3204508	.0084818
L10.	.3847959	.080528	4.78	0.000	.226964	.5426279
L11.	-.086681	.0724992	-1.20	0.232	-.2287768	.0554148
FF						
L1.	.1673296	.0483135	3.46	0.001	.0726368	.2620224
L2.	-.1731852	.056669	-3.06	0.002	-.2842544	-.0621161
L3.	.1261085	.0641941	1.96	0.049	.0002904	.2519266
L4.	.0759565	.0573788	1.32	0.186	-.0365039	.188417
L5.	-.2229213	.0541272	-4.12	0.000	-.3290087	-.1168339
L6.	.1825957	.0536323	3.40	0.001	.0774783	.2877132
L7.	.1071977	.0546186	1.96	0.050	.0001473	.2142481
L8.	-.1988327	.0552231	-3.60	0.000	-.307068	-.0905973
L9.	.1150621	.0458713	2.51	0.012	.025156	.2049682
L10.	.0883755	.0142681	6.19	0.000	.0604106	.1163405
L11.	-.0094751	.0147512	-0.64	0.521	-.0383869	.0194367
dummy	.004386	.0008019	5.47	0.000	.0028143	.0059576
vacgrowth	.0017852	.0004242	4.21	0.000	.0009539	.0026166
_cons	-.0267044	.0056507	-4.73	0.000	-.0377796	-.0156291

CLgrowth_detrended						
casesgrowth						
L1.	-.002035	.0005627	-3.62	0.000	-.0031378	-.0009322
L2.	.0012352	.0006234	1.98	0.048	.0000134	.002457
L3.	-.0011682	.0006319	-1.85	0.064	-.0024067	.0000703
L4.	-.0008126	.0005821	-1.40	0.163	-.0019534	.0003282
L5.	-.0002543	.0005907	-0.43	0.667	-.0014121	.0009036
L6.	-.0022706	.0005801	-3.91	0.000	-.0034074	-.0011337
L7.	.0024681	.000627	3.94	0.000	.0012393	.0036969
L8.	-.0003571	.0005981	-0.60	0.551	-.0015293	.0008152
L9.	.0012958	.0005243	2.47	0.013	.0002682	.0023233
L10.	-.0013625	.0005312	-2.56	0.010	-.0024037	-.0003213
L11.	-.0010583	.0005721	-1.85	0.064	-.0021797	.000063
dWeiInterp						
L1.	-.0001874	.0003032	-0.62	0.537	-.0007817	.0004069
L2.	-.0008054	.0002881	-2.80	0.005	-.0013701	-.0002407
L3.	.0005008	.0003298	1.52	0.129	-.0001456	.0011472
L4.	-.0008541	.0003525	-2.42	0.015	-.001545	-.0001633
L5.	.0007975	.0003639	2.19	0.028	.0000844	.0015107
L6.	-.0002539	.0003306	-0.77	0.443	-.0009018	.0003941
L7.	.0008928	.0003428	2.60	0.009	.0002209	.0015646
L8.	-.0004434	.0003391	-1.31	0.191	-.0011081	.0002213
L9.	-.000163	.0003117	-0.52	0.601	-.0007739	.000448
L10.	-.0008178	.0003015	-2.71	0.007	-.0014087	-.0002269
L11.	.0000264	.0003066	0.09	0.931	-.0005746	.0006273
CILgrowth						
L1.	-.0758346	.0356201	-2.13	0.033	-.1456487	-.0060204
L2.	-.0185472	.0344197	-0.54	0.590	-.0860087	.0489143
L3.	.0080144	.0345706	0.23	0.817	-.0597428	.0757715
L4.	.0180193	.0363071	0.50	0.620	-.0531414	.0891799
L5.	-.0623997	.0373555	-1.67	0.095	-.1356151	.0108156
L6.	-.0429637	.0364327	-1.18	0.238	-.1143705	.0284431
L7.	.1083639	.0375255	2.89	0.004	.0348154	.1819124
L8.	.0436981	.0382687	1.14	0.254	-.0313071	.1187034
L9.	-.0892004	.0351407	-2.54	0.011	-.1580748	-.0203259
L10.	.0261949	.0323899	0.81	0.419	-.037288	.0896779
L11.	.0206494	.0285511	0.72	0.470	-.0353097	.0766084
CLgrowth_detrended						
L1.	-.1553796	.0999761	-1.55	0.120	-.3513291	.04057
L2.	.1690931	.094078	1.80	0.072	-.0152964	.3534827
L3.	.130438	.0973906	1.34	0.180	-.060444	.32132
L4.	.0187667	.1208387	0.16	0.877	-.2180728	.2556062
L5.	-.082257	.1236635	-0.67	0.506	-.324633	.160119
L6.	.2176637	.1151497	1.89	0.059	-.0080255	.4433529
L7.	.0505491	.1093489	0.46	0.644	-.1637708	.264869
L8.	.0755605	.103763	0.73	0.466	-.1278112	.2789322
L9.	-.0016702	.0888828	-0.02	0.985	-.1758774	.1725369
L10.	.3083051	.0772974	3.99	0.000	.156805	.4598052
L11.	-.1749601	.082079	-2.13	0.033	-.335832	-.0140881
OLLgrowth						
L1.	.0087859	.0447667	0.20	0.844	-.0789552	.096527
L2.	-.0685097	.0444875	-1.54	0.124	-.1557036	.0186842
L3.	-.0678708	.0441275	-1.54	0.124	-.1543592	.0186176
L4.	-.1086652	.0405009	-2.68	0.007	-.1880455	-.0292849
L5.	.053163	.0415137	1.28	0.200	-.0282024	.1345283
L6.	.1994557	.0389876	5.12	0.000	.1230415	.2758699
L7.	-.0132325	.0436783	-0.30	0.762	-.0988403	.0723753
L8.	-.0271388	.0401203	-0.68	0.499	-.1057732	.0514955
L9.	-.1052103	.0364836	-2.88	0.004	-.1767168	-.0337038
L10.	.063953	.0350119	1.83	0.068	-.004669	.132575
L11.	-.0192493	.0315211	-0.61	0.541	-.0810296	.042531
FF						
L1.	.0066622	.0210057	0.32	0.751	-.0345082	.0478327
L2.	-.0908117	.0246385	-3.69	0.000	-.1391023	-.0425212
L3.	.0643056	.0279102	2.30	0.021	.0096025	.1190087
L4.	-.0212896	.0249471	-0.85	0.393	-.0701851	.0276058
L5.	.02074	.0235334	0.88	0.378	-.0253846	.0668646
L6.	.0279742	.0233182	1.20	0.230	-.0177287	.073677
L7.	-.0169528	.023747	-0.71	0.475	-.0634961	.0295904
L8.	-.0378384	.0240099	-1.58	0.115	-.0848969	.0092201
L9.	-.0075426	.0199439	-0.38	0.705	-.0466319	.0315467
L10.	.0035228	.0062035	0.57	0.570	-.0086357	.0156814
L11.	.0138737	.0064135	2.16	0.031	.0013035	.026444
dummy	-.0005296	.0003486	-1.52	0.129	-.001213	.0001537
vacgrowth	-.0000852	.0001844	-0.46	0.644	-.0004466	.0002763
_cons	.0039509	.0024568	1.61	0.108	-.0008644	.0087662

OLLgrowth						
casesgrowth						
L1.	.002256	.001282	1.76	0.078	-.0002566	.0047687
L2.	.0002976	.0014203	0.21	0.834	-.0024861	.0030813
L3.	.0012955	.0014397	0.90	0.368	-.0015264	.0041173
L4.	-.0014491	.0013262	-1.09	0.275	-.0040484	.0011501
L5.	-.0020258	.001346	-1.51	0.132	-.0046638	.0006123
L6.	-.0007301	.0013216	-0.55	0.581	-.0033204	.0018602
L7.	.0030446	.0014285	2.13	0.033	.0002448	.0058443
L8.	.0017203	.0013627	1.26	0.207	-.0009506	.0043912
L9.	-.0015982	.0011945	-1.34	0.181	-.0039395	.000743
L10.	-.0031302	.0012103	-2.59	0.010	-.0055024	-.000758
L11.	.0012233	.0013035	0.94	0.348	-.0013316	.0037781
dWeiInterp						
L1.	.0002493	.0006909	0.36	0.718	-.0011048	.0016034
L2.	.0002182	.0006565	0.33	0.740	-.0010684	.0015049
L3.	.0005498	.0007514	0.73	0.464	-.000923	.0020226
L4.	.0027989	.0008031	3.49	0.000	.0012249	.0043729
L5.	.0009676	.000829	1.17	0.243	-.0006573	.0025924
L6.	-.0000259	.0007532	-0.03	0.973	-.0015021	.0014503
L7.	-.0002666	.000781	-0.34	0.733	-.0017973	.0012641
L8.	-.0040308	.0007727	-5.22	0.000	-.0055453	-.0025163
L9.	.0008903	.0007102	1.25	0.210	-.0005017	.0022823
L10.	.0000993	.0006869	0.14	0.885	-.001247	.0014457
L11.	.0056274	.0006986	8.06	0.000	.0042582	.0069966
CILgrowth						
L1.	.0873394	.0811576	1.08	0.282	-.0717265	.2464052
L2.	-.172662	.0784226	-2.20	0.028	-.3263675	-.0189565
L3.	.0634769	.0787663	0.81	0.420	-.0909023	.217856
L4.	.1126113	.0827229	1.36	0.173	-.0495226	.2747451
L5.	-.1234358	.0851114	-1.45	0.147	-.290251	.0433794
L6.	-.2487626	.083009	-3.00	0.003	-.4114573	-.0860679
L7.	.0405752	.0854987	0.47	0.635	-.1269992	.2081496
L8.	-.0006019	.0871921	-0.01	0.994	-.1714954	.1702916
L9.	-.3519855	.0800652	-4.40	0.000	-.5089104	-.1950606
L10.	-.083742	.0737977	-1.13	0.256	-.2283828	.0608988
L11.	.0629961	.0650513	0.97	0.333	-.0645021	.1904943
CLgrowth_detrended						
L1.	-.201501	.2277874	-0.88	0.376	-.6479561	.2449541
L2.	.8797054	.2143492	4.10	0.000	.4595887	1.299822
L3.	1.027821	.2218965	4.63	0.000	.5929117	1.46273
L4.	-.9396232	.2753212	-3.41	0.001	-1.479243	-.4000035
L5.	-1.630725	.2817573	-5.79	0.000	-2.182959	-1.078491
L6.	-.7317075	.2623592	-2.79	0.005	-1.245922	-.2174929
L7.	-.950491	.2491426	-3.82	0.000	-1.438802	-.4621805
L8.	-.2973757	.2364156	-1.26	0.208	-.7607418	.1659903
L9.	-.4518259	.2025124	-2.23	0.026	-.8487428	-.054909
L10.	-.4317083	.1761159	-2.45	0.014	-.7768891	-.0865275
L11.	.2079909	.1870105	1.11	0.266	-.1585428	.5745247
OLLgrowth						
L1.	-.0168935	.1019973	-0.17	0.868	-.2168045	.1830175
L2.	.2032433	.1013612	2.01	0.045	.004579	.4019076
L3.	.1972018	.1005411	1.96	0.050	.000145	.3942587
L4.	.2125864	.0922781	2.30	0.021	.0317247	.393448
L5.	.1442554	.0945856	1.53	0.127	-.041129	.3296397
L6.	.1096333	.08883	1.23	0.217	-.0644704	.2837369
L7.	-.0938143	.0995174	-0.94	0.346	-.2888647	.1012362
L8.	-.5064198	.0914108	-5.54	0.000	-.6855818	-.3272579
L9.	-.2274776	.0831249	-2.74	0.006	-.3903995	-.0645558
L10.	.0103531	.0797717	0.13	0.897	-.1459966	.1667029
L11.	.191151	.0718184	2.66	0.008	.0503896	.3319125
FF						
L1.	.3354795	.0478598	7.01	0.000	.241676	.4292831
L2.	-.2300305	.0561368	-4.10	0.000	-.3400566	-.1200044
L3.	-.083326	.0635912	-1.31	0.190	-.2079625	.0413106
L4.	.2781969	.05684	4.89	0.000	.1667926	.3896013
L5.	-.1607947	.0536189	-3.00	0.003	-.2658858	-.0557035
L6.	.0199804	.0531287	0.38	0.707	-.0841499	.1241108
L7.	.1515032	.0541057	2.80	0.005	.0454581	.2575484
L8.	-.1093685	.0547045	-2.00	0.046	-.2165874	-.0021495
L9.	-.0089033	.0454405	-0.20	0.845	-.0979652	.0801585
L10.	.0490295	.0141341	3.47	0.001	.0213272	.0767319
L11.	.0053889	.0146127	0.37	0.712	-.0232514	.0340293
dummy	.003747	.0007944	4.72	0.000	.0021901	.0053039
vacgrowth	.0009309	.0004202	2.22	0.027	.0001073	.0017544
_cons	-.0231012	.0055977	-4.13	0.000	-.0340724	-.01213

