ERASMUS UNIVERSITY ROTTERDAM

Erasmus School of Economics

Master Thesis Economics and Business Economics

Wallstreet up, Mainstreet down?

Analysis of the Effect of Uncertainty Shocks on the Synchronization of the Stock Prices and Real Macroeconomic Variables Using a Structural Vector Autoregressive Method

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April 2021

# Abstract

This thesis empirically tests the synchronisation of the S&P 500 and the U.S. real economy after uncertainty shocks from 1959 until 2021. First, the synchronisation of the S&P 500 and the macro variables income, production, consumption and unemployment have been quantified by Spearman Rank correlation coefficients, calculated over a 12-month rolling window. It showed that the synchronization was high in the periods 1960 – 1975 and 1995 – 2007 and fell after recessions. During the period 1975 – 1995, the correlation of the S&P 500 and the macro variables was mostly negative and close to zero. Secondly, the impact of uncertainty shocks on the calculated correlation coefficients has been calculated using a structural VAR. The impulse response functions showed a significant positive impact of uncertainty shocks on the synchronisation of the S&P 500 and consumption after 9 until 20 months after the shock. The impacts of the uncertainty shocks on the synchronisation of the S&P 500 and the other macro variables were not significant.

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1. Introduction

The recent Covid-19 pandemic has had a great impact on both the equity markets as well as the real economy. The insecurity that came along with the pandemic rose questions within all layers of our advanced society. Will I still have a job after the pandemic? Will my business survive the 'Great Lockdown'? Is it still possible to import products from China or Italy?

The impact of the Corona crisis has become tangible in the U.S. in an unprecedented fashion. In April, the unemployment rate increased by more than 10 percentage point which has been the largest over-the-month increase in the history of the data. The Covid-19 pandemic led to a 7.2 million job loss (U.S. Bureau of Labor Statistics, 2020). The Dutch central bank's (DNB) economic forecast was also a very pessimistic one. The DNB expected the Dutch GDP to shrink by 6.4 percent in 2020. This decrease in the GDP is the largest since World War II and twice the downfall recorded during the recession in 2009. The unemployment rate is expected to fall by 1.4% in 2020 and 2.7% in 2021, becoming twice as high as it was in 2019 (De Nederlandsche Bank, 2020).

Besides the real economy, the stock market has also been impacted by the Covid-19 pandemic. The American stock index S&P 500 did set an all-time high on the 19th of February 2020, but once the uncertainty surrounding the Covid-19 virus got a grip on the investors, the downfall of the markets became enormous. The S&P 500 fell by more than 35% before it started a strong recovery from the 23rd of March onwards. While the potential impact of the virus on the real economy came to the surface, the S&P 500 and other stock market indexes are already back at the level they were during the winter of 2019. While the fall of the stock market seems understandable, the immediate recovery caught many by surprise.

To clarify the above-described disentanglement of the equity cycle and the real economic cycle during times of high uncertainty, this thesis empirically tests the synchronisation of both cycles in the impact of uncertainty shocks. Hence, the research question of this thesis is:

How does uncertainty affect the synchronization of the equity market cycles and the real economy cycles in the United States?

This research question is answered in two steps. First, the co-movement of the equity market and the real business cycle in the U.S. is quantified from 01/1959 until 01/2021 in this thesis. This has been done by constructing Spearman Rank correlation coefficients and allows to statistically test the conventional assumption of growing independence of the S&P 500 from the real economy. Second, the effect of uncertainty shocks, such as the COVID-pandemic, on the constructed covariance coefficient, the S&P 500 and the real economy has been estimated within a structural vector autoregressive model.

This thesis is organized as follows. In the following section, a literature review will showcase previous research in the field of macro-finance regarding uncertainty and cycle synchronisation. Next, the data that is used for the empirical analyses is discussed. The methodology of this analyses is explained in section 4. Section 5 reports the obtained results which will be discussed further in section 6. Section 7 discusses the limitations of this thesis. Within section 8, the thesis is summarized, and conclusions are made.

