Consumer sentiment is the inverse of economic uncertainty

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Abstract

The objective of this thesis is to test the hypothesis that consumer sentiment, as measured by the University of Michigan's consumer sentiment survey, can be used to approximate the underlying uncertainty in the economy. Previous work regarding uncertainty shocks to the economy have used the VXO, the price of gold, and newspaper headlines to measure uncertainty, but no one true measure of uncertainty has been accepted. This thesis finds that consumer sentiment is a strong instrument to estimate uncertainty shocks in a proxy structural vector autoregressive model (SVAR). The results are compared to an uncertainty shock instrumented by the VXO, which shows a similar, but underestimated, impulse response.

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1. Introduction

The objective of this thesis is to test the hypothesis that consumer sentiment, as measured by the University of Michigan's consumer sentiment survey, can be used to approximate the underlying uncertainty in the economy. The underlying uncertainty in the economy is important to understand since it can affect decisions around hiring, investment, consumption, and monetary policy. Previous studies have used various measures such as the price of gold, the VXO, or scraping newspaper headlines to develop an index for uncertainty, but no one true measure has been accepted. This thesis finds that consumer sentiment is a strong instrument to estimate uncertainty shocks in a proxy structural vector autoregressive model (SVAR) and passes a series of robustness tests. On impulse the results suggest an underestimation for an uncertainty shock that uses the VXO.

Consumer sentiment as measured by the University of Michigan index is defined as: "how consumers view prospects for their own financial situation, how they view prospects for the general economy over the near term, and their view of prospects for the economy over the long term." This measure captures how consumers view their financial situation, regardless of their actual financial situation. This is a critical point, since even if a consumer has financial security, if they perceive that they don't, this hypothesis says it will affect their spending decisions. This measure simply asks consumers directly their degree of uncertainty, rather than trying to estimate it via a tangential measure such as stock market volatility. The consumer sentiment survey acts to distill out consumers behavior in this manner, and through the SVAR framework the overarching effect on the economy is estimated.

Although previous studies have used consumer sentiment in a VAR framework, or analyzed the impact to consumer sentiment from another shock, there has not been a study which directly compares consumer sentiment as an instrument for uncertainty. This thesis aims to fill this gap in the literature.

The concept of stated vs actual preferences suggests that households may not answer surveys truthfully but would rather "vote with their dollars" to communicate their certainty or lack thereof. This hesitation stems from the inherent "emotional" human nature leading to "irrational" consumer behavior. The argument suggests that the University of Michigan consumer sentiment survey aims to measure how consumers view their financial situation, and if humans are emotional the results from this survey may be inaccurate, even if consumers are attempting to communicate their own emotions, or sense of financial security. The presented hypothesis that consumer sentiment is the inverse of uncertainty intentionally includes this information. If consumers are inaccurately identifying their own financial security it shouldn't matter for their spending and saving decisions, it is their view of their economic prospects.

Methodology and Results

The methodology in this thesis follows closely two studies in the literature involving economic uncertainty. (Piffer and Podstawski, 2018) who proxy an uncertainty shock using the price of gold, and (Aastveit, Natvik and Sola, 2017) who study an interacted SVAR to show the effect of monetary policy transmission when uncertainty is high and low. These methodologies are replicated but substituted with the University of Michigan Consumer Sentiment survey in an attempt to show that consumer sentiment can be used in exchange with uncertainty. For an uncertainty shock proxied by sentiment, the general response is consistent compared to that of a shock proxied by uncertainty, although on impact GDP, investment, and consumption are more affected by the shock. For a monetary policy shock, there are contrasting results that the effect of a standard deviation increase in the federal funds rate is more impactful when sentiment is low compared to when uncertainty is low. (Aastveit, Natvik and Sola, 2017) hypothesize this is due to consumers putting off decisions if they are uncertain, waiting until economic clarity resumes to resume major spending decisions. However, (Piffer and Podstawski, 2018) observe that investors will flee to safe haven investments such as gold during events of high economic uncertainty. In this way, one might expect that a rate increase when uncertainty is high, or sentiment is low, would be more impactful as consumers would further choose to decrease consumption and investments to weather the uncertainty.

This thesis follows the above methodology to demonstrate that consumer sentiment is comparable to a commonly used metric for uncertainty, the VXO. However, further studies would be needed to more convincingly demonstrate that consumer sentiment is the inverse of economic uncertainty. For instance, a comparison may be drawn with other measures of uncertainty such as the economic policy uncertainty index (EPU) (Baker, Bloom and Davis, 2016).

The baseline model then undergoes a series of robustness tests, including replacing the relevant endogenous variables with equivalent Euro area variables, changing the number of lags, splitting the data to use pre-pandemic data, and the use of an IVAR to study a monetary policy shock at high and low consumer sentiment.

Additionally in this thesis, a connection is made to recent developments in a subfield of game theory termed "Chemical Game Theory." The conclusions from this thesis are considered in the framework of Chemical Game Theory to demonstrate a microeconomic foundation for the context of this macroeconomic study.

2. Literature review

Uncertainty

Economic uncertainty is typically defined as agents' inability to forecast the likelihood of events happening, and it is important since it may depress hiring, investment, and consumption (Jurado, Ludvigson and Ng, 2015). This point may be made evident by the Covid-19 pandemic in which there was a severe increase in uncertainty of the danger of the disease and what effect it would have on the population, and henceforth the economy. Additionally, the International Monetary Fund and Federal Open Market Committee indicate that uncertainty about U.S. and European fiscal, monetary, and regulatory policies had contributed to the steep economic decline observed in the Great Recession from 2008-2009 and the ensuing slow recoveries (Baker, Bloom and Davis, 2016).

However, there is not a generally accepted "true" measure of uncertainty. Proxies such as the VXO, which is a measure of stock market volatility and widely used as an indicator of uncertainty, may vary even if there is no underlying change in uncertainty. Therefore, there is a large amount literature attempting to measure the amount of uncertainty in the economy. Previous studies have used forecasting error (Jurado, Ludvigson and Ng, 2015), key words in newspaper headlines (Baker, Bloom and Davis, 2016), the VXO (Aastveit, Natvik and Sola, 2017), the price of gold (Piffer and Podstawski, 2018), and variation in oil futures based on OPEC announcements (Känzig, 2018) as measures of uncertainty. Such studies attempt to identify uncertainty in the economy via measurements that do not acknowledge the opinion of the consumer.

Sentiment

In their influential paper developing the Economic Policy Uncertainty index, (Baker, Bloom and Davis, 2016) speculated that sentiment contains overlapping information with uncertainty. They use the University of Michigan consumer sentiment survey as a robustness test for the EPU index, placing it before and after uncertainty in the VAR ordering to estimate the difference of a policy uncertainty shock. In each case the effect of the shock reduces, indicating overlapping information. A similar premise is investigated in (Ilut and Schneider, 2012), which studies business cycle models with agents who are averse to ambiguity. This model assumes that agents do not think in terms of probabilities for all relevant events, but when there is high uncertainty their confidence in their probabilities are decreased.

Consumer sentiment is also demonstrated to be affected by news shocks (Doms and Morin, 2004) (Blood and Phillips, 1995). This study considers a measure of the volume of economic reporting using an R-word index of The Economist publication. It shows that there are periods when reporting on the economy is inconsistent with economic events such as the early 1990's. This suggests consumer sentiment can be driven away from economic fundamentals. Additionally, consumer expectations are updated more frequently under periods of high news reporting than low. Lastly, the authors attribute nonlinearities in consumer sentiment and diffusion of information to the result that under some conditions an increased number of articles mentioning recession can lead to an increase in sentiment. This study is important in the context of this thesis because news shocks have previously been shown to be a proxy for economic uncertainty (Piffer and Podstawski, 2018).

Consumer sentiment has also been shown to have a contemporaneous relationship with stock prices (Otoo, 1999). It also aids in forecasting the evolution of economic activity over a number of countries (Golinelli and Parigi, 2004) and aggregate consumer spending (Huth, Eppright and Taube, 1994). Additionally, it can explain empirical findings in monetary policy (Debes et al., 2014).

Perhaps the closest study to this thesis is (Leduc and Liu, 2016). The authors investigate the relationship of search frictions in the labor market and uncertainty's effect on economic activity. They find that an increase in uncertainty resembles an aggregate demand shock since unemployment increases and inflation decreases. The authors compare the VIX with a measure based on the University of Michigan consumer sentiment survey in a VAR framework. They attribute 70% of the empirical increase in unemployment following an uncertainty shock to search frictions and nominal rigidities. This study differs from the main hypothesis in this thesis however, since both sentiment and uncertainty are compared in a VAR framework, as opposed to directly substituting sentiment for uncertainty. In addition, the authors here consider a Cholesky decomposition as their identification method, instead of an external instruments approach used in this thesis. Another study (van Aarle and Moons, 2017) directly evaluates consumer sentiment in a VAR, showing that sentiment and uncertainty affect economic adjustment in the Euro area. Here, a VAR for economic activity, sentiment, and uncertainty in industry, retail, services, and construction sectors is used to show non-negligible effects of sentiment on economic activity.

Recursive identification SVAR

The recursive identification approach is most common in the SVAR literature, however it is less restrictive than the external instruments approach. (Stock and Watson, 2001) describe how an SVAR framework may be used by macroeconomists to summarize macroeconomic data, make forecasts, advance knowledge on the state of the economy, and advise policy makers. (Christiano, Eichenbaum and Evans, 1998) investigate the case of a shock to monetary policy, while other studies focus on uncertainty shocks. (Bloom, 2009) uses firm level data to estimate the effect of an uncertainty shock, while (Caggiano, Castelnuovo and Groshenny, 2014) estimates a smooth transition VAR, finding that the effects of an uncertainty shock are much larger than a standard linear VAR. (Jurado, Ludvigson and Ng, 2015) develop a separate measure for uncertainty, and find that often times stock market volatility overestimates the amount of uncertainty for a given period.

