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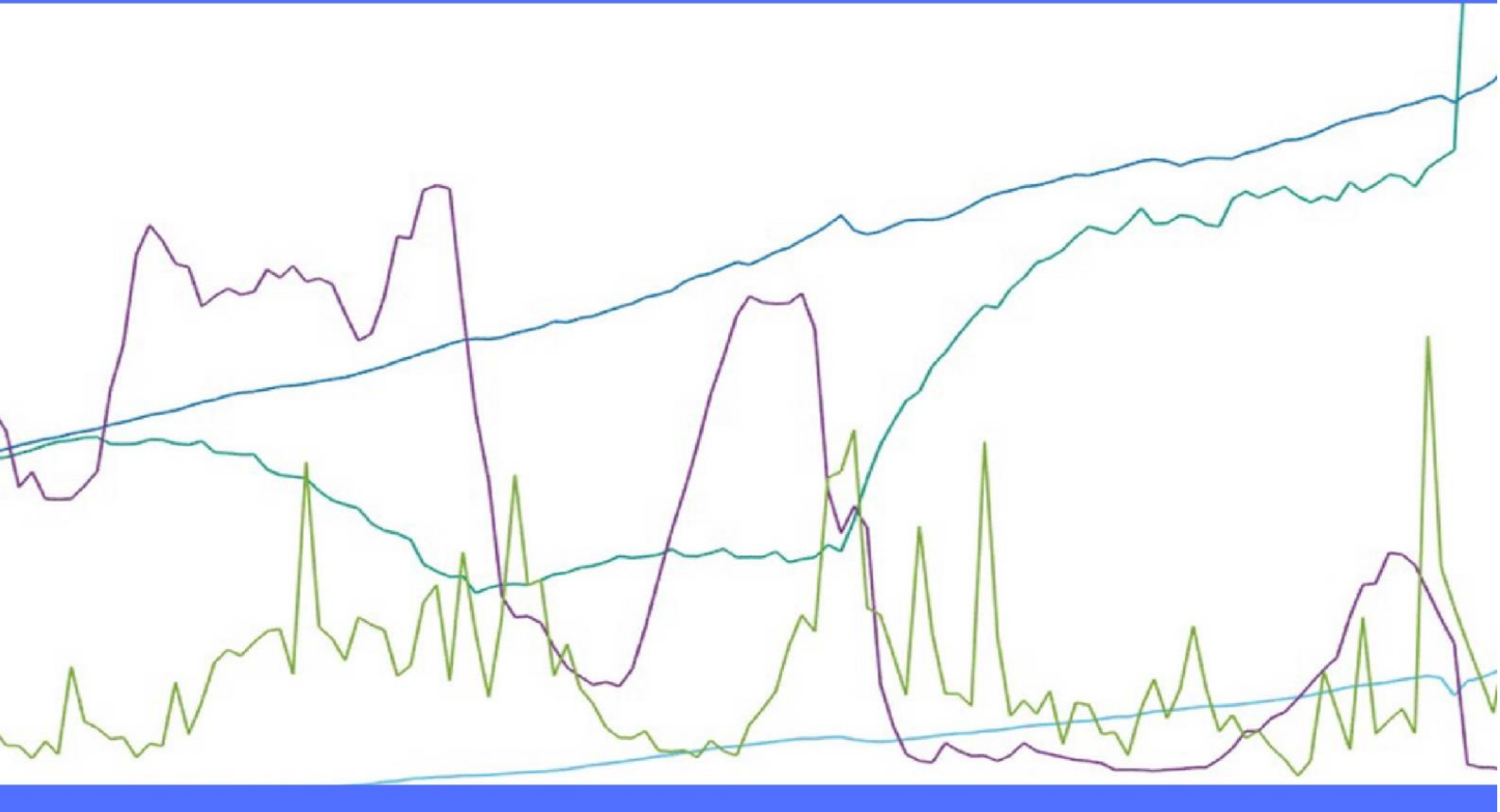
Fiscal policy in different times of uncertainty in the U.S.



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ABSTRACT

This paper seeks to investigate changing dynamic behavior of fiscal policy shocks in the US economy from January 1990 to October 2021. Using quarterly data on gross domestic production, consumer price index, government debt-to-GDP ratio, short-term interest rate and CBOE Volatility Index (VIX), this paper estimates vector autoregressive (VAR) models to investigate the interaction of these variables. By employing a Threshold-switching model (TS) on our VAR models, the VIX variable endogenously determines structural changes and different states of the dataset. Introducing impulse responses – that simulates fiscal policy shocks - to our TSVAR model, our main findings suggest that the impact of expansionary fiscal policy depends on level of uncertainty in the macroeconomic environment. The paper finds that expansionary fiscal policy shocks will stimulate economic growth in times of low uncertainty. This impact is even more significant in times of high uncertainty with prominent output growth and steep upsurge in inflation. This paper therefore stresses the importance of policy makers considering the level of uncertainty before performing fiscal policies.

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1. INTRODUCTION

Former President Barack Obama signed the American Recovery and Reinvestment Act of 2009. In 2020 former President Donald J. Trump signed the Coronavirus Aid, Relief and Economic Security Act. Most recently, The American Rescue Plan was signed into law by President Joe Biden. These are all examples of expansionary fiscal policy employed in the United States to stimulate the economy in times of recession (*Coronavirus Aid, Relief, and Economic Security Act*, 2020; *American Rescue Plan*, 2021; *American Recovery and Reinvestment Act of 2009*, 2009).

Extensive fiscal instruments in economic recessions like the above mentioned are not unique to the U.S. government but has especially been common in most economies during the COVID-19 pandemic. Still, debate reigns of whether expansionary fiscal policy is an effective tool to stimulate the economy, especially in the context of uncertainty. Moreover, some perspectives even claim that expansionary fiscal policy is weakening the economy (Coleman, 2010).

With no consensus on the topic regarding the effects of fiscal policy neither in “normal” nor “uncertain” times, the topic on the effects of fiscal policy must be addressed further in macroeconomic research. Although, consensus exists on monetary policy being the preferred economic tool, fiscal instruments were seen used seen during the global financial crisis of 2008 and COVID-19, where monetary tools were deemed insufficient (Afonso & Baxa, 2011; Azad et al., 2021; Jørgensen & Ravn, 2022; Rother, 2004). Considering that fiscal policy is predominantly applied in times of uncertainty, more research distinguishing between normal and uncertain times is particularly important to conduct. Research on the topic can contribute with knowledge ensuring that the right policies are implemented. Even more crucial, it can prevent governments from implementing fiscal policy that has direct deteriorating impacts on already weakened economies.

The innovation in fiscal policy strategies during COVID-19 across the globe, emphasizes the relevance of research on changing effects of fiscal policy. Covering the inter-state complexities is beyond the scope of this paper. To limit the scope of this study, it will instead seek to answer the following research question: ***how does the effect of fiscal policy change with the level of uncertainty in the United States?***

To answer the research question (RQ), a quantitative approach is applied, using a Thresholdswitching vector autoregressive model (TSVAR). The study is inherently inductive but will draw on a framework of varying macroeconomic theories, when interpreting the findings emerging in the following sections. The choice of the TSVAR model is two-fold. First, vector autoregression implies an ability to better represent complex dynamics in the economy, which a univariate non-autoregressive model would not suffice to do. Secondly, Thresholdswitching enables the construction of a non-linear model, which makes it possible to distinguish between effects in different regimes of uncertainty. Moreover, uncertainty is operationalized as the risk-aversion in the financial market, using the CBOE Volatility Index (VIX). This will serve as a proxy for the uncertainty prevailing in the macroeconomic environment. Thus, a switch from the low to high regime of uncertainty will occur, when the VIX variable exceeds the time-varying threshold, hence no fixed value will determine the switch in regime. This reasoning is based on the extremely high levels of uncertainty during COVID-19, which would increase a fixed threshold considerably and potentially exclude all other periods of relatively high uncertainty in the U.S. economy.

The main findings suggest that the effect of expansionary fiscal policy is consistent across the regimes of low and high uncertainty. Although, the effects on output and inflation are more amplified in times of high uncertainty. Interestingly, we find that fiscal policy shocks have a negative influence on VIX, but only in regimes of already high uncertainty. Moreover, the study finds that uncertainty alone is not an adequate factor when predicting the effects of expansionary fiscal policy.

The paper will proceed as follows: the second section will introduce relevant literature on the topic of fiscal policy and the application of VIX as a measure of uncertainty. Hereafter, the third section elaborates on the theoretical framework in which classical economic thoughts on the effects of fiscal policy will be introduced. In the fourth part, the data and variables of the model are presented, followed by the fifth part explaining the methods applied in the data processing and model creation. In the sixth section, the results emerging from the application of the selected methods are exhibited and simultaneously explained. The seventh section includes a discussion of the findings related to policy implications and thoughts on the methodological choices. Finally, the conclusion of the paper is stated in the eight section.

2. LITERATURE REVIEW

The effects of fiscal policy have been difficult to detect, due to annual negotiation and implementation, compared to more flexible monetary policy instruments, where direct cause and effect is easier to monitor (Rother, 2004, p. 11). However, during the COVID-19 pandemic, rapid fiscal measures have been activated to mitigate the economic downturn. The abandoning of the fiscal policy rigidity poses as an ideal opportunity for producing more literature on the direct effects of fiscal policy, in a case, where sudden decisions and implementation enables more transparency between cause and effects.

2.1 Ambiguity in the research on fiscal policy

Despite vast literature on the area, no broad consensus exists on the effects of fiscal policies. Instead the matter is subject for debate and contradicting research. Caldara & Kamps (2008) and Galí et al2007) contribute with findings supporting the conventional New Keynesian theoretical approach. Their research point towards growth in consumption and output, increased inflation, and declining investment following fiscal stimuli. Ferrara et al. (2020) finds that government spendings in the U.S. is inflationary and is associated with a decrease in consumption. Also, a deficit in the trade balance occurs stemming from real exchange rate appreciation. Other research contradicts the inflationary effect. Ricco et al. (2016), find no or even negative effects on inflation as response to a government spending shock.

Recent research by Jørgensen & Ravn (2022) backs up the findings of no or negative correlation between fiscal shocks and inflation. In the study, the authors use a structured vector autoregression model (SVAR) for the U. S. economy to examine the effects of government spending. Based on a data sample from 1966:Q4-2019:Q4, positive government spending shocks do not lead to price increases. Surprisingly, in the period of the zero lower bound (ZLB) beginning in December 2008, the fiscal multiplier is even lower and leads to a drop in prices. The data sample in the ZLB period is relatively small compared to the whole data sample, why no significant conclusions can be drawn from this variation. However, it is an indication of some divergence in the effects of government spending between times of “normality” and recession. A limitation to the study is the scarcity in observations constraining the authors from making any inferences on varying effects of fiscal policies in different settings. Further, the purpose of the study is an overall assessment of impacts of government spending and does not seek to distinguish between the economic conditions. This leaves a gap for research disclosing, whether significant variance exists in the effects of fiscal policy across different macroeconomic environments.

2.2 Fiscal policy in different settings

Most existing literature demonstrating the change in effect of fiscal policies in different economic conditions, lacks up-to-date data, namely the years of COVID-19. However, the literature is very relevant, since it assesses fiscal effects in varying states and contributes with essential methodological insight. Afonso & Baxa (2011) uses a Threshold-switching VAR (TSVAR) model to analyse how fiscal policy affects the economy differently, depending on the present level of financial stress. The findings show that the initial economic conditions impact the effect of fiscal policy, but overall, in both high and low stress regimes, the fiscal shocks affect the output growth positively. The variation in impulse responses differs across countries and the difference between the regimes is less significant in the U.S. Although, in the high stress regime the peak of output growth occurs sooner than in low stress regime in the U.S.

Anzuini et al. (2020) study the effects of uncertainty originating from fiscal policy decisions in Italy. The authors adopt a VAR approach and estimate a fiscal reaction function responding differently to fiscal policy volatility. The authors find that an unexpected increase in fiscal policy uncertainty (FPU) is negatively related to GDP. The main implication is that the same change in government budget can generate different outcomes, depending on, whether the fiscal policy is associated with a fall or rise in FPU.

Further, Ko & Morita (2019) identify macroeconomic regimes in Japan’s economy with different effects of fiscal policy. The authors estimate a Markov-switching VAR (MSVAR) model to examine automatic fiscal responses to output and discretionary fiscal shocks. Overall, the fiscal multiplier varies across regimes. Interestingly, it shows that in contrast to the other four regimes, expansionary fiscal shocks lead to depression in output and consumption in the third regime in the 1990s.

The impact of varying macroeconomic settings on the effects fiscal policy is most recently addressed by Azad et al. (2021), using data from the global financial crisis in 2008 and the COVID-19 pandemic in Canada. The study applies a regime switching approach and estimates a structural VAR to describe diverging reactions and effects of fiscal policy. The authors find that in the active regime of fiscal policy, tax rate is negatively correlated to debt-to-GDP, contrary to positively correlated in passive regimes. This implies that taxes decrease as debt-to-GDP increases. Further, the authors find that during the two regimes, active fiscal policy is more utilized compared to active monetary policy. Lastly, the findings suggest that deficit spending has a short-term positive effect on GDP and private consumption, which terminates, when the fiscal stimulus is no longer used. On a long-term perspective, investment falls while interest rates and inflation rise.

Afonso & Baxa (2011), Anzuini et al. (2020), Ko & Morita (2019) and Azad et al. (2021) focus on different aspects surrounding fiscal effects in different regimes, but agree that effects of fiscal policies are conditioned on the specific context. The research on the varying response to fiscal policies, insinuate complex market dynamics that cannot fit in a linear-model. The research expands the traditional conceptualization of fiscal policy and adds to the explanation of, why no broader consensus prevails in previous literature, where context has been subordinated. A research gap that still exists, is changing effects of fiscal policy, incorporating recent data from the period of COVID-19.

2.3 Market volatility capturing uncertainty

To address the issue of 'uncertainty' and its implications on the effects of fiscal policy, exisiting literature is useful to choose a proper variable that captures uncertainty in the best possible way. Afonso et al. (2011) applies the financial stress index (FSI) as the threshold variable to draw the distinction between regimes of "good" and "bad" times. The FSI is a combination of many indicators, including changes in stock market, exchange rate volatility and interest rate spread, which makes it suitable for assessing overall financial instability (Afonso & Baxa, 2011; Kliesen & McCracken, 2020).

Meanwhile, to assess the implications of uncertainty in a more direct form, other proxies may be more relevant. Bloom (2014) contributes to the operationalization of 'uncertainty', stating that no perfect measure captures all aspects of the term. Therefore, different alternatives can constitute as proxies for uncertainty. One of these options assessing market uncertainty is the CBOE Volatility index (VIX), which is the implied volatility on the S&P 500 stock market index over the next 30 days. The VIX is a measure of risk aversion, signaling uncertainty, since in times of uncertainty, people are more risk averse and will pay higher premiums to attain an option on the underlying stocks. As with the FSI, the VIX is closely associated with economic recessions, where Bloom finds that the VIX increase by 58 percent on average.

Dell'Erba & Sola (2011) contributes with research on how fiscal policy affects long term interest rates and risk premia. They use VIX to expand their findings and estimate how open economies respond to an increase in the risk aversion captured by the VIX. VIX is also used in existing literature as a baseline variable, measuring uncertainty in the economy that enables the assessment of different effects of fiscal policy (Macroeconomic Advisers, 2013). The authors also apply other measures to strengthen their findings, which only supports the statement by Bloom, suggesting no perfect measure of uncertainty.

2.4 Conclusion

Existing literature propose contradicting effects of fiscal policy. Moreover, previous research indicates that fiscal multipliers depend on the context of the fiscal stimuli. Azad et al., (2021) finds that in times of uncertainty, active fiscal policies are more utilized. Therefore, it is important to expand research on the effects of fiscal policy in contexts of high uncertainty, to improve economic policy, when addressing challenges in the economy. According to our knowledge, no previous research has addressed effects of fiscal policy in the U.S. in different times of uncertainty, with the inclusion of data from COVID-19. Therefore, this paper will contribute to existing literature on effects of fiscal policy in the U.S. by distinguishing between low and high levels of uncertainty and through the inclusion of data from the COVID-19 pandemic.

3. THEORETICAL FRAMEWORK

The following section will provide a brief overview of the most prevalent theories on fiscal policy and its effect on the economy. Firstly, this paper will introduce theories that advocates in favor of using fiscal policy, namely demand- and supply-side policies. While each theory suggests a different tool to perform economic stimulus, they both agree that fiscal expansion is key for stimulating economic growth. Following these positive readings of fiscal stimuli, objecting views in the form of crowding out effects will be introduced. This will cover diminishing effects of the fiscal multiplier through the interest rate, exchange rate, and price increases. This will be followed by an introduction to the Ricardian equivalence and how the rational expectations of private actors potentially can shift the size and the sign of the fiscal multiplier. In combination, these theoretical reflections will serve as the foundation for our analysis and discussion of our findings. This is also why opposing theories is presented, as they serve as explanatory tools, but not guiding our methodological procedure.

3.1 Demand-side theory

Demand-side policies assign the government an active role in stimulating economic activity and growth. Connected directly to Keynesian economics, demand-side policies focus its attention to aggregate demand as it determines output. John Maynard Keynes developed this theory in response to the great depression in the 1930s, in which he argued that the declining output and economic downturn could be resolved by the government spurring aggregate demand (Mitchell et al., 2019b, pp. 434–436). Underlying this theory, is the Keynesian idea of a fiscal multiplier. The fiscal multiplier measures the effect on GDP from an increase in government expenditure associated with expansionary fiscal policy. Central to these thoughts is the concept of the marginal propensity to consume (MPC), which measures individuals' preferences for consuming versus saving. This is used to quantify the proportion of an increase in income that will be spent on consumption. The theory holds, that a long as the MPC is > 0, a government spending will automatically lead to a disproportionally increase in economic growth (Cziráky, 1997, p. 3; Hemming, Kell, & Mahfouz, 2002, p. 17).

Extension of the simplest Keynesian model allows for some crowding out effect, reflected in the IS-LM model. A fiscal expenditure will most likelihood lead to an increase in the interest rate because of higher money-demand due to an increase in private income. As private investment corresponds negatively to the interest rate in the IS-LM framework, it will lead to a decrease in total investment. While this crowds out the size of the fiscal multiplier, it does not change the sign of the fiscal multiplier (Hemming, Kell, & Mahfouz, 2002, pp. 4–5; Mitchell et al., 2019d). More severe interpretations of the same crowding out effects will be discussed later on, when introducing the ideas of classical economics.

3.2 Supply-side theory

In contrast to the focus on consumption by demand-side economics, supply-side economics emphasize on increased production to foster economic growth. The theory won ground in the early 1980s, with President Ronald Reagan and Prime Minister Margaret Thatcher adopting and promoting this economic belief. The theory holds that to stimulate economic growth, the government must incentivize the supply-side to increase production. This can be done through three means; either by cutting taxes (for the rich), lowering borrowing rates or deregulating attractive industries. These actions would make the rich save more, which could expand and enhance the production and thereby benefitting total supply (Hemming, Kell, & Mahfouz, 2002, p. 9; Mitchell et al., 2019b, p. 435). These ideas are rooted in two components of the theory, namely the Laffer curve and the Trickle-down effect. The Laffer Curve propose an optimal tax-rate for maximizing taxation revenue and growth. The theory states, that if tax-rates are too high, business actors will be discouraged to perform taxed activities, such as working or investing, which ultimately hurts the economy. It can therefore be beneficial for government to reduce taxes if in deficit, as people will be incentivized to actively perform taxed activities. This tax relief will be offset by increased tax revenues due to more people stimulating the economy, which will lead to economic growth. The second notion, the Trickle-down effect, advocates adopting policies benefiting the corporations and the prosperous. The reasoning behind, is jobs and tax revenues will increase from such actions, and eventually 'trickle down' to the rest of the economy (Mitchell et al., 2019b, p. 435).