FF						
casesgrowth						
L1.	-.0045642	.002339	-1.95	0.051	-.0091486	.0000202
L2.	.0020768	.0025913	0.80	0.423	-.0030021	.0071557
L3.	-.0016085	.0026268	-0.61	0.540	-.006757	.00354
L4.	.0013678	.0024196	0.57	0.572	-.0033746	.0061102
L5.	-.0007685	.0024557	-0.31	0.754	-.0055817	.0040447
L6.	-.0021846	.0024113	-0.91	0.365	-.0069107	.0025415
L7.	.0069134	.0026063	2.65	0.008	.0018053	.0120216
L8.	-.005799	.0024863	-2.33	0.020	-.0106721	-.0009259
L9.	.0063786	.0021794	2.93	0.003	.002107	.0106502
L10.	-.0096206	.0022083	-4.36	0.000	-.0139488	-.0052924
L11.	.0057814	.0023783	2.43	0.015	.00112	.0104427
dWeiInterp						
L1.	.0021543	.0012605	1.71	0.087	-.0003163	.0046249
L2.	.0014137	.0011978	1.18	0.238	-.0009339	.0037612
L3.	-.0005385	.001371	-0.39	0.695	-.0032256	.0021487
L4.	.0019672	.0014652	1.34	0.179	-.0009046	.004839
L5.	-.0001359	.0015126	-0.09	0.928	-.0031004	.0028287
L6.	-.0003847	.0013742	-0.28	0.780	-.0030781	.0023087
L7.	.0013419	.0014249	0.94	0.346	-.0014509	.0041346
L8.	-.0026042	.0014098	-1.85	0.065	-.0053675	.000159
L9.	-.0046198	.0012958	-3.57	0.000	-.0071595	-.0020801
L10.	-.0057243	.0012533	-4.57	0.000	-.0081807	-.0032678
L11.	.0027385	.0012746	2.15	0.032	.0002404	.0052366
CILgrowth						
L1.	-.3953495	.1480739	-2.67	0.008	-.685569	-.1051299
L2.	.4251575	.1430839	2.97	0.003	.1447182	.7055969
L3.	-.1791147	.1437111	-1.25	0.213	-.4607832	.1025538
L4.	-.3058457	.1509298	-2.03	0.043	-.6016627	-.0100286
L5.	-.3021513	.1552878	-1.95	0.052	-.6065097	.0022071
L6.	.3197917	.1514519	2.11	0.035	.0229514	.616632
L7.	-.2175878	.1559944	-1.39	0.163	-.5233312	.0881557
L8.	-.4758772	.1590842	-2.99	0.003	-.7876765	-.164078
L9.	-.3531873	.1460809	-2.42	0.016	-.6395005	-.0668741
L10.	-.2520161	.1346456	-1.87	0.061	-.5159167	.0118845
L11.	-.263457	.1186876	-2.22	0.026	-.4960805	-.0308336
CLgrowth_detrended						
L1.	.6496363	.4156036	1.56	0.118	-.1649318	1.464204
L2.	-1.196947	.3910852	-3.06	0.002	-1.96346	-.4304342
L3.	.15935	.4048556	0.39	0.694	-.6341523	.9528523
L4.	.1475838	.5023302	0.29	0.769	-.8369653	1.132133
L5.	.5279434	.514073	1.03	0.304	-.4796212	1.535508
L6.	.4425242	.4786807	0.92	0.355	-.4956726	1.380721
L7.	-1.596512	.4545667	-3.51	0.000	-2.487447	-.705578
L8.	-.2165842	.4313459	-0.50	0.616	-1.062007	.6288381
L9.	-.3815675	.3694886	-1.03	0.302	-1.105752	.342617
L10.	.4804569	.3213277	1.50	0.135	-.1493337	1.110248
L11.	-1.251301	.3412051	-3.67	0.000	-1.920051	-.5825518
OLLgrowth						
L1.	-.0027068	.1860965	-0.01	0.988	-.3674493	.3620356
L2.	.2297596	.184936	1.24	0.214	-.1327082	.5922274
L3.	.3293697	.1834396	1.80	0.073	-.0301652	.6889047
L4.	.055106	.1683635	0.33	0.743	-.2748804	.3850924
L5.	.9023443	.1725736	5.23	0.000	.5641062	1.240582
L6.	.2288198	.1620725	1.41	0.158	-.0888364	.546476
L7.	-.0872728	.1815718	-0.48	0.631	-.4431471	.2686014
L8.	.2917874	.1667813	1.75	0.080	-.0350979	.6186727
L9.	-.3525104	.1516634	-2.32	0.020	-.6497652	-.0552556
L10.	.1357933	.1455455	0.93	0.351	-.1494706	.4210572
L11.	-.4520944	.1310344	-3.45	0.001	-.708917	-.1952718
FF						
L1.	.6824872	.0873214	7.82	0.000	.5113403	.853634
L2.	-.150857	.1024229	-1.47	0.141	-.3516022	.0498883
L3.	-.114056	.1160237	-0.98	0.326	-.3414583	.1133464
L4.	-.0755308	.1037059	-0.73	0.466	-.2787907	.1277291
L5.	.1930128	.097829	1.97	0.049	.0012715	.3847541
L6.	-.4757472	.0969346	-4.91	0.000	-.6657355	-.2857589
L7.	.2187541	.0987171	2.22	0.027	.0252723	.412236
L8.	.1496663	.0998098	1.50	0.134	-.0459572	.3452898
L9.	-.3929397	.0829074	-4.74	0.000	-.5554352	-.2304443
L10.	.0381825	.025788	1.48	0.139	-.0123611	.0887261
L11.	.0242488	.0266612	0.91	0.363	-.0280062	.0765037
dummy	-.0020348	.0014493	-1.40	0.160	-.0048754	.0008058
vacgrowth	-.004483	.0007666	-5.85	0.000	-.0059856	-.0029804
_cons	.0742935	.0102131	7.27	0.000	.0542763	.0943108

```
. varlmar, mlag(11)

  Lagrange-multiplier test
```

lag	chi2	df	Prob > chi2
1	30.4527	36	0.72940
2	38.5508	36	0.35494
3	43.7779	36	0.17484
4	32.1365	36	0.65296
5	22.2916	36	0.96421
6	44.9724	36	0.14511
7	35.0651	36	0.51289
8	34.0357	36	0.56230
9	38.3582	36	0.36305
10	31.2960	36	0.69181
11	34.7077	36	0.52999

```
  H0: no autocorrelation at lag order
```

Figure C.68 – VAR(11) estimation and Lagrange multiplier test for the serial correlation between residuals for a model with optimal lag, p=11.

```
. summarize rescasesgrowth resCILgrowth resCLgrowth_detrended resOLLgrowth resdWeiInterp resFF
```

Variable	Obs	Mean	Std. Dev.	Min	Max
rescasesgr~h	94	-6.44e-11	.1016356	-.211891	.2938452
resCILgrowth	94	-3.93e-12	.0013887	-.0040471	.0033309
resCLgrowt~d	94	3.39e-12	.0006038	-.0014247	.0011808
resOLLgrowth	94	4.45e-13	.0013756	-.002649	.0035189
resdWeiInt~p	94	4.45e-10	.2255616	-.508144	.6366937
resFF	94	3.51e-12	.0025098	-.0099631	.006845

Figure C.69 – Residuals of the variables for the model with optimal lag (p=11).

```
. corr rescasesgrowth resCILgrowth resCLgrowth_detrended resOLLgrowth resdWeiInterp resFF, cov
(obs=94)
```

	rescas~h	resCIL~h	resCLg~d	resOLL~h	resdWe~p	resFF
rescasesgr~h	.01033					
resCILgrowth	2.8e-06	1.9e-06				
resCLgrowt~d	-.000011	-7.6e-08	3.6e-07			
resOLLgrowth	.000048	6.2e-07	-4.6e-08	1.9e-06		
resdWeiInt~p	.001048	3.2e-06	-.000011	-.000075	.050878	
resFF	-.000048	-4.1e-07	1.6e-07	4.9e-08	-.000079	6.3e-06

Figure C.70 – Covariance between residuals for the model with optimal lag (p=11).

```
. corr rescasesgrowth resCILgrowth resCLgrowth_detrended resOLLgrowth resdWeiInterp resFF
(obs=94)
```

	rescas~h	resCIL~h	resCLg~d	resOLL~h	resdWe~p	resFF
rescasesgr~h	1.0000					
resCILgrowth	0.0202	1.0000				
resCLgrowt~d	-0.1803	-0.0904	1.0000			
resOLLgrowth	0.3398	0.3242	-0.0559	1.0000		
resdWeiInt~p	0.0457	0.0101	-0.0829	-0.2402	1.0000	
resFF	-0.1887	-0.1182	0.1049	0.0141	-0.1390	1.0000

Figure C.71 – Correlation between residuals for the model with optimal lag (p=11).