However, the requirement that the ordering of variables matters in the recursive identification method is subject to criticism. By definition some variables are not allowed to contemporaneously respond to each other, which does not capture the simultaneity of uncertainty and the rest of the economy. A Cholesky decomposition used in this methodology produces a lower triangular matrix, where some variables may not be able to respond contemporaneously to a shock to uncertainty, unless uncertainty is ordered first in which case it would only be affected contemporaneously by its own shock. Since the data used in this thesis is quarterly, it is harder to justify the 0 restrictions imposed that a variable ordered first only is able to respond to lags of the other variables in the system.

External instruments SVAR

The SVAR methodology developed by (Stock and Watson, 2012) and (Mertens and Ravn, 2013) is utilized to identify structural VARs using external instruments, including the models developed in this thesis. The external instruments approach is more restrictive than under recursive identification because the reduced form coefficient matrix isn't required to be lower triangular, as under a Cholesky decomposition, and on impact the response doesn't need to be 0 for variables ordered before the variable which is shocked. In fact, the ordering is arbitrary. The variables in the VAR are allowed to react contemporaneously with the shock as well. Typically, one external instrument is used to identify one structural shock of interest. But this may not necessarily be the case, as (Mertens and Ravn, 2013) use two correlated instruments to identify two shocks.

Other methods include (Baker and Bloom, 2013) who use dummy variables for extreme events in a model of GDP growth, and (Carriero et al., 2015) who also use a dummy variable for VXO peaks and a Monte Carlo simulation to study the effect of measurement errors on the estimation of impulse responses.

Interacted VAR

There is a large amount of literature around interacted VARs regarding the state effects of uncertainty or monetary policy shocks. (Caggiano, Castelnuovo and Groshenny, 2014) study unemployment dynamics with regards to uncertainty shocks in a smooth transition VAR framework, and find that linear models underestimate the effect of a shock to uncertainty. (Caggiano, Castelnuovo and Figueres, 2020) then estimate the spillover effects from economic policy uncertainty shocks in Canada from US economic policy uncertainty. They find that economic policy uncertainty in Canada results from uncertainty in the US, and leads to a temporary increase in the unemployment rate. (Paccagnini and Colombo, 2020) find that reactions of investment and consumption are state dependent, and that the fluctuations drive changes in GDP in a nonlinear VAR model of uncertainty shocks. (Pellegrino, 2017) finds that monetary policy shocks are significantly less powerful during uncertain times, in an interacted VAR which considers uncertainty endogenously. This conclusion is similar to that of (Aastveit, Natvik and Sola, 2017), which also use an interacted VAR during periods of high and low uncertainty to study the effect of monetary policy transmission.

Additionally (Auerbach and Gorodnichenko, 2012), (Riera-Crichton, Vegh and Vuletin, 2014) show that shocks to investment have larger reactions during recessions than in expansions. (Ilzetzki, Mendoza and Végh, 2013) show that shocks depend on debt, fixed regimes, and economies more open to trade. (Izquierdo et al., 2019) show that shocks depend on the initial stock of public capital, and (Christiano, Eichenbaum and Rebelo, 2011), (Coenen, Straub and Trabandt, 2013) show that shocks are more effective when monetary policy is loose compared to the zero lower bound. (Jackson, Kliesen and Owyang, 2019) study whether uncertainty shocks are dependent on periods of high or low uncertainty.

Bayesian Estimation

This thesis uses a Bayesian estimator similar to (Aastveit, Natvik and Sola, 2017), (Sims and Zha, 1998), (Uhlig, 2005) and (Sá, Towbin and Wieladek, 2014) with a normal Wishart distribution imposed on the prior of the regression coefficients covariance matrix. Using uninformative priors and drawing jointly from the posterior, the parameters of the VAR were estimated.

Bayesian estimation is used to estimate coefficients which combine evidence from the sample with information contained in the prior. It avoids potentially biased coefficients obtained when using few data points in maximum likelihood estimation. However, since the priors used in this study were non-informative, the Bayesian predictions would be similar to coefficients which were estimated via maximum likelihood. In an extension of this study it would be interesting to use informative priors, and would likely follow the methodology outlined in (Sims and Zha, 1998) since identified Bayesian VAR models under an informative prior previously had not previously been handled in a consistent way.

3. Theoretical and Empirical framework

Theory

In the general reduced form of SVAR framework (Equation 1) the errors may be written as a linear combination of structural shocks ε where $r_t = S\varepsilon_t$

$$Y_t = \alpha + \sum_{j=1}^{L} B_j Y_{t-j} + r_t \qquad r_t \sim N(0, \Sigma)$$

Equation 1. Reduced form time varying SVAR where j is the number of lags, Y_t is a vector of economic indicators, α and B are estimated parameters, and r_t is a set of error terms normally distributed with Σ variance.

Here, the structural shocks are uncorrelated ($\mathrm{Var}(\varepsilon_t) = \Omega$ is diagonal). As such, $\Sigma = S\Omega S'$ and B may be estimated through a Cholesky decomposition.

An SVAR framework helps identify causality in the economy. Since there is endogeneity in economic variables, this framework identifies a model in which each variable depends on lagged terms of every other variable in the system. In this way, one can determine the effect on each other variable if there is a shock to one variable. In the model for both the interacted VAR and external instruments a lag length of 2 is used consistent with (Aastveit, Natvik and Sola, 2017), and 2 quarters is approximately consistent with a lag length of 5 months used in (Piffer and Podstawski, 2018). This thesis considers using consumer sentiment as an interacted term in an interacted SVAR model to estimate the transmission of monetary policy, and as an external instrument to estimate the effect of an uncertainty shock.

Interacted VAR

The effect of time varying consumer sentiment on the transmission of monetary policy is estimated via an interacted structural vector autoregressive model (IVAR). Consumer sentiment is interacted with federal funds rate, allowing for state contingent effects of a shock to monetary policy.

$$\mathrm{Y_t} = \alpha + \sum_{j=1}^{L} \mathrm{B_j Y_{t-j}} + \sum_{j=1}^{L} \mathrm{C_j} * \mathrm{ffr_{t-j}} * \mathrm{CS_{t-j}} + \varepsilon_t \qquad \varepsilon_t \sim \mathrm{N}(0, \Sigma)$$

Equation 2. Where ffr is the Federal Funds Rate and CS is consumer sentiment. Y_t is a vector of economic indicators including GDP, consumption, investment, CPI, and Federal Funds Rate. GDP, consumption, investment, and CPI are transformed using log differences.

In Equation 2 α, B, C are coefficients and ε_t is a vector of error terms with a variance covariance matrix Σ. The interaction term between federal funds rate and consumer sentiment makes the interacted VAR different from the standard VAR. For each lag j, there is a vector of coefficients C_j which captures the state dependent effects of a shock to federal funds rate, conditional on the state of consumer sentiment.

Following (Aastveit, Natvik and Sola, 2017) and to illustrate the importance of the interaction terms, impulse responses with sentiment in its upper and lower decile (90^{th} and 10^{th} percentile) of its historical distribution were graphed in section 5. Here sentiment is fixed, such that there is no feedback from the endogenous variables, and impulse responses to a monetary policy shock can be computed as a linear VAR. This approach is similar to studies involving regime switching models such as (Caggiano, Castelnuovo and Groshenny, 2014) and (Auerbach and Gorodnichenko, 2012). Normally under nonlinear VARs, impulse responses depend on the initial conditions, or where the shock occurs in time, however this approach avoids this problem since sentiment is being held constant. However, since sentiment is mean reverting (Figure 2) it may exaggerate the difference in state dependent effects. When the level of sentiment is fixed, Equation 2 reduces to Equations 3.

$$\mathrm{Y}_t^{high} = \widehat{\mathrm{D}}_0^{high} + \sum_{j=1}^{L} \widehat{\mathrm{D}}_j^{high} \mathrm{Y}_{t-j} + \widehat{\mathrm{U}}_t$$

$$\mathrm{Y}_t^{low} = \widehat{\mathrm{D}}_0^{low} + \sum_{j=1}^{L} \widehat{\mathrm{D}}_j^{low} \mathrm{Y}_{t-j} + \widehat{\mathrm{U}}_t$$

$$\widehat{\mathrm{D}}_0^{high} = \alpha + \sum_{j=1}^{L} \mathrm{C}_j \mathrm{CS}^{high}$$

$$\widehat{\mathrm{D}}_0^{low} = \alpha + \sum_{j=1}^{L} \mathrm{C}_j \mathrm{CS}^{low}$$

$$\widehat{\mathrm{D}}_p^{high} = \alpha + \mathrm{B}_j \mathrm{CS}^{high}$$

$$\widehat{\mathrm{D}}_p^{low} = \alpha + \mathrm{B}_j \mathrm{CS}^{low}$$

Equations 3 Standard reduced form VAR models following (Aastveit, Natvik and Sola, 2017) where the level of uncertainty is fixed in an interacted VAR which reduces to a linear VAR

External Instruments

External instruments are used when a time series (z_t) is assumed to be correlated to the structural shock identified in the VAR (relevance condition), but not the other structural shocks (exogeneity condition.)

$$\mathrm{E}\left(z_t \varepsilon_{1,t}\right) = \gamma \neq 0$$
$$\mathrm{E}\left(z_t \varepsilon_{2:n,t}\right) = 0$$

In an SVAR framework, the relevance and exogeneity conditions are non-testable since the shock of interest is not observed. However, it is possible to test the relationship between the instrument and VAR innovations. A statistically significant relationship between the instrument and residuals of the VAR model is necessary for acceptance as a useful tool to understand the underlying drivers of the residuals.