2. Literature review

2.1. Stock price believes and business cycles

How the equity price cycles and the business cycles can be harmonized is a long-standing question in macro-finance. In the existing literature, economists provide dynamic stochastic general-equilibrium (DSGE) models, which are general equilibrium models of fluctuations with a microeconomic foundation, to understand the factors influencing the harmonization of both cycles. The existing models mostly differ in the assumptions that are relaxed or the factors that may be included.

Adam and Merkel (2019) created a model that combines real business cycle model with extrapolative belief formation in stock price cycles. They concluded that a belief-driven equity boom may start a recession in the real economy. Their model matched the huge volatility differences between the relatively smooth business cycles and the volatile stock prices. This quantitative tension is solved by using extrapolative stock price beliefs. To do so, they had to depart from the rational expectations hypothesis (REH) of the stock market. Their model predicts boom-bust cycles which are triggered by shocks invoking relatively high productivity growth and periods of low risk-free interest rates. Due to withdrawing the REH, the authors allowed for subjective components in stock pricing and therefore also for believe-driven mispricing. Mispricing of stocks impacts the real economy as it changes agents' optimal choices for investment, consumption and hours worked and therefore leads to a misallocation of resources. An unreasonably large capital stock during a boom period will fall, together with investment and labour, when the believe-driven stock price boom comes to an end because the capital gains lack relative to the beliefs.

Gilchrist and Zakrajšek (2012) empirically studied the relation between business cycle fluctuations and corporate bond credit spreads. They find that shocks to the excess bond premia do have negative future implications for the real economy. Larger volatility in the pricing of bonds above the expected default risk moves risk-averse investors away from the financial markets resulting in less credit supply and lower asset prices. Eventually, this will negatively impact investments and hence economic activity.

2.2. Global co-movement of the cycles

Jordà, Schularick, Taylor and Ward (2018) investigated the international co-movement of the real economy, financial markets, and the equity markets. The financial cycles over the 17 countries included in the analysis synchronized significantly more over time. Therefore, according to the authors, one could nowadays speak of a global financial cycle whose effects have a great global impact. Regarding real variables, equity return premium and dividends, they find a similar upward trend of international co-movement. Due to modern-day globalization and the deeper economic integration during the eighties, these findings on international synchronization are in line with expectations.

Similar results regarding international synchronization of credit cycles were found by Meller and Metiu (2017). They tested bilateral cycle phase synchronization for 14 advanced economies and found two significant breaks in the overall level of synchronization. The first break was found in 1922, the second in 1972. Surprisingly, in the period prior to 1922, a higher level of credit synchronization was found than in the period 1922-1972. Due to the increasing level of financial integration and international banking, the synchronization of the cycles increased rapidly after 1972.

2.3. Real activity and stock pricing

The relationship between a company's productivity and its stock value has been widely reviewed in financial research. One of the first to study the linkage between production-based asset pricing and economic fluctuation was Cochrane (1991). His production-based model predicts a synchronous relationship of asset returns and investment returns

Croce (2014) enriched the literature by "distinguishing the specific impact that different sources of productivity uncertainty can have on stock prices". Croce showed a positive empirical link between productivity and the other variables including asset pricing, consumption and investment. The model constructed in the paper shows a significant role for long-run productivity uncertainty on the valuation of stocks. Short- and long-run shock account for 70% of the volatility in the macro variables. Due to the elasticity of intertemporal substitution (EIS), the volatility caused in macro variables such as consumption translates to increasing volatility in asset pricing. EIS makes economic agents want to smooth their consumption over time. Therefore, long-term uncertainty makes agents react by adjusting their investments to smooth consumption over time.