It is worth commenting, that supply-side policies have traditionally been connected to a more 'long-term' perspective, while fiscal policies often has been associated with short-term demand-side policies (Hemming, Kell, & Mahfouz, 2002, p. 9). While some have disputed the empirical validity of the theory, supply-side policies have been actively used to stimulate economic growth ever since its introduction. The latest example being former President Donald J. Trump enacting the Tax Cut and Jobs Act (TCJA) in 2017, which included tax reliefs for the rich and corporations in aim of stimulating growth. Therefore, such distinguishment between short-term and long-term policies will not be made in our assignment, as our policy-variable debt-to-GDP ratio reflects both a cutting in tax [supply-side policies] as well as increased government spending [demand-side policies].

3.3 Crowding out effects

Earlier we introduced the phrase 'crowding out' in relation to the extended version of Keynesianism. The LM-curve was added to the IS-curve, as it acknowledged that the fiscal multiplier might be weakened due to an increase in the interest rate. While this was seen as a minor side-effect in Keynesianism, classical economics attribute the effects of crowding out to be more significant. They regard it as potentially outweighing the positive effects of the fiscal multiplier and in in worst case scenario, leading to a negative multiplier. Crowding out effects can be assumed to be competing with the fiscal multiplier effect, as it refers to all the ways in which debt-financed fiscal stimuli will have a limited impact on output (Hemming, Kell, & Mahfouz, 2002, pp. 4–5). Building on this notion, the crowding out theory will represent an umbrella term for multiple channels in which the multiplier effect can be deteriorated or negative, in worst case. The term builds further on classical economics idea of no involuntary unemployment put forward in the 1920's and 1930's. Since there is assumed to be no such thing as involuntary unemployment, fiscal expansion will merely imply goods and services being provided by the government instead of private actors. This idea is said to be the direct crowding out effect (Blanchard, 2018). Following this logic, the idea of the fiscal multiplier being crowded out, has spread to multiple arenas. We have chosen to cover the economic channels of private investment, exchange rate, price flexibility, rational expectations and lastly the Ricardian equivalence.

3.3.1 Private investment and the interest rate

The notion of crowding out is also said to be observable through private investments. Underlying this idea, is the basic premise that there is a limited supply of private sector savings, which the public and private sector will compete for. This means that when the government tries to borrow more by issuing and selling bonds, it will compete with the private sector also seeking finance for investment. This competition will push up the interest rate, and hurt private actors as a result, since some firms might decide not to borrow due to the higher borrowing cost. This will reduce overall investment, and furthermore push back private consumption as some of it is usually financed by borrowing (Mitchell et al., 2019a, pp. 336–337).

3.3.2 Exchange rate

Another way in which the fiscal multiplier might be crowded out, is through the exchange rate adaptations in an open economy. The extent of the effect is contingent on whether the exchange rate is flexible or fixed. If a country has flexible exchange-rates, a higher domestic interest rate will lead to capital inflows from foreign countries which will appreciate the exchange rate. This will eventually lead to a total crowd out of the fiscal expansion, as capital inflows will continue until there is no arbitrage to be made. At this point exchange rates and interest will be in equilibrium, an effect known as the interest Rate Parity (IRP). Oppositely, when there is a fixed exchange rate, a fiscal expansion will have a smaller impact on interest rates and a fiscal stimulus might be fruitful. As the exchange rate stays the same, foreign capital inflows will travel into the economy, which will lead to the interest rate not rising at all. This will result in the domestic interest rate being the same as the foreign interest rate, and fiscal expansions is thus an effective tool (Hemming, Kell, & Mahfouz, 2002, pp. 4–5).

3.3.3 Inflation and price flexibility

A common channel in which the multiplier is also crowded out is through price flexibility leading to inflation. Even with some stickiness of wages and prices, there will tend to be price increases with a higher demand secured by the fiscal expansion. This will effectively minimize the fiscal multiplier, even if the impact is minimum in the short-term (Hemming, Kell, & Mahfouz, 2002, pp. 5–6; Mitchell et al., 2019a, pp. 334–337). It is however worth noticing that this effect is tightly connected to exchange rates when they are flexible. If we assume that domestic prices rise with the appreciation of the exchange rate, the latter will push back domestic prices, and the crowd out effect of price flexibility might not be as great. Nevertheless, price flexibility impacts the fiscal multiplier to some extent, and is acknowledged by both economic side to some degree (Hemming, Kell, Mahfouz, et al., 2002, p. 5).

When mentioning the crowding out effect of price flexibility, classical and monetarist economics often refer to the example of the labor force. Let us assume that a government performs Keynesian stimulus policies to indiscriminately pump-up domestic consumption, to achieve full employment. Yet, as the issue of unemployment is not equally distributed among sectors, there will be already tight-conditioned sectors, where workers will negotiate for higher wages. This will lead to higher prices in these sectors, while there might still be substantial issues of unemployment in other sectors. This means that inflation will be evident before full employment is reached in these slacked sectors, due to a time lag of the implementation of the fiscal policy. In such instances, governments might abandon to follow the rest of the fiscal stimulus package, as they observe countercyclical effects. In such instances, the fiscal multiplier will be negative (Blanchard, 2018; Mitchell et al., 2019a, p. 337).

3.3.4 The Ricardian equivalence theorem and rational expectations

The Ricardian equivalence theorem (RET) was developed as a critique to Keynesian assumptions of fiscal stimulus leading to increased consumption (Hayo & Neumeier, 2017). RET holds the main belief that since consumers are forward looking and have perfect information on the financing of the government's debt, they (consumers) will be aware that higher taxes await. RET is founded on the notion that a current fiscal expansion must be financed somehow in the future, which implies that when a government pursues fiscal stimuli, the consumers are aware of their permanent income being unaffected. Therefore, a reduction in government savings or increased debt, will be fully offset by higher private savings, which implies the fiscal multiplier being zero (Cziráky, 1997, pp. 2–4). The RET also focuses on instances of government expenditures being financed by higher taxes in the future. In such cases, consumers' permanent income will be affected negatively, which implies the fiscal stimuli potentially having a negative fiscal multiplier(Hemming, Kell, Mahfouz, et al., 2002, pp. 6–8).

However, it should be noticed that the stated hypothetical situations of a zero or negative impact of a fiscal stimuli, is conditioned on strong assumptions about the households' behavior and information level. Households must rationally incorporate the government budget constraint into their own budget. This implies being forward looking and furthermore, imposing liquidity constraints on themselves. Therefore, the practical significance of the RET is limited, at least in perfect form, which is reflected in incomplete empirical evidence (Hayo & Neumeier, 2017; Hemming, Kell, Mahfouz, et al., 2002, pp. 6–8). This does not mean that the RET has no use in explaining economic reality. The RET has been and is still used heavily in economics to describe Ricardian behavior of consumers. For example, most governments are often bound by some fiscal law requiring the fiscal expansion being reversed within some limited timeframe. In such instances, citizens have perfect knowledge of such limitations, and prepare their budget for future tax increases. Another more severe example, is the condition where citizens assume that the government debt is out of control and unmaintainable. In such instances, future debt will be required to lower the current debt, why citizens are saving even more to prepare themselves for future obligations. Here the Ricardian behavior of consumers will more than offset the fiscal multiplier, and actually have a negative impact on economic growth (Cziráky, 1997, pp. 2–4; Hemming, Kell, Mahfouz, et al., 2002, pp. 6–8).

3.4 Conclusion

The preceding section sought to provide a brief overview of the most prominent theories on the effects of fiscal expansions. Firstly, theories attributing fiscal expansion a key role in stimulating growth was presented. Here it was brought forward how each theory provides different means and focus to ensure expansionary stimulus. While demand-side policies seek to increase aggregate consumption through government expenditure, supply-side policies focus on increasing supply through deregulation and tax cuts. Followingly, objections against fiscal expansion as an economic tool was presented under the umbrella term 'crowding out effects', which included the Ricardian equivalence theorem. While it was chosen to present these theories as a for and against side, it should be noticed that such clear distinction is clearly hard to make and partially wrong. The theories in their ideal forms are hardly representative for a sequence of macroeconomic events, which explains why it is still a disputed topic to this day. This is also the reason for several theories being chosen, as we intend to 'pick and choose', when analyzing and discussing our findings.

4. DATA

4.1 Data collection

In the following section, each variable of our time series model will be presented, including a brief explanation of why and to what use this variable was chosen. The identification of possible variables to include in our model, relied heavily on the presented literature as well as the theoretical framework. Both elements introduced separately in earlier sections. After a trial-and-error process[i], we found the following variables to collectively be the best fit: gross domestic product (GDP), consumer price index (CPI), short-term interest rate (SI), debt-to-GDP ratio (DtGDP) and the CBOE Volatility Index (VIX). The variables trialed but discarded due to lack of significant outcomes will naturally not be presented in the following section.

Regarding the time frame, our initial idea was to focus primarily on the uncertainty stemming from the COVID-19 period. Yet, it became evident that a dataset refraining from including previous periods of uncertainty resulted in an insufficient observation set. Therefore, we decided to extend our timeframe and include previous periods of uncertainty. While this shifted the focus away from macroeconomic relationships only found present under COVID-19, it made us able to conduct more general observations about the relationship between the effectiveness of fiscal stimuli and the uncertainty in the economy. Therefore, our time interval included data from the 1st of January 1990 to the 31st of December 2021. The variables chosen was available on a quarterly basis, which resulted in 128 observations.

We will first introduce descriptive statistics of our variables, which is great for understanding the properties of our data. Table 1 is in level form, while table 2 is in natural logarithm form, which is the form used to construct the TSVAR model. This will be elaborated on in the following methodology section.

4.1.1 Descriptive statistics

DESCRIPTIVE STATISTICS – LEVEL-FORM					
Variable	**Observation**	**Mean**	**Standard deviation**	**Min**	**Max**
GDP	128	1.4418e+04	3.073e+03	9.2753e+03	1.9806e+04
CPI	128	0.2279	0.3060	-1.0101	1.0309
DtGDP	128	53.5968	19.1002	30.8914	105.4983
SI	128	2.9203	2.3853	0.1000	8.3333
VIX	128	19.6387	7.7744	9.5100	53.5400

Table 1 Descriptive statistics in level-form.

DESCRIPTIVE STATISTICS – LOG TRANSFORMATION					
Variable	**Observation**	**Mean**	**Standard Deviation**	**Min**	**Max**
GDP	128	9.5527	0.2218	9.1351	9.8938
CPI[ii]	128	0.108+0.0245i	1.0039	-2.3984	0.7570
DtGDP	128	3.9226	0.3395	3.4305	4.6587
SI	128	0.4397	1.3757	-2.3026	2.1203
VIX	128	2.9133	0.3471	2.2523	3.9804

Table 2 Descriptive statistics in log transformation form.

4.2 Gross Domestic Product

Gross domestic product (GDP) is a key indicator of the economy, as it measures the size of the economy and can therefore be used as a measure of growth. A simple GDP equation is comprised of total final consumption expenditure, total private investment, total government expenditure and net exports (Mitchell et al., 2019c, p. 84). In relation to fiscal stimuli, GDP will provide an overall indication of the impacts following the fiscal policies. Hereby it will also be evidential whether the effects of the fiscal multiplier have been crowded out. In case of a positive effect of a fiscal stimulus, the fiscal multiplier will be positive which will be reflected in a rise in GDP. Oppositely, a negative effect of a fiscal expansion will imply a negative fiscal multiplier and a decrease in GDP. The data on GDP is drawn from the public database of the Federal Reserve Bank of St. Louis and is in billions of dollars in nominal terms on a quarterly basis.

4.3 Consumer Price Index

The consumer price index (CPI) also serves as a key parameter of the economy, as it is measured and used as a proxy of inflation[iii]. This is done by measuring the rate of which the prices of consumption goods and services have changed from one period to another. In most countries, the central bank – including the Federal Reserve – target a 2 % inflation rate in the economy, as they estimate it as consistent with *"maximum employment and price stability"* (Board of governors of the Federal Reserve System, 2020, l. 5). In short, the main reasoning behind target, is that households and businesses can then assuredly make economic decisions such as investing, saving, and borrowing. When inflation exceeds the 2 % inflation aim, as observed currently in the U.S., it will affect the rest of the economy through increased stress and financial uncertainty. This is tightly connected to our research, as fiscal expansions are usually conducted in times of recession [when inflation is initially low] but can potentially create spikes of worrisome inflation[iv]. Furthermore, inflation is a variable where crowding out effects of the fiscal expansion has been historically evidential, as one can measure the price flexibility directly. Hence this variable, presents itself as a crucial parameter to measure the effects of fiscal policy.

We extracted the index data on CPI from the public database of the Federal Reserve Bank of St. Louis with index year of 1982-1984. The data is provided in monthly form and is seasonally adjusted.

4.4 Short-term interest rate

Short-term interest rates (SI) are used as a monetary policy set by the Central Bank, and naturally also a key economic parameter. It is the daily average rate of two components. One being the rate at which short-term borrowings are traded between financial institutions and the second is the rate at which short-term government paper is traded in the market. In relation to our research, this variable is also an important indicator as different effects will be reflected in the variable. Firstly, in relation to crowding out effects, it is expected that a fiscal expansion will cause an increased interest rate because of a higher money demand. This will lead to a weakened fiscal multiplier. Another potential effect pulling the interest rate in opposite direction is higher uncertainty, as people and businesses could be expected to withhold their investment due to an unsound business environment[v]. Overall, this becomes an interesting variable to include, as it measures and reflect the effects of many economic relationships. The data on the short-term interest rate is taken from the OECD database and is recorded as daily observations of the three-month money market rates available.

4.5 Government debt-to-GDP ratio

Following Afonso et. Al (2011), we used government debt-to-GDP ratio (DtGDP) to describe and capture fiscal policies and its development. Usually, the fiscal balance has been used to capture fiscal policy, as governments tend to focus on the balance rather than the development of debt. However, DtGDP has many advantages, as extraordinary government actions might not be fully represented in the fiscal balance. The DtGDP reflects both revenues and expenditures and is a key metric to determine whether the pursued economy is fiscally sustainable. Moreover, DtGDP reflects the risk revolving refinancing of the outstanding stocks of government debt, while it also influences the interest rate (Afonso et al., 2011, pp. 20–21). In total, this variable reflects the potential root to many of the crowding out effects, as it reflects debt financed fiscal expenditure. We retrieved data on the DtGDP from the Federal Reserve Bank of St. Louis, where the data provided is in quarterly terms.

4.6 The CBOE Volatility index

The CBOE Volatility Index (VIX) is a signal of the level of fear in the stock market with the S&P 500 index representing a proxy for the market. It is widely known as the fear or uncertainty index, as the higher the level of the VIX, the greater the levels of fear or uncertainty in the market. Therefore we have chosen to operationalize uncertainty as the VIX variable, since uncertainty and fear is interchangeably linked[vi] (CBOE, 2022). The VIX is based on the prices of the S&P 500 Index call and put options. This means that the VIX represents the premium for holding the option to sell or buy a stock in the future. Since it is based on the S&P 500, it primarily captures the effect of developed market volatility, which is appropriate when seeking to analyze macroeconomic parameters in the U.S. (Chudik et al., 2021, l. 7). The variable was therefore chosen as our threshold variable, representing the uncertainty in the U.S. economy, and thus determining which regime our observations appear in – either low or high uncertainty. In relevance to our research, this variable becomes an interesting measure, as fiscal expansions often are conducted in times of recessions, in which we could expect high uncertainty and fear. Oppositely, high(er) interest rates and other counteracting parameters to the fiscal stimuli policy could also be expected when there is high uncertainty. The variable therefore becomes a crucial indicator of which economic relationships is present – and oppositely, which are not – given the uncertainty in the macroeconomic environment. The VIX index is calculated on 30-day expected Volatility based on USD. The data is withdrawn from Yahoo.Finance in daily observations.

5. METHODOLOGY

5.1 Philosophy of science

As embedded in the nature of quantitative research, this paper has been informed by a positivist philosophy of science. Positivism is shaped by an ontological realism, which sees that an external social reality exists independent of our awareness. Applying moderated positivism, we acknowledge that unobservable phenomena also exist. This differs from strong positivism, which only acknowledges the existence of things if they are observable. Therefore, strong positivism seeks to explain theoretical phenomena by providing 'covering laws'. This contrasts the intention of moderated positivism and hence our research paper. Our epistemology is built on a quest for uncovering some probabilistic relationship and attach a causal argument when explaining the case. We seek to explain a phenomenon, rather than predicting with covering laws. Applied to our research, this means that it is not within the purpose of this paper to predict what impact fiscal policy will have in the future, but rather we seek to explain how the impact of fiscal policy can vary in accordance with the macroeconomic environment.

Our research has been built on an inductive approach. The analysis was inspired by the fiscal stimuli packages applied in the U.S. in an environment of uncertainty. Meanwhile, the U.S. economy was experiencing a rise in inflation. We therefore sought to investigate if the effect of fiscal policies depends on the uncertainty level in the macroeconomic environment. Yet, the characterization of either an inductive or deductive approach, has not been a clear-cut in our case. As covered in this theory section, this paper has been greatly informed by traditional economic theories and their assumptions on the effectiveness of fiscal policy and potential implications. This has served as the baseline for our research question, choice of economic variables and implied some form of theory-testing, which shows elements of a deductive approach as well.

5.2 Time series

The RQ asks: ***how does the effect of fiscal policy change with the level of uncertainty in the United States?*** Addressing this RQ with quantitative methods, the study will conduct an econometric analysis of the introduced data from the U.S. economy over time. The selected data is thus examples of time series, where each of the five variables describes the development in one economic parameter over quarterly time intervals. Firstly, the reasoning behind this choice is that time series enable a longitudinal case study of the U.S. economy, where it is possible to compare results in different times exhibiting different levels of uncertainty. Additionally, time series provide the possibility to conduct autoregressive analysis, where the incorporation of lagged values is used to assess how observations in time, t depend on values in time $t - n \ldots t - 1$ (Stock & Watson, 2020). Autoregression can further provide estimates about the future depending on the lagged versions of the entity described in the time series. Autoregression enables the assessment of immediate and subsequent effects of fiscal policies in the U.S. economy.

5.3 Stationarity

Prior to conducting the analysis, an important feature of the time series is addressed, namely whether the data is *stationary*. Stationarity is a characteristic implying that the properties of a stochastic process is invariant over time. Stationarity is fulfilled through three criteria. First, the process has a constant mean over time, t, (meaning, no trend). Secondly, the variance is time invariant. Thirdly, the covariance does not depend on time t, but on the distance between $t_!$ and $t_"$ (Lütkepohl & Krätzig, 2004a). Meanwhile if these criteria are not all fulfilled, the process is said to be non-stationary.

The analysis of this paper deals with time series of economic data that often tend to revolve around deterministic or stochastic trends, implying non-stationarity (Stock & Watson, 2020). Deterministic trends can approximately be described with a fixed coefficient, determining the development. Whereas a stochastic trend describes random processes. An example being a long period of growth followed by a sudden drop, caused by exogenous factors, such as shocks to the economy, demographic change, and political events. Given the unpredictability of these exogenous factors, the trend in economic series, are random rather than predictable and therefore described as stochastic. The implication of estimating models based on non-stationary time series with deterministic or stochastic trends is the risk of spurious regression. This refers to variables appearing correlated due to their trends, even though they are independent (Jin et al., 2013, p. 25). The issue of stationarity and how to convert non-stationary time series to stationary must therefore be addressed prior to conducting further analysis of the time series and the relationship between them.