Unlike in the recursive identification method, the ordering of variables under the external instruments approach is arbitrary. This is due to the identifying restrictions imposed upon the system, which is no longer lower triangular. A reordering of variables in the reduced form of the model is equivalent to a reordering of rows of the standard form model.

It is helpful to show Equations 4 to consider the effect of shifting the order of variables.

$$BB' = \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} \begin{pmatrix} b_{11} & b_{21} \\ b_{12} & b_{22} \end{pmatrix} = \begin{pmatrix} {b_{11}}^2 + {b_{12}}^2 & b_{11}b_{21} + b_{12}b_{22} \\ b_{11}b_{21} + b_{12}b_{22} & {b_{22}}^2 + {b_{21}}^2 \end{pmatrix}$$

$$BB' = \begin{pmatrix} b_{12} & b_{11} \\ b_{22} & b_{21} \end{pmatrix} \begin{pmatrix} b_{12} & b_{22} \\ b_{11} & b_{21} \end{pmatrix} = \begin{pmatrix} {b_{12}}^2 + {b_{11}}^2 & b_{12}b_{22} + b_{11}b_{21} \\ b_{12}b_{22} + b_{11}b_{21} & {b_{21}}^2 + {b_{22}}^2 \end{pmatrix}$$

Equations 4. Example taken from Piffer Notes on VARs with external instruments

In this thesis, consumer sentiment is used as an external instrument for a shock to uncertainty, which is taken to be the VXO.

Bayesian Estimation

Taking a similar approach as (Aastveit, Natvik and Sola, 2017), this thesis estimates the relevant parameters in the interacted VAR via Bayesian estimation. For simplicity, rewrite Equation 1 as Equation 5.

$$Y = X\beta + \varepsilon$$

Equation 5. Simplified VAR for Bayesian estimation

Where X contains all regressors including lagged, endogenous, exogenous, and interacted, and ε has a variance Σ. The Bayesian estimation uses noninformative priors, β is assumed to be normally distributed and Σ follows a Wishart distribution. A Gibbs sampler is used to sequentially draw from the normal and Wishart distributions.

$$(\beta|Y,\Sigma^{-1}) \sim N(\overline{\beta},\overline{V})$$
$$(\Sigma^{-1}|Y,\beta) \sim \mathcal{W}(\overline{H},\overline{v})$$

Where $\overline{\beta} = \overline{V}(\underline{V}^{-1} + \sum_{t=1}^{T} X'^{\Sigma^{-1}} Y)$, $\overline{V} = (\underline{V}^{-1} + \sum_{t=1}^{T} X'\Sigma^{-1} X)^{-1}$, $\overline{v} = T$ and $\overline{H} = (\sum_{t=1}^{T} X'\,\Sigma^{-1}(Y - X\beta)(Y - X\beta)')^{-1}$

Typically in a Bayesian estimation method there is a step which involves "burning" initial iterations of the Gibbs Sampler, then taking the mean of the leftover iterations at some "n" interval. This is done to avoid autocorrelation, and to retrieve the stationary distribution of the Markov chain, which may not be the case for the initial parameters input in the algorithm. In this thesis, the first third iterations were burned, but the resulting iterations were not further burned in an attempt to avoid autocorrelation, since the impact on the coefficients was estimated to be small for the increase in time needed to run the computations. The initial parameters for the matrix of coefficients and variances was estimated via OLS. Additionally, the bootstrapping method creates pseudo data based on the residuals of the model estimated via the Bayes estimator and Gibbs sampler, but uses OLS estimation for creating models based on that pseudo data.

4. Data Description

All data used in this thesis is taken from the Federal Reserve Bank of St. Louis Database (FRED) using its Python API extension. FRED is a reputable database containing more than 765,000 economic time series from 96 sources.

The baseline model takes data from Q1 1986 to Q3, 2021. These date ranges were selected since the VXO starts on January 1, 1986. In a robustness test, the effect of using pre-pandemic data, from Q1 1986 to Q1 2020, is considered. This range was selected due to Covid-19 existing primarily outside of the US until the start of Q2 2020.

Table 1 describes the data variable, the identifying tag via the FRED database, and the transformation done on the variable.

Table 1 Economic variables considered, corresponding FRED tag, and transformation

	US Tag	Euro Tag	Transformation
Sentiment	UMCSENT	CSCICP03EZM665S	Log difference
Uncertainty	VXOCLS	EUEPUINDXM	NA
Federal Funds Rate	FEDFUNDS	ECBDFR	NA
Consumer Price Index	CPIAUCSL	CP0000EZ19M086NEST	Log difference
Gross Domestic Product	GDPC1	CPMNACSCAB1GQEU272020	Log difference
Real Gross Domestic Investment	GPDIC1	PRMNVG01EZQ661S	Log difference
Real Personal Consumption Expenditures	PCECC96	NAEXKP02EZQ189S	Log difference

The data focuses on the US economy, which was chosen due to the desire to use the University of Michigan consumer sentiment survey. The process was repeated for the euro area as a robustness test using the OECD sentiment indicator. The OECD indicator is similar to the

University of Michigan consumer sentiment survey, as it asks households questions regarding their expected financial situation, unemployment, and saving capability.

The European uncertainty data series is the economic policy uncertainty index, which is a news based index for 5 countries: Germany, the United Kingdom, France, Italy, and Spain. The European equivalent interest rate is the ECB Deposit Rate, which is the rate on deposit facility, which banks use to make overnight deposits. For CPI, the Harmonized index of consumer prices for all items in the Euro area (19 countries) was used. GDP for the European Union (27 countries from 2020) was used for US GDP, and total production of investment goods for manufacturing in the Euro area was used for Investment. Although this is not equivalent to Real Gross Domestic Investment in the United States, it may be a valid indicator for the level of investment in Europe. Lastly, gross domestic product by expenditure in constant prices: final private consumption expenditure for the Euro area was used for consumption.

Figure 1 shows time series plots of the relevant variables presented in this thesis. Log differences were taken on select variables to ensure stationarity. Since University of Michigan sentiment acts as an instrument for uncertainty, it does not need to be stationary, but was taken to be a log difference in an attempt to mimic the information gained or lost when taking transformations of the other endogenous variables in the system.

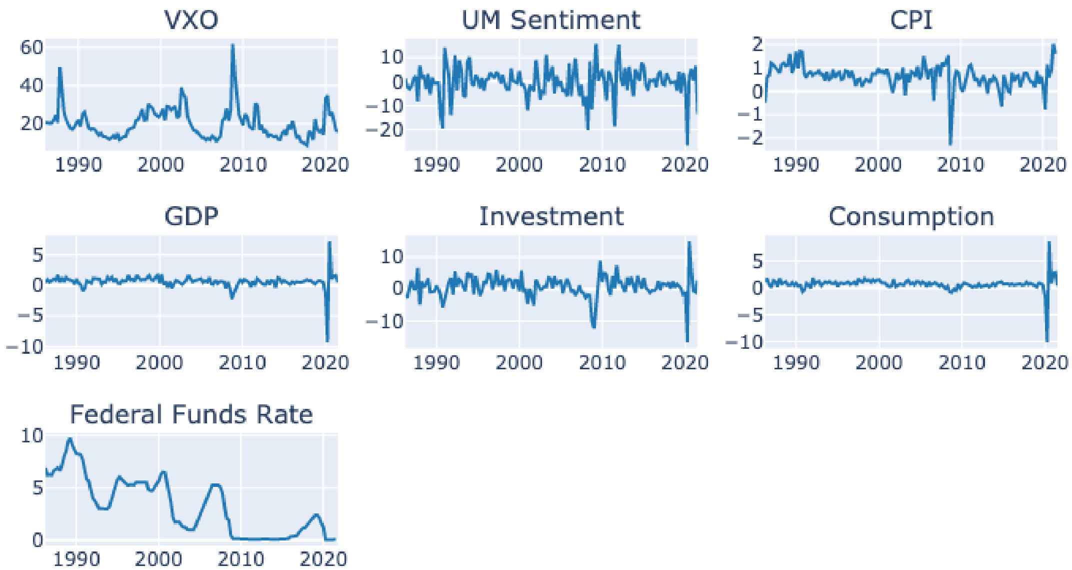

Figure 1 Time series plots for relevant endogenous variables in the VAR

Is consumer sentiment the same as the VXO?

One of the key insights from this thesis is that the consumer sentiment survey contains information that other measures of uncertainty, such as the VXO, does not. Therefore, to ensure that the VXO and EPU are not the same as consumer sentiment with a different magnitude, the series were demeaned, standardized, and graphed in Figure 2. Additionally, the correlation coefficient between the VXO and consumer sentiment is -0.2, and -0.54 for the EPU and sentiment. These correlations indicate a weakly and moderately correlated inverse relationship between the sentiment and uncertainty. The inverse relationship is expected, where when sentiment is high uncertainty is low, but since there is a weak relationship between the VXO and sentiment it indicates that there may be additional information in the VXO which isn't capturing economic uncertainty properly compared to the survey. Since sentiment is more correlated with EPU, this is a positive indication that it may be used to proxy uncertainty yet it is not a perfectly inverse relationship.