2.4. Uncertainty

The Chicago economist Frank Knight (1921) defined uncertainty as peoples' inability to forecast the likelihood of events happening. Therefore, in economics, volatility of the stock market and GDP are regularly used as indicator of uncertainty since future outcomes become harder to predict as they become more volatile. Bernake (1983) and Hassler (1996) were two of the first researchers to emphasize the importance of uncertainty within economics. Building on their work, Bloom (2009) wrote a leading paper in which he designed a framework to analyse the impact of macro uncertainty shocks using a reduced form VAR. Bloom distinguishes first (levels), and second moment (uncertainty) shocks and concludes that there is little literature regarding uncertainty shocks compared to first moment shocks. The model predicts a short recession and quick rebound in GDP and employment occurs after a second moment, uncertainty shock. Due to the occurring uncertainty, the value of waiting increases. Thus, growing firms pause their investments and hiring while shirking firms postpone laying off employees. Reallocation of employment from less productive firms to productive firms temporarily pauses. Hence, the net effect is negative on aggregate productivity and employment. So, Bloom states that recessions could be periods without negative productivity shocks but of high uncertainty.

Bianchi, Ilut and Schneider (2014) added to the literature by introducing time-varying ambiguity on the household side and introducing financing costs on the firm side. Hence, the main interest of their model is the response of households and firms to changes in uncertainty on the movement of the stock prices. The sources of uncertainty that the model allows for are shocks to the fixed operating costs and shocks to the marginal product of capital. The model suggests that a narrow focus on business cycle influencing shocks is not likely to explain high stock price volatility during recessions as it ignores the dominant cycle component in stock prices. Including time-varying uncertainty in the model has helped understand asset prices and the decision making of firms and investors as it affects the optimal choices of the agents. The uncertainty about fixed operating costs and therefore the earnings of the firms are a plausible explanation of asset prices.

Because earlier RBC and DSGE models largely failed to estimate the behaviour of risk premia, Gourio (2012) created a model that introduces a small risk of an economic "disaster", a large real economic shock as the current Covid-19 crisis, to the standard RBC model. The model shows that risk aversion affects the economy significantly if risk is large and time-varying, it thereby adds to the literature regarding uncertainty shocks. A “disaster” will negatively impact production and capital. The model predicts that an increase in the probability of a large economic shock will increase risk of investment and lower expectations due to uncertainty. This has implications on both the business cycle and the stock prices, a change in risk will impact both output and expected returns. A main finding of the paper is that increase in disaster risk leads to a recession. This happens due to risk aversion and uncertainty; extra uncertainty in depreciation and productivity makes risk averse consumers invest less in risky capital. Also, demand for precautionary savings increases and consumers prefer to move their capital to more safe assets, this negatively influences yields of these safe assets and increases those of the risky assets. Since the premia on risky assets increases, the risk premia are countercyclical.

Whereas Bloom (2009) has focussed his research on the stock market related indicators of uncertainty, Jurado, Ludvigson and Ng (2015) investigate the uncertainty from the perspective of macroeconomic activity. Therefore, they assume that economic decision making depends on the predictability of the economy rather than the volatility of particular economic indicators such as the commonly used stock market volatility. The estimated macroeconomic uncertainty is more persistent than stock market volatility and they find a greater level of independent variation in uncertainty. Hence, movement in stock market volatility is not the driver of most of the economic uncertainty. According to Jurado, Ludvigson and Ng (2015), the influence of commonly used uncertainty proxies on real activity is exaggerated.