5.3.1 Augmented Dickey-Fuller Test

Sometimes, non-stationarity is obvious and can be detected by looking at the plotted graphs of the time series. But to ensure the correct treatment of the selected data, statistical tests are performed. Specifically, the Augmented Dickey-Fuller test is employed in this analysis to test for unit roots, causing non-stationarity. This paper will not address unit roots exhaustively, but a simplified way to address unit roots is by looking at a function of an autoregressive model with 1 lag, AR(1):

$$Y_t = \varphi Y_{t-1} + \varepsilon_t \quad , \quad t = 1, 2, \dots T$$

In this case $Y_0 = 0$, φ is the coefficient expressing the dependence on the lagged value when estimating Y_t, and ε_t is the estimation error assumed to be a normal distribution with mean 0 and variance σ^2 (Dickey & Fuller, 1979, p. 427). When $|\varphi| = 1$, the mean, expressed as the expected value $\mathbb{E}Y_t$ is: $1 \times \mathbb{E}Y_{t-1} = \mathbb{E}Y_{t-1}$, which again will have the expected value $\mathbb{E}Y_{t-1} = \mathbb{E}Y_{t-2} = \cdots \mathbb{E}Y_0 = 0$. This fulfils the criteria of constant mean. Although, the variance will be time variant, $t\sigma^2$, where increasing values of t implies increasing variance. If $|\varphi| > 1$, the expected value of Y_t would be exponential, since $\mathbb{E}Y_t = \varphi\mathbb{E}Y_{t-1} = \varphi^2\mathbb{E}Y_{t-2} = \varphi^3\mathbb{E}Y_{t-3}$ ... and so forth. Therefore, time series must have $|\varphi| < 1$ to fulfil the criteria of stationarity. Exponential means are easy to detect in a visual investigation, whereas the cases of unit roots are not always obvious due to the constant mean.

The function, `adftest` in Matlab tests for the null hypothesis of a unit root: $|\varphi| = 1$, and returns the rejection decision with the alternative hypothesis being $|\varphi| < 1$ (MathWorks, 2022a). The `adftest` by default conducts a *Dickey-Fuller* test with no lagged differences, which can be used, when testing for occurrence of a unit root in a simple AR(1) model. However, an Augmented Dickey-Fuller test, can evaluate more complex models, AR(p), where $p > 1$ and y_t depends on y_{t-1}, y_{t-2} … . y_{t-p}. When specifying the number of lags, p, in the `adftest`, the function will assess the null hypothesis of a unit root in time series AR(p):

$$y_t = c + \delta t + \varphi y_{t-1} + \beta_1 \Delta y_{t-1} + \cdots + \beta_p \Delta y_{t-p} + \varepsilon_t$$

Δ: the differencing operator, where $\Delta y_t = y_t - y_{t-1}$

p: number of lagged differences

c: the drift coefficient (in case of stochastic trend)

δ: the deterministic coefficient (in case of deterministic trend)

ε_t: the error at time t, being a mean zero innovation process (MathWorks, 2022a).

5.3.2 Data transformation

Non-stationary time series are transformed into stationary by taking the natural logarithm (log) of the values and taking the first difference of the logs (Lütkepohl & Krätzig, 2004b, p. 18).

$$\Delta \ln(Y_t) = \ln(Y_t) - \ln(Y_{t-1})$$

In case of seasonality in the time series, which is expected in certain economic variables, the data transformation instead implies taking the year-over-year difference. As we employ quarterly data, the seasonal difference is described by the following equation:

$$\Delta_4 \ln(Y_t) = \ln(Y_t) - \ln(Y_{t-4})$$

Using the natural log will offset an exacerbated variance, while taking the difference of logs omit the trend from the time series. Integration orders $KI(d)N$ refer to how many times, d, the difference must be applied to make the time series stationary (Lütkepohl & Krätzig, 2004b, p. 21). E.g., in the case of our data, some time series are $KI(2)N$, where the transformation is done by taking the first difference of the seasonal difference in log. The transformation of non-stationary time series ensure reliability, since potential timedependent trends and variance will be adjusted for avoiding spurious regression.

5.4 Vector Autoregressive Models

Given the economic theories suggesting interdependent relationships between economic parameters, it is regarded inadequate to conduct a univariate analysis to assess the effect of fiscal policies. To answer the RQ, the method employed to address the interdependence between multiple variables is vector autoregression (VAR). A VAR is a linear model with n equations for n variables. Each variable depends on the lagged values of itself and lagged values of the other variables in the model. The simple form of a VAR(p) model with k number of variables is:

$$y_t = c + A_1 y_{t-1} + \cdots + A_p y_{t-p} + \varepsilon_t$$

c is a vector with the length k with the intercept constants for each variable, ε_t is a vector with length k containing estimation innovations, converging to random distributions with mean 0. A_1 represents the matrix of $(k \times k)$ regression coefficients for the first lag, while A_p represents the regression coefficient matrix of the p lag (Krolzig, 1997, p. 10). A simple form of a first-order model, VAR(1), where the values of the first lag of all variables are determining present values, can be written out with matrices as following:

$$Y_t = \begin{bmatrix} y_{1,t} \\ y_{2,t} \\ \vdots \\ y_{k,t} \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_k \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1k} \\ a_{21} & a_{22} & \dots & a_{2k} \\ \vdots & & & \vdots \\ a_{k1} & a_{k2} & \dots & a_{kk} \end{bmatrix} \times \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \\ \vdots \\ y_{k,t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \vdots \\ \varepsilon_{k,t} \end{bmatrix}$$

In Matlab, `varm` objects are created, where values of k and p are specified, but without specifying any of the coefficients (MathWorks, 2022f). Instead, the coefficient matrices of the VAR(p) model is estimated, using the function `estimate`. This function applies a maximum log likelihood approach, where the coefficients are chosen, resulting in a best fitted model to the provided data sample (MathWorks, 2022b).

5.5 Granger Causality Test

When using a VAR framework, there is a chance of getting false results of correlation and coherence. If we have three different times series variables, y_{1t}, y_{2t}, and y_{3t}, a relationship between y_{1t} and y_{2t} might be inferred, which is caused by y_{3t} having an influence on both variables (Granger, 1969, pp. 424–426). Granger (1969) sought to overcome such issues, as he introduced partial cross-spectral methods, which today is known in econometric literature as testing for Granger causality. The statistical hypothesis assesses whether present and lagged values of the 'cause' variables, e.g., y_{2t}, improves the forecasting hsteps into the future of the 'effect' variable, e.g., y_{1t}. If we conduct an optimal h-step forecast of y_{1t} based on all 'relevant' information in the universe, Ω_t, we can assume y_{2t} not to be Granger causing y_{1t} if the following equation holds:

$$y_{1,t+h|\Omega_t} = y_{1,t+h|\Omega_t \setminus \{y_{2,s}|s \le t\}}, \qquad h = 1,2 \ldots \ldots$$

(Lütkepohl & Krätzig, 2004a)

The $A \setminus B$ refers to all the elements in the set A which is not contained in set B – in other words, all elements included in A minus B. The equation states, that if we remove the lagged values of y_{2t} it does not change the optimal forecast. Oppositely, y_{2t} would be Granger- causal for y_{1t} if the equation does not hold for at least one h – and thereby a better forecast is made by including the past values of y_{2t} in the information set. We notice that the model looks uniquely at how the cause variable, y_{2t}, impact the effect variable, Y_{1t}. No other variable influence the effect variable, which makes this great for testing for correlation and coherence in a VAR model (Lütkepohl & Krätzig, 2004a).

To conduct these Granger causality tests, the `gctest` package is used in Matlab, which performs `Block-Wise test`, `leave-one-out Test`, and `Exclude-All Test`. This paper will use `leave-one-out test`, which test the null hypotheses that a variable j does not Granger-cause variable k, conditioned on all the other time series in the model (MathWorks, 2022c).

5.6 Optimal Lag test

To secure the best fit between the collected data and the estimated model, the optimal order of lags needs to be decided on. This can be determined using either F-test or information criteria test. As F-test tends to produce larger models, minimizing the information criteria has instead been chosen. There are two known information criteria in econometrics, namely the Bayes information criterion (BIC) and the Akaike's Information Criterion (AIC). Both models are built on the same selection procedures, as it balances between minimizing squared residuals but also penalizing for adding an additional lag to the model (Stock & Watson, 2020, pp. 578–581). The formula for AIC is as follows:

$$\text{AIC (p)} = \ln\left(\frac{SSR(K)}{T}\right) + K\frac{2(T)}{T}$$ [vii].

(Stock & Watson, 2020, pp. 581, Equation 15.25).

The first term refers to the sum of the squared residuals (SSR), which necessarily decreases when adding an additional regression coefficient – lag – to the model. Oppositely, does the second term increase when including another lag as it punishes for introducing additional estimation error into the forecast. By a trial-and-error process, the model thereby chooses the amount of lag that minimizes the AIC.

To conduct these information criteria models, the `aicbic` function in Matlab has been used. The function fits competing models to the data, and thereby returns information criteria given the loglikelihood values. With this function, both information criteria candidates have been estimated in our analysis, where the model most suitable has been selected. This has led to the choice of the AIC being preferred in our analysis. Second, it has been decided that it is required that all our predictors have the same amount of lag, to make the computational demands within the feasibility of this project.

5.7 Threshold-switching vector autoregression model

When conducting a time series analysis, we might be interested in whether the behavior of the time series changes across different periods, or regimes. Our research itself lies on a puzzle regarding whether the behavior of the economic parameters depend on the macroeconomic environment. In such instances, regime switching models with times series become prudent. Within the classification of regime switching models are the Markovswitching model and the Threshold-switching model. The essential difference between the two models lies in the transition between states. The Markov-switching model's transition is non-deterministic and governed by a transition probability, while the Threshold-switching model is deterministic and governed by an observable data. (MathWorks, 2022e). To fit the RQ, *whether the effect of fiscal policies depend on the uncertainty in the economy*, a threshold model becomes the intuitive choice, as we can use an uncertainty variable to represent the threshold.

As introduced, the Threshold-switching model is deterministically governed by an observable variable, where the state transition occurs when $s_{\#\$!}$(in our case VIX) crosses a transition mid-level. The threshold variable can be exogenous or endogenous to the model, the latter returning a self-exciting model (Afonso & Baxa, 2011, pp. 13–14). Our model represents an instance of such, as our chosen threshold variable, VIX, also is in the system of our model. This has many advantages, one of them being able to make inferences on what impact other variables has on the threshold variable itself. In our instance, this includes looking into what impact fiscal stimulus has on the uncertainty variable itself in different states of uncertainty. This will be further elaborated in the analysis. Furthermore, the choice of either a discrete or smooth transition is decided upon, where in our case, this transition is discrete, which means an abrupt change from one regime to another (Afonso & Baxa, 2011). The threshold VAR can be defined formally as follows:

$$Y_{\#} = A^{!}Y_{\#} + B^{!}(L)Y_{\#\$!} + (A^{\&}Y_{\#} + B^{\&}(L)Y_{\#} - 1 \qquad)I[s_{\#\$!} > \gamma] + U_{\#}$$

(Afonso & Baxa, 2011, pp. 13, equation 1.)

5.8 Gibbs sampling

A practical issue with the threshold model is the identification of a threshold variable and estimation of a threshold value. Often it becomes a subjective matter, where a threshold value or variable is determined by the observation of some plots (Chen & Lee, 1995). To avoid such bias, the Gibbs sampling becomes a prudent tool to obtain an objective estimation of threshold parameters. Gibbs sampling provides the needed marginal posterior densities of the threshold value, using the Monte Carlo method. It uses a simulation technique to extract this marginal distribution from a conditional distribution when the joint distribution is not easily obtained (Chen & Lee, 1995). This means that we can gain the distribution of our uncertainty variable, using conditioned values of the other variables. While it is beyond the scope of this paper to further explain the theoretical foundation of Gibbs sampling and the Monte Carlo method, we instead emphasize the effectiveness of this model to ensure internal validity by avoiding projection biases.

To conduct the procedure above and estimate our TSVAR model, this research has used the codes and functions provided by Chen and J.C. Lee (2004). Here stationary data as well as lag preferences is inserted into the function, which in return provides an estimation of a time-varying threshold. The function can be customized to fit the model to our data, by controlling the number of Gibbs samplings replications, BURNS, and other variables relevant to the procedure.

5.9 Linear impulse responses

Given the composition of a VAR model, looking at the individual coefficients are inadequate to explain the effects of a shock in one of the endogenous variables. Thus, to address the RQ and examine the effects of fiscal policies in the different regimes of uncertainty, impulse response functions are constructed. This method evaluates the properties of the estimated VAR model and examines the effect of a shock in the time series.

Impulse response functions measure the response of $y_{\#\text{-}9}$ to an impulse δ at time t. In linear models, impulse response functions are derived by taking the difference of two realizations in $y_{\#\text{-}9}$. In the first realization, the function has been hit by a shock ε of size δ at time t, which is held against a 'benchmark profile' which is a second realization where there is performed no shock in time t. In the period between time t and time $t + h$, all shocks are set to be 0. The linear impulse response function has some characteristic properties. Firstly, it is assumed that the impulse response functions are symmetric in the sense that a shock of $-\delta$ has precisely the opposite effect of shock of size $+\delta$. Secondly, it is said to be linear, as the impulse response is proportional to the size of the shock $\varepsilon_{\#}$. Lastly, it is assumed the impulse response is history independent as it does not rely on any particular history or information from prior periods $\omega_{\#\$!}$ (Franses & van Dijk, 2000, pp. 125–128).

There can be contradictions if seeking to impose such linear impulse responses on a nonlinear or regime switching model. The main complication lies within the Wold proposition, which is the assumption of 0 shocks in the intermediate period. This does not hold in nonlinear models, as the effect of a shock $\varepsilon_{\#}$ depends on other current and past shocks. Furthermore, the effect of a shock may be further amplified or weakened as a shock lead to switches between the regimes. This means, that impulse responses are not linear nor symmetric, and history is taking into the equation $\omega_{\#\$!}$ (Franses & van Dijk, 2000). Koop, Pesaran and Potters (1996) introduced Generalized impulse response Function (GIRF) as a solution to the mentioned problems. However, due to the limits of this paper, it was chosen to conduct linear impulse responses, but take another procedure to still mitigate the mentioned hurdles.

In practice, the estimated threshold for the two regimes, extracted from the TSVAR model is used to define two new VAR models. The data frame of each VAR is conditioned on a dummy variable taking either the value 0 or 1, which reflect whether the given observation belong to the regime of low or high uncertainty, respectively. With the two new VAR models, each reflecting a regime, impulse response functions are created without facing the shortfalls of performing linear impulse responses on a non-linear model, since all data in each of the two different data sets occur in the same regime. To generate the impulse response function, the `irf` function in Matlab is applied. The output of the `irf` is the estimated cumulative response over time of the variables to a one standard deviation shock to a chosen variable in the VAR(p) model (MathWorks, 2022d). The 95% confidence intervals are generated, using bootstrapping of the residuals. This implies randomly selecting residuals and re-estimating the impulse responses including the residuals in a specified (preferably large) number of times (Lütkepohl, 2000, p. 4).

An implication of using the linear impulse response function, `irf` in Matlab, is that the produced function captures a finite response of the variables to a one standard deviation shock in one of the endogenous variables. This implies that the function does not capture contemporaneous reactions, which would imply further responses in the variables. Contrary, a recursive structure such as the mentioned GIRF approach, generates impulse response functions, where contemporaneous effects are captured and historic data is incorporated (Franses & van Dijk, 2000, pp. 125–129)).

5.10 Robustness tests

Finally, to assess the robustness of the estimated TSVAR(p) model, two additional models are constructed. In the first, the period will be limited to not include the data from the COVID-19 pandemic. Secondly, the DtGDP will be replaced with another fiscal policy variable, namely Financial Surplus or Deficit, which captures the balance between government revenue and government spending (Federal Reserve Bank of St. Louis, 2022a). The first robustness test model will indicate whether the estimated model is robust over different periods of low and high uncertainty, while the latter will assess the consistency of the model regarding the choice of fiscal policy indicator.

6 ANALYSIS

6.1 Stationarity and data transformation

Assessment of the stationarity is the first step, when analyzing time series data. First, a visualization of the quarterly levels of the time series is useful to assess whether the stationarity criterion is fulfilled. Below is the visualization of the five variables: GDP, CPI, DtGDP (debt-to-GDP ratio), SI (short-term interest rate) and VIX index.

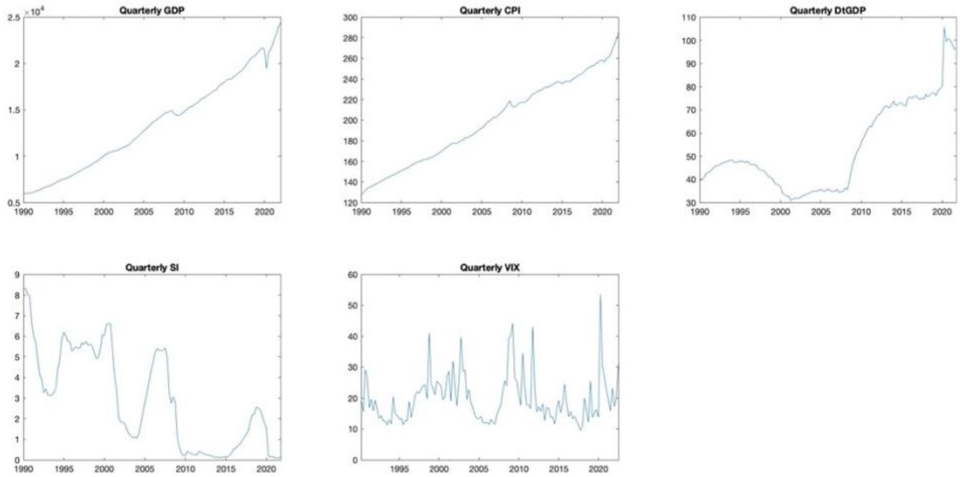

Figure 1 *Data in level-form showing quarterly developments in GDP, CPI, SI, DtGDP and VIX.*

Obvious increasing trends can be seen in the visualization of GDP, CPI and DtGDP. The SI exhibits a decreasing trend and time-varying variance. The stationarity of the VIX is more difficult to determine since it appears as a time series with a constant mean. Although, the variance appears time-varying, considering the increasing variances in later years. Thus, the visualization indicates non-stationarity in all the time series, but ADF tests for each time series are necessary to get a more qualified evaluation.

The `adftest` returns the decision whether to reject the null hypothesis of nonstationarity. The initial number of lags, p is set to two, when conducting the tests. The test will conduct 3 tests, with no lagged differences included in the first test, one lagged difference in the second and two lagged differences in the third test, when testing for the presence of a unit root (Federal Reserve Bank of St. Louis, 2022b).

6.1.1 Gross domestic production (GDP)

Looking at the visualization, GDP has an upward trend, exhibiting continuous economic growth in the U.S. economy throughout the period. It indicates a deterministic trend, only with few drops in the levels around 2008 and 2020, associated with the global financial crisis and COVID-19 pandemic. Results from the `adftest` supports the assumption, when the level-form time series is evaluated, why data transformation is necessary. The `log` function adjusts the y-scale, by bringing down the values from billions to natural logarithms. Afterwards, the seasonal difference is applied, adjusting for structural seasonal differences. Since the seasonal difference is not adequate in this case to transform the data to a stationary time series, the first difference of the seasonal differences is also applied. The results of the ADF tests with 0-2 lagged differences are shown below and indicates that GDP is integrated at order 2, $I(2)$, since the null hypothesis is not rejected until the first difference of the seasonal difference is applied.

	$\boldsymbol{GDP_{level}}$		$\Delta_S \ln(\boldsymbol{GDP_t})$		$\Delta(\Delta_s \ln(\boldsymbol{GDP_t}))$	
Lagged difference	H	P-value	H	P-value	H	P-value
0	0	0.999	0	0.0919	1	0.001
1	0	0.999	0	0.1747	1	0.001
2	0	0.999	0	0.1285	1	0.001

Table 3 *ADF test on the GDP Variable.*
H:0 indicates no rejection of the null hypothesis of non-stationary at confidence level 95%.
H:1 indicate rejection of the null hypothesis of non-stationarity at confidence level 95 %

The visualization below shows graphically how the data becomes increasingly more stationary, taking first the seasonal difference, followed by the first difference.