Note that sentiment severely decreases during the Great Recession from 2008-2009, the Covid-19 pandemic (Q2 2020), the ".com" bubble in 2000, and 9/11 in 2001. These troughs are roughly in line with peaks of uncertainty given by the uncertainty indices.

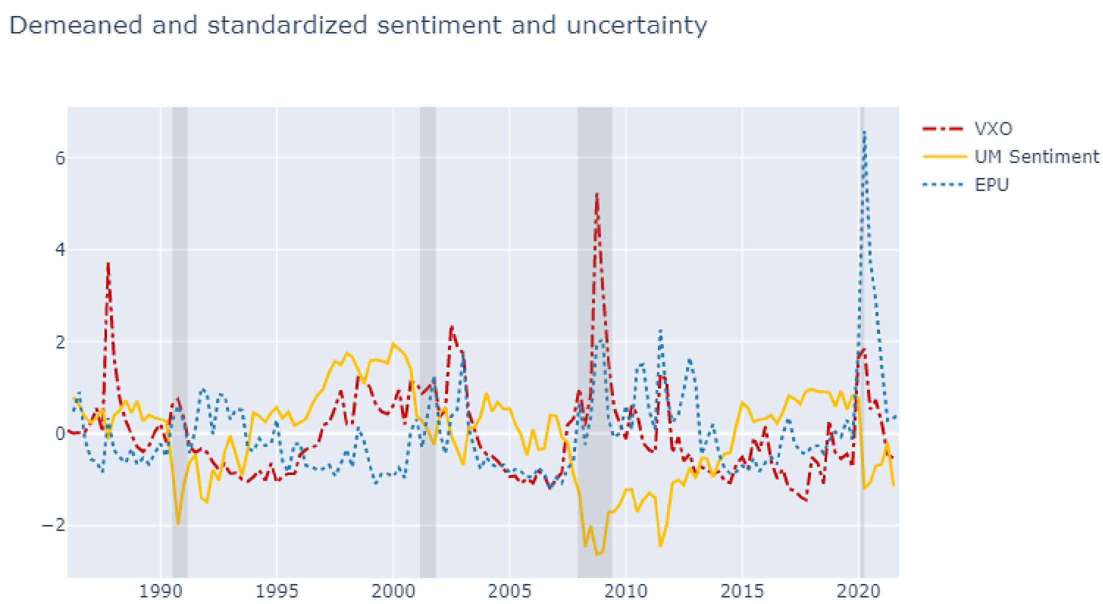

Figure 2 Time series plot of the VXO, Economic Policy Uncertainty Index, and University of Michigan Consumer sentiment survey, which shows that there is not an exact inverse relationship between the measures for uncertainty and sentiment. The grey bars are times of recession in the United States as defined by the NBER.

Test for cointegration

A regression using nonstationary processes yields a nonstationary process, however there may be a circumstance where when multiplied by a scalar, the difference in the processes yields a stationary process. When this happens, the variables are said to be cointegrated. To test for cointegration, the model is rearranged solving for the residuals, and the general AR(1) model is estimated with a t test given the null hypothesis that X_t and Y_t are not cointegrated, which is the same as testing for a unit root (Equation 6.)

$$Y_t = \mu + \beta X_t + u_t$$
$$\hat{u}_t = (Y_t - \overline{Y}) - b(X_t - \overline{X})$$
$$\hat{u}_t = \alpha \hat{u}_{t-1} + \zeta_t$$

Equation 6. Estimating the regressor for a unit root, which determines if the series are cointegrated

Table 2 shows the estimated coefficient “α” in Equation 6, which suggests there is cointegration if it is equal to 1. This is important to retrieve nonbiased coefficients in the model. None of the relevant variables are close to unit root, and the Augmented Dickey Fuller test statistic and p-value confirms that that each of the series are stationary.

Table 2 Test for cointegration of endogenous variables to ensure stationarity

	α	**ADF test stat**	**ADF p-value**
CPI	-0.001	-11.656	1.99E-21
GDP	-0.049	-12.317	6.89E-23
Investment	-0.054	-12.443	3.72E-23
Consumption	-0.054	-12.381	5.03E-23
Fed Funds Rate	-0.049	-5.090	1.47E-05
Uncertainty	-0.012	-11.858	6.94E-22
Sentiment	-0.033	-12.094	2.09E-22
Sentiment*FFR	-0.023	-12.014	3.13E-22

5. Empirical Results

Test the strength of the instrument

In a similar fashion to (Gertler and Karadi, 2015), the strength of the instrument was considered using a regression involving the instrument and reduced form shocks from Equation 1. If there were to be a statistically insignificant relationship between the instrument and residuals, it would suggest a lack of relationship between the instrument and the underlying shocks driving the VAR (Equation 7).

$$r = \alpha + \beta_i m_t^l + \eta_{it} \quad i = 1, 2, \ldots, k \quad l = u, s$$

Equation 7. Where r is the estimated reduced form shock, m_t^u is the proxy for uncertainty (VXO) and m_t^s is the proxy for sentiment, k is the number of lags

As shown in Table 3, consumer sentiment is observed to be a strong instrument for uncertainty as measured by the VXO. In addition, it would be a strong instrument for several of the other variables in the VAR.

Table 3 Results from regressions for reduced form shock

Proxy for uncertainty shock is uncertainty

	Uncertainty	CPI	GDP	Investment	Consumption	FFR
β	0.40***	-0.02***	-0.04***	-0.08**	-0.03***	0.123**
T	141	141	141	141	141	141
F	59.6	10.1	10.1	6.3	8.1	6.0
R^2	0.30	0.07	0.07	0.04	0.06	0.04

Proxy for uncertainty shock is sentiment

	Uncertainty	CPI	GDP	Investment	Consumption	FFR
β	-0.35***	-0.004	0.05***	0.11***	0.05***	0.01***
T	141	141	141	141	141	141
F	24.0	0.44	13.45	7.05	11.25	9.05
R^2	0.15	0.003	0.09	0.05	0.07	0.06

As shown in Table 3 the coefficient for uncertainty is negatively related to the proxy, which is expected due to the inverse relationship between uncertainty and sentiment. It is the only significantly negative coefficient, where GDP, Investment, Consumption, and the Federal Funds Rate all show significantly positive coefficients. CPI was found to be unrelated to the instrument. The F statistic for the null hypothesis that B = 0 was found to be greater than 10 for Uncertainty, GDP and Consumption, suggesting that it may be a strong instrument for these variables (Stock and Watson, 2001). Since these measures mostly respond significantly with the expected signs, the instrument can be said to be a strong one.

Baseline Model

The baseline model considered in this thesis takes an external instruments identification approach to estimate the effect of an uncertainty shock in the economy. The shock as proxied by the VXO is compared to a shock proxied by consumer sentiment.

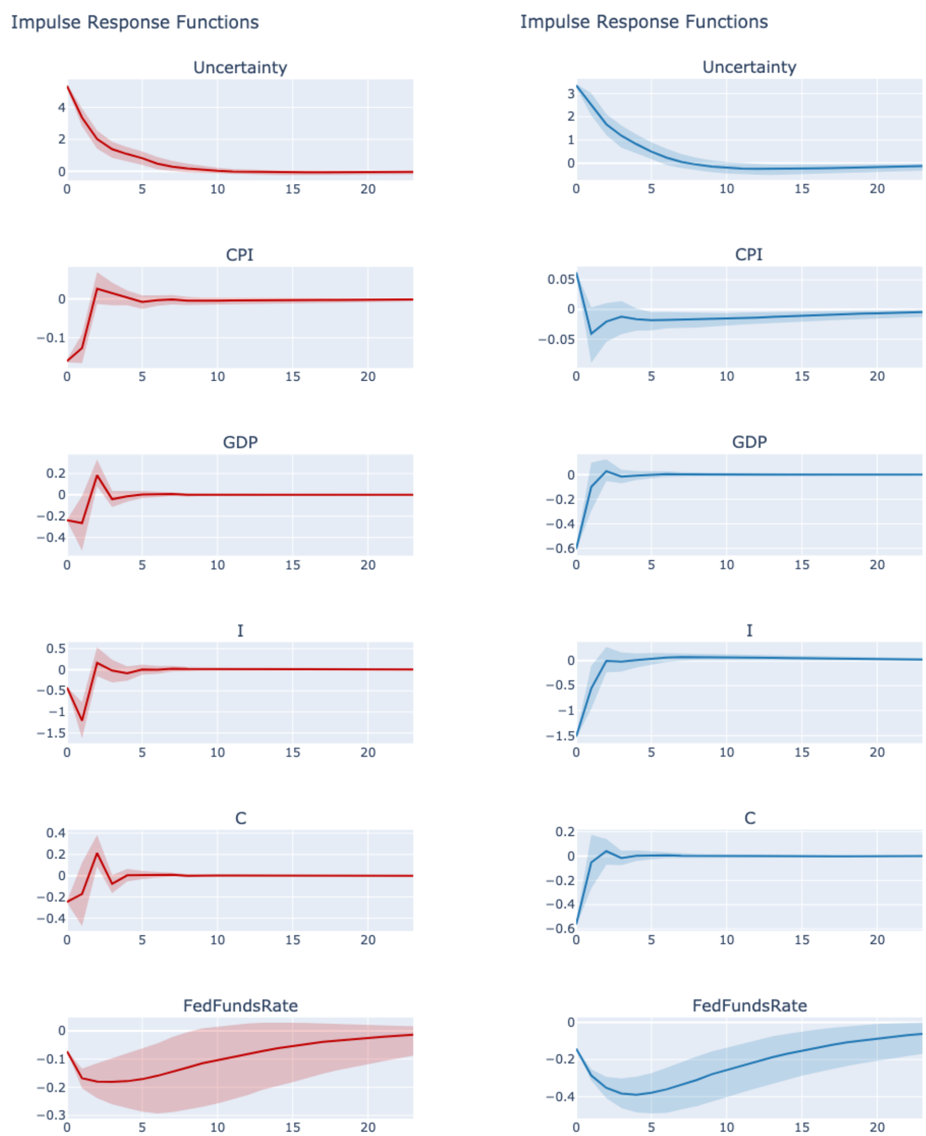

Figure 3 Impulse response functions for the baseline standard deviation uncertainty shock proxied by instruments of uncertainty (left) and consumer sentiment (right) with 84th percentile confidence bands for 24 quarters after the shock and 2 lags.