The papers of Bloom (2009) and Croce (2014), Gourio (2012) and Jurado, Ludvigson and Ng (2015) have a different view on the role of uncertainty in its influence on business cycles. While Bloom argues that uncertainty is the exogenous force that sets the discussed mechanism that results in an economic recession in motion, Jurado, Ludvigson and Ng and others see uncertainty as a consequence of business cycle fluctuations. Another difference in their views compared to Bloom’s regarding uncertainty is that Bloom is focussed on financial uncertainty, visible in increased volatility of equity prices, while Jurado, Ludvigson and Ng, Groce and Gourio are focused on macro uncertainty. In doing so, Bloom (2009) finds far more episodes of uncertainty than Jurado, Ludvigson and Ng (2015). Ludvigson, Ma and Ng (2018) tried to econometrically test this dispute. The question whether uncertainty is primarily a source of business cycle fluctuation or a consequence of it and what the different relationships of real and financial uncertainty are to business cycle fluctuations. They find that shocks to financial uncertainty are more often the source of economic fluctuation than shocks to macro uncertainty. Macro uncertainty may not cause economic recessions, it substantially amplifies economic downturns initiated by different factors. They conclude by stating that macro uncertainty should be considered as endogenously responding to shocks, while financial uncertainty can cause economic recessions.

3. Data

To perform the analysis needed to answer the research question, macroeconomic, financial economic and uncertainty time series data was collected. The data used in this paper is gathered from multiple resources; FRED, GFD Finaeon and Ludvigson's website.

3.1. Macroeconomic data

The macroeconomic data is collected from the FRED-MD monthly database (McCracken & Ng, 2016). This database exists out of 129 monthly macroeconomic indicators over the period 1/1/1959 until 1/01/2021. McCracken and Ng constructed this database in cooperation with the FRED intending to reduce overhead costs of macroeconomic analysis. Another benefit of a universally used database is that it facilitates replication and comparison of results. The database is divided into eight groups, all including variables of a different side of the economy. The following groups are included; Output and Income, Labor Market, Consumption and Orders, Orders and Inventories, Money and Credit, Interest rate and Exchange Rates, Prices, and Stock Market. For the analysis performed in this analysis, the 4 most relevant indicators of the 129 variables in the database are included in the model. The indicators included are the real personal income, real personal consumption, industrial production index and the unemployment rate. Within this thesis, there will be referred to these indicators as income, consumption, production and unemployment. An overview of the used variables can be found in table 3 in the appendix.

Added to the FRED-MD monthly indicators is a proxy variable that takes a value of 1 in the years of an economic recession according to the NBER and takes the value of 0 if it is not. The NBER defines a recession as a 'significant decline in economic activity that is spread across the economy and lasts more than a few months' (NBER, 2021). During the analysed period, nine recessions are indicated by the NBER. The recessions differ in duration.

3.2. Equity data

The financial data used in this paper is obtained via Global Financial Data Finaeon. Monthly S&P 500 closing data is collected via Global Financial Data Finaeon.

3.3. Uncertainty indicators

The uncertainty indicators used in this thesis are constructed by Jurado, Ludvigson and Ng (2015). The indicators can be downloaded from Ludvigson's website (2021) and are updated regularly.

The data used in this thesis cover the period 1960:07 until 2020:12. Jurado, Ludvigson and Ng (2015) constructed three series of the uncertainty index, differing in forecasted months $h = \{1,3,12\}$. The macroeconomic indicator is on the dataset FRED-MD, except for the S&P 100 Volatility Index, the VXO, all variables are included in the estimation of $U_{Mt}(h)$. The database used for constructing $U_{Ft}(h)$ exists out of 726 variables that are monthly observed. The database includes aggregate financial indicators and indicators of assets returns (Ludvigson & Ng, 2020).

As discussed in the literature review, a commonly used economic indicator for time-varying uncertainty is the volatility index of the S&P 500 the CBOE VIX or the almost identical CBOE S&P 100 Volatility Index, the VXO (Bloom, 2009).