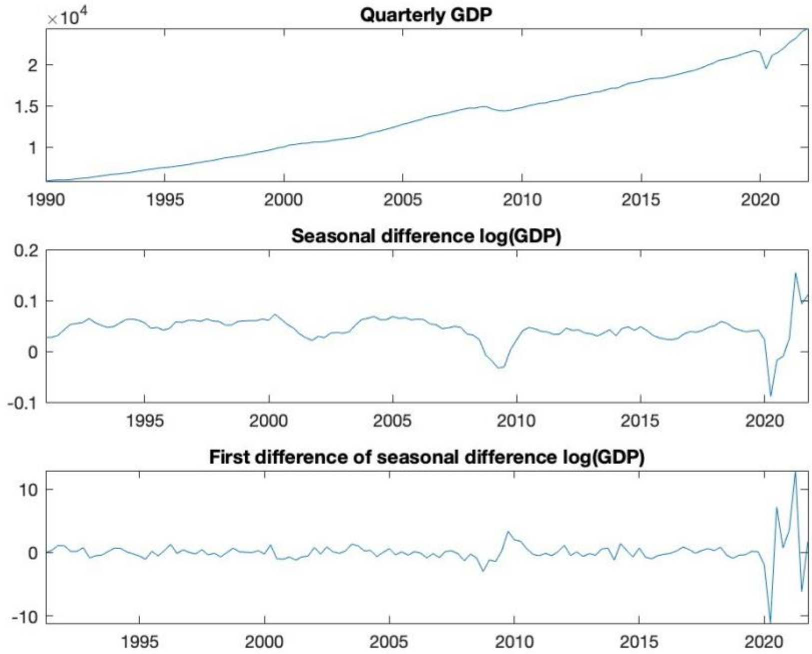

Figure 2 *GDP time series with level-form, seasonal difference, and first seasonal difference*

6.1.2 Consumer price index (CPI)

Given the visual similarity between GDP and CPI, when looking at the time series in levels, similar assumptions are made concerning the stationarity of CPI. The upward trend appears deterministic and is related to the increasing GDP. Increasing production is logically associated with higher prices, because more money will circulate in the economy and producers of goods and services can charge a higher premium for the same products that people will be willing to pay due to a higher averaged wealth.

The test results show that CPI is a time series of $I(2)$, why the first difference of seasonal difference is used in the further analysis.

	CPI_{level}		$\Delta_S \ln(CPI_t)$		$\Delta(\Delta_s \ln(CPI_t))$	
Lagged difference	H	P-value	H	P-value	H	P-value
0	0	0.999	0	0.2102	1	0.001
1	0	0.999	0	0.1343	1	0.001
2	0	0.999	0	0.2057	1	0.001

Table 4 *ADF test on the CPI Variable.*
H:0 indicates no rejection of the null hypothesis of non-stationary at confidence level 95%.
H:1 indicate rejection of the null hypothesis of non-stationarity at confidence level 95 %

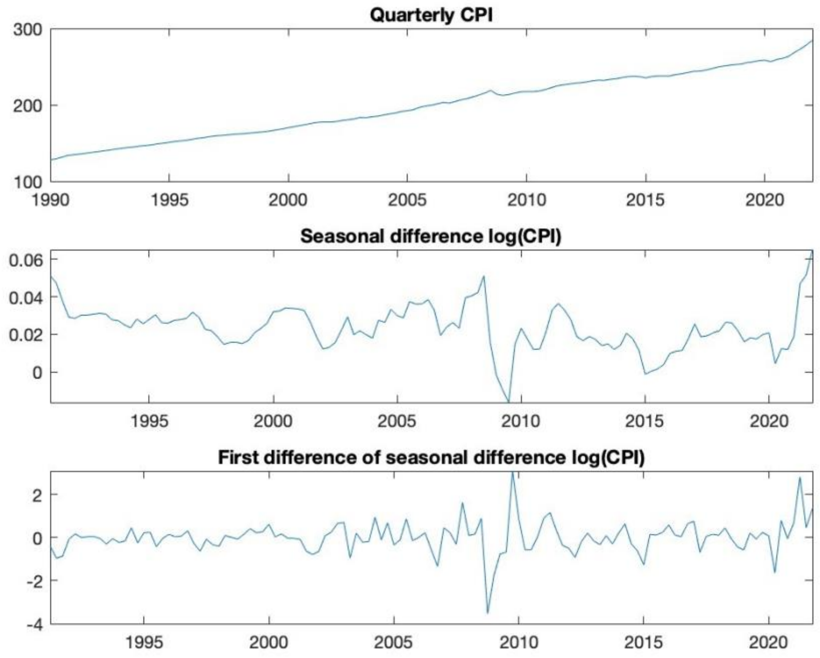

Figure 3 *CPI time series with level-form, seasonal difference, and first seasonal difference*

6.1.3 Debt-to-GDP ratio (DtGDP)

The trend in DtGDP appears less deterministic, compared to GDP and CPI. Although, an upward trend is obvious indicating a time-variant mean. The difference is again adjusting for seasonality, but instead of continuing transforming the data using a first difference, the ADF test indicates that DtGDP is $I(1)$, thus one difference is enough to make the data stationary.

	$DtGDP_{level}$		$\Delta_S \ln(DtGDP_t)$	
Lagged difference	H	P-value	H	P-value
0	0	0.9913	1	0.0052
1	0	0.9950	1	0.0044
2	0	0.9876	1	0.0022

Table 5 ADF test on the DtGDP Variable.
H:0 indicates no rejection of the null hypothesis of non-stationary at confidence level 95%.
H:1 indicate rejection of the null hypothesis of non-stationarity at confidence level 95 %

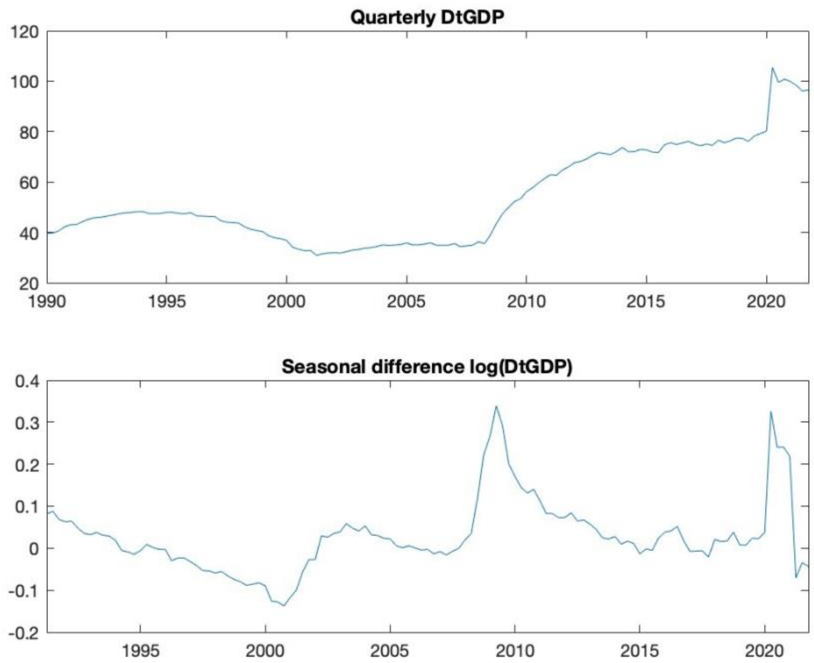

Figure 4 DtGDP time series with level-form, seasonal difference, and first seasonal difference

6.1.4 Short-term interest rate (SI)

The stationarity of short-term interest rate is more difficult to assess. The mean appears to be trending downwards, and further the variance is not constant, but jumps up in some periods, indicating a stochastic trend. Meanwhile, the results from the ADF test rejects the null hypothesis of non-stationarity when tests are conducted assessing 0-2 lagged differences. Based on the prior assessment of the visualized time series, a second ADF test is conducted, including more lagged differences. Adding more lags minimizes the risk of type I error, where the null hypothesis of non-stationarity is mistakenly rejected. This precaution resulted in a first difference transformation, since the test including 4 lagged values failed to reject the null hypothesis. The ADF tests with 0-4 lagged differences provide the following results:

	SI_{level}		$\Delta_S \ln(DtGDP_t)$	
Lagged difference	H	P-value	H	P-value
0	1	0.0128	1	0.0053
1	1	0.0206	1	0.001
2	1	0.0279	1	0.001
3	1	0.0215	1	0.001
4	0	0.0705	1	0.0138

Table 6 ADF test on the SI Variable.
H:0 indicates no rejection of the null hypothesis of non-stationary at confidence level 95%.
H:1 indicate rejection of the null hypothesis of non-stationarity at confidence level 95 %

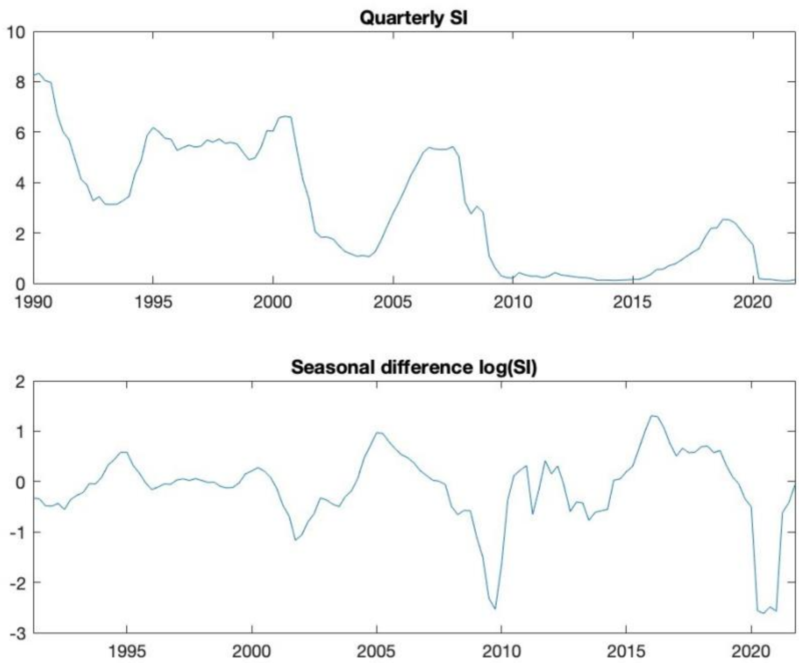

Figure 5 SI time series with level-form, seasonal difference, and first seasonal difference

Comparing the level-form with the seasonal difference of short-term interest, the transformed data appear more stationary revolving around a constant mean, compared to the time-varying mean trending downwards in the first graph.

6.1.5 The CBOE Volatility Index (VIX)

The VIX in level-form seems closer to qualify as a stationary time series, since there is no obvious trend. However, there appears to be increasing variation, indicating time-varying variance. The results from the ADF test back up the assumption of non-stationarity, why the seasonal difference of log is applied, making the data stationary.

	VIX_{level}		$\Delta_S \ln(VIX_t)$	
Lagged difference	H	P-value	H	P-value
0	0	0.0516	1	0.001
1	0	0.2133	1	0.001
2	0	0.2648	1	0.001

Table 7 ADF test on the VIX Variable.
H:0 indicates no rejection of the null hypothesis of non-stationary at confidence level 95%.
H:1 indicate rejection of the null hypothesis of non-stationarity at confidence level 95 %

The difference between the level-form and the seasonal difference of log, is not as obvious, compared to the other transformations. Although, it is clear how the variance is more even throughout the period.

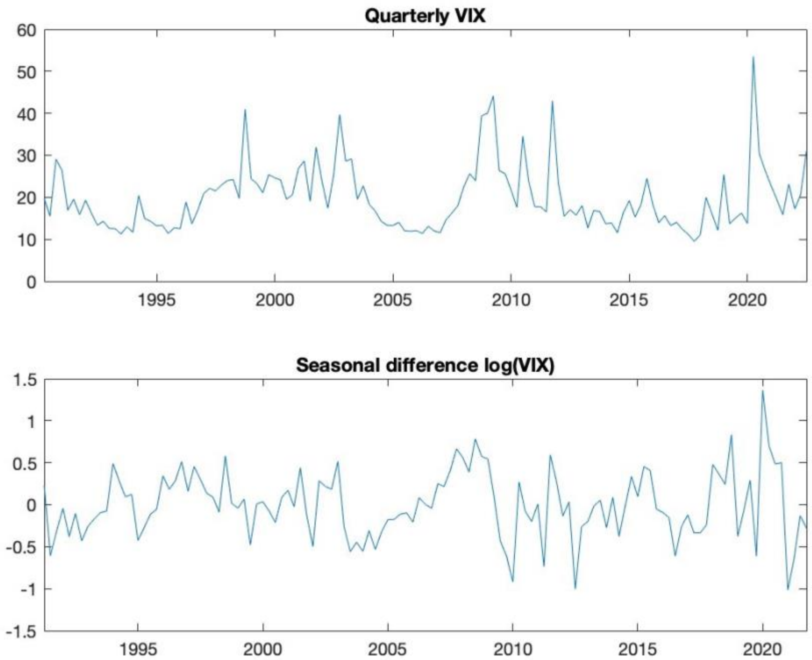

Figure 6 *VIX time series with level-form, seasonal difference, and first seasonal difference*

6.2 Granger Causation

As outlined in the methodology part, we conducted a `leave-one-out test` in Matlab to test for Granger causality. This test assesses whether present and lagged values of a variable improve the forecasting of another variable. We use our stationary data when conducting this test to avoid spurious regression because of similarly trending data (MathWorks, 2022a). The test first estimates a best-fitted VAR model, followed by a statistical hypothesis testing. Here we are provided with the following results, see Appendix 1.

Firstly, we observe that the test identifies 5 lags (p) as the optimal order of lags for securing the best fitted model using the AIC information criteria. This will be used for comparison measures, when computing the log-likelihood and information criteria next. Following this, a 20 statistical hyphotesis test is conducted on Granger causation. To summarize our findings, we find the following at a 5 % level of signficance:

1. *We can reject the claim that DtGDP ratio is* not *the 1-step Granger-cause of GDP, conditioned on all other variables.*
2. *We can reject the claim that GDP, CPI, DtGDP and VIX is not the 1-step GrangerCause of SI conditioned on all the other variables.*

3. *We can reject the claim that VIX is not the 1-step Granger-cause of GDP and DtGDP, conditioned on all the other variables.*

The first two findings suggest that DtGDP is useful in forecasting GDP and GDP, CPI, DtGDP and VIX is useful for predicting the SI. This supports the choice of DtGDP as our policy variable, as it seems able to forecast the other key macroeconomic variables. The second statement suggests that the SI can be predicted by our other variables which is not to any surprise, as the interest rate is determined by financial markets and their demand for loanable funds. Thirdly, we observe an interesting finding of the ability of VIX to predict GDP and DtGDP. The forecasting power of VIX, supports our initial reasoning behind the choice of the TSVAR model and the VIX as our threshold variable. This is because the uncertainty variable contains information that have some forecasting impact on the level of output and debt undertaken - to support a fiscal policy. This must necessarily also indicate, that dividing our dataset into two periods of low and high uncertainty, can only further improve the forecasting abilities of the VIX variable. As this is *not* causality in the form of a cause and effect, but only an indication of some prediction power of one variable over another, therefor information is only used as pointers of potential implications, but not interpreted as a significant result.

The `leave-one-out test` was also used as a robustness tests to ensure we included the best variables. As mentioned in the data selection, we trialed different variables in the initial state of picking the most optimal model. This included macroeconomic indicators such as the T-bond rate, Exchange Rate, Unemployment Rate, Government spending, Industrial Production and Global Economic Policy Uncertainty. This process implied both the construction of separate models with other variables, but later in the process, we also introduced other variables to our main model. An example of such process was the trial of replacing short-term interest rate with long-term interest rate. These tests ensured us that our model had construct validity in measuring the effects of fiscal policy.

Furthermore, the Granger causality test was useful in securing the most optimal order of variables. To realize the impulse response (IRF), a lower-triangular Cholesky decomposition is used by Matlab. While it is beyond the limits of this paper to go in-depth with the

Cholesky factorizations, it is important to understand the underlying mechanism to secure the best results in our analysis. The main idea behind the lower-triangular Cholesky decomposition is that the ordering of variables should be done after an exogeneity criterium. This implies that the most exogenous variable is put first followed by the second most exogenous… (Stock & Watson, 2020, p. 585). Therefore, the last variable in the multivariate equation should all other time series have an impact on.

Building on the results of the Granger causality test, we furthermore use findings of optimal ordering from similar literature. Here we especially rely greatly on Afonso et. al., and their analysis on fiscal developments and financial distress also using a TSVAR method (Granger, 1969; MathWorks, 2022c). Using their ordering of variables as a baseline, the selected order of variables is chosen as followed; GDP, CPI, DtGDP, SI, VIX. This has the following implications 1) Output does not react contemporaneously to shocks to other variables in the system 2) CPI reacts on shock in output, but does not react to shocks in DtGDP, SI or VIX 3) The debt-ratio, representing the fiscal variable, can react to GDP and CPI shocks, but not to any contemporaneously shocks in SI and VIX 4) The short-term interest rate does not react to any contemporaneously VIX shocks, but will react to contemporaneously shocks in GDP, CPI and DtGDP 5) VIX will react to contemporaneously shocks in any of the other variables in the system.

The rationale behind this variable ordering is grounded in some assumptions behind the economy, with the main ideas being presented in the following: 1) CPI is placed after GDP as the level of inflation could be assumed to be contemporaneously affected by shocks in output. 2) GDP and CPI are placed before DtGDP since any shock in output or inflation have immediate impact on the DtGDP ratio. 3) Adding to this reasoning of the ordering of the DtGDP variable, it can be justified that any shocks in DtGDP, will first be observable in output or inflation after one quarter, as there are implementation lags of fiscal policy expansions as mentioned by Blanchard and Perotti (2002). Any reaction in either variable (GDP or CPI) to a fiscal policy within one period could be expected to be the effects of automatic stabilizers such as progressive tax or unemployment benefits. (Afonso et al., 2011, l. 14). 4) DtGDP is placed before SI and VIX as we could expect any change in fiscal expansion to be unrelated to the business cycle and hence it seems reasonable to assume that government spending is not affected contemporaneously to any shocks from the private sector. 5) The SI reflecting the money-demand of business actors, will and can react contemporaneously to a shock in either output, inflation or increased government debt (Afonso et al., 2011, pt. 14; Caldara & Kamps, 2008, pts. 13–14). 6) Lastly, we place our uncertainty variable, VIX, last in the system, similarly to Afonso et. al, placing their financial stress index (FSI) last. Like SI this is built on the key assumption that all changes and shocks in fiscal policy is shown in the financial markets within one quarter (Caldara & Kamps, 2008, pts. 13–14). VIX is placed after SI as interest rates is not purely corresponding to the market, since the rate is initially set by the FED. This implies that there are potentially some implementation lags within the variable of SI, which is not expected with the VIX as it purely reflects financial markets volatility expectations.

It should be noticed, that after the period in which the shock occurs, all variables in the equation are allowed to interact freely. This for example implies that DtGDP can impact GDP after the quarter in which the shock has occurred.

6.3 Optimal lag order

To secure the best fitted model, a computation of information criteria is done to choose the optimal length of lags. Before being able to conduct AIC and BIC test, data on the loglikelihood for each possible model needs to be computed. Therefore, VAR models with 1 to 10 lags are estimated, in which we obtain the log-likelihood for each model as well as the number of parameters. This we gather in the following data frame:

```
Tbl =

  10×2 table
```

	logL	numParam
Model1Lag	494.66	30
Model2Lag	532.65	55
Model3Lag	553.12	80
Model4Lag	622.42	105
Model5Lag	657.49	130
Model6Lag	647.33	155
Model7Lag	682.95	180
Model8Lag	711.76	205
Model9Lag	732.16	230
Model10Lag	762.49	255

Table 8 *log-likelihood from 1-10 lags for our estimated model.*

While we observe the log-likelihood and hence the goodness of fit increase as we add another lag, it is important to notice that adding more predictors will always increase the log-likelihood even if it is not improving the prediction. Therefore, we cannot compare these results directly without conducting the AIC and the BIC test which takes number of predictors into account. We conduct the AIC and BIC on all candidate models, and the following results are estimated:

```
ans =

  10×2 table

      aic        bic
    _______    _______

    -929.31    -845.19
    -955.31    -801.09
    -946.23    -721.91
    -1034.8    -740.41
      -1055    -690.45
    -984.67    -550.04
    -1005.9    -501.18
    -1013.5     -438.7
    -1004.3     -359.4
      -1015    -299.96
```

Table 9 AIC and BIC information criteria for 1-10 lags for our estimated model.