As shown in the impulse response functions (Figure 3), a shock to uncertainty upon impact increases CPI, and decreases GDP, investment, consumption, and Federal Funds Rate. This makes sense as an increase in uncertainty would lead consumers to reduce their consumption, and an overall contraction in the economy. In both the sets of responses, the shock is quickly absorbed by the economy after about 5 quarters, with the exception of the Federal Funds Rate which returns to 0 after about 24 quarters. Interestingly, the uncertainty shock identified by consumer sentiment has a lower effect on uncertainty upon impact, but a larger effect for Federal Funds Rate, consumption, investment, and GDP, although the shape of the responses in advance of the shock are generally similar. CPI however, differs between the two sets of plots. On impact for the shock identified using sentiment the response is positive rather than negative when it is identified using uncertainty. However, it may be the case that this is a small impact indistinguishable from 0 for the model instrumented with sentiment.

Specifically, the impact of GDP and consumption is about 4 times more negative when considering consumer sentiment as a proxy, both about -0.6, compared to uncertainty, which are both about -0.2. Investment is about 3 times more negative, with an impact of -1.5 for sentiment and -0.5 for uncertainty. This is in line with the literature which suggests that consumer sentiment has a large predictive power for consumption (Huth, Eppright and Taube, 1994).

In this model the coefficients were estimated using Bayesian techniques for conjugate priors using a Gibbs sampler with uninformative priors and 1000 iterations, burning the first third and taking the mean of the remaining runs. In addition, 1000 bootstrap replications are generated, to calculate the 84th, 50th, and 16th percentile error bands shown in the figure.

The conclusion that the effect of an uncertainty shock is underestimated is in line with (Caggiano, Castelnuovo and Groshenny, 2014) who study interacted VARs with uncertainty shocks (see Section 2).

Robustness tests

As a robustness test, the methodology was repeated using relevant variables for the euro area.

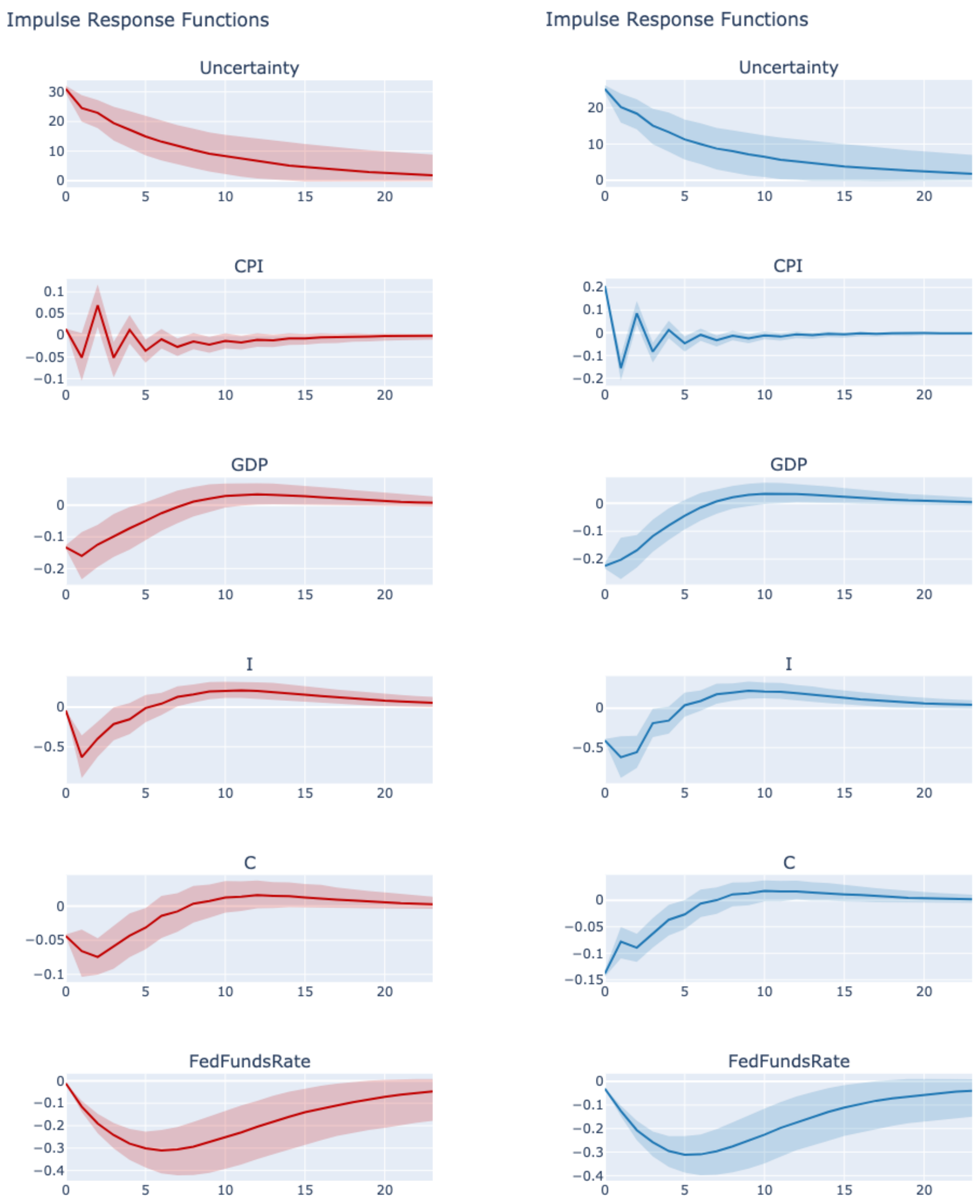

Figure 4. SVAR model identified using external instruments of uncertainty (left) and consumer sentiment (right) with Euro area endogenous variables. Model uses 2 lags and error bands are the 84th and 16th percentile

As seen in Figure 4 with the process repeated for variables in the Euro area, the trends are relatively the same, although compared to the US the relevant variables do not return to their original levels as quickly. Comparing the effect on the endogenous variables using sentiment as a proxy to uncertainty, on impact the effect to investment is much larger, -0.5 compared to near 0, for consumption, -0.15 compared to -0.05 and GDP, -0.2 compared to -0.1. Again, the effect on impact on CPI comparing the two instruments is vague, with high oscillations in the ensuing quarters. The magnitude of the uncertainty shock is a function of the numerical difference in the OECD European economic policy uncertainty index and the VXO. The VXO ranges roughly from 0-100 while the OECD European economic policy index ranges from roughly 40 to 440. In each case a standard deviation shock was imposed to uncertainty and the effect on the rest of the endogenous variables in the VAR were plotted via the impulse response functions.

Using pre-pandemic data

As shown in Figure 5, when pre-pandemic data, that is from Q1 1986 to Q1 2020, is used under the methodology outlined above the results are similar, but less drastic. This can be observed especially in consumption. In the pre-pandemic case where uncertainty was proxied by the VXO, the effect was about half on impact as that with the pandemic data included. Additionally consumption returned to its original level quickly in the ensuing quarters, and underwent a positive change about 3 quarters from its starting point, albeit a small one (Figure 5) compared to the baseline model (Figure 3). This difference can be attributed to the strong response of consumers, either due to lower interest rates, fiscal stimulus, shifting preferences or some other sense of obligation to increase spending during the pandemic. In the case of uncertainty proxied by sentiment, the effect on impact is much more negative, roughly 4 times as large, than the response without including data from the pandemic. This may be attributed to the fact that consumers could not spend on things they typically would have like entertainment or travel. Then after about 3 quarters from its starting point the recovery in spending was again strong but not as positive as in the case of uncertainty proxied by VXO, which may be more realistic as such a swing wasn't observed in the time series of consumption during the pandemic.

A similar story can be said for GDP. Under the case where uncertainty was proxied by VXO, the impact response was about -0.15 using pre-pandemic data, and about -0.2 including it. Again, in the case where pandemic data was included, there was a strong recovery towards a positive change after about 3 quarters. For uncertainty proxied by consumer sentiment, the effect was about -0.2 on impact when excluding pandemic data and -0.6 with it included. This likely is affected by the large change in consumption, which GDP includes in its definition. In the consumer sentiment proxy, there is again a quick recovery, but one that does not shift towards a strong positive change from its starting point. Investment shows a similar story, with an impact that is more drastic when pandemic data is included. The Federal Funds rate looks to be roughly constant when comparing the split data.