Granger causality

```
. vargranger
```

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
casesgrowth	dWeiInterp	68.531	11	0.000
casesgrowth	CILgrowth	53.385	11	0.000
casesgrowth	CLgrowth_detren~d	53.374	11	0.000
casesgrowth	OLLgrowth	54.758	11	0.000
casesgrowth	FF	49.334	11	0.000
casesgrowth	ALL	184.22	55	0.000
dWeiInterp	casesgrowth	54.022	11	0.000
dWeiInterp	CILgrowth	98.834	11	0.000
dWeiInterp	CLgrowth_detren~d	49.244	11	0.000
dWeiInterp	OLLgrowth	37.404	11	0.000
dWeiInterp	FF	19.64	11	0.051
dWeiInterp	ALL	195.63	55	0.000
CILgrowth	casesgrowth	61.323	11	0.000
CILgrowth	dWeiInterp	80.314	11	0.000
CILgrowth	CLgrowth_detren~d	148.6	11	0.000
CILgrowth	OLLgrowth	114.58	11	0.000
CILgrowth	FF	74.076	11	0.000
CILgrowth	ALL	447.59	55	0.000
CLgrowth_detren~d	casesgrowth	57.737	11	0.000
CLgrowth_detren~d	dWeiInterp	20.805	11	0.035
CLgrowth_detren~d	CILgrowth	37.216	11	0.000
CLgrowth_detren~d	OLLgrowth	69.579	11	0.000
CLgrowth_detren~d	FF	41.861	11	0.000
CLgrowth_detren~d	ALL	303.07	55	0.000
OLLgrowth	casesgrowth	26.124	11	0.006
OLLgrowth	dWeiInterp	98.311	11	0.000
OLLgrowth	CILgrowth	44.867	11	0.000
OLLgrowth	CLgrowth_detren~d	84.395	11	0.000
OLLgrowth	FF	79.335	11	0.000
OLLgrowth	ALL	383.54	55	0.000
FF	casesgrowth	28.846	11	0.002
FF	dWeiInterp	93.758	11	0.000
FF	CILgrowth	47.908	11	0.000
FF	CLgrowth_detren~d	40.738	11	0.000
FF	OLLgrowth	47.96	11	0.000
FF	ALL	340.18	55	0.000

Figure C.72 – Granger causality between variables for the model with optimal lag (p=11).

Orthogonalized impulse response functions

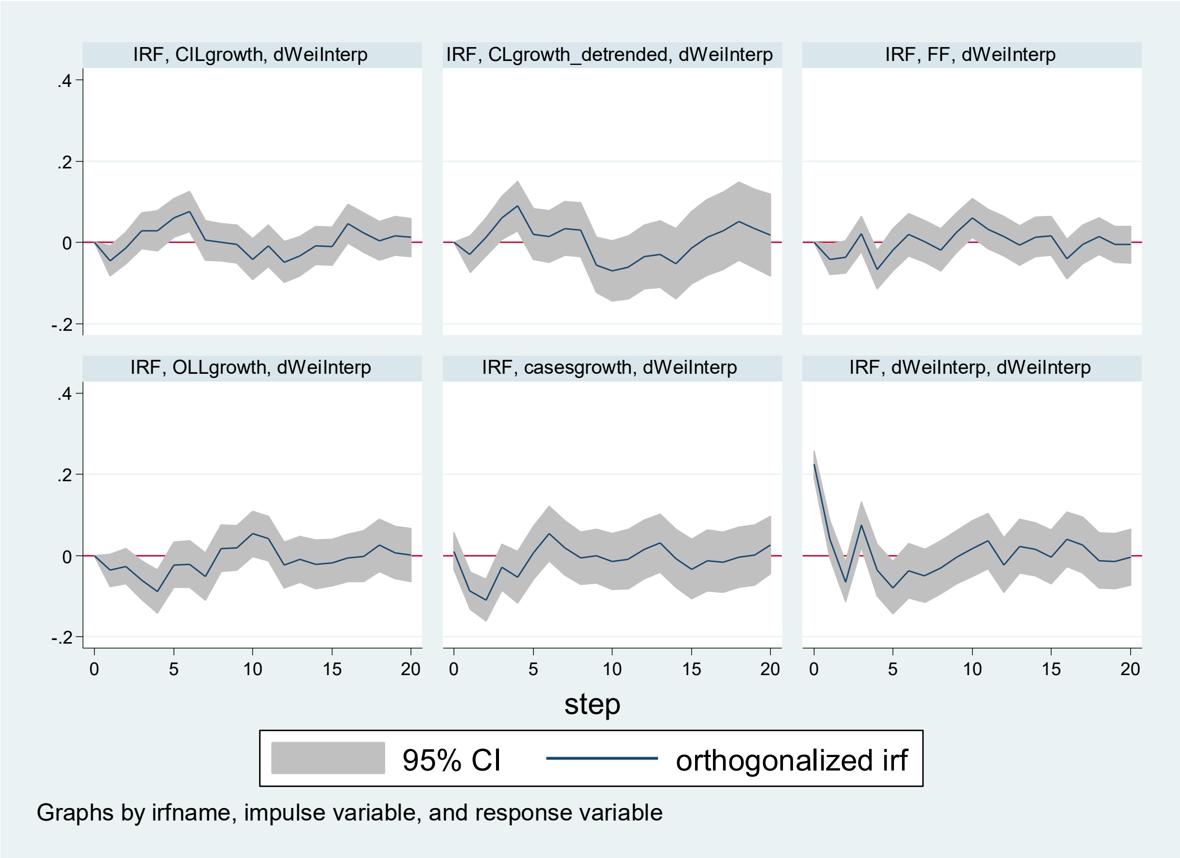


Figure C.73 – All OIRF for the model with optimal lag (p=11).

Cumulative orthogonalized impulse response functions

Again in Stata, we start by creating an IRF entry in a file called *IRF* to hold the results of the VAR(11) and run the IRF effect horizon out 20 weeks. Next, the order of the variables is listed again in the IRFs command.

```
. irf create IRF, set(IRF, replace) step (40) order(casesgrowth dWeiInterp CILgrowth CLgrowth_detrended OLLgrowth FF)
(file IRF.irf created)
(file IRF.irf now active)
```

The final step to attaining the output is to plot the orthogonal impulse response functions and table their values. In order to compute the COIRFs case, it is just necessary to run *coirf* instead of *irf* or *oirf*.

```
. irf graph coirf, set(IRF) irf(IRF) impulse (casesgrowth dWeiInterp CILgrowth CLgrowth_detrended OLLgrowth FF) response(dW
> eiInterp) yline(0)
(file IRF.irf now active)
```

This command will provide all COIRFs results in the same graphic, which can make interpretation of some values difficult regarding the different scales of effects caused. If the output containing the table with the values is desired, the same command is applied, replacing *graph* with *table*.

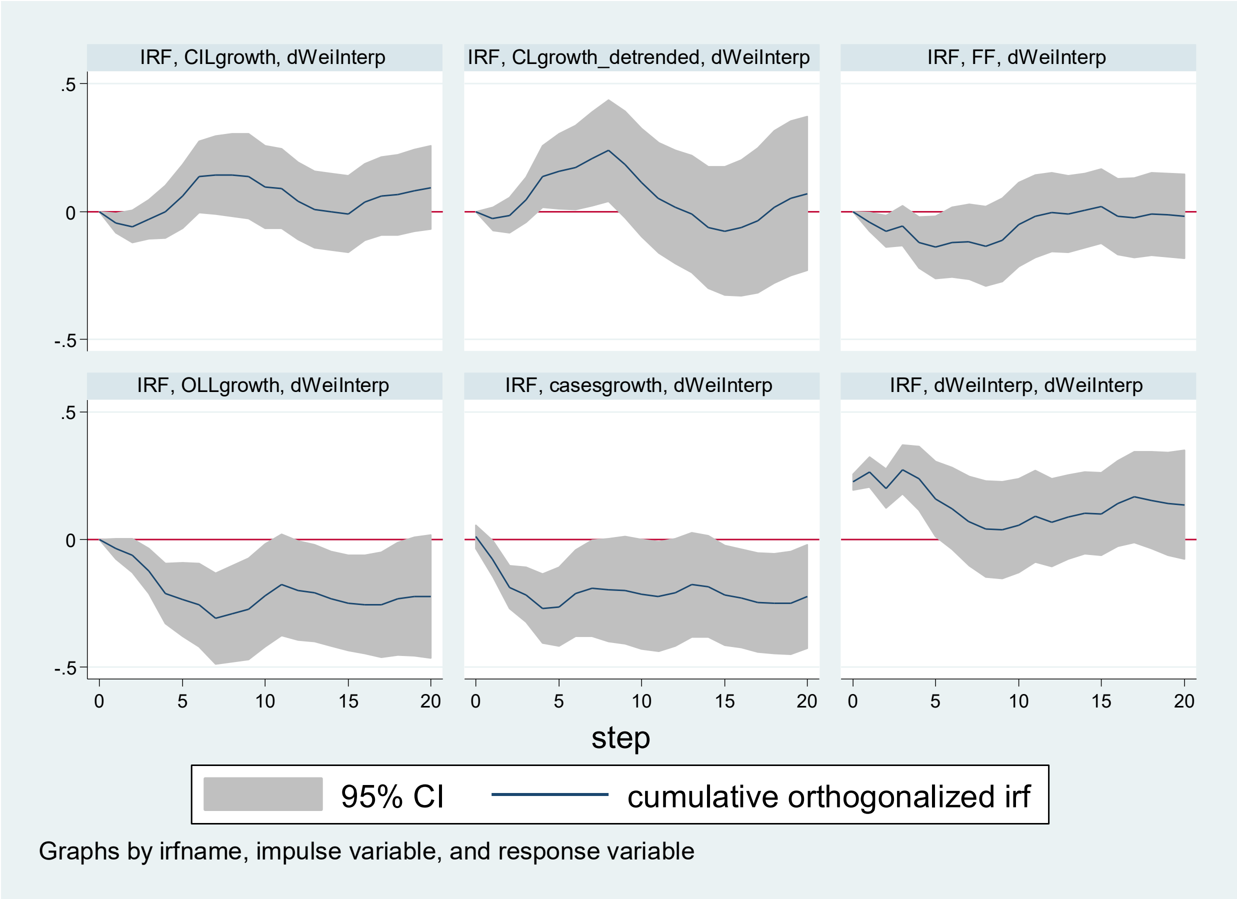


Figure C.74 – All COIRF for the model with optimal lag (p=11).