As explained in the methodology section, the lowest information score is preferred (not in absolute terms). The AIC finds the best-in-sample fit a fifth-order lag model, while the BIC suggests a simpler first-order lag model. This disagreement of optimal-lag order is not to any surprise, as it showcases how the BIC imposes a greater penalty for adding extra predictors. We choose to proceed with the AIC model as it provides us the best model for estimating our threshold value. This will be elaborated on further when providing the results of the Threshold-switching model.

Hence the analysis proceeds with the 5 variables, and the estimated optimal order of 5 lags decided with the AIC information criteria. The following equation is the estimated VAR (5) model:

$GDP_{,"\%\&}$

||⌈ $DtGDP^{GDPCPI_{,",”}}$]| |⌈−−000..154190016.0083^{e}|⌉⌈|−−00..28590575 ++ 00..35282255

+− 10..55614405 −− 00..06570269 −− 00..15850442⌉ ⌈| $CPI_{,"\%\&}$

]||

$Y_t = \| \; SI_t \; \| = \| \; -00.0204.0131 \; \| +$

|||−000..92170760.0782++−100..12363579.0397+++310..22264512.8099−++010..18240361.0118−
++000..32533748.0359||| × |||DtGDPVIXSI,",%"%&,"&%& ||||

⌊ VIX," ⌋

−0.1396 − 0.0850 − 2.2615 + 0.1079 + 0.1363 ⌈ GDCPIP,",″%%″ ⌉|

\+ ⌈|−00.1236.0047−+00.1455.0691++00.5554.3339+−00.0218.
0239+−00.0452.0325||| × ||DtGDP,"%' ||

|−0.5858 + 0.0594 − 7.5284 − 0.2774 + 0.2367| | SI"%' |

⌊ 0.4224 + 0.3100 − 2.1201 − 0.2109 + 0.1929 ⌋ ⌊ VIX,"%' ⌋

⌈|−0.2782 + 0.3977 − 0.0032 − 0.0687 − 0.0825|⌈ GDPCPI,",″%%((⌉|

−0.0481 + 0.1652 − 0.0754 + 0.0477 − 0.0193| |

\+ |0.0964 − 0.0353 + 0.2765 + 1.3686e + 0.0208| × |DtGDP,"%(|

|||−00.1696.5787−+00.2844.6742−+12.0319.3457++00.1945.2484+−00.1786.1056|||

||| VSIXI,",%"%((|||

⌈

\+

|||−−−0000.1909...003720360031−+−−1000.0129...584210753948+++−4021.0502...121366642195
−−+−0000.6874...093004930182++−−0000.0438...005405050035|||| ×
|||||DtGDPGDPCPISI,",%",″%%),″))%) |||||

⌊−0.3366 + 0.1885 − 2.3812 + 0.0804 − 0.5725⌋ ⌊ VIX,"%) ⌋

⌈ 0.0947 + 0.4545 − 1.7116 + 0.0775 − 0.0896 ⌉ ⌈ GDP,″,"%%** ⌉| | ε+,-," ⌉

CPI ⌈ ε/-0,"

\+ ||−00.0079.0480−+00.1012.2447+−00.6294.2448−−00.0034.0044+−00.0177.0175|| ×
||DtGDP,"%*| + |ε,"+,-," || viii

| 0.5824 + 0.1530 − 2.1790 + 0.4167 − 0.0519 || SI,"%* ||| ε10," ||⌊0.0266 − 0.42728
\+ 3.3893 − 0.0387 + 0.4324⌋|⌊ VIX,"%* ⌋|⌊ ε203," ⌋

6.4 Threshold-switching vector autoregressive model (TSVAR)

6.4.1 Time-varying threshold

After estimating the optimal lag of 1 or 5 according to the BIC and AIC tests, respectively, the estimated VAR(1) and VAR(5) models of the data sample are tested in the code provided by

Chen and J.C. Lee (2004) to estimate the Threshold-switching VAR. The output, when using 1 lag is a TSVAR with regime 1 only containing the very low levels of uncertainty and regime 2 capturing the rest. Since the research seeks to cover different effects of fiscal policy, distinguished by low to moderate levels of uncertainty in one regime and high uncertainty in the other, the results using VAR(1) is discarded. Instead, the VAR(5) is applied, resulting in the intended distinction of two regimes: one with lower values of the seasonal difference in VIX and one with high values, hereafter referred to as the low and high regime, respectively. Given the simulation with 20000 Gibbs replications, the estimation of the time-varying threshold, Y^* will vary, when the code is repeated. One simulation is presented below, while a second is provided in appendix 2, which provides similar distinctions between low and high regimes of uncertainty with 91 cases of low regimes and 27 cases of high regimes of uncertainty in both simulations.

The distribution of low and high regimes in terms of uncertainty captured by the VIXvariable, is seen above. The time-varying threshold variable is depicted as the blue graph. The grey bars mark the low uncertainty regimes, where the VIX is below the threshold and the white areas mark the high uncertainty regimes, where the VIX exceeds the threshold. The time-varying threshold provides a relative threshold, instead of an absolute value. This means that the algorithm considers the macroeconomic environments in each quarter and assesses at what value of VIX, the dynamics shift from one regime into another at the given time.

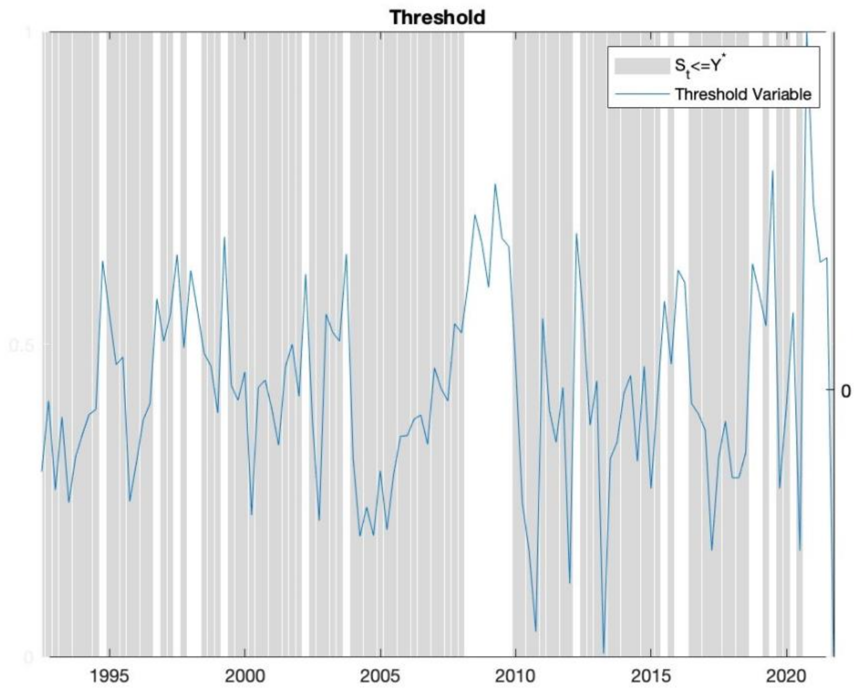

Figure 7 *Time-varying threshold across the sample period.*

6.4.2 VAR models for low and high regime

To estimate VAR models with the data from the low and high regime, the dummy variable for the high regime is used to subset the data sample into two sets of data. The dummy variable for the high regime returns the logical value 0 if false and 1 if true. The data tables created using the dummy variable are presented in the appendix 3. The algorithm producing the time-varying threshold, uses data from the period 1991:Q2 to 1992:Q2 to initiate the estimation of the threshold. The use of a pre-sample in the TSVAR model estimation, supports the choice of looking at a longer period, compared to only focusing at e.g., COVID19 with less observations.

Given the reduction of observations (from 128 to 118) stemming from the pre-sample period and the separation into two separate data sets, the order of the VAR(p) models are chosen *a priori*, instead of conducting another AIC test. The challenge of the few observations is similar to the one faced by Afonso et al. (2011), where the issue is solved in the same manner, choosing 1 lag for estimating the VAR models for the two regimes with few observations. Using 1 lag, the estimated coefficients of $\text{VAR}_{\text{low}}(1)$ and $\text{VAR}_{\text{high}}(1)$ are as follows:

GDP

$DtGDCPI_tP_t$

000..00320079.002

−−000.0377..00731395

$Y_t =$

SI_t −0.173 1.7919

VIX_t −0.0116 0.3500

−0.0940 0.2433 −0.0025 −0.0141
0.0806 0.0475 0.0186 0.0172
−0.0350 0.7901 0.00079
0.3619 0.5588 0.6467
0.5491 −0.8501 −0.0400

−0.0133
0.0165
0.1265

$\times$ $DtGDGCPDPI_{t-1}P_{t-1}$ $+$ ε

SI_{t-1} ε

VIX_{t-1} ε

GDP

$DtGDCPI_tP_t$

−000..00620.0106001

−000..00711232.1618

$Y_t =$

SI_t −0.0346 −1.2097

VIX_t −0.0375

−0.1389

−0.5047 0.0544 −0.0899 −0.3375
−0.2485 −0.2296 −0.0486
−0.2061 0.6542 0.0141
3.1057 −1.9584 0.3734 −0.1509
−0.0524 0.1027
−0.3087
−0.7780 0.0469 0.1656

$\times$ $DtGDGDGCPPI_{t-1}P_{t-1}$ $+$ ε

SI_{t-1} ε

VIX_{t-1} ε

6.5 Impulse response functions

This analysis will only elaborate on the changing dynamics related to DtGDP, which addresses the research question of this paper, namely ***how does the effect of fiscal policy change with the level of uncertainty in the United States?*** Impulse response functions (IRF) from a one standard deviation in DtGDP are therefore created based on the estimated $\text{VAR}_{low}(1)$ and $\text{VAR}_{high}(1)$.

6.5.1 IRF of GDP with a shock in DtGDP in low and high regime

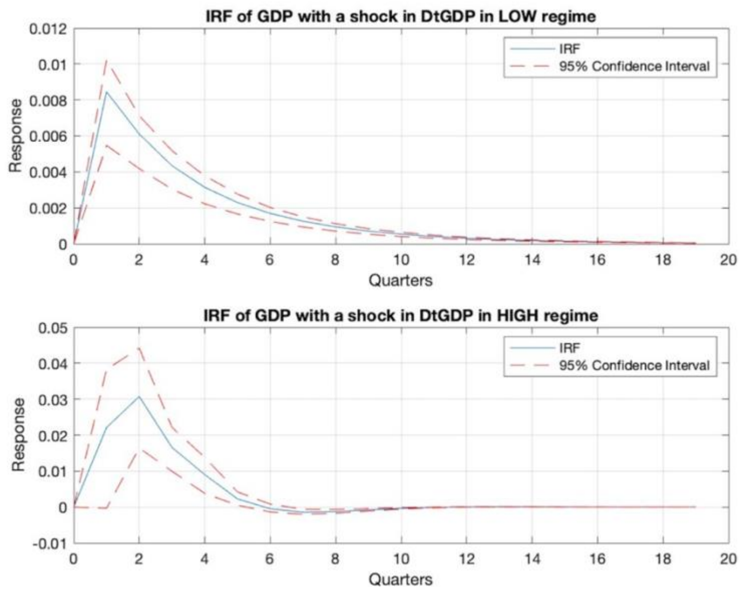

Figure 8 *IRF of GDP with a shock in DtGDP in low and high uncertainty regimes.*

The effects on GDP from a one standard deviation (SD) positive shock in DtGDP can be read from the IRFs in figure 8. The response of GDP in the low regime is presented in the upper graph, while the effect in the high regime is presented in the bottom. The blue graph represents the estimated cumulative IRF, while the red dotted lines are the lower and upper 95% confidence intervals. In the low regime there is an immediate significant increase in output, where both the lower and upper confidence intervals exceed zero. The output growth is subsequently increasing but at a lower rate until around the 16th quarter, where the effect is zero. The explanation of the immediate boost in output depends on the type of fiscal expansion. In the case of demand-side policies, government spending may invest in large projects, e.g. the construction of new infrastructure. The immediate boost in output is then generated by the demand for products and services to carry out the project. On a midterm horizon the demand for employees to undertake activities and sustain the project leads to lower unemployment, which increases demand and household consumption, implying increasing output. The projects may also have spillover effects in local communities, generating more projects and attracting private and public economic activity.

Another type of fiscal expansion, leading to increased GDP is through more direct stimulus in terms of cash transfers, often seen to be targeting low-income individuals or by decreasing tax revenues. Such transfers imply a direct improvement of people's purchasing power. These direct expansionary fiscal strategies give an immediate boost to output but are less permanent.

Looking at the IRF of GDP in the high regime, the fiscal multiplier is observed with one quarter delay, but peaks in the second quarter at a significant higher level compared to the low regime. However, the significant growth is less long-lived, since the positive effect dies out in the 6th quarter. The stronger response in times of uncertainty, may be caused by the crowding in effects of private consumption and investment, described in Goemans (2022). In times of high uncertainty, the private consumption will be at a depressed initial level, compared to times of low uncertainty. Therefore, the same fiscal expansion, will have proportionally larger impact on private consumption and employment in the high uncertainty regime (Goemans, 2022).

The two IRFs of GDP are quite similar in shape, although the short-term impulse in a high regime of uncertainty is remarkably larger. The difference can be explained, referring to the difference in the initial levels of consumption and unemployment prior to the shock. Additionally, a combination of elements from Goemans (2022) and Weinstock (2021) provides an interesting explanation to the difference in IRF of GDP across the regimes of uncertainty. Goemans finds that during times of uncertainty, governments employ revenue decreasing policies through tax cuts, whereas both revenue decreasing and government spending policies are employed during times of uncertainty. Further, Weinstock suggests that a higher fiscal multiplier is derived from government spending tools compared to tax cuts. The observed variation in the IRFs between the low and high regimes can therefore potentially be explained by the employment of different fiscal strategies with varying fiscal multipliers.

6.5.2 IRF of CPI with a shock in DtGDP in low and high regime

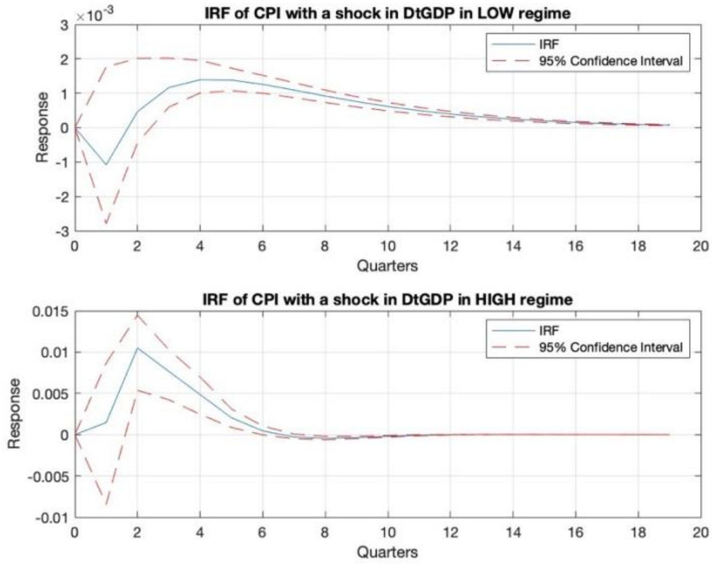

Figure 9 IRF of CPI with a shock in DtGDP in low and high uncertainty regimes.

In the presented graph we observe the effects of a shock in the DtGDP of one SD on the CPI variable serving as a proxy for the inflation. The upper graph, representing the lower uncertainty regime, shows insignificant results until the second quarter, whereafter a statistically significant positive relationship can be identified. This is seen by the upper and lower confidence intervals are above 0. This is in ordinance with agreements among economists that fiscal policy usually leads to (some extent of) inflation as price stickiness is temporary. This is reasoned by price flexibility will respond to the higher demand by increasing wages as well. While this will lead to temporary growth in output due to increased consumption, eventually producers will also increase their prices to offset this increased cost of production. This will channel through the rest of the economy and crowd out the effectiveness of the fiscal policy (Weinstock, 2021, pp. 3–4). This crowding out effect is evidential in the graph, as we observe significant increase in inflation until the 18th quarter.

Same mechanisms as noticed in the low uncertainty regime, can be said to be present in the high uncertainty regime - only more intensified. In the high regime, a steep increase is observed, peaking in the second quarter. Afterwards the effect slowly erodes, although CPI still increases significantly until the end of the 5th quarter. The amplified effect, in contrast to the low uncertainty regime, might be explained by depressed demand being a more disproportionate problem in the high regime. If we continue our example above, we might observe some sectoral or regional parts of the economy experiencing recession, while other holding normal economic conditions. As the government seeks to fight this problem of depressed demand, they pump up the economy through fiscal expansions. Yet, in such situations these actions might further hurt the economy. In the already tight sectors or regions, the increased demand might create a 'bottleneck' as employees will negotiate for higher wages. This will initially push up the prices in these regions and sectors, which will quickly spread to rest of economy, leading to overall inflation. Often this inflation will be evident before the full realization of the infrastructure spillovers can contribute to the demand in the depressed parts of the economy. In such instances, these government actions implies a negative fiscal multiplier, as individual income in the slagged parts of the economy will be worth less (due to increased prices) and thereby further depressing consumption (Goemans, 2022). Thus, these uneven economic conditions could potentially cause a negative fiscal multiplier.

In short, we observe the same trend in both regimes confirming theory that fiscal policy leads to increased prices due to higher demand. This implies that the potential effects of a fiscal policy might be partially crowded out due to an increase in prices. More surprising is the finding that a fiscal expansion affects inflation greater in times of high economic uncertainty. This might be explained by tightness in some specific sectors leading to significant price increases as governments pursue fiscal expansion. This interesting finding as well as its potential implication will be discussed later on.

6.5.3 IRF of SI with a shock in DtGDP in low and high regime

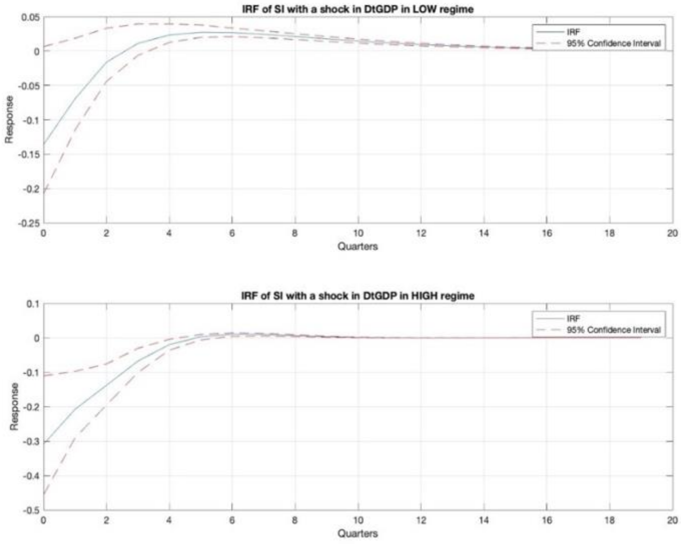

Figure 10 *IRF of SI with a shock in DtGDP in low and high uncertainty regimes.*

This graph shows the effect of a one SD shock in DtGDP on SI. We start by looking at the low regime in the upper graph. Initially there are no signs of significant impulse response in the SI, as we observe that the confidence interval embraces 0. However, a small increase in the SI is observable from the fourth to 15th quarter. These ambiguous results might be an example of the crowding out effect taking place. As the government increases their borrowing or debt to finance an expansionary fiscal policy, it necessarily puts a pressure on the demand for money. As the demand for loanable funds increases, the interest rate must subsequently increase to reflect the higher demand. This implies that it becomes more expensive for households and businesses to undertake investments, which diminish privateactors spending (Mitchell et al., 2019a, p. 341). It should be noticed that this impact is only minimal, implying a limited crowding out effect.