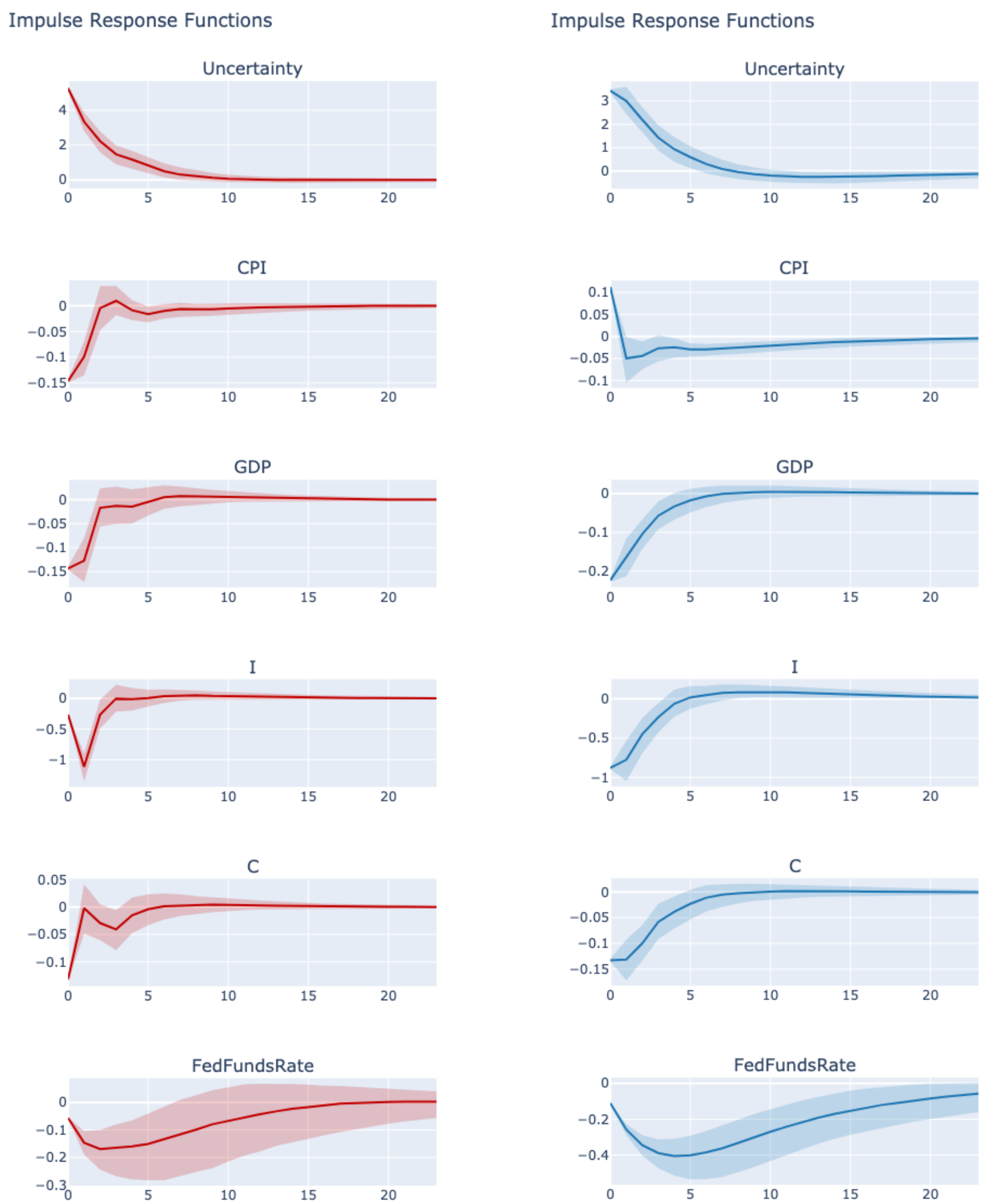

Figure 5. SVAR model identified through external instruments uncertainty (left) and consumer sentiment (right) using pre-pandemic data (until Q1 2020). Model uses 2 lags and error bands are the 84th and 16th percentile

Changing Lags

As another robustness test, the effect of changing the number of lags was observed. The optimal number of lags was tested using an Akaike information criteria test on each of the variables in the model with lags varying from 1 to 8. In an Akaike information criteria test, the preferred model is the one with the minimum AIC value.

Table 4 Results of a Akaike information criteria test for OLS regressions run on individual variables in the SVAR model at varying lag lengths.

	Lags							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Uncertainty	863.63	860.09	859.66	855.83	854.53	852.3	854.77	<u>815.33</u>
CPI	174.43	<u>171.01</u>	181.65	190.87	199.33	197.93	197.56	195.55
GDP	<u>197.14</u>	199.35	198.93	208.71	219.19	219.12	224.43	225
I	617.28	615.11	609.01	611.64	616.28	606.94	600.4	<u>593.54</u>
C	173.56	179.34	<u>165.94</u>	172.66	178.65	183.73	185.49	181.61
FedFundsRate	132.65	63.06	60.68	63.45	<u>59.78</u>	62.49	72.53	68.79

In Table 4, the minimum value of the Akaike test is underlined. However, across the variables considered, there is not a consistent number of lags, so the number of lags chosen for the baseline model was determined to be 2 based on previous literature values. As a robustness test, the methodology was repeated with 8 lags, as shown in Figure 6.

In general, the responses in Figure 6 are similar to those of the baseline Figure 3 except there is more variation across the time periods from the impulse. This may be due to the increased “memory” in the SVAR with 8 lags, and may be an over specified model since it seems unlikely that a shock which occurred 8 quarters ago would still have an effect on the system. Although, considering about 6 quarters have passed from the start of Covid-19 to the time of this writing and the effects seemingly are still propagating through the economy, it may not be so far-fetched. On the other hand, it may be inappropriate to call Covid-19 a one standard deviation uncertainty shock, or even one shock in itself.

On impact, the model using 8 lags has a more negative effect for CPI, GDP, and investment, and about the same effect for consumption and the federal funds rate using the VXO as a proxy. However, the effect is less negative for GDP, investment, and consumption for using sentiment as a proxy. Federal funds rate and CPI are roughly similar on impact.

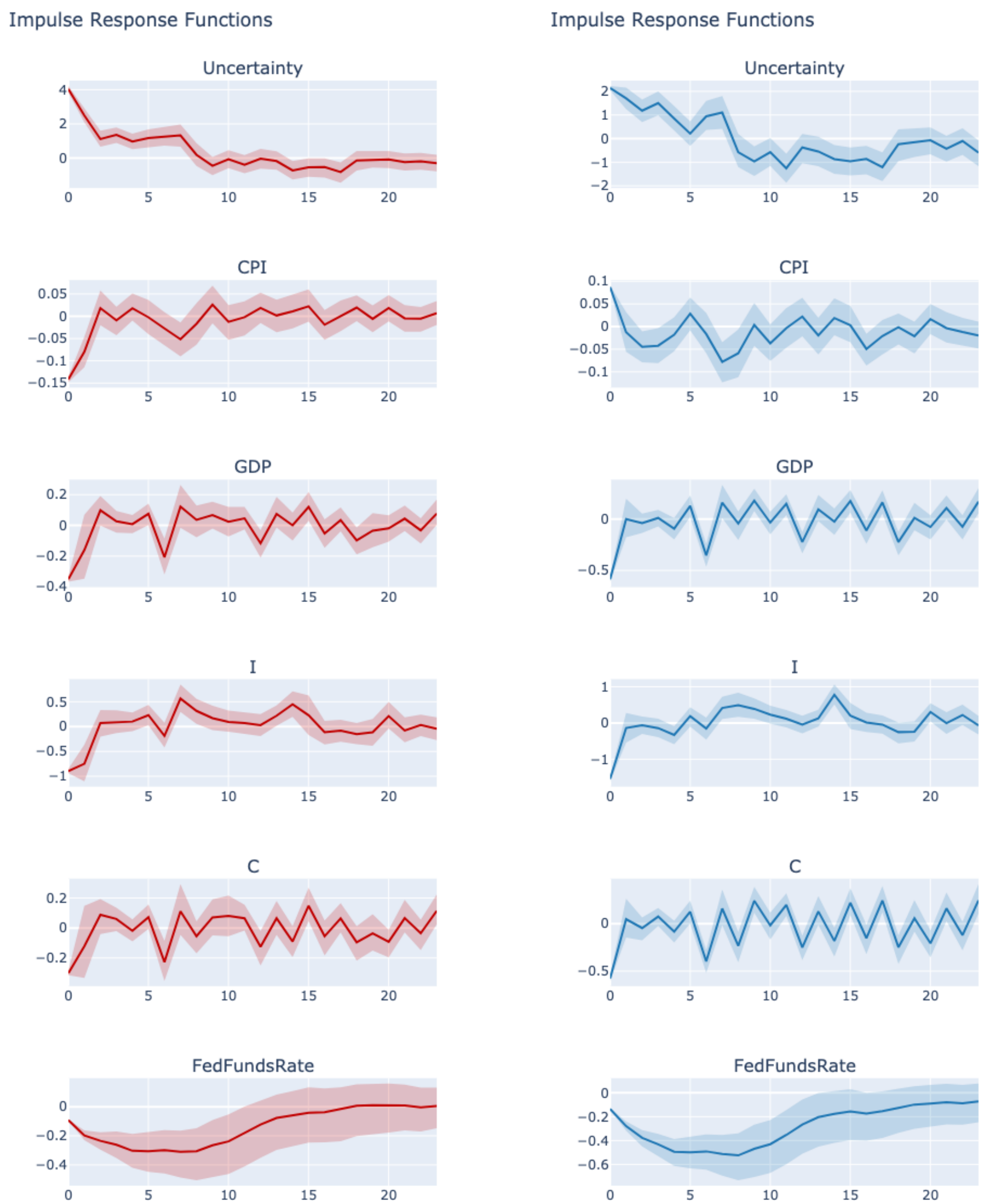

Figure 6. SVAR model identified using external instruments uncertainty (left) and consumer sentiment (right) and 8 lags. Error bands are the 84th and 16th percentile

Monetary policy shock at high and low sentiment

In addition to considering consumer sentiment as an instrument for uncertainty, this thesis studies a monetary policy shock for an interacted SVAR model. To convince the reader that uncertainty can be measured by the inverse of consumer sentiment, it is insufficient to solely consider consumer sentiment as an instrument for uncertainty. This exercise in itself does not provide conclusive evidence in favor of the claim that consumer sentiment is the inverse of economic uncertainty but aims to provide additional evidence to support it. Additionally, (Debes *et al.*, 2014) show that consumer sentiment is known to account for empirical findings of monetary policy shocks, so there may be insights derived from using consumer sentiment as a measure of uncertainty when analyzing a monetary policy shock.