VAR model with new confirmed Covid-19 deaths growth rate

Stability condition

```
. varstable

  Eigenvalue stability condition
```

Eigenvalue	Modulus
.9179901 + .3365498*i*	.977738
.9179901 - .3365498*i*	.977738
-.1291341 + .9635175*i*	.972133
-.1291341 - .9635175*i*	.972133
.8436717 + .476695*i*	.96903
.8436717 - .476695*i*	.96903
-.5388468 + .782821*i*	.95035
-.5388468 - .782821*i*	.95035
.8017201 + .501735*i*	.945777
.8017201 - .501735*i*	.945777
.09919485 + .9340987*i*	.939351
.09919485 - .9340987*i*	.939351
-.9157684 + .2005362*i*	.937468
-.9157684 - .2005362*i*	.937468
-.3642565 + .8592681*i*	.933287
-.3642565 - .8592681*i*	.933287
-.3145739 + .8745275*i*	.929384
-.3145739 - .8745275*i*	.929384
.4744979 + .7986667*i*	.928987
.4744979 - .7986667*i*	.928987
.3488042 + .8569514*i*	.925219
.3488042 - .8569514*i*	.925219
.9094962 + .1197292*i*	.917343
.9094962 - .1197292*i*	.917343
-.8589319 + .3186973*i*	.916151
-.8589319 - .3186973*i*	.916151
.5875577 + .7009784*i*	.914656
.5875577 - .7009784*i*	.914656
-.7571517 + .5005064*i*	.907626
-.7571517 - .5005064*i*	.907626
-.9029877	.902988
.8599444 + .2713381*i*	.901737
.8599444 - .2713381*i*	.901737
.1793453 + .878198*i*	.896324
.1793453 - .878198*i*	.896324
-.8035301 + .3719705*i*	.885451
-.8035301 - .3719705*i*	.885451
-.6437222 + .6032692*i*	.88222
-.6437222 - .6032692*i*	.88222
-.5452432 + .6175107*i*	.823778
-.5452432 - .6175107*i*	.823778
.5743082 + .5803996*i*	.816513
.5743082 - .5803996*i*	.816513
.7083422 + .3931467*i*	.810131
.7083422 - .3931467*i*	.810131
-.1916476 + .7790228*i*	.80225
-.1916476 - .7790228*i*	.80225
.04714923 + .7770417*i*	.778471
.04714923 - .7770417*i*	.778471
.3400391 + .6987079*i*	.777058
.3400391 - .6987079*i*	.777058
-.7302611 + .1197074*i*	.740007
-.7302611 - .1197074*i*	.740007
-.4807348 + .4940955*i*	.689374
-.4807348 - .4940955*i*	.689374
.6417939	.641794
-.3955077 + .2293962*i*	.457219
-.3955077 - .2293962*i*	.457219
.4496309	.449631
.3386135	.338614

```
  All the eigenvalues lie inside the unit circle.
  VAR satisfies stability condition.
```

Figure C.75 – Stability test for the fourth VAR model

Optimal lag selection

Minimum information criteria

```
. varsoc deathsgrowth dWeiInterp CILgrowth CLgrowth_detrended OLLgrowth FF, exog (dummy vacgrowth) maxlag(10)
```

Selection-order criteria
Sample: 2020w20 - 2022w10   Number of obs   =   95

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	1524.72				6.7e-22	-31.7205	-31.5249	-31.2366
1	1634.92	220.39	36	0.000	1.4e-22*	-33.2825	-32.6959*	-31.8308*
2	1654.06	38.288	36	0.366	2.1e-22	-32.9277	-31.95	-30.5082
3	1682.94	57.755	36	0.012	2.5e-22	-32.7777	-31.409	-29.3905
4	1719.08	72.278	36	0.000	2.6e-22	-32.7806	-31.0209	-28.4256
5	1743.68	49.204	36	0.070	3.6e-22	-32.5407	-30.3899	-27.2179
6	1782.88	78.389	36	0.000	3.8e-22	-32.6079	-30.0661	-26.3173
7	1806.66	47.563	36	0.094	5.9e-22	-32.3507	-29.4178	-25.0923
8	1843.81	74.3	36	0.000	7.5e-22	-32.3749	-29.0509	-24.1487
9	1876.85	66.074	36	0.002	1.1e-21	-32.3125	-28.5975	-23.1186
10	1983.13	212.57*	36	0.000	4.3e-22	-33.7922*	-29.6861	-23.6305

Endogenous: deathsgrowth dWeiInterp CILgrowth CLgrowth_detrended OLLgrowth FF
Exogenous: dummy vacgrowth _cons

Figure C.76 – Fourth Var model optimal lag criteria selection

Wald lag-exclusion statistics test

```
. varwle
```

Equation: deathsgrowth

lag	chi2	df	Prob > chi2
1	12.61257	6	0.050
2	16.3111	6	0.012
3	26.58865	6	0.000
4	24.25627	6	0.000
5	15.0966	6	0.020
6	17.38707	6	0.008
7	19.99312	6	0.003
8	17.3495	6	0.008
9	36.13823	6	0.000
10	57.11982	6	0.000

Equation: dWeiInterp

lag	chi2	df	Prob > chi2
1	35.47564	6	0.000
2	30.24581	6	0.000
3	27.84061	6	0.000
4	25.17667	6	0.000
5	27.36505	6	0.000
6	32.98038	6	0.000
7	3.240393	6	0.778
8	12.96412	6	0.044
9	7.244089	6	0.299
10	6.886969	6	0.331

Equation: OLLgrowth

lag	chi2	df	Prob > chi2
1	25.34027	6	0.000
2	33.91344	6	0.000
3	8.336128	6	0.214
4	17.17327	6	0.009
5	22.26513	6	0.001
6	8.394097	6	0.211
7	17.70301	6	0.007
8	26.14055	6	0.000
9	19.19078	6	0.004
10	17.98058	6	0.006

Equation: CILgrowth

lag	chi2	df	Prob > chi2
1	11.12675	6	0.085
2	23.68086	6	0.001
3	51.14743	6	0.000
4	21.09313	6	0.002
5	79.49127	6	0.000
6	66.94128	6	0.000
7	56.42772	6	0.000
8	88.60381	6	0.000
9	30.05971	6	0.000
10	67.21582	6	0.000

Equation: FF

lag	chi2	df	Prob > chi2
1	73.44392	6	0.000
2	19.95689	6	0.003
3	25.51912	6	0.000
4	23.0898	6	0.001
5	14.54041	6	0.024
6	10.1906	6	0.117
7	8.131467	6	0.229
8	4.346272	6	0.630
9	56.44545	6	0.000
10	94.19643	6	0.000

Equation: CLgrowth_detrended

lag	chi2	df	Prob > chi2
1	23.36096	6	0.001
2	35.89818	6	0.000
3	4.323375	6	0.633
4	7.873095	6	0.248
5	29.09292	6	0.000
6	21.75087	6	0.001
7	12.63957	6	0.049
8	19.52841	6	0.003
9	7.859377	6	0.249
10	12.59232	6	0.050

Equation: All

lag	chi2	df	Prob > chi2
1	227.0273	36	0.000
2	194.9182	36	0.000
3	198.0472	36	0.000
4	113.7203	36	0.000
5	189.7499	36	0.000
6	168.681	36	0.000
7	164.0638	36	0.000
8	201.2827	36	0.000
9	253.5257	36	0.000
10	449.7418	36	0.000

Figure C.77 - Wald lag-exclusion statistics test for p=10.

Residual diagnostics

```
. varlmar, mlag(4)

  Lagrange-multiplier test

  lag      chi2      df    Prob > chi2
   1     163.6690    36      0.00000
   2      37.2661    36      0.41063
   3      38.7747    36      0.34563
   4      37.7392    36      0.38970

  H0: no autocorrelation at lag order
```

Figure C.78- Lagrange multiplier test for the serial correlation between residuals for a model with optimal lag, p=1.

```
. var deathsgrowth dWeiInterp CILgrowth CLgrowth_detrended OLLgrowth FF, exog (dummy vacgrowth) lags (1/10)
```

Vector autoregression

Sample:	2020w20 - 2022w10	Number of obs	= 95
Log likelihood =	1983.13	AIC	= -33.79221
FPE =	4.31e-22	HQIC	= -29.6861
Det(Sigma_ml) =	2.97e-26	SBIC	= -23.63047

Equation	Parms	RMSE	R-sq	chi2	P>chi2
deathsgrowth	63	.250424	0.6970	218.5646	0.0000
dWeiInterp	63	.461768	0.8109	407.3611	0.0000
CILgrowth	63	.003004	0.8581	574.3936	0.0000
CLgrowth_detre~d	63	.001218	0.7427	274.2015	0.0000
OLLgrowth	63	.003383	0.7094	231.8871	0.0000
FF	63	.004597	0.9521	1888.875	0.0000