Additionally, the IRF of GDP to a shock in DtGDP in the low regime, supports this explanation of an increase in the SI. Immediately GDP increases (see figure 8), which is associated with higher domestic consumption and demand, including demand for interest-sensitive goods and services. Such products could be cars and real estate, which require households to take on loans, and hence this increases the demand for borrowing funds, leading to the delayed response of an increased SI as observed above.

Looking next at the high uncertainty regime, we observe the opposite tendency. Here the impact of a shock in DtGDP has a negative impact on SI. While this immediate impact is eventually flattened out, it remains significantly negative until the 5th quarter. This tendency might be explained by the Ricardian equivalence and private actors' rational expectations. If we assume them to be rational, forward-looking and have some information of the current government deficit level, they might react negatively to a fiscal expansion pursued in an uncertain economic environment. As consumers and business actors are aware that the debt undertaken by the government needs to be paid back, it might offset a reaction of increased saving and risk-aversion. Such response might be further amplified if private actors assume that the debt undertaken is unsustainable in an already uncertain economic environment. This impacts the interest rate oppositely to the low uncertainty regime, as the depressed demand is reflected in the market with a reduction in the interest rate (Weinstock, 2021, pp. 1–2). It is however worth noticing that this potential significant negative impact is only observed shortly, as it bounces back to initial levels, which could suggest that this suppression of demand only being a temporary effect.

The two graphs of the IRFs of SI on a shock in DtGDP represent different macroeconomic relationships being activated depending on the uncertainty environment. In a low uncertainty regime, a fiscal stimulus plan can lead to an increase in SI. These rising interest rates directly crowd out the effects of the fiscal multiplier, as it diminishes private sector spending. Oppositely, in a high uncertainty regime, an additional demand for loanable funds might not increase the interest rates as the demand is already depressed. Yet, as we observed in the graph, the impact might still be crowded out due to Ricardian households and business actors saving more because they are worried about the potential future.

6.5.4 IRF of VIX with a shock in DtGDP in low and high regime

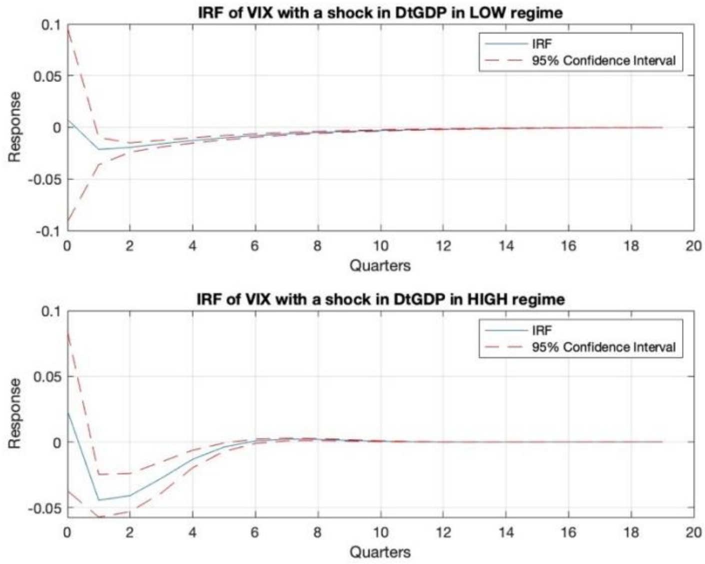

Figure 11 *IRF of VIX with a shock in DtGDP in low and high uncertainty regimes.*

This graph presents the IRF of the VIX from a one SD shock in DtGDP. If we look at the upper graph, representing the low uncertainty regime, we observe a minimum significant impact on the IRF of the VIX. The confidence intervals tightly follow the estimated IRF, suggesting high certainty of low impact. As VIX corresponds to market expectations about future volatility, it might be reasoned that they do not react to an increase in government debt. As the shock, resembling a fiscal policy, is executed in a low uncertainty regime, private actors may not worry of a fiscal policy leading to an unsustainable debt.

In the high uncertainty regime, we observe a small, but significant negative effect on the IRF of the VIX, which implies a direction towards lower uncertainty. As the VIX index is a reflection of the market responding to every piece of information available to the market, this reflects a positive reaction of business actors to the government pursuing fiscal stimuli. We assume this effect to only be a reflection of the market responding to the policy adaptation, rather than the actual effects of the stimuli, as there is always a time lag before such effects reaches the economy. This is an interesting finding, as this implies that a nondirect effect of a fiscal expansion is business actors perceiving the market to be 'safer' when the government actively intervenes and stimulates the economy in a high uncertainty regime. This is opposite to the reaction observed in figure 10, where we saw business actors responding more defensively to a shock in DtGDP, which could imply concerns on whether the government debt is sustainable or not.

In summary these two IRFs of VIX reflect the response of financial market to the government pursuing a fiscal policy. In the low uncertainty regime, private business actors seem to be indifferent to whether the government pursues fiscal policy or not, as prices for options remain the same. As this fiscal policy reflects merely a popular policy rather than a necessity such as in a high uncertainty regime, they (business actors) do not worry of this being unsustainable financed or not. A more interesting response is seen in the high uncertainty regime, as we observe the market responding positively to an increased government debt which is reflected in a decrease in market volatility. This might imply an unexpected crowding in effect of performing fiscal policy in a high uncertainty regime, as markets reacts positively to the government intervening.

6.6 Robustness test

To assess the robustness of the estimated TSVAR model, two different models have been created. In the first model, the length of the period has been shortened to not include the years of the COVID-19 pandemic. In the second model measuring robustness, the debt-toGDP policy variable is substituted with a Federal Surplus or Deficit variable (FSoD). The FSoD measures the fiscal budget balance between government revenue and expenses. The variable captures whether the government is running a surplus or a deficit, implying that in case of government spending, which is not financed by increased tax-revenue, the budget will fall in surplus/increase in deficit. Compared to the DtGDP variable, the FSoD captures both sides of the fiscal budget, but it does not consider the size of the economy.

6.6.1 Omitting the observations of COVID-19

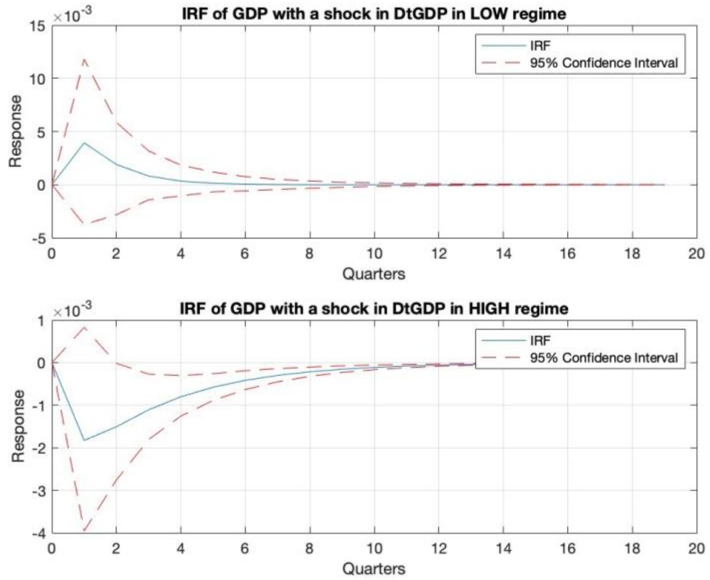

Figure 12 *IRF of GDP with a shock in DtGDP in low and high uncertainty regimes omitting observations from the period of COVID-19 from the data set.*

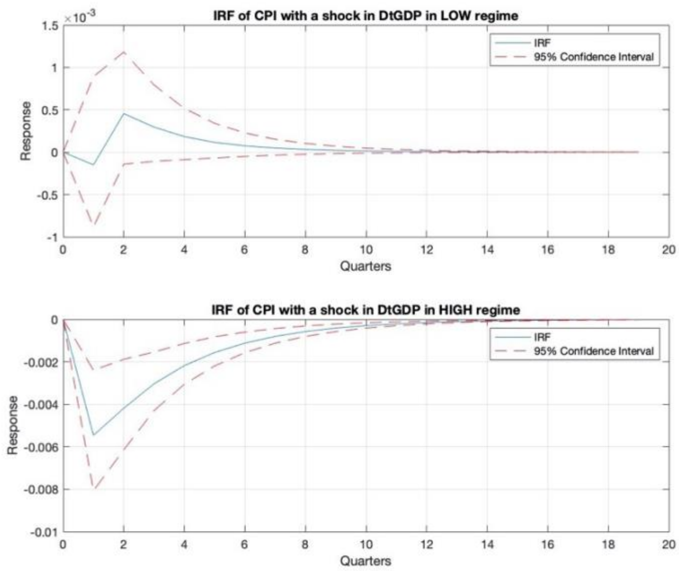

Figure 13 *IRF of CPI with a shock in DtGDP in low and high uncertainty regimes omitting observation from the period of COVID-19 from the data set.*

In our first model, we have followed the same procedure as in our standard model but have restrained the dataset to only include the timeframe from the 1st of January 1990 to 1st of October 2019. We perform a positive shock of one SD in DtGDP, in which we receive the presented results. We have chosen to focus on the IRFs of GDP and CPI, as these responses are significant and most relevant for our analysis. Firstly, looking at the IRFs of GDP and CPI in the low uncertainty regime, we observe similar responses of increased output and inflation, as we observed in low uncertainty regimes including the COVID-19 period. This shows that the observed economic relationship of fiscal policy leading to increased output which in return increases prices, can be generalized as robust in times of low uncertainty. More interestingly, are the shocks seen in the high uncertainty regimes without the COVID19 data frame. In the IRF of the GDP we observe a statistically significant relationship of declining output after the second quarter, tilting towards a negative fiscal multiplier. This tendency can naturally be explained by a crowding out effect because of financial markets and the Ricardian consumer. When looking at the IRF of the CPI we also observe a contrasting response (compared to our main model), as the inflation level falls with a shock in the CPI. This supports the findings in the GDP graph, as we observe depressed economic activity due to consumers worrying about the government taking on more debt in an already uncertain environment.

These two findings imply that our model might not be as robust when looking across different uncertainty regimes, which is seen by different economic mechanisms being activated when refraining from including the COVID-19 period. While this will become a topic which we will elaborate further on in the discussion, it shows how the effect of fiscal expansion not only is dependent on whether there is high or low uncertainty, but also on which form of uncertainty and other mechanisms are present in the market.

6.6.2 Replacing our fiscal policy variable with Federal Surplus or Deficit

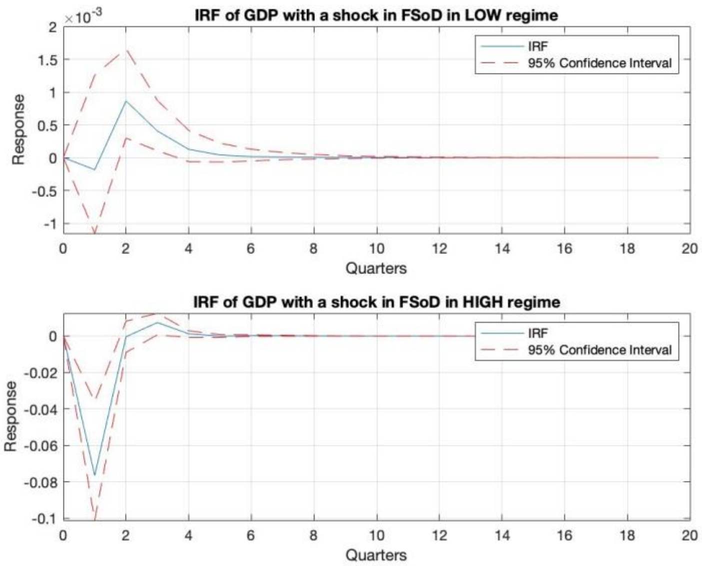

Figure 14 *IRF of GDP with a shock in FSoD in low and high uncertainty regimes.*

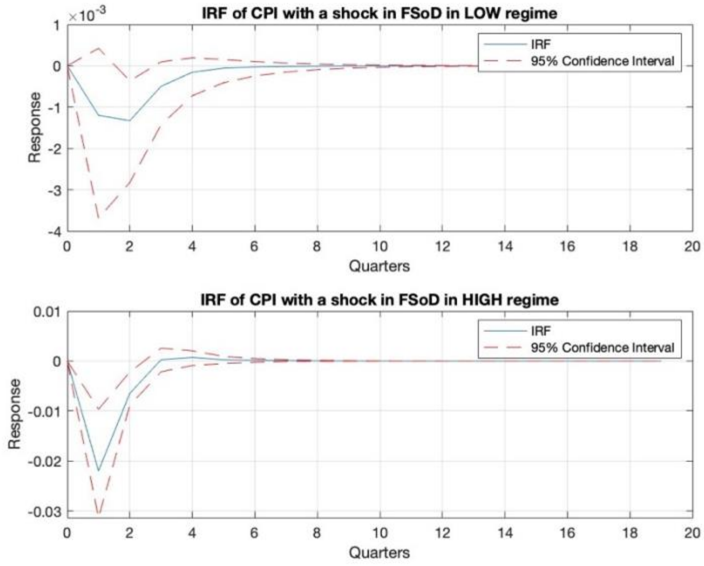

Figure 15 IRF of CPI with a shock in FSoD in low and high uncertainty regimes.

In the model checking for the robustness regarding the fiscal policy variable, the substitution of DtGDP with FSoD provides somewhat ambiguous results. A positive shock to the FSoD is expected to have the opposite effect on GDP, since a one SD increase in FSoD is associated with higher revenue compared to expenses, whereas an increase in DtGDP implies larger deficit. The increase in FSoD is associated with a small significant increase in GDP in the second until fourth quarter. It shows some inconsistency compared to the effect of a shock to DtGDP. However, the effect in the high uncertainty regime corresponds with the direction of the IRF of GDP from an SD in DtGDP in the main model.

Considering the IRFs of CPI, a similar assessment of the inconsistency between using the DtGDP and FSoD can be made. In the low regime, only a very small fall in CPI is significant in the second quarter. If the IRF should be corresponding with the IRF from a shock in DtGDP, it should be a prolonged drop in the CPI. Meanwhile, the DtGDP and FSoD generate similar IRFs of CPI in the high regime. The jump seen in CPI following a shock in DtGDP is although delayed compared to the drop following a shock in FSoD, but the direction and duration correspond.

The IRF of SI and VIX from a shock in FSoD provides similar results in both regimes, when compared to the IRFs following a shock in DtGDP. (See appendix 4). The findings from the model with FSoD strengthens the robustness of our model, since the substitution of the fiscal policy variable provides similar results in most cases. Although, the low regimes concerning GDP and CPI diverge, implying that different variables measuring the fiscal policies will affect the results of the estimated model.

7. DISCUSSION

Policy implications can be drawn from the findings concerning the necessity to consider uncertainty in the existing macroeconomic environment, when implementing fiscal strategies. Meanwhile, the ambiguity in our findings, stress the importance of a more complex analysis incorporating the specific factors in place constituting the uncertainty, which this paper does not accomplish to do. The following paragraphs will first interpret the policy implications of this paper in relation to existing literature. Secondly, a discussion on whether the implications can be generalized will follow. The last part addresses how other time series models could be applied considering their strengths and limitations in relation to our research.

7.1 Policy implications

After having interpreted our findings in the analysis, our results point towards that changing economic dynamics of fiscal policy shocks can be found based on the uncertainty present in the U.S. economy. Furthermore, expansive fiscal policy will stimulate the U. S. economy across regimes of uncertainty, but have a more amplified effect, when uncertainty is high.

In an environment of low uncertainty, fiscal stimuli work as intended, since economic growth follows. As theorized, we observe crowding out effects through an increase in the inflation rate as well as the short-term interest rate. While this impacts the size of the fiscal multiplier, it also implies that expansive fiscal policy in the U.S. is effective in stimulating the economy, since increases in both GDP and CPI reflect higher demand.

In the high uncertainty regimes, we observe some of the same dynamics followed by a shock in DtGDP, only more extensive. Output rises significantly, which is followed by a steeper increase in inflation – something that could point towards more disproportionate levels of depressed demand. This implication contributes to explaining the current high level of annual inflation rate in the U. S. The inflation rate peaked at 8.5 % in March 2022 in light of the the stimulus packages implemented during the COVID-19 pandemic by the Trump and later the Biden Administration (Weinstock, 2021). Moreover, the findings concerning the effect on GDP and inflation contribute to strengthening results from existing literature addressed in the literature review. The positive effect of expansionary fiscal policy on output in U.S. corresponds with Caldara & Kamps (2008), Galí et al. (2007) and Afonso & Baxa (2011). However, contrary to Afonso & Baxa (2011) this study does not find that the output growth peak occurs sooner in the high regime.

Further the present results diverge from the findings of Galí et al. (2007), who find that interest rate increases, causing lower investment, supporting the traditional assumptions implied in the IS-LM curve. These findings can't be consolidated by this paper, where no effect on short-term interest rate is apparent in the low regime. Contrary to Galí et al. (2007), we find a minor decline in short-term interest in the high regime. This might be explained by risk-aversion among businesses and private households, corresponding to the more uncertain environment, which in itself is defined as an environment of higher riskaversion.

More interesting findings from this paper is regarding VIX, where a small decrease is observed in the high uncertainty regime. This imply a temporary positive response of the market to the government performing fiscal stimuli. This is a conflicting perspective to the findings of Anzuini et al. (2020), who suggest that uncertainty breeds uncertainty. Contrary, this paper finds a diminishing effect, which underpins that especially in times of high uncertainty, expansive fiscal policy may be an effective tool to stimulate the economy and mitigate uncertainty.

7.2 Inability to generalize

However, we should be cautious with generalizing the abovementioned implications. The contradicting findings from the robustness tests implies that the change in the effects of fiscal policy is not unambiguous across time of uncertainty and measure of fiscal policies. By omitting the observations from the COVID-19 pandemic, we find that our model is robust, when seeking to explain economic dynamics in low uncertainty periods. However, the effects of a shock in DtGDP are remarkably different in the high uncertainty regimes. The IRF’s of GDP and CPI both decline following a shock, which naturally implies deteriorated demand and thus that the fiscal multiplier is close to zero.

The contradicting findings from the robustness test without data from the COVID-19 pandemic, suggests that other factors than uncertainty in terms of VIX explain the economic dynamics in the U.S economy during the past years. Possible factors are the disruption of supply chains and lockdown measures, which have restricted production, employment and consumption (Trading Economics, 2022). The fiscal stimulus will increase money supply, but with disrupted supply chains and maximum employment, a larger money supply will only target the same amount of goods and services, which will inflate the price level.

Additionally, COVID-19 has hit more disproportionately compared to previous crisis, which adds to the explanation of peaking inflation. The workforce with lowest paid jobs has been hit most severely by job losses, with major parts of the accommodation and food services sector shutting down. Meanwhile the increasing wages was experienced among an already higher paid workforce, e.g. in the financial and information sectors (Bonadio et al., 2020; Kamble & Mor, 2021). The higher wages imply higher input costs, leading to higher prices for goods and services supplied by these “high-wage” sectors, pushing up the prices. Recent literature as Bonadio et al. (2020) and Kamble & Mor (2021) can contribute with candidate variables considering supply chains which could be used for further research.