The IVAR model was identified using the popular recursive identification method ordered such that the interest rate is able to respond within the same quarter to the macroeconomic variables but not vice versa. That is, the endogenous variables are unable to contemporaneously respond to a shock to interest rate, but only after a lag. This may or may not be realistic as many economic reporters and firms are interested in forward guidance from the Federal Reserve, which by the time the rate increase comes into effect the overarching adjustment from the other relevant variables in the economy may have already accounted for this shift.

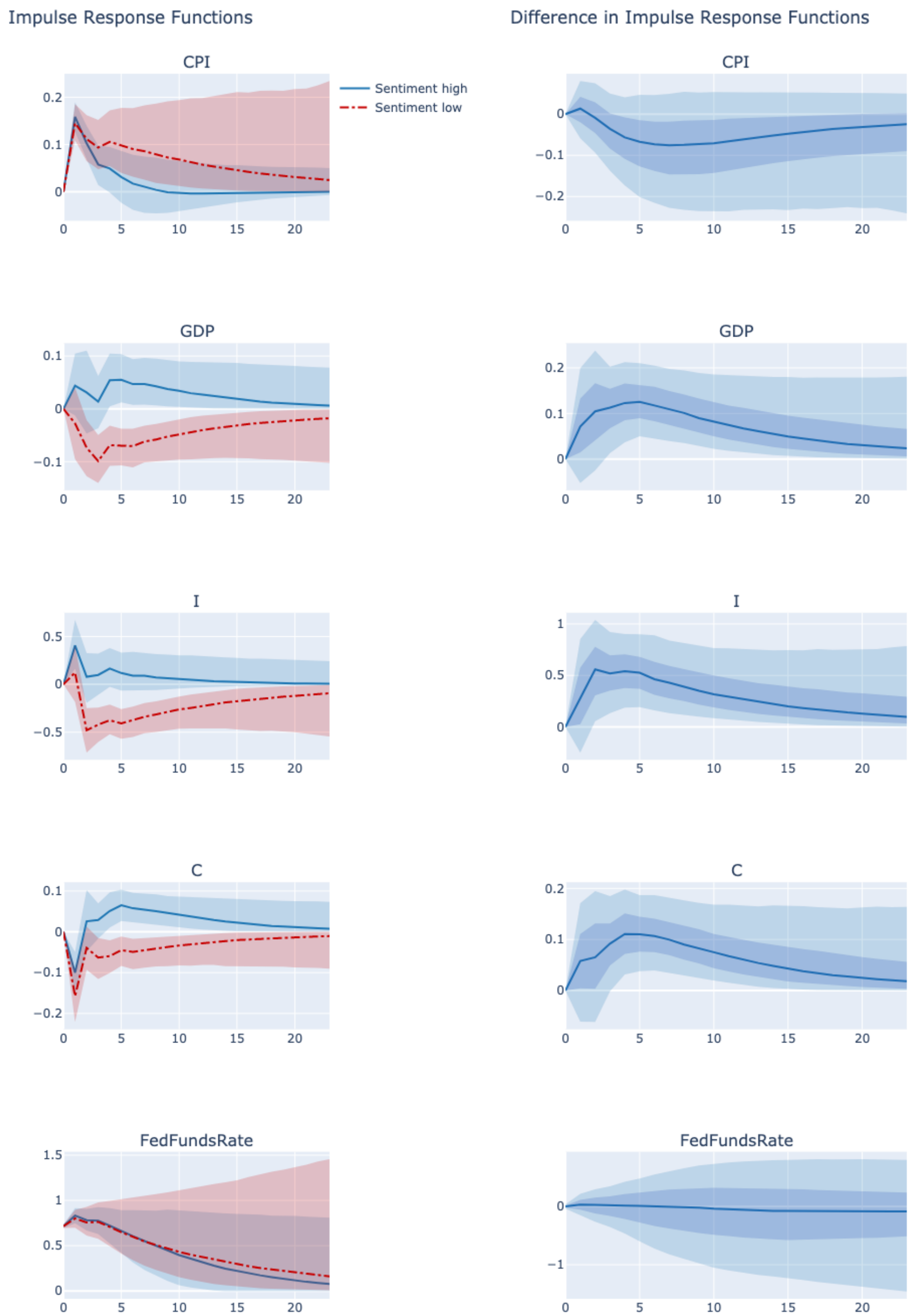

Figure 7 Impulse responses and difference in responses to a positive standard deviation shock to the Federal Funds Rate when consumer sentiment is high vs. low. Identification here is done through a Cholesky decomposition with sentiment fixed at its upper and lower deciles in the interacted VAR following (Aastveit, Natvik and Sola, 2017).

As observed in Figure 7, a shock to monetary policy when sentiment is low is more impactful at cooling spending than when it is high. In fact, when sentiment is high, GDP, CPI, and investment see an increase on impact. Consumption sees an initial decrease, followed by a strong rebound to an increase relative to its original level. The error bands for the set of plots to the left are the 84th and 16th percentiles from a bootstrap method using 1000 iterations calculated in the same way as the external instrument method. For the set of differences in impulse response plots to the right, the interior error bands are the 84th and 16th percentiles from the bootstrap method, while the outer error bands are the 95th and 5th percentiles.

These results should be taken with caution, since it seems unlikely however that the Federal Reserve would set a rate increase when consumer sentiment is in its lower decile since this typically correlates with high uncertainty and a recessionary period. As stated in (Aastveit, Natvik and Sola, 2017), these results should be considered the maximum effect for a rate increase at high and low sentiment.

The higher response to a rate increase when sentiment is low indicates that consumers are more willing to adjust their behavior towards saving to take advantage of a higher interest rate when they are feeling poorly about their future economic prospects. Then a contraction in the economy ensues, and a decrease in consumption and investment are distinctly different as judged by the lack of overlap in 84th percentile confidence intervals. This finding runs counterintuitive to (Aastveit, Natvik and Sola, 2017) and (Pellegrino, 2017), which find that when uncertainty is low, monetary policy is more effective at cooling spending. They attribute this finding to consumers delaying spending decisions due to the economic uncertainty. An increase in uncertainty under this set of assumptions causes monetary policy to be less effective at encouraging consumers to save rather than spend, as consumers are unsure of what to do. This may be counter however to what was observed during the Covid-19 pandemic, which saw an increase of 14.5 percent year over year in Q3 2020 for personal consumption expenditures durable goods (FRED tag PCEDG). In this case, even when there was a very high degree of uncertainty, consumers were quick to respond, shifting consumption for the "new normal" Covid economy. Additionally, it may be the case that with an updated data set the results could have shifted since the time of publication of (Aastveit, Natvik and Sola, 2017), that the underlying information contained in the consumer sentiment survey is more realistic a measure of uncertainty than the VXO, or that the Cholesky identification restrictions were not realistic when considering the VAR framework. Notably, the error bands on the impulse responses in Figure 7 are much wider than those in Figure 3. This may be attributed to the identification procedure in that a model identified via Cholesky decomposition is less restrictive than one identified via external instruments.

These results suggest that if the Federal Reserve is considering a rate hike during a period of low uncertainty, GDP, consumption and investment would all be expected to decrease, with a slow recovery period back to their original levels by around 24 quarters. It shows a directional change in the endogenous variables, depending on if sentiment is high or low. However, the magnitude of these decreases is small for GDP and consumption. This is not the case for investment, which sees roughly a 0.5 unit discrepancy for the 50^{th} percentile between high and low levels of uncertainty from 2 to 5 quarters after the shock to monetary policy. By the 5^{th} quarter after the shock there is about a 0.2 to 0.9 unit difference in the high and low sentiment case for the 5^{th} and 95^{th} percentiles. This difference in investment is a reflection of the monetary policy transmission, resulting in an increased investment when sentiment is high, as consumers choose to take advantage of the high interest rate and seek a return on their savings, while in times of low sentiment consumers may be choosing to hold on to their savings, potentially anticipating layoffs or other financial hardships in the future.

Chemical Game Theory

A common critique of macroeconomic analysis is that it draws from microeconomic foundations but is treated in a separate analysis with separate models. This thesis aims to connect its findings to a novel way of studying contested-decision making in game theory, in order to align the macroeconomic outcomes with microeconomic theory. It attempts to fill in a gap in knowledge for the role of temperature in modelling individual decisions with regards to Chemical Game Theory (CGT) (Velegol et al., 2018).