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
deathsgrowth						
deathsgrowth						
L1.	-.2340557	.0895775	-2.61	0.009	-.4096243	-.0584871
L2.	.0506211	.0871812	0.58	0.561	-.120251	.2214932
L3.	.2138541	.09144	2.34	0.019	.034635	.3930733
L4.	.1193314	.094501	1.26	0.207	-.0658872	.3045499
L5.	-.0581677	.0902949	-0.64	0.519	-.2351425	.1188071
L6.	-.2099171	.0979895	-2.14	0.032	-.4019731	-.0178611
L7.	-.0971763	.0941003	-1.03	0.302	-.2816096	.087257
L8.	-.3001727	.0896337	-3.35	0.001	-.4758515	-.124494
L9.	-.0797468	.077577	-1.03	0.304	-.2317948	.0723013
L10.	-.2318176	.0584828	-3.96	0.000	-.3464418	-.1171933
dWeiInterp						
L1.	-.0699112	.0602696	-1.16	0.246	-.1880374	.048215
L2.	.0584117	.0584144	1.00	0.317	-.0560785	.1729018
L3.	-.0431888	.0611768	-0.71	0.480	-.1630931	.0767156
L4.	.1130396	.0678859	1.67	0.096	-.0200143	.2460934
L5.	-.0642228	.0685275	-0.94	0.349	-.1985343	.0700886
L6.	.0900183	.0661676	1.36	0.174	-.0396677	.2197043
L7.	-.0810858	.0661842	-1.23	0.221	-.2108044	.0486328
L8.	.0340881	.0604481	0.56	0.573	-.0843879	.1525642
L9.	-.1199344	.0569674	-2.11	0.035	-.2315885	-.0082804
L10.	-.0455645	.0546831	-0.83	0.405	-.1527413	.0616124
CILgrowth						
L1.	-4.359051	7.943834	-0.55	0.583	-19.92868	11.21058
L2.	-24.95014	7.86816	-3.17	0.002	-40.37145	-9.528827
L3.	-21.57847	7.733321	-2.79	0.005	-36.7355	-6.421435
L4.	28.74179	7.632427	3.77	0.000	13.7825	43.70107
L5.	-14.6835	7.892852	-1.86	0.063	-30.15321	.7862043
L6.	13.65935	6.618092	2.06	0.039	.6881318	26.63058
L7.	5.904631	7.72565	0.76	0.445	-9.237365	21.04663
L8.	-13.85464	7.333331	-1.89	0.059	-28.22771	.5184208
L9.	-19.6485	6.659775	-2.95	0.003	-32.70142	-6.59558
L10.	-12.58393	5.459096	-2.31	0.021	-23.28356	-1.884301
CLgrowth_detrended						
L1.	-13.71532	21.45239	-0.64	0.523	-55.76122	28.33058
L2.	-5.30221	20.74937	-0.26	0.798	-45.97023	35.36581
L3.	81.92225	21.63751	3.79	0.000	39.51351	124.331
L4.	-4.858656	26.62174	-0.18	0.855	-57.0363	47.31899
L5.	-8.695608	24.26703	-0.36	0.720	-56.25812	38.8669
L6.	-65.6452	25.42864	-2.58	0.010	-115.4844	-15.80598
L7.	-73.98261	21.72132	-3.41	0.001	-116.5556	-31.4096
L8.	-8.727038	17.25377	-0.51	0.613	-42.54381	25.08973
L9.	-.7130676	15.36452	-0.05	0.963	-30.82698	29.40085
L10.	-30.97646	15.21081	-2.04	0.042	-60.7891	-1.163827
OLLgrowth						
L1.	-.9995302	7.909719	-0.13	0.899	-16.50229	14.50323
L2.	-7.963003	8.189796	-0.97	0.331	-24.01471	8.088703
L3.	-18.5352	7.763743	-2.39	0.017	-33.75185	-3.31854
L4.	16.88206	7.758565	2.18	0.030	1.675553	32.08857
L5.	22.7705	7.779004	2.93	0.003	7.523934	38.01707
L6.	2.8715	7.881678	0.36	0.716	-12.5763	18.3193
L7.	7.615144	8.404136	0.91	0.365	-8.85666	24.08695
L8.	-12.04057	7.670938	-1.57	0.117	-27.07534	2.994188
L9.	-3.096728	7.987076	-0.39	0.698	-18.75111	12.55765
L10.	-6.290046	7.281003	-0.86	0.388	-20.56055	7.980457
FF						
L1.	-1.513107	4.090051	-0.37	0.711	-9.52946	6.503246
L2.	3.325728	4.893208	0.68	0.497	-6.264784	12.91624
L3.	-.8030244	5.137015	-0.16	0.876	-10.87139	9.26534
L4.	.4392783	5.188459	0.08	0.933	-9.729915	10.60847
L5.	3.870476	4.986314	0.78	0.438	-5.90252	13.64347
L6.	3.668505	5.115829	0.72	0.473	-6.358335	13.69534
L7.	-3.22989	5.223415	-0.62	0.536	-13.4676	7.007816
L8.	-2.439772	4.089627	-0.60	0.551	-10.45529	5.575749
L9.	-8.859961	2.155493	-4.11	0.000	-13.08465	-4.635274
L10.	10.21463	1.485533	6.88	0.000	7.303036	13.12622
dummy	.149091	.0716062	2.08	0.037	.0087455	.2894364
vacgrowth	.0162015	.0388176	0.42	0.676	-.0598795	.0922826
_cons	-.4734074	.4177838	-1.13	0.257	-1.292249	.3454338

dWeiInterp						
deathsgrowth						
L1.	-.2351492	.1651757	-1.42	0.155	-.5588876	.0885892
L2.	-.4840437	.1607571	-3.01	0.003	-.799122	-.1689655
L3.	-.0918356	.1686101	-0.54	0.586	-.4223053	.2386341
L4.	-.0093063	.1742544	-0.05	0.957	-.3508386	.332226
L5.	.6092949	.1664986	3.66	0.000	.2829636	.9356261
L6.	-.0851783	.180687	-0.47	0.637	-.4393184	.2689618
L7.	-.2283407	.1735156	-1.32	0.188	-.568425	.1117436
L8.	-.3066779	.1652793	-1.86	0.064	-.6306193	.0172635
L9.	-.179937	.1430474	-1.26	0.208	-.4603047	.1004308
L10.	-.1641165	.107839	-1.52	0.128	-.3754771	.047244
dWeiInterp						
L1.	.2933838	.1111336	2.64	0.008	.0755659	.5112018
L2.	-.3786341	.1077128	-3.52	0.000	-.5897473	-.167521
L3.	.3925543	.1128065	3.48	0.001	.1714577	.6136508
L4.	-.4044498	.1251776	-3.23	0.001	-.6497934	-.1591062
L5.	.1735432	.1263608	1.37	0.170	-.0741194	.4212058
L6.	-.1081191	.1220091	-0.89	0.376	-.3472526	.1310144
L7.	.1453299	.1220398	1.19	0.234	-.0938636	.3845235
L8.	-.011662	.1114627	-0.10	0.917	-.230125	.2068009
L9.	-.105543	.1050446	-1.00	0.315	-.3114266	.1003406
L10.	-.1141488	.1008324	-1.13	0.258	-.3117766	.0834791
CILgrowth						
L1.	-13.29817	14.64797	-0.91	0.364	-42.00767	15.41132
L2.	19.47627	14.50843	1.34	0.179	-8.959731	47.91227
L3.	8.435238	14.2598	0.59	0.554	-19.51345	36.38393
L4.	8.808163	14.07375	0.63	0.531	-18.77589	36.39221
L5.	3.822016	14.55396	0.26	0.793	-24.70322	32.34726
L6.	58.02026	12.20338	4.75	0.000	34.10208	81.93844
L7.	-2.021488	14.24565	-0.14	0.887	-29.94245	25.89947
L8.	28.59253	13.52224	2.11	0.034	2.089431	55.09562
L9.	.7495169	12.28024	0.06	0.951	-23.31931	24.81834
L10.	-6.10303	10.06626	-0.61	0.544	-25.83253	13.62647
CLgrowth_detrended						
L1.	-3.547633	39.55695	-0.09	0.929	-81.07784	73.98257
L2.	-26.22924	38.26063	-0.69	0.493	-101.2187	48.76023
L3.	76.28124	39.89831	1.91	0.056	-1.918009	154.4805
L4.	147.5524	49.08894	3.01	0.003	51.33983	243.7649
L5.	114.2504	44.747	2.55	0.011	26.54784	201.9529
L6.	-3.115923	46.88894	-0.07	0.947	-95.01655	88.7847
L7.	-30.28611	40.05286	-0.76	0.450	-108.7883	48.21605
L8.	15.25544	31.81495	0.48	0.632	-47.10072	77.6116
L9.	10.18739	28.33129	0.36	0.719	-45.34092	65.7157
L10.	32.31145	28.04785	1.15	0.249	-22.66132	87.28422
OLLgrowth						
L1.	-44.19261	14.58506	-3.03	0.002	-72.7788	-15.60641
L2.	-32.74033	15.10151	-2.17	0.030	-62.33875	-3.141919
L3.	-34.26011	14.31589	-2.39	0.017	-62.31874	-6.201479
L4.	-35.04264	14.30634	-2.45	0.014	-63.08256	-7.002723
L5.	-4.073359	14.34403	-0.28	0.776	-32.18715	24.04043
L6.	22.27766	14.53336	1.53	0.125	-6.207191	50.76252
L7.	4.818451	15.49674	0.31	0.756	-25.5546	35.1915
L8.	26.48147	14.14477	1.87	0.061	-1.241761	54.2047
L9.	-27.51128	14.72771	-1.87	0.062	-56.37705	1.354494
L10.	2.750121	13.42575	0.20	0.838	-23.56386	29.0641
FF						
L1.	-3.723631	7.541817	-0.49	0.621	-18.50532	11.05806
L2.	17.77613	9.022792	1.97	0.049	.091783	35.46048
L3.	-3.878015	9.472358	-0.41	0.682	-22.44349	14.68746
L4.	-17.2022	9.567218	-1.80	0.072	-35.9536	1.5492
L5.	23.81276	9.194475	2.59	0.010	5.791921	41.8336
L6.	-8.203851	9.433292	-0.87	0.384	-26.69276	10.28506
L7.	4.302741	9.631675	0.45	0.655	-14.57499	23.18048
L8.	1.631217	7.541035	0.22	0.829	-13.14894	16.41137
L9.	-1.585164	3.974603	-0.40	0.690	-9.375244	6.204915
L10.	3.263995	2.739236	1.19	0.233	-2.104809	8.632798
dummy	-.0908556	.1320376	-0.69	0.491	-.3496445	.1679334
vacgrowth	.2439553	.0715773	3.41	0.001	.1036663	.3842444
_cons	-.9323407	.7703691	-1.21	0.226	-2.442236	.577555