However, in the earlier discussed paper Measuring Uncertainty (Jurado, Ludvigson, & Ng, 2015) the authors argue that the VIX nor the VXO is a sufficient indicator of time-varying uncertainty. Therefore, the authors construct two separate uncertainty indicators, a financial uncertainty indicator $U_{Ft}(h)$ and a macroeconomic uncertainty indicator $U_{Mt}(h)$ (Ludvigson, Ma, & Ng, 2018). The uncertainty indicator for category $C = \{F, M\}$ is constructed as follows; first uncertainty is constructed for individual economic agents j,

$$U_{jt}^{C}(h) = \sqrt{E[(y_{jt+h}^{C} - E[y_{jt+h}^{C}|I_t])^2|I_t]} \quad (1)$$

where the expectation $E(\cdot\,|t)$ is taken with respect to the information I_t available to economic agents at time t. The equation shows that uncertainty increases if the forecasted value of y_{jt+h} is expected to differ more from its actual value. Hence, if agent j expects that he/she can predict the future less accurate, uncertainty grows. Aggregating the individual uncertainties and using aggregation weights w_j gives macroeconomic uncertainty index.

$$U_{Ct}(h) = \operatorname*{plim}_{N_C \to \infty} \sum_{j=1}^{N_C} w_j U_{jt}^{C}(h) \equiv E_M\,[U_{jt}^{C}(h)] \quad (2)$$

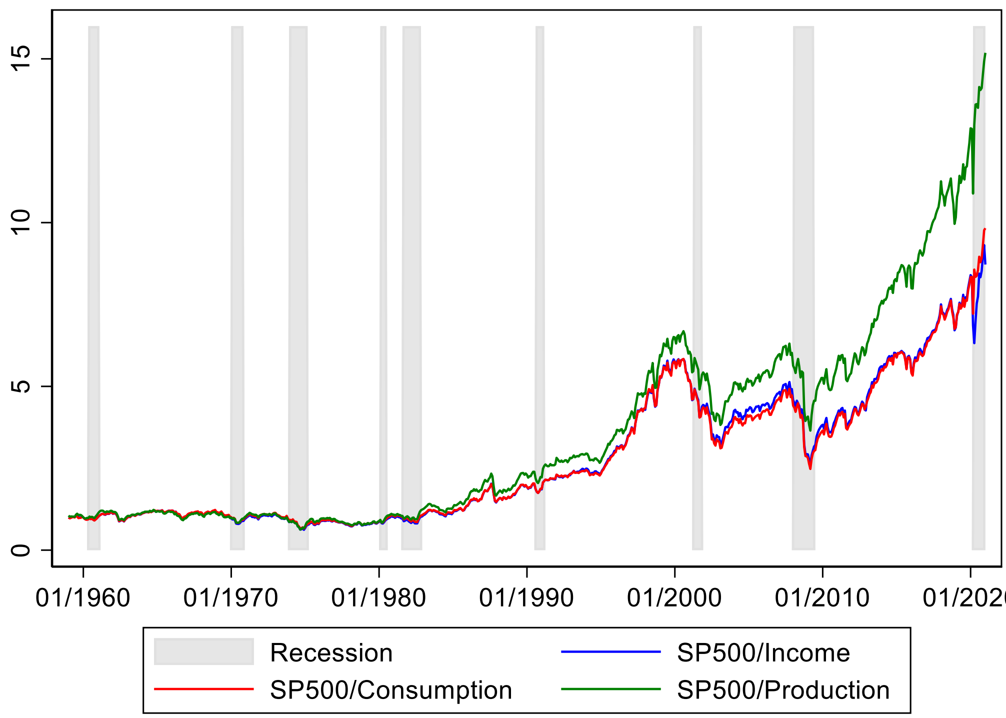
3.4. Data trends

In the observed period, several empirical facts occur. As is often observed in financial literature, the S&P 500 started to grow faster than most macro variables during the start of the ’80s (Greenwald, Lettau, & Ludvigson, 2019). Table 1 validates that the same observations can be made within the data used in this paper. While the growth rate of all macro variables has diminished after 1980, the S&P 500 has accelerated its growth. Figure 1 displays this trend by showing the growth index of the S&P 500 relative to the macroeconomic variables’ growth indexes.