In CGT, decisions between players are modelled using molecules which enter into a series of reactors in order to predict how humans will play a contested-decision making game. The relative concentration of molecules which are produced, given via extents of reaction, are calculated via the free energy of the system and ultimately give a prediction which is able to model empirical results. The payoffs of the given game, as well as initial concentrations set as parameters by the modeler, are used in equations 8 to calculate the equilibrium constant, and extents of reaction.

$$\Delta G^\circ = -RT\ln K$$

$$K = \frac{[C]^c[D]^d}{[A]^a[B]^b}$$

Equations 8. Gibbs equation for free energy as a function of the gas constant R, temperature T, and the equilibrium constant K. The equilibrium constant is determined by the relative concentration of molecules given in the general reaction $aA + bB \leftrightarrow cC + dD$

In CGT, players choices are treated as metaphorical molecules and outcomes are predicted using chemical reaction mechanisms. CGT differs from traditional game theory in that it is normative, prescribing what rational players should do. CGT rather, predicts what players will do based on a set of initial parameters. Previously, the role of temperature in the system of chemical reactions has gone untested. This is not to be confused with the “temperature of the economy” but rather in the framework of CGT temperature refers to the chemical sense of the word, how quickly molecules are moving in solution.

(Velegol et al., 2018) wonder if the temperature of the chemical reaction relates to the emotional state of the players, and the concept of this emotional frame of mind has been previously speculated (Andreoni, 1995). One state of mind a player may have when playing a game is called pure altruism, where the subjects care about the payoffs for other players, compared to impure altruism where players care about the act of doing good for others, termed "warm glow." This state of mind influences how the players play the game. Whether the players are purely or impurely altruistic, selfish, or fair impacts their decisions when faced with a tragedy of the commons game (Morrissey, 2018). This thesis shows that sentiment may be used to approximate the uncertainty in the economy, which has been shown to affect aggregate spending decisions. In turn, these micro level spending decisions outlined by CGT may be aggregated and manifest in macroeconomic variables, dependent on each player's state of mind, or their sentiment.

(Velegol et al., 2018) do not delve into studying temperature, rather keeping it constant for their study. In the CGT framework, an increase in temperature would translate to a lower free energy of reaction, indicating a larger propensity towards creating the products of that reaction. A higher temperature in the CGT framework may lead to a difference in the final decision of each actor or conclusion of the game. If consumer sentiment were to be analogous to the temperature of the reaction, one would expect that at higher temperature there would be more frequent interactions, or opportunities for transactions, and an overall positive affect on macroeconomic variables: more consumption, more investment, more hiring. This is analogous to lower uncertainty. In CGT, a higher temperature would lead to a higher degree of cooperation since the total social utility is maximized under more cooperation. The total free energy of the system is minimized when there is maximum cooperation, in the same way that aggregate social utility is maximized. That is, for two (or more) players in the prisoner's dilemma (or its multiplayer extension the tragedy of the commons) the frequency that players would cooperate would be higher under higher sentiment. This is exactly what is observed in the literature (Andreoni, 1995)

Additionally, the test of if CGT would predict greater cooperation under a higher temperature has actually already been shown. Figure 8 shows the cooperation rate against the number of players in a tragedy of the commons game for various levels of Gibbs free energy.

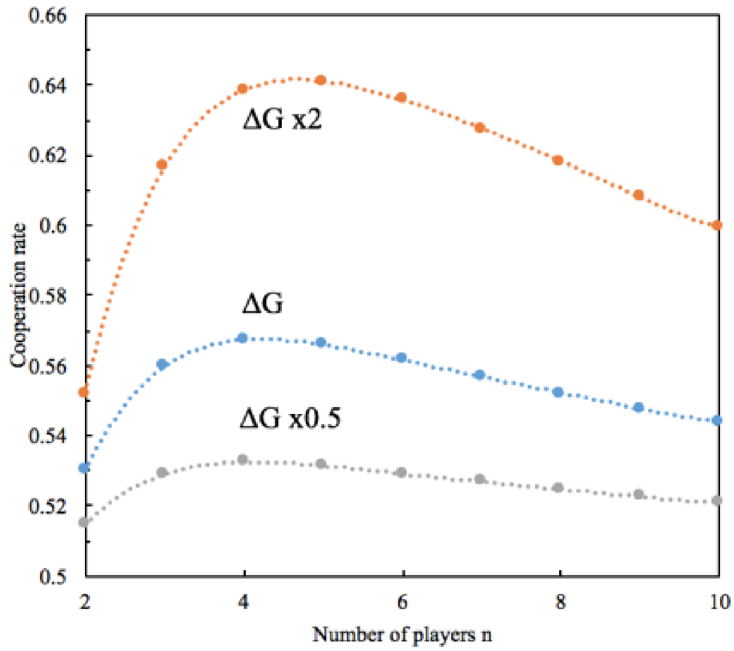

Figure 8. Taken from (Gentile, 2019) for logarithmically increasing pains (pains here is a term to indicate a negative payoff) in a tragedy of the commons game with uniform bias.

The set of payoffs (if negative termed "pains") were arbitrarily set, and scaling them up and down by a factor of two is equivalent to increasing or decreasing the temperature of the system (Equations 8). This conclusion was not made evident in (Gentile, 2019), however the hypothesis conjectured in this thesis corroborates this finding, as it is aligned with the underlying microeconomic and now macroeconomic theory.

Conclusion

In conclusion, this thesis proposes using consumer sentiment, as measured by the University of Michigan consumer sentiment survey, as a measure for economic uncertainty. Previous work has used the VXO, counting mentions of the word “recession” in newspapers, the price of gold, or other measures to estimate uncertainty but an agreed upon measure of uncertainty has not been established.

In order to provide evidence for this proposal, a SVAR framework was established including endogenous variables GDP, CPI, Real Personal Consumption Expenditures, Real Gross Domestic Investment, Uncertainty and the Federal Funds Rate. Then, consumer sentiment was used to proxy uncertainty using the identification method of external instruments developed by (Mertens and Ravn, 2013). The results indicate an underestimation of the effect of an uncertainty shock, especially in consumption. This may be unsurprising, given the strong connection between consumption and consumer sentiment.

Then the baseline model underwent a series of robustness tests. The strength of the instrument was tested via regressions of the residuals from the model with the instrument. An F test was conducted to indicate whether the instrument in question had a strong relationship with the underlying endogenous variable. The F test for using consumer sentiment as an instrument for uncertainty was 24.0, indicating that in fact it was a strong instrument.

The methodology was repeated changing the number of lags in the VAR. An Akaike information criteria test was performed on each of the variables in the model with lags varying from 1 to 8. No consistent lag was determined for each of the endogenous variables, so 8 lags were considered. The results using 8 lags were similar, although perhaps overestimated since 8 lags translates to 2 years’ worth of time for a shock to propagate through the VAR, which may not be very realistic from an economics perspective. The two previous studies this thesis heavily draws from (Piffer and Podstawski, 2018) and (Aastveit, Natvik and Sola, 2017) consider 5 lags using monthly data, and 2 lags using quarterly data. For this reason, 2 lags were used in the baseline model.

Additionally, the methodology was repeated using Euro area data and the OECD consumer sentiment survey. The results using these variables were similar to the baseline model, indicating that using consumer sentiment as a measure for economic uncertainty may not be a uniquely US phenomenon.

The data was split to use pre-pandemic data as well, which produces results similar to the baseline model, but less drastic. This could be expected, since the Covid-19 pandemic was surely a drastic event, and one that saw one of the quickest responses by consumers, governments, and businesses to rapidly changing information and policies.

In order to connect to microeconomic theory, the results of this thesis were applied to a novel field of game theory, called Chemical Game Theory. In this subfield, traditional games are modelled using molecules to predict human behavior, but the effect of the temperature of the reaction was previously untested. Consumer sentiment was argued to be analogous to temperature in this framework, which increases the frequency of collisions of the molecules in solution leading to a higher cooperation rate and increased social utility. The same is true regarding consumer sentiment, which translates to higher consumption, investment, and hence social utility.

Although this thesis aims to provide another measure for economic uncertainty and test its validity through state-of-the-art econometric techniques including external instruments and interacted VAR identification methods, it does not provide conclusive evidence in favor of its claim. Further studies are needed to validate the use of consumer sentiment as economic uncertainty. Such studies may include substituting sentiment for uncertainty in a nonlinear VAR framework to study specific historical events, drawing a comparison between uncertainty proxied by sentiment and uncertainty proxied by the EPU index in an external instruments approach, or using an extended dataset with different endogenous variables to analyze the effect of a shock to uncertainty either through recursive identification or external instruments. The effect of changing endogenous variables may be an interesting exercise, one which may benefit from a machine learning algorithm to iterate through various combinations of variables to produce the most accurate forecasting model.

The effect of a monetary policy shock during times of high and low sentiment was also investigated. This discussion may be of particular interest to policymakers when deciding on a rate increase since it shows that the directional effect of a rate increase may be different depending on the level of consumer sentiment. Additionally, GDP and investment may actually increase on impact after a rate hike, and consumption may increase in the medium term after about 4 quarters. This is a timely analysis to the time of writing this thesis as consumer sentiment is relatively low at 71.7 for October 2021, compared to 101.0 in February 2020. As the central bank is considering rate increases, it may be important to consider the effects on GDP, consumption, investment, and CPI.

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Appendix

Notes on calculation methods

The model presented in this thesis was estimated, and figures were created, using python packages: pandas, numpy, Fred, plotly, and scipy, drawing heavily on codes developed by Michele Piffer found at: https://sites.google.com/site/michelepiffereconomics/other

The developed scripts can be found at: https://github.com/frank-gentile/MastersThesis