CILgrowth						
deathsgrowth						
L1.	-.0011764	.0010744	-1.09	0.274	-.0032822	.0009293
L2.	-.0012733	.0010456	-1.22	0.223	-.0033227	.0007761
L3.	-.0028608	.0010967	-2.61	0.009	-.0050103	-.0007112
L4.	-.0002067	.0011334	-0.18	0.855	-.0024281	.0020148
L5.	-.0019928	.001083	-1.84	0.066	-.0041154	.0001298
L6.	-.0021348	.0011753	-1.82	0.069	-.0044383	.0001687
L7.	-.0038403	.0011286	-3.40	0.001	-.0060524	-.0016283
L8.	-.0054936	.001075	-5.11	0.000	-.0076006	-.0033865
L9.	-.0015665	.0009304	-1.68	0.092	-.0033901	.0002572
L10.	-.0009969	.0007014	-1.42	0.155	-.0023717	.0003779
dWeiInterp						
L1.	.000048	.0007229	0.07	0.947	-.0013688	.0014648
L2.	.0018225	.0007006	2.60	0.009	.0004494	.0031957
L3.	.0011491	.0007337	1.57	0.117	-.000289	.0025872
L4.	.0005652	.0008142	0.69	0.488	-.0010306	.002161
L5.	-.0013885	.0008219	-1.69	0.091	-.0029994	.0002224
L6.	-.0019762	.0007936	-2.49	0.013	-.0035317	-.0004208
L7.	-.0004145	.0007938	-0.52	0.602	-.0019703	.0011413
L8.	-.0014827	.000725	-2.05	0.041	-.0029037	-.0000617
L9.	.0004145	.0006833	0.61	0.544	-.0009247	.0017536
L10.	.00084	.0006559	1.28	0.200	-.0004454	.0021255
CILgrowth						
L1.	.084075	.0952767	0.88	0.378	-.102664	.270814
L2.	-.0306353	.0943691	-0.32	0.745	-.2155954	.1543247
L3.	-.2867973	.0927519	-3.09	0.002	-.4685877	-.1050069
L4.	-.1180391	.0915418	-1.29	0.197	-.2974577	.0613795
L5.	-.115929	.0946653	-1.22	0.221	-.3014696	.0696115
L6.	-.4864154	.0793761	-6.13	0.000	-.6419897	-.3308412
L7.	-.2418124	.0926599	-2.61	0.009	-.4234225	-.0602024
L8.	-.3943826	.0879545	-4.48	0.000	-.5667702	-.221995
L9.	-.2986969	.079876	-3.74	0.000	-.455251	-.1421428
L10.	-.364332	.0654753	-5.56	0.000	-.4926612	-.2360028
CLgrowth_detrended						
L1.	.0032851	.2572956	0.01	0.990	-.5010049	.5075752
L2.	-.5083349	.2488637	-2.04	0.041	-.9960989	-.0205709
L3.	-1.192826	.2595159	-4.60	0.000	-1.701468	-.6841841
L4.	-1.321771	.3192958	-4.14	0.000	-1.947579	-.6959626
L5.	-1.954759	.2910539	-6.72	0.000	-2.525214	-1.384304
L6.	-1.488019	.304986	-4.88	0.000	-2.085781	-.8902577
L7.	-1.947197	.2605211	-7.47	0.000	-2.457809	-1.436585
L8.	-1.478169	.2069382	-7.14	0.000	-1.883761	-1.072578
L9.	.2132878	.184279	1.16	0.247	-.1478924	.574468
L10.	-.2004404	.1824354	-1.10	0.272	-.5580071	.1571264
OLLgrowth						
L1.	.2315005	.0948676	2.44	0.015	.0455635	.4174375
L2.	.3496128	.0982268	3.56	0.000	.1570919	.5421337
L3.	.0798606	.0931168	0.86	0.391	-.1026449	.2623661
L4.	.067305	.0930547	0.72	0.470	-.1150788	.2496888
L5.	-.0161196	.0932998	-0.17	0.863	-.1989838	.1667447
L6.	-.2859696	.0945313	-3.03	0.002	-.4712475	-.1006918
L7.	.0240025	.1007975	0.24	0.812	-.173557	.221562
L8.	-.5377737	.0920037	-5.85	0.000	-.7180976	-.3574498
L9.	-.3069279	.0957954	-3.20	0.001	-.4946833	-.1191724
L10.	.1022909	.0873269	1.17	0.241	-.0688667	.2734484
FF						
L1.	.0201898	.0490552	0.41	0.681	-.0759567	.1163363
L2.	-.0867836	.0586882	-1.48	0.139	-.2018103	.0282431
L3.	.0300298	.0616123	0.49	0.626	-.0907282	.1507877
L4.	.0617641	.0622293	0.99	0.321	-.0602032	.1837313
L5.	-.2519515	.0598048	-4.21	0.000	-.3691669	-.1347362
L6.	.103687	.0613582	1.69	0.091	-.0165729	.2239469
L7.	.0822881	.0626486	1.31	0.189	-.0405008	.2050771
L8.	-.0811648	.0490502	-1.65	0.098	-.1773014	.0149717
L9.	-.0162711	.0258525	-0.63	0.529	-.0669411	.034399
L10.	.098105	.0178172	5.51	0.000	.063184	.133026
dummy	.0040313	.0008588	4.69	0.000	.002348	.0057145
vacgrowth	.0013052	.0004656	2.80	0.005	.0003927	.0022177
_cons	-.0026126	.0050108	-0.52	0.602	-.0124336	.0072084

CLgrowth_detrended						
deathsgrowth						
L1.	-.0008718	.0004357	-2.00	0.045	-.0017259	-.0000178
L2.	-.0012447	.0004241	-2.93	0.003	-.0020759	-.0004135
L3.	.0001705	.0004448	0.38	0.702	-.0007013	.0010423
L4.	-.0003305	.0004597	-0.72	0.472	-.0012315	.0005705
L5.	-.0008051	.0004392	-1.83	0.067	-.001666	.0000557
L6.	-.0003886	.0004767	-0.82	0.415	-.0013229	.0005456
L7.	-.0003677	.0004577	-0.80	0.422	-.0012649	.0005294
L8.	-.000502	.000436	-1.15	0.250	-.0013566	.0003526
L9.	-.0001008	.0003774	-0.27	0.789	-.0008405	.0006388
L10.	-.0005143	.0002845	-1.81	0.071	-.0010719	.0000433
dWeiInterp						
L1.	-.0000472	.0002932	-0.16	0.872	-.0006218	.0005274
L2.	-.0000182	.0002842	-0.06	0.949	-.0005752	.0005387
L3.	-.0000774	.0002976	-0.26	0.795	-.0006607	.0005058
L4.	-4.06e-06	.0003302	-0.01	0.990	-.0006513	.0006432
L5.	.0003289	.0003333	0.99	0.324	-.0003245	.0009823
L6.	-.0006355	.0003219	-1.97	0.048	-.0012663	-4.64e-06
L7.	.0004653	.0003219	1.45	0.148	-.0001657	.0010963
L8.	-.0006152	.000294	-2.09	0.036	-.0011915	-.0000389
L9.	.0001557	.0002771	0.56	0.574	-.0003874	.0006988
L10.	-.0001987	.000266	-0.75	0.455	-.00072	.0003227
CILgrowth						
L1.	-.1065272	.0386424	-2.76	0.006	-.1822649	-.0307895
L2.	-.063941	.0382743	-1.67	0.095	-.1389572	.0110752
L3.	-.0084373	.0376184	-0.22	0.823	-.0821679	.0652934
L4.	-.0213856	.0371276	-0.58	0.565	-.0941543	.0513831
L5.	-.1341358	.0383944	-3.49	0.000	-.2093874	-.0588842
L6.	-.0482389	.0321934	-1.50	0.134	-.1113368	.014859
L7.	.002939	.0375811	0.08	0.938	-.0707185	.0765965
L8.	-.0727178	.0356726	-2.04	0.042	-.1426349	-.0028007
L9.	-.053595	.0323962	-1.65	0.098	-.1170903	.0099003
L10.	.0023821	.0265555	0.09	0.929	-.0496658	.0544299
CLgrowth_detrended						
L1.	-.2433381	.1043541	-2.33	0.020	-.4478683	-.0388078
L2.	.1891422	.1009343	1.87	0.061	-.0086854	.3869697
L3.	-.0366177	.1052546	-0.35	0.728	-.2429129	.1696775
L4.	-.1973167	.1295002	-1.52	0.128	-.4511323	.056499
L5.	-.3699639	.1180458	-3.13	0.002	-.6013294	-.1385984
L6.	-.0912127	.1236964	-0.74	0.461	-.3336531	.1512278
L7.	-.1700579	.1056623	-1.61	0.108	-.3771522	.0370365
L8.	-.1297084	.0839301	-1.55	0.122	-.2942085	.0347916
L9.	.0166844	.07474	0.22	0.823	-.1298033	.1631721
L10.	.1408506	.0739922	1.90	0.057	-.0041715	.2858727
OLLgrowth						
L1.	.0540183	.0384764	1.40	0.160	-.0213941	.1294308
L2.	.0362714	.0398389	0.91	0.363	-.0418113	.1143542
L3.	-.0697055	.0377663	-1.85	0.065	-.1437262	.0043151
L4.	-.0714809	.0377412	-1.89	0.058	-.1454522	.0024904
L5.	.0250401	.0378406	0.66	0.508	-.0491261	.0992063
L6.	.1283392	.03834	3.35	0.001	.0531941	.2034843
L7.	-.0785403	.0408815	-1.92	0.055	-.1586666	.001586
L8.	-.1370798	.0373149	-3.67	0.000	-.2102157	-.063944
L9.	-.0904094	.0388527	-2.33	0.020	-.1665594	-.0142594
L10.	.0391358	.0354181	1.10	0.269	-.0302824	.108554
FF						
L1.	.0035282	.0198959	0.18	0.859	-.0354669	.0425234
L2.	-.0890006	.0238028	-3.74	0.000	-.1356531	-.042348
L3.	.0106981	.0249888	0.43	0.669	-.038279	.0596752
L4.	.029633	.025239	1.17	0.240	-.0198346	.0791005
L5.	-.0288273	.0242557	-1.19	0.235	-.0763676	.018713
L6.	.043285	.0248857	1.74	0.082	-.0054901	.0920601
L7.	-.0015522	.0254091	-0.06	0.951	-.051353	.0482486
L8.	-.0349039	.0198938	-1.75	0.079	-.073895	.0040872
L9.	.0039579	.0104853	0.38	0.706	-.0165929	.0245087
L10.	.0143508	.0072263	1.99	0.047	.0001875	.0285141
dummy	.0001851	.0003483	0.53	0.595	-.0004976	.0008679
vacgrowth	.0001695	.0001888	0.90	0.369	-.0002006	.0005396
_cons	.0037513	.0020323	1.85	0.065	-.0002319	.0077345