Table 1: Average Quarterly Growth Rate

Sub sample	Obs.	SP500	Income	Consumption	Production
1980q1 - 2020q4	492	8.62%	2.97%	3.11%	1.69%
1960q1 - 1979q4	251	3.16%	4.00%	3.87%	4.09%

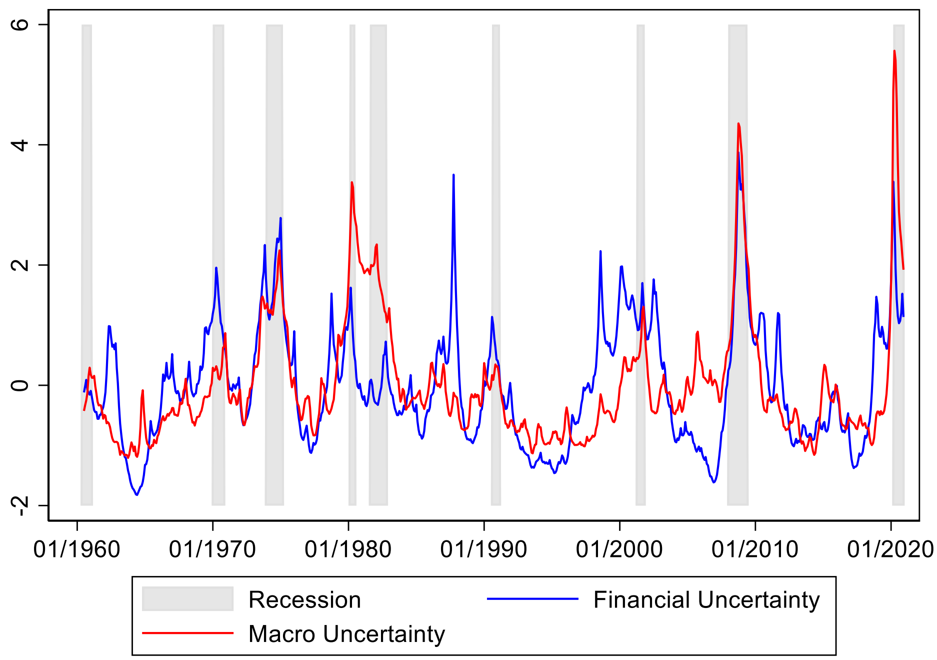
Figure 1: S&P 500 Ratio's



Notes: To make the ratios comparable, each variable has been indexed to 100 in 1960:q1 before the ratios have been calculated.

The uncertainty data strings have been standardized to unity to construct figure 2. It shows three periods wherein the uncertainty clearly peaks: The Great Depression, the Financial Crisis, and the current Covid pandemic. As discussed during the literature review, the uncertainty data constructed by Ludvigson acknowledged fewer periods of uncertainty compared to Bloom's method based on the CBOE VIX. The observed periods of uncertainty are often followed by a period of relatively low uncertainty. The uncertainty tends to be higher and more volatile over the longer periods (h=12) as it becomes harder to forecast the period.

Figure 2: Uncertainty indicators



Notes: Uncertainty data has been standardized to unity, h=3 for both data strings.

4. Methodology

The approach used to answer the research question of this thesis is structured in two parts. In the first part, a variable will be constructed that quantifies the synchronisation of the S&P500 and the macro variables. The method that will be used is based on the methodology used by Jordà, Schularick, Taylor and Ward (2018). A 12-month rolling window Spearman rank correlation will show that the harmonization of the S&P 500 and the real economic variables is time-variant and whether the SP500 has become more, or less synchronized with the real economy. Secondly, a structural vector autoregression (SVAR) will be performed based on the methodology used by Lütkepohl (2005) and Antolin Diaz and Rubio-Ramirez (2018). This part asses the effect of an uncertainty shock on the constructed covariances, the S&P 500 and the macro variables.

4.1. Synchronization