Addressing the results from the robustness model with data from COVID-19, but a replacement of DtGDP with Federal Surplus or Deficit, we find similar dynamics during high uncertainty, although some contradictions when looking at the low regimes. Implications from these findings suggest that further models ought to be tested to find the better candidate of measuring fiscal policy. Another resolution could be the application of a more complex framework using multiple variables capturing fiscal policy. Although this may have further implications to be considered during the estimation of the model, compared to the more parsimonious model applied in this paper.

7.3 Methodological considerations and future research

With the discussed issues of our findings including its limited ability to generalize, a natural question then becomes of whether the correct model was chosen to fit our data.

While our TSVAR model indicated that the time series had some time-varying dynamics, our robustness test also pointed toward the cause of uncertainty playing a role. This might indicate that our threshold variable has not provided the regime switches. A possible way to solve such a problem could be the estimation of a Markov-Switching model instead of a TSVAR, as the model allows for latent regime switches (Ludvigson et al., 2020). The model holds many of the same positive properties as the TSVAR, as both allows for discrete switches and takes into considerations the non-linear effects of a fiscal policy. The regimes are however not decided by any observable variable, but rather determined by a stochasticprocess known as a Markov-chain. The switches between regimes are therefore not decided by any threshold, but rather a transition probability of the regime staying the same or changing. While this model usually allows for great improvement of the absolute residuals, the process of endogenously identifying breaks makes it difficult to make inferences from the model as it is based on an unobservable chain (Franses & van Dijk, 2000). This would have made it hard to answer our research question of how the level of uncertainty determines the effectiveness of fiscal policy, as the level of uncertainty would not necessarily determine any regime.

But if the observable threshold variable makes our model stronger in terms of answering our research question, could identifying more distinct regimes then account for the different properties of uncertainty? With our model only identifying two regimes, low or high uncertainty, our vague generalization abilities might have been reasoned by the properties of our time series not being fully captured. An issue which possibly could have been resolved by identifying more regimes. As introduced in the literature review, Ko et. al (2019) constructs similar research for Japan's economy but estimate five regimes to fully capture the different effects of fiscal policy (Di Persio & Vettori, 2014, pp. 5–6; Kuan, 2002, pp. 2–4). Such monotonic model comes of strong in terms of fully being able to capture the dynamics of fiscal policy in previous history but has one major weakness; its failure to generalize across time. In that sense, the 5 regime-model identified by Ko et. al (2019) becomes a descriptive study of Japan's fiscal experiences rather than predictive. The strength of our research lied in the opposite, as identifying only two regimes secured a parsimonious model. With this, we were able to make some policy inferences in terms of the level of uncertainty, at least partially, effecting the success of a fiscal policy.

Another shortcoming of our choice of model, was its incapability to capture the contemporaneous effects of a shock to our variables. As our TSVAR model was built on two separate reduced form VARs, the parameters and hence IRFs only depended on the lagged values of the other time series. To capture the recursive effects of the variables, a structural vector autoregressive model (SVAR) could have been estimated instead. The SVAR model focuses on the errors of the system instead of the (autoregressive) coefficient of the model, which is interpreted as a set of exogenous shocks. Which implies easily interpreted results and dynamics (Ko & Morita, 2019). Yet, an issue arises when applying the SVAR-model to an uncovered research area. As Caldara and Kamps (2008) displays, SVAR-models on the effects of fiscal stimuli often results in a wide range of fiscal multipliers. These is because of the differences in the identification scheme of the underlying shock, which is built on different assumptions of the systematic component. This systematic response of tax and spending policies to output, will inevitably lead to different sign and size of the fiscal multiplier (Lütkepohl & Krätzig, 2004b, pp. 159–160). This implies, that the determination of appropriate restrictions based on previous literature is needed, which does not conform to the inductive research we intended to conduct. While research on uncertainty and fiscal policy had been conducted before[ix], it has not included the timeframe of COVID-19. Therefore, our research is built on a clean canvas. For future research, it could be interesting to build onto our estimated VAR models and impose the appropriate restrictions. This would allow us to get a better grasp of the dynamic effects of fiscal policy in times of uncertainty.

8 CONCLUSION

This paper has sought to contribute to the existing debate on the effects of fiscal policy and how its behavior changes with the level of uncertainty in the economy. Firstly, it has been done so, by using a non-linear time series model to capture the changing dynamics of a fiscal policy stimulation in the US economy. Precisely, a Threshold-switching model has been used to identify the structural changes with the identification of a low and high uncertainty regime. Secondly, the CBOE volatility index has been used as proxy for uncertainty, and endogenously determined which state [low or high uncertainty] each datapoint in the multivariate equation is placed in. The use of an observable threshold parameter has allowed us to directly measure the varying effects of fiscal policy dependent on the uncertainty in the economy. Lastly, the inclusion of present data marked by an upsurge in inflation complimented by extreme levels of economic uncertainty, this paper contributes to shed light on the dynamics between fiscal policy and uncertainty. The paper has therefore specifically addressed, ***how does the effect of fiscal policy change with the level of uncertainty in the United States?***

This paper has completed in doing so, by estimating a Threshold-switching vector autoregressive model which has incorporated key macroeconomic parameters. In ordinance with Granger causation test as well as previous literature, the following variables was chosen to reflect the effects of fiscal policy; *gross-domestic product, consumer price index, government-debt-to-GDP ratio, short-term interest rate and the CBOE Volatility index.* By imposing a one standard deviation shock in the government-debt-to-GDP ratio, a fiscal policy shock has been simulated. The analysis has indicated that changing economic dynamics of fiscal policy shocks can be found in the U.S. economy dependent on the level of uncertainty. In a low uncertainty environment, fiscal policy works as intended and economic growth follows. While some crowding out effects is observed with an increase in the inflation rate as well as the short-term interest rate, it does not result in a negative fiscal multiplier. In a high uncertainty regime, we observe same dynamics, only significantly more prominent. While the growth in output raises significantly, we also observe a steep uprise in inflation. Further interesting findings were made, when conducting robustness tests. If we omitted the observations from the period of COVID-19, we observed different dynamic behavior of a fiscal policy shock in the high uncertainty regime. The response in inflation did not seem to react as steep as seen in the response with COVID-19. Secondly, we observed changing response in the lower regimes as output seemed to plunge with a fiscal policy shock. This points towards our model not being as generalizable as desired and suggests further research to investigate this puzzle.

Several policy implications follow from our research, highlighting the importance of the U.S. government to consider the level of uncertainty before performing any fiscal policy. Moreover, the inability to construct a robust model over different periods of high uncertainty, suggests that the level of uncertainty alone, is not sufficient to assess, when deciding on fiscal policy. Instead, the ambiguous findings suggest that uncertainty has many underlying facets and the entirety of those cannot be determined with a simple classification of low or high. In line with the hypothesis stated by classical economics, we found that disproportionate low demand and unemployment, might be a crucial factor in explaining the rise in inflation. This corresponds with the disruptions in supply-chain and the job layoff in particular sectors, leading to an uneven depression in the economy. In summary, this suggests that policy makers must not only consider the variety of uncertainty in the economy, but also the specific setting and environment of the uncertainty, before executing fiscal policies.

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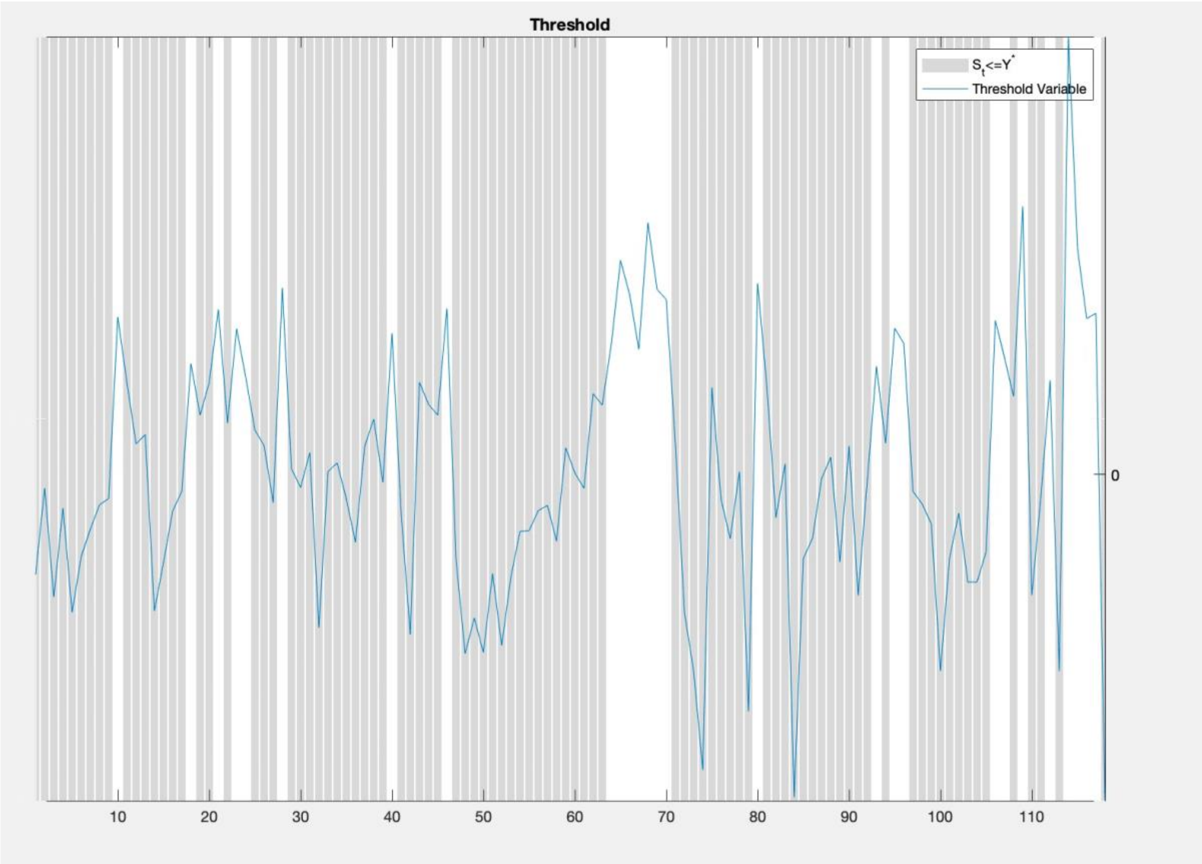
10 APPENDICES

Appendix 1 – Results from statistical hypothesis test

```
BestMdl =

  varm with properties:

     Description: "AR-Stationary 5-Dimensional VAR(5) Model"
     SeriesNames: "GDP"  "CPI"  "DtGDP"  ... and 2 more
       NumSeries: 5
               P: 5
        Constant: [-0.00832779 -0.000154189 0.00162397 ... and 2 more]'
              AR: {5×5 matrices} at lags [1 2 3 ... and 2 more]
           Trend: [5×1 vector of zeros]
            Beta: [5×0 matrix]
      Covariance: [5×5 matrix]
                          H0                              Decision          Distribution↙
Statistic      PValue      CriticalValue
    ______________________________________    __________________    ____________↙

_________    __________    _____________

    "Exclude lagged CPI in GDP equation"      "Cannot reject H0"     "Chi2(5)"↙
6.6819         0.2454         11.07
    "Exclude lagged DtGDP in GDP equation"    "Reject H0"            "Chi2(5)"↙
12.221         0.03188        11.07
    "Exclude lagged SI in GDP equation"       "Cannot reject H0"     "Chi2(5)"↙
7.0872         0.21424        11.07
    "Exclude lagged VIX in GDP equation"      "Reject H0"            "Chi2(5)"↙
23.401      0.00028295        11.07
    "Exclude lagged GDP in CPI equation"      "Cannot reject H0"     "Chi2(5)"↙
2.6044         0.7607         11.07
    "Exclude lagged DtGDP in CPI equation"    "Cannot reject H0"     "Chi2(5)"↙
1.901         0.86267         11.07
    "Exclude lagged SI in CPI equation"       "Cannot reject H0"     "Chi2(5)"↙
4.621         0.46385         11.07
    "Exclude lagged VIX in CPI equation"      "Cannot reject H0"     "Chi2(5)"↙
10.575        0.060492        11.07
    "Exclude lagged GDP in DtGDP equation"    "Cannot reject H0"     "Chi2(5)"↙
5.2948         0.38097        11.07
    "Exclude lagged CPI in DtGDP equation"    "Cannot reject H0"     "Chi2(5)"↙
5.8071         0.32544        11.07
    "Exclude lagged SI in DtGDP equation"     "Cannot reject H0"     "Chi2(5)"↙
2.2347         0.81581        11.07
    "Exclude lagged VIX in DtGDP equation"    "Reject H0"            "Chi2(5)"↙
20.198       0.0011472        11.07
    "Exclude lagged GDP in SI equation"       "Reject H0"            "Chi2(5)"↙
11.587        0.040907        11.07
    "Exclude lagged CPI in SI equation"       "Reject H0"            "Chi2(5)"↙
11.773        0.038035        11.07
    "Exclude lagged DtGDP in SI equation"     "Reject H0"            "Chi2(5)"↙
13.91         0.016193        11.07
    "Exclude lagged VIX in SI equation"       "Reject H0"            "Chi2(5)"↙
20.775      0.00089347        11.07
    "Exclude lagged GDP in VIX equation"      "Cannot reject H0"     "Chi2(5)"↙
1.1132         0.95293        11.07
    "Exclude lagged CPI in VIX equation"      "Cannot reject H0"     "Chi2(5)"↙
2.4497         0.78405        11.07
    "Exclude lagged DtGDP in VIX equation"    "Cannot reject H0"     "Chi2(5)"↙
7.3941         0.19294        11.07
    "Exclude lagged SI in VIX equation"       "Cannot reject H0"     "Chi2(5)"↙
3.5496         0.61589        11.07
```

Appendix 2 – simulation of TSVAR(5)



Appendix 3 – Data sets for low and high regimes

LOW REGIME

Time	GDP	CPI	DtGDP	SI	VIX
1992-07-01	0.01884704	0.00011176	0.04803865	-0.5556762	-0.1043095
1992-10-01	0.07837004	0.00458827	0.03513062	-0.3564811	-0.42931
1993-01-01	-0.0835427	0.00495427	0.03250421	-0.272439	-0.2556501
1993-04-01	-0.0503648	-0.0046609	0.03757529	-0.2171683	-0.1702598
1993-07-01	-0.0402117	-0.0298885	0.03084201	-0.0405672	-0.0946801
1993-10-01	0.01711498	-0.0046629	0.02908094	-0.0466124	-0.0751488
1994-01-01	0.07169503	-0.0223755	0.01872962	0.09415143	0.48985716
1994-04-01	0.06539651	-0.0153233	-0.0053946	0.32731205	0.28479158
1994-07-01	0.00856854	0.04605053	-0.0086106	0.4361296	0.09468013
1994-10-01	0	0	0	0	0
1995-01-01	-0.0547917	0.02306517	-0.005802	0.58348322	-0.4249695
1995-04-01	-0.1050696	0.02477301	0.00918478	0.3240154	-0.2741908
1995-07-01	0.0183755	-0.0419292	0.00176671	0.17000626	-0.1141133
1995-10-01	-0.0522485	-0.0036702	-0.0026307	-0.0253323	-0.0528895
1996-01-01	0.03313552	0.01534564	-0.0030634	-0.1585628	0.34508972
1996-04-01	0.12900518	0.00419941	-0.0297297	-0.1082612	0.18407748
1996-07-01	-0.0118569	0.00710099	-0.023167	-0.0492536	0.28552124
1996-10-01	0	0	0	0	0
1997-01-01	0.00118645	-0.0277853	-0.032085	0.03109691	0.15928277
1997-04-01	-0.021723	-0.062674	-0.041258	0.05354669	0.45351245
1997-07-01	0	0	0	0	0
1997-10-01	-0.0383343	-0.0327551	-0.0540741	0.05746644	0.13776477
1998-01-01	0	0	0	0	0
1998-04-01	0	0	0	0	0
1998-07-01	-0.0002427	0.00126513	-0.0658127	-0.0131817	0.58077834
1998-10-01	0.06948639	-0.006933	-0.074038	-0.0976981	0.01693206
1999-01-01	0.0117574	0.01589166	-0.0798917	-0.1251631	-0.0404435
1999-04-01	0	0	0	0	0
1999-07-01	-0.0003874	0.02289681	-0.0856587	-0.0262772	-0.477209
1999-10-01	0.03027676	0.02667381	-0.0823393	0.15369234	0.00896863
2000-01-01	-0.0233248	0.06197577	-0.0893395	0.20806439	0.03589159
2000-04-01	0.12157009	0.00349005	-0.1257868	0.27826082	-0.0763353
2000-07-01	-0.0984853	0.01693395	-0.1276855	0.20779426	-0.2113091
2000-10-01	-0.1047475	-0.0024552	-0.1374565	0.08384355	0.08589472
2001-01-01	-0.0695189	-0.0032622	-0.1169725	-0.1378024	0.17217757
2001-04-01	-0.120287	-0.0082087	-0.0991753	-0.4728473	-0.0248719
2001-07-01	-0.0694316	-0.0627837	-0.0561886	-0.6861296	0.4397123
2001-10-01	-0.0545605	-0.0785469	-0.0271176	-1.1644666	-0.1205803
2002-01-01	0.08175898	-0.0633285	-0.0267802	-1.058831	-0.4983341
2002-04-01	0	0	0	0	0
2002-07-01	0.08924108	0.02553119	0.02631659	-0.6396586	0.21755323
2002-10-01	0.01146396	0.0664518	0.03515004	-0.32455	0.18442027

2003-01-01	-0.0133851	0.07044734	0.03911874	-0.3669127	0.51598471
2003-04-01	0.02736147	-0.0946888	0.05866343	-0.4519847	-0.2633096
2003-07-01	0.13364136	0.02065801	0.04776229	-0.4976552	-0.5578537
2003-10-01	0	0	0	0	0
2004-01-01	0.02626448	-0.0180537	0.05336618	-0.181794	-0.5546538
2004-04-01	0.03426558	0.0946245	0.03192695	0.06632262	-0.3083867
2004-07-01	-0.0642913	-0.010806	0.03037169	0.46492827	-0.5324785
2004-10-01	0.00256657	0.06892083	0.02363978	0.71259462	-0.3204354
2005-01-01	0.0621963	-0.0338897	0.02214471	0.97168971	-0.1773162
2005-04-01	-0.0366125	-0.0108985	0.00594548	0.95200855	-0.1748184
2005-07-01	0.01113359	0.08675664	0.00112685	0.78560712	-0.1125494
2005-10-01	-0.0415259	-0.0139832	0.00593953	0.64690939	-0.0962888
2006-01-01	0.01443075	0.00156152	0.00051001	0.52815967	-0.2077491
2006-04-01	-0.0081615	0.02248395	-0.0044197	0.47167928	0.08284991
2006-07-01	-0.0842603	-0.0563681	-0.0026584	0.36696952	0.00502093
2006-10-01	-0.015829	-0.1339214	-0.0134808	0.21426001	-0.0431722
2007-01-01	-0.0796131	0.0456226	-0.0077699	0.11778304	0.25102173
2007-04-01	0.01749454	0.02278294	-0.0161903	0.02668519	0.21577704
2007-07-01	0.02734007	-0.0308576	-0.007158	0.00554701	0.40713317
2007-10-01	-0.0182671	0.16301953	-0.0001432	-0.0580058	0.66596445
2008-01-01	-0.1304365	0.01017434	0.0199268	-0.4971097	0.55922543
2008-04-01	0	0	0	0	0
2008-07-01	0	0	0	0	0
2008-10-01	0	0	0	0	0
2009-01-01	0	0	0	0	0
2009-04-01	0	0	0	0	0
2009-07-01	0	0	0	0	0
2009-10-01	0	0	0	0	0
2010-01-01	0.19919402	0.08486243	0.17044904	-1.6566903	-0.9200358
2010-04-01	0.17943202	-0.0565624	0.14470091	-0.3761689	0.27064983
2010-07-01	0.06024651	-0.0563995	0.13131023	0.11531095	-0.0775078
2010-10-01	-0.0288307	0.0026579	0.14031239	0.22612433	-0.2000047
2011-01-01	-0.0496976	0.09031852	0.11309983	0.31551659	0.00849142
2011-04-01	-0.0116015	0.11658739	0.08281872	-0.6545323	-0.7375463
2011-07-01	-0.0493975	0.03572312	0.08253835	-0.1607732	0.59479434
2011-10-01	0.01333364	-0.0358565	0.07241017	0.41337021	0.27635051
2012-01-01	0.11461618	-0.0499971	0.07328452	0.15246871	-0.134982
2012-04-01	0	0	0	0	0
2012-07-01	0.01134254	-0.0199495	0.06479132	-0.0723207	-1.0046997
2012-10-01	-0.0619832	0.02148533	0.06716218	-0.5956919	-0.2612538
2013-01-01	-0.0157195	-0.0160443	0.05755855	-0.4054651	-0.199238
2013-04-01	-0.043396	-0.0320424	0.04489093	-0.4222721	-0.0129642
2013-07-01	0.05674592	0.00889319	0.02518066	-0.7711091	0.05383298
2013-10-01	0.06884315	-0.0293666	0.02174132	-0.6109087	-0.2726276
2014-01-01	-0.1197599	0.02197061	0.02818264	-0.5787371	0.08884696
2014-04-01	0.14172034	0.06392188	0.00969773	-0.5511774	-0.3765285
2014-07-01	0.0335003	-0.0283879	0.01690197	0.02666878	-0.0176243
2014-10-01	-0.0690283	-0.0617838	0.01157052	0.05129278	0.33605571