OLLgrowth						
deathsgrowth						
L1.	.0000739	.0012101	0.06	0.951	-.0022978	.0024457
L2.	-.0018816	.0011777	-1.60	0.110	-.00419	.0004267
L3.	-.0005501	.0012353	-0.45	0.656	-.0029712	.001871
L4.	.0014766	.0012766	1.16	0.247	-.0010256	.0039787
L5.	-.0013183	.0012198	-1.08	0.280	-.0037091	.0010724
L6.	-.0007492	.0013237	-0.57	0.571	-.0033437	.0018453
L7.	-.0003959	.0012712	-0.31	0.755	-.0028875	.0020956
L8.	-.0022174	.0012109	-1.83	0.067	-.0045906	.0001559
L9.	.0003815	.001048	0.36	0.716	-.0016725	.0024355
L10.	.0008053	.00079	1.02	0.308	-.0007431	.0023538
dWeiInterp						
L1.	-.0004982	.0008142	-0.61	0.541	-.0020939	.0010976
L2.	.0000682	.0007891	0.09	0.931	-.0014784	.0016149
L3.	.0013536	.0008264	1.64	0.101	-.0002662	.0029734
L4.	.0017784	.0009171	1.94	0.052	-.0000191	.0035758
L5.	.0006945	.0009257	0.75	0.453	-.0011199	.0025089
L6.	-.0005671	.0008939	-0.63	0.526	-.002319	.0011848
L7.	-.0008904	.0008941	-1.00	0.319	-.0026428	.000862
L8.	-.0016429	.0008166	-2.01	0.044	-.0032434	-.0000424
L9.	-.0005334	.0007696	-0.69	0.488	-.0020417	.000975
L10.	.0020508	.0007387	2.78	0.006	.0006029	.0034987
CILgrowth						
L1.	.0209161	.1073138	0.19	0.845	-.189415	.2312473
L2.	-.1361922	.1062915	-1.28	0.200	-.3445197	.0721353
L3.	.0590985	.1044699	0.57	0.572	-.1456588	.2638559
L4.	.0902181	.103107	0.87	0.382	-.1118678	.292304
L5.	-.0761306	.1066251	-0.71	0.475	-.2851119	.1328506
L6.	-.1918607	.0894042	-2.15	0.032	-.3670898	-.0166317
L7.	-.0606945	.1043663	-0.58	0.561	-.2652487	.1438597
L8.	-.0278255	.0990664	-0.28	0.779	-.2219922	.1663412
L9.	-.3684473	.0899673	-4.10	0.000	-.5447801	-.1921146
L10.	-.0288581	.0737473	-0.39	0.696	-.1734001	.1156839
CLgrowth_detrended						
L1.	-.6289554	.2898017	-2.17	0.030	-1.196956	-.0609545
L2.	.7164749	.2803046	2.56	0.011	.1670881	1.265862
L3.	.5231967	.2923025	1.79	0.073	-.0497057	1.096099
L4.	-.5402469	.3596348	-1.50	0.133	-1.245118	.1646244
L5.	-.8292243	.3278249	-2.53	0.011	-1.471749	-.1866992
L6.	-.4550341	.3435172	-1.32	0.185	-1.128315	.2182472
L7.	-.4510208	.2934348	-1.54	0.124	-1.026142	.1241007
L8.	-.4742515	.2330823	-2.03	0.042	-.9310844	-.0174185
L9.	-.0004763	.2075604	-0.00	0.998	-.4072871	.4063346
L10.	-.0398504	.2054838	-0.19	0.846	-.4425912	.3628905
OLLgrowth						
L1.	.0847068	.1068529	0.79	0.428	-.124721	.2941347
L2.	.2692611	.1106365	2.43	0.015	.0524176	.4861047
L3.	.1101823	.1048809	1.05	0.293	-.0953805	.3157451
L4.	.1044429	.104811	1.00	0.319	-.1009828	.3098686
L5.	.0305473	.1050871	0.29	0.771	-.1754195	.2365142
L6.	.1701805	.1064741	1.60	0.110	-.0385049	.3788659
L7.	.1472332	.113532	1.30	0.195	-.0752855	.3697519
L8.	-.3867295	.1036272	-3.73	0.000	-.5898351	-.1836239
L9.	-.2113734	.1078979	-1.96	0.050	-.4228495	.0001027
L10.	.0474441	.0983595	0.48	0.630	-.1453371	.2402253
FF						
L1.	.2473725	.0552528	4.48	0.000	.1390791	.3556659
L2.	-.2773656	.0661027	-4.20	0.000	-.4069245	-.1478068
L3.	-.0278698	.0693963	-0.40	0.688	-.163884	.1081443
L4.	.2089482	.0700912	2.98	0.003	.0715719	.3463245
L5.	-.2163845	.0673604	-3.21	0.001	-.3484085	-.0843604
L6.	-.0115962	.0691101	-0.17	0.867	-.1470494	.123857
L7.	.2593825	.0705635	3.68	0.000	.1210807	.3976843
L8.	-.1757777	.055247	-3.18	0.001	-.2840599	-.0674955
L9.	-.0040292	.0291187	-0.14	0.890	-.0611007	.0530424
L10.	.0423076	.0200682	2.11	0.035	.0029747	.0816405
dummy	.0028797	.0009673	2.98	0.003	.0009837	.0047756
vacgrowth	.0002284	.0005244	0.44	0.663	-.0007994	.0012562
_cons	-.0052253	.0056439	-0.93	0.355	-.0162871	.0058365

FF						
deathsgrowth						
L1.	.0000924	.0016444	0.06	0.955	-.0031305	.0033154
L2.	-.0051007	.0016004	-3.19	0.001	-.0082374	-.001964
L3.	.0005625	.0016786	0.34	0.738	-.0027274	.0038525
L4.	.001245	.0017348	0.72	0.473	-.0021551	.004645
L5.	-.0023879	.0016575	-1.44	0.150	-.0056366	.0008608
L6.	-.0006873	.0017988	-0.38	0.702	-.0042129	.0028382
L7.	.0007479	.0017274	0.43	0.665	-.0026378	.0041336
L8.	-.0005296	.0016454	-0.32	0.748	-.0037546	.0026953
L9.	-.0003263	.0014241	-0.23	0.819	-.0031174	.0024649
L10.	-.0078515	.0010736	-7.31	0.000	-.0099556	-.0057473
dWeiInterp						
L1.	-.0002544	.0011064	-0.23	0.818	-.0024228	.0019141
L2.	.0013431	.0010723	1.25	0.210	-.0007586	.0034448
L3.	-.0041696	.001123	-3.71	0.000	-.0063707	-.0019685
L4.	.0031502	.0012462	2.53	0.011	.0007078	.0055927
L5.	-.0031952	.001258	-2.54	0.011	-.0056608	-.0007297
L6.	-.000469	.0012146	-0.39	0.699	-.0028496	.0019117
L7.	-.0012459	.0012149	-1.03	0.305	-.0036271	.0011354
L8.	-.0016562	.0011096	-1.49	0.136	-.0038311	.0005186
L9.	-.0035284	.0010458	-3.37	0.001	-.005578	-.0014787
L10.	-.0029418	.0010038	-2.93	0.003	-.0049092	-.0009743
CILgrowth						
L1.	-.4798209	.1458254	-3.29	0.001	-.7656335	-.1940083
L2.	.1327112	.1444363	0.92	0.358	-.1503787	.4158011
L3.	-.2835935	.141961	-2.00	0.046	-.5618321	-.005355
L4.	-.0416231	.1401089	-0.30	0.766	-.3162316	.2329853
L5.	-.3113021	.1448895	-2.15	0.032	-.5952804	-.0273238
L6.	.2026487	.1214887	1.67	0.095	-.0354648	.4407622
L7.	-.2051556	.1418202	-1.45	0.148	-.4831181	.0728069
L8.	-.179163	.1346184	-1.33	0.183	-.4430102	.0846842
L9.	-.0941929	.1222539	-0.77	0.441	-.3338061	.1454203
L10.	-.2586256	.1002129	-2.58	0.010	-.4550394	-.0622119
CLgrowth_detrended						
L1.	-.2300934	.3938027	-0.58	0.559	-1.001933	.5417457
L2.	-.6222068	.3808974	-1.63	0.102	-1.368752	.1243383
L3.	.4520358	.397201	1.14	0.255	-.3264639	1.230535
L4.	-.0713787	.4886968	-0.15	0.884	-1.029207	.8864494
L5.	-.1310406	.4454713	-0.29	0.769	-1.004148	.7420671
L6.	.187579	.466795	0.40	0.688	-.7273225	1.10248
L7.	-.5791167	.3987396	-1.45	0.146	-1.360632	.2023985
L8.	-.0010936	.3167285	-0.00	0.997	-.62187	.6196828
L9.	.1863662	.2820475	0.66	0.509	-.3664367	.7391691
L10.	.5896847	.2792257	2.11	0.035	.0424123	1.136957
OLLgrowth						
L1.	-.0649645	.1451992	-0.45	0.655	-.3495496	.2196206
L2.	.3052465	.1503406	2.03	0.042	.0105844	.5999086
L3.	-.1914172	.1425195	-1.34	0.179	-.4707502	.0879159
L4.	-.2817473	.1424244	-1.98	0.048	-.5608941	-.0026006
L5.	.1695973	.1427996	1.19	0.235	-.1102848	.4494794
L6.	-.0018557	.1446844	-0.01	0.990	-.2854319	.2817206
L7.	-.1016396	.1542752	-0.66	0.510	-.4040135	.2007342
L8.	-.168123	.1408159	-1.19	0.233	-.444117	.1078711
L9.	-.2292007	.1466192	-1.56	0.118	-.5165691	.0581677
L10.	.0682021	.1336578	0.51	0.610	-.1937624	.3301666
FF						
L1.	.5877814	.0750813	7.83	0.000	.4406247	.7349381
L2.	-.1659036	.0898249	-1.85	0.065	-.3419572	.01015
L3.	-.25785	.0943005	-2.73	0.006	-.4426756	-.0730244
L4.	.2591277	.0952448	2.72	0.007	.0724512	.4458042
L5.	-.0268355	.0915341	-0.29	0.769	-.206239	.152568
L6.	-.268324	.0939116	-2.86	0.004	-.4523873	-.0842607
L7.	.2074056	.0958865	2.16	0.031	.0194714	.3953398
L8.	-.0264515	.0750735	-0.35	0.725	-.1735929	.1206899
L9.	-.2460426	.0395685	-6.22	0.000	-.3235955	-.1684898
L10.	.153079	.02727	5.61	0.000	.0996307	.2065272
dummy	-.0003944	.0013145	-0.30	0.764	-.0029707	.002182
vacgrowth	-.0023859	.0007126	-3.35	0.001	-.0037825	-.0009893
_cons	.0672381	.0076693	8.77	0.000	.0522066	.0822696

```
. varlmar, mlag(10)

  Lagrange-multiplier test
```

lag	chi2	df	Prob > chi2
1	54.4130	36	0.02513
2	46.3041	36	0.11671
3	32.5500	36	0.63346
4	41.5786	36	0.24073
5	44.9467	36	0.14571
6	33.9704	36	0.56545
7	30.4367	36	0.73010
8	27.9256	36	0.82984
9	32.7067	36	0.62603
10	33.1341	36	0.60563

```
  H0: no autocorrelation at lag order
```