2015-01-01	0.07093614	-0.127024	-0.0134834	0.19574485	0.09675006
2015-04-01	-0.0721791	0.01499602	-0.0017774	0.30228095	0.45465305
2015-07-01	0	0	0	0	0
2015-10-01	-0.0477077	0.02411849	0.02409981	1.00246859	-0.0529395
2016-01-01	0	0	0	0	0
2016-04-01	0	0	0	0	0
2016-07-01	0.02559139	0.00465868	0.05198053	1.07044141	-0.6116612
2016-10-01	0.08833705	0.06403442	0.01846619	0.74673156	-0.2600604
2017-01-01	0.04678897	0.07633825	-0.0073568	0.50478341	-0.1202053
2017-04-01	-0.0127593	-0.0681292	-0.0068702	0.66274964	-0.3350657
2017-07-01	0.03363197	0.00533284	-0.0059326	0.57178632	-0.334668
2017-10-01	0.06238627	0.01596067	-0.0208761	0.58294375	-0.2403854
2018-01-01	0.03277577	0.01108251	0.02091488	0.69132731	0.47895691
2018-04-01	0.08381217	0.04554317	0.01580616	0.70389157	0.36407149
2018-07-01	-0.0403046	-0.0043296	0.01732107	0.57334598	0.2425131
2018-10-01	0	0	0	0	0
2019-01-01	0	0	0	0	0
2019-04-01	-0.035613	0.02119708	0.00737994	0.09600392	-0.0648286
2019-07-01	0	0	0	0	0
2019-10-01	0.01333402	0.02425088	0.02260581	-0.3425275	-0.612318
2020-01-01	-0.1887572	0.00842708	0.03751099	-0.4989912	1.36230356
2020-04-01	0	0	0	0	0
2020-07-01	0.71759517	0.08023012	0.24057513	-2.6186645	0.4847497
2020-10-01	0	0	0	0	0
2021-01-01	0	0	0	0	0
2021-04-01	0	0	0	0	0
2021-07-01	0	0	0	0	0
2021-10-01	0.18006938	0.13496683	-0.0434454	-0.0689929	-0.2784937

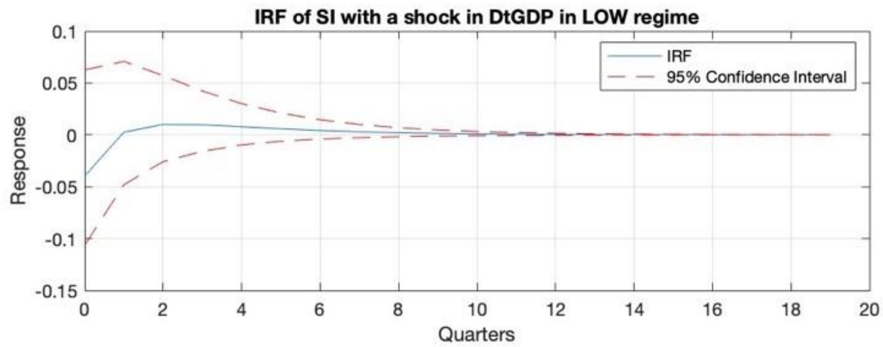
HIGH REGIME

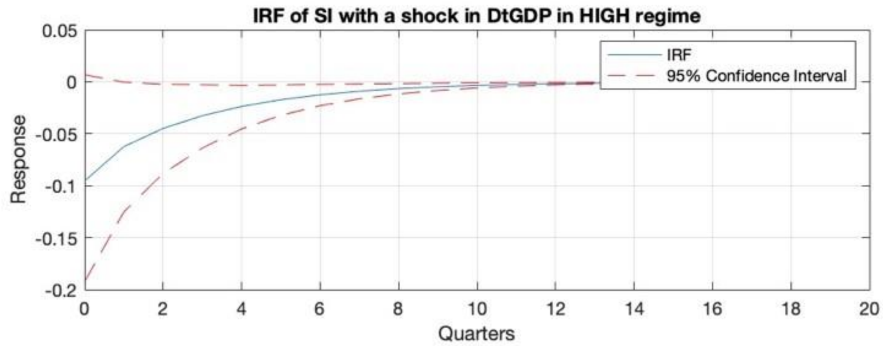
Time	GDP	CPI	DtGDP	SI	VIX
1992-07-01	0	0	0	0	0
1992-10-01	0	0	0	0	0
1993-01-01	0	0	0	0	0
1993-04-01	0	0	0	0	0
1993-07-01	0	0	0	0	0
1993-10-01	0	0	0	0	0
1994-01-01	0	0	0	0	0
1994-04-01	0	0	0	0	0
1994-07-01	0	0	0	0	0
1994-10-01	-0.0214583	-0.0245145	-0.0145711	0.57985915	0.12405265
1995-01-01	0	0	0	0	0
1995-04-01	0	0	0	0	0
1995-07-01	0	0	0	0	0
1995-10-01	0	0	0	0	0
1996-01-01	0	0	0	0	0
1996-04-01	0	0	0	0	0
1996-07-01	0	0	0	0	0
1996-10-01	0.04086207	0.03214187	-0.0230315	-0.0551369	0.51337827
1997-01-01	0	0	0	0	0
1997-04-01	0	0	0	0	0
1997-07-01	0.04566275	-0.0075044	-0.0531481	0.0216615	0.3013056
1997-10-01	0	0	0	0	0
1998-01-01	-0.0097122	-0.0401422	-0.0590334	0.02000673	0.08979281
1998-04-01	-0.0692822	0.00992477	-0.0553102	-0.017731	-0.0883213
1998-07-01	0	0	0	0	0
1998-10-01	0	0	0	0	0
1999-01-01	0	0	0	0	0
1999-04-01	0.00521018	0.04172186	-0.088345	-0.1162191	0.06767292
1999-07-01	0	0	0	0	0
1999-10-01	0	0	0	0	0
2000-01-01	0	0	0	0	0
2000-04-01	0	0	0	0	0
2000-07-01	0	0	0	0	0
2000-10-01	0	0	0	0	0
2001-01-01	0	0	0	0	0
2001-04-01	0	0	0	0	0
2001-07-01	0	0	0	0	0
2001-10-01	0	0	0	0	0
2002-01-01	0	0	0	0	0
2002-04-01	-0.0262909	0.00844385	0.02937395	-0.8040381	0.28715733
2002-07-01	0	0	0	0	0
2002-10-01	0	0	0	0	0

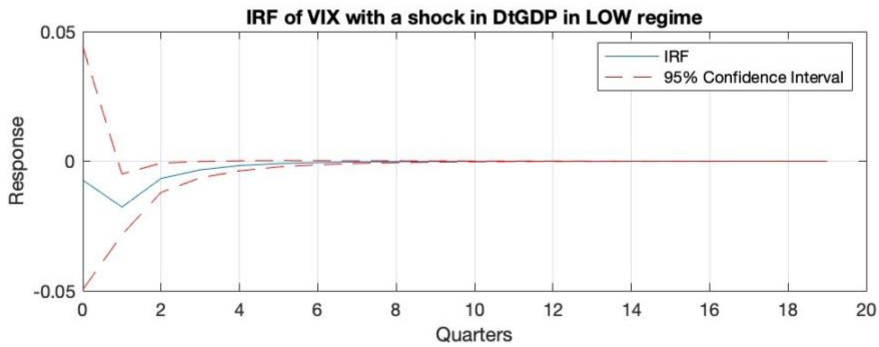
2003-01-01	0	0	0	0	0
2003-04-01	0	0	0	0	0
2003-07-01	0	0	0	0	0
2003-10-01	0.10594864	-0.0210606	0.04095818	-0.2982011	-0.4466585
2004-01-01	0	0	0	0	0
2004-04-01	0	0	0	0	0
2004-07-01	0	0	0	0	0
2004-10-01	0	0	0	0	0
2005-01-01	0	0	0	0	0
2005-04-01	0	0	0	0	0
2005-07-01	0	0	0	0	0
2005-10-01	0	0	0	0	0
2006-01-01	0	0	0	0	0
2006-04-01	0	0	0	0	0
2006-07-01	0	0	0	0	0
2006-10-01	0	0	0	0	0
2007-01-01	0	0	0	0	0
2007-04-01	0	0	0	0	0
2007-07-01	0	0	0	0	0
2007-10-01	0	0	0	0	0
2008-01-01	0	0	0	0	0
2008-04-01	-0.0226478	0.01663594	0.03521415	-0.6568243	0.38910698
2008-07-01	-0.0895057	0.0899097	0.11833868	-0.5733855	0.78314019
2008-10-01	-0.3002103	-0.3536002	0.22297267	-0.5785396	0.57536414
2009-01-01	-0.1163259	-0.176761	0.26706207	-1.0924397	0.54438344
2009-04-01	-0.1421197	-0.07622	0.33906188	-1.4974489	0.09549991
2009-07-01	0.02455324	-0.0673401	0.29251517	-2.3212979	-0.430529
2009-10-01	0.33618945	0.30967069	0.2010054	-2.5346443	-0.6124893
2010-01-01	0	0	0	0	0
2010-04-01	0	0	0	0	0
2010-07-01	0	0	0	0	0
2010-10-01	0	0	0	0	0
2011-01-01	0	0	0	0	0
2011-04-01	0	0	0	0	0
2011-07-01	0	0	0	0	0
2011-10-01	0	0	0	0	0
2012-01-01	0	0	0	0	0
2012-04-01	-0.0476527	-0.0919719	0.08441571	0.31015493	0.03333642
2012-07-01	0	0	0	0	0
2012-10-01	0	0	0	0	0
2013-01-01	0	0	0	0	0
2013-04-01	0	0	0	0	0
2013-07-01	0	0	0	0	0
2013-10-01	0	0	0	0	0
2014-01-01	0	0	0	0	0
2014-04-01	0	0	0	0	0
2014-07-01	0	0	0	0	0
2014-10-01	0	0	0	0	0

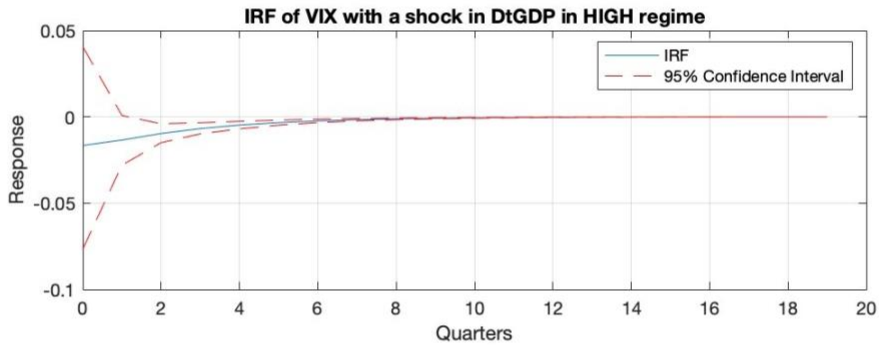
2015-01-01	0	0	0	0	0
2015-04-01	0	0	0	0	0
2015-07-01	-0.0973097	0.01214821	-0.0051111	0.6390797	0.40689476
2015-10-01	0	0	0	0	0
2016-01-01	-0.0267261	0.05872784	0.03833107	1.30532524	-0.0917195
2016-04-01	-0.0112388	0.01169684	0.04115436	1.28935269	-0.1538764
2016-07-01	0	0	0	0	0
2016-10-01	0	0	0	0	0
2017-01-01	0	0	0	0	0
2017-04-01	0	0	0	0	0
2017-07-01	0	0	0	0	0
2017-10-01	0	0	0	0	0
2018-01-01	0	0	0	0	0
2018-04-01	0	0	0	0	0
2018-07-01	0	0	0	0	0
2018-10-01	-0.0900608	-0.0427769	0.03818951	0.61492345	0.83401122
2019-01-01	-0.0402425	-0.0573885	0.0080235	0.31994293	-0.3761056
2019-04-01	0	0	0	0	0
2019-07-01	0.01985506	-0.0065285	0.02412626	-0.0449341	0.29262035
2019-10-01	0	0	0	0	0
2020-01-01	0	0	0	0	0
2020-04-01	-1.1153373	-0.1636897	0.32642541	-2.564256	0.7020596
2020-07-01	0	0	0	0	0
2020-10-01	0.07140057	-0.00531	0.24094123	-2.4867566	0.50134688
2021-01-01	0.35639027	0.06865405	0.21918066	-2.5737019	-1.015156
2021-04-01	1.29317999	0.28214897	-0.070708	-0.6151856	-0.6535221
2021-07-01	-0.617568	0.04543636	-0.0346161	-0.4274438	-0.1306644
2021-10-01	0	0	0	0	0

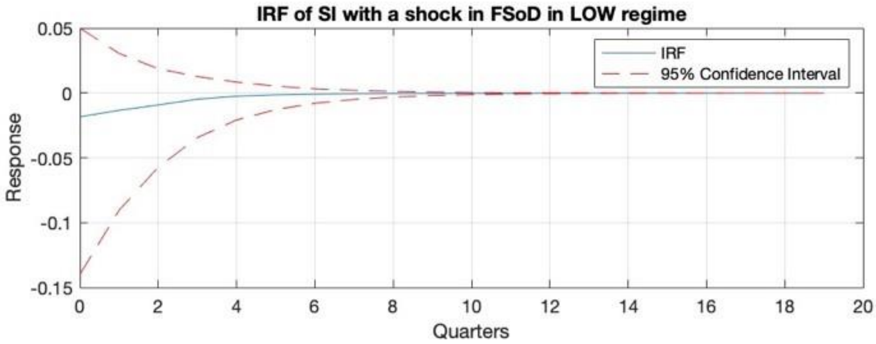
Appendix 4 – IRFs of SI and VIX in the robustness models

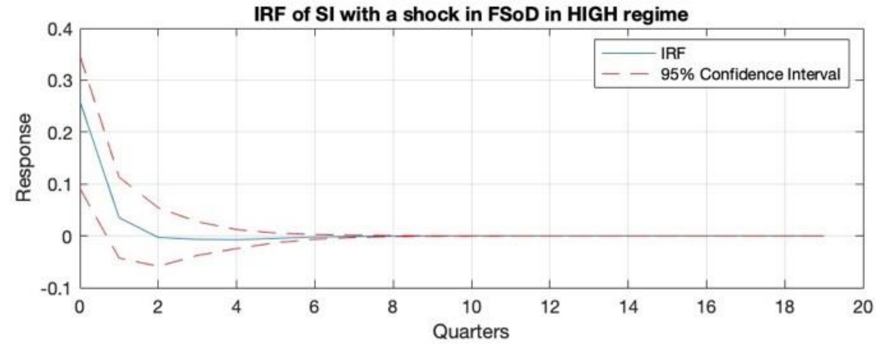

IRF of SI with a shock in DtGDP in LOW regime
IRF
95% Confidence Interval
Response
0.1
0.05
0
-0.05
-0.1
-0.15
0
2
4
6
8
10
12
14
16
18
20
Quarters

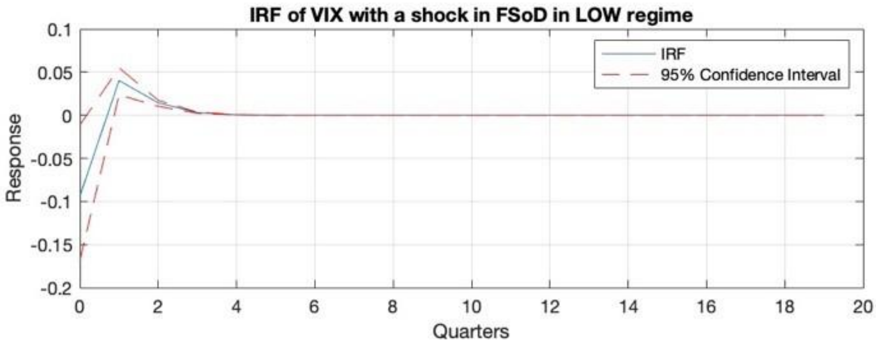

IRF of SI with a shock in DtGDP in HIGH regime
IRF
95% Confidence Interval
Response
0.05
0
-0.05
-0.1
-0.15
-0.2
0
2
4
6
8
10
12
14
16
18
20
Quarters

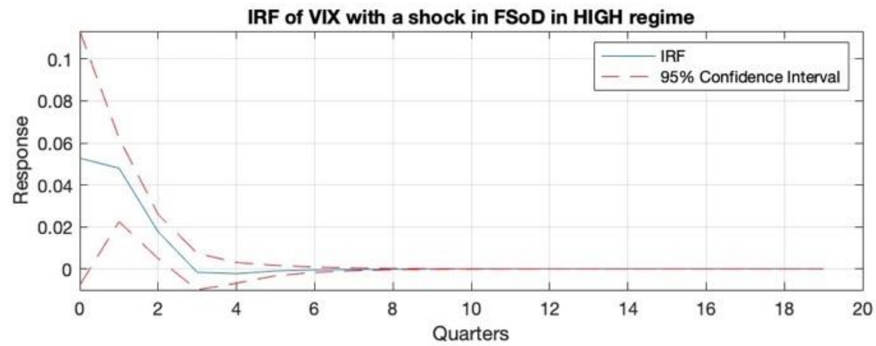

IRF of VIX with a shock in DtGDP in LOW regime
IRF
95% Confidence Interval
Response
0.05
0
-0.05
0
2
4
6
8
10
12
14
16
18
20
Quarters


IRF of VIX with a shock in DtGDP in HIGH regime
IRF
95% Confidence Interval
Response
0.05
0
-0.05
-0.1
0
2
4
6
8
10
12
14
16
18
20
Quarters









11 ENDNOTES

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[i] This process of choosing the correct variables will be elaborated on in the methodology and data section.

[ii] We added a constant of 1.0101, the minimum value in level-form, to perform the log transformation of

negative values. [iii] Proceeding further in this paper, the two terms will be used interchangeably. [iv] As elaborated in the theoretical framework under inflation and price flexibility section.

[v] These effects are explained further in the theoretical framework under section exchange rate and demand side Theory.

[vi] The potential limitations of this operationalizing have been considered and will highlighted in the [vii] Notice the term 2 is replaced by ln(T) in the BIC, and therefore is the second term in BIC greater. [viii] For equation specification, we refer to the standard equation of VAR provided in the methodology section.

[ix] This was further covered in the literature review.