Figure C.79 - Lagrange multiplier test for the serial correlation between residuals for a model with optimal lag, p=10.

```
. summarize resdeathsgrowth resCILgrowth resCLgrowth_detrended resOLLgrowth resdWeiInterp resFF
```

Variable	Obs	Mean	Std. Dev.	Min	Max
resdeathsg~h	95	-4.17e-11	.1461125	-.3214279	.6567341
resCILgrowth	95	-4.05e-12	.0017524	-.0046808	.0042846
resCLgrowt~d	95	-3.58e-13	.0007108	-.0016479	.0017383
resOLLgrowth	95	4.48e-12	.0019738	-.0053764	.0049652
resdWeiInt~p	95	5.46e-10	.2694229	-.7693755	.7139583
resFF	95	6.87e-12	.0026822	-.0132141	.0059111

Figure C.80– Residuals of the variables for the model with optimal lag (p=10).

```
. corr resdeathsgrowth resCILgrowth resCLgrowth_detrended resOLLgrowth resdWeiInterp resFF, cov
(obs=95)
```

	resdea~h	resCIL~h	resCLg~d	resOLL~h	resdWe~p	resFF
resdeathsg~h	.021349					
resCILgrowth	8.0e-07	3.1e-06				
resCLgrowt~d	-.000038	8.2e-08	5.1e-07			
resOLLgrowth	-.000019	1.2e-06	5.6e-08	3.9e-06		
resdWeiInt~p	.004445	-.000133	4.6e-06	-.000169	.072589	
resFF	-.000135	-9.3e-07	3.4e-08	1.9e-07	-.000207	7.2e-06

Figure C.81 – Covariance between residuals for the model with optimal lag (p=10).

```
. corr resdeathsgrowth resCILgrowth resCLgrowth_detrended resOLLgrowth resdWeiInterp resFF
(obs=95)
```

	resdea~h	resCIL~h	resCLg~d	resOLL~h	resdWe~p	resFF
resdeathsg~h	1.0000					
resCILgrowth	0.0031	1.0000				
resCLgrowt~d	-0.3616	0.0661	1.0000			
resOLLgrowth	-0.0674	0.3537	0.0398	1.0000		
resdWeiInt~p	0.1129	-0.2815	0.0239	-0.3186	1.0000	
resFF	-0.3436	-0.1986	0.0181	0.0368	-0.2867	1.0000

Figure C.82 – Correlation between residuals for the model with optimal lag (p=10).

Granger causality

```
. vargranger
```

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
deathsgrowth	dWeiInterp	11.306	10	0.334
deathsgrowth	CILgrowth	65.241	10	0.000
deathsgrowth	CLgrowth_detren~d	37.254	10	0.000
deathsgrowth	OLLgrowth	25.956	10	0.004
deathsgrowth	FF	72.953	10	0.000
deathsgrowth	ALL	189.87	50	0.000
dWeiInterp	deathsgrowth	27.931	10	0.002
dWeiInterp	CILgrowth	37.955	10	0.000
dWeiInterp	CLgrowth_detren~d	18.517	10	0.047
dWeiInterp	OLLgrowth	35.596	10	0.000
dWeiInterp	FF	17.908	10	0.057
dWeiInterp	ALL	110.73	50	0.000
CILgrowth	deathsgrowth	52.272	10	0.000
CILgrowth	dWeiInterp	38.64	10	0.000
CILgrowth	CLgrowth_detren~d	145.25	10	0.000
CILgrowth	OLLgrowth	63.96	10	0.000
CILgrowth	FF	48.907	10	0.000
CILgrowth	ALL	274.27	50	0.000
CLgrowth_detren~d	deathsgrowth	22.859	10	0.011
CLgrowth_detren~d	dWeiInterp	9.9611	10	0.444
CLgrowth_detren~d	CILgrowth	30.01	10	0.001
CLgrowth_detren~d	OLLgrowth	48.446	10	0.000
CLgrowth_detren~d	FF	32.153	10	0.000
CLgrowth_detren~d	ALL	206.52	50	0.000
OLLgrowth	deathsgrowth	12.366	10	0.261
OLLgrowth	dWeiInterp	26.442	10	0.003
OLLgrowth	CILgrowth	24.702	10	0.006
OLLgrowth	CLgrowth_detren~d	24.517	10	0.006
OLLgrowth	FF	36.494	10	0.000
OLLgrowth	ALL	139.79	50	0.000
FF	deathsgrowth	61.966	10	0.000
FF	dWeiInterp	103.72	10	0.000
FF	CILgrowth	35.505	10	0.000
FF	CLgrowth_detren~d	16.445	10	0.088
FF	OLLgrowth	19.127	10	0.039
FF	ALL	305.5	50	0.000

Figure C.83 – Granger causality between variables for the model with optimal lag (p=10).

Orthogonalized impulse response functions

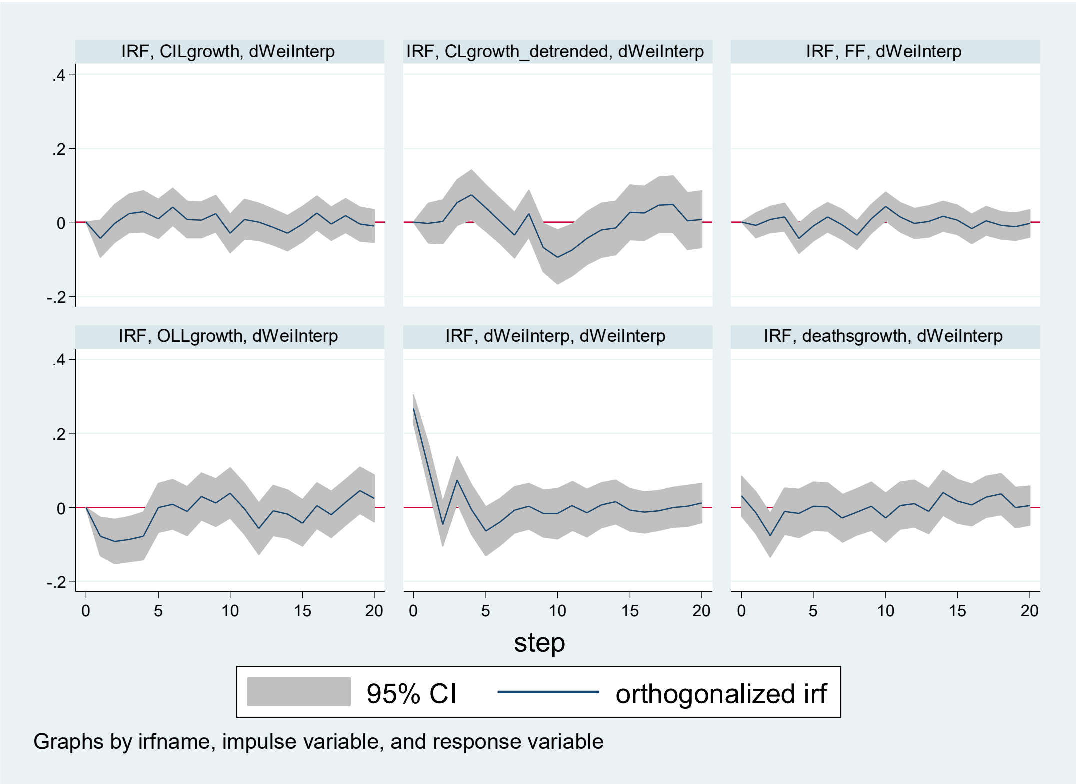


Figure C.84 – All OIRF for the model with optimal lag (p=10).

Cumulative orthogonalized impulse response functions

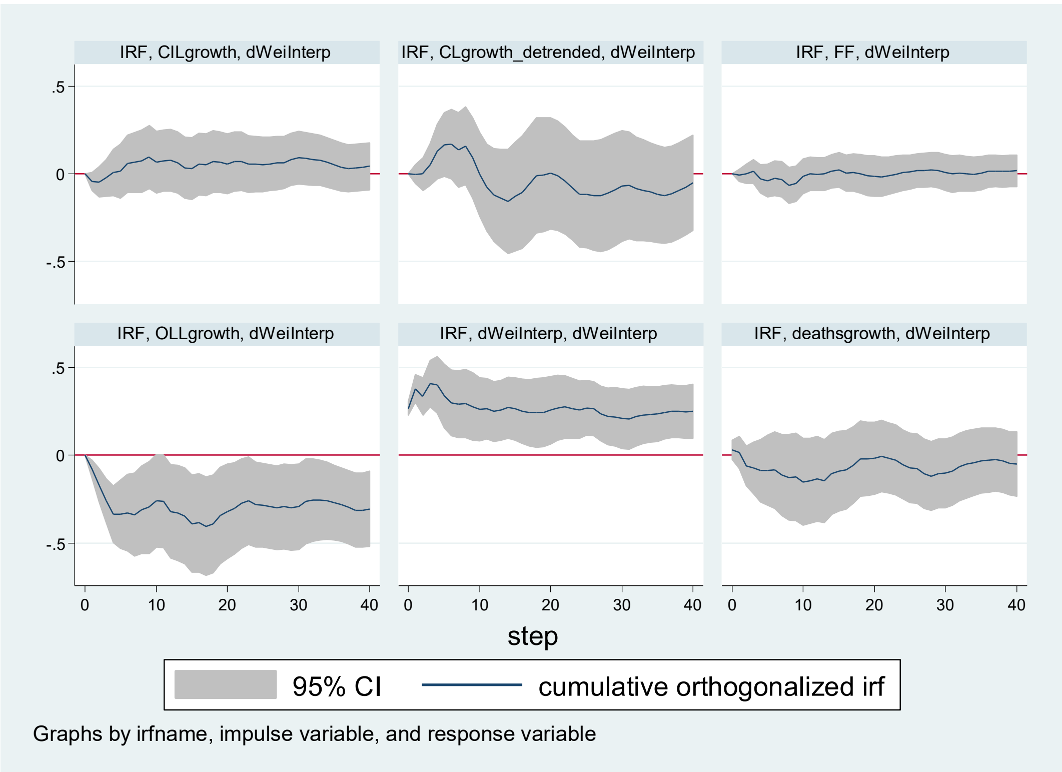


Figure C.85 – All COIRF for the model with optimal lag (p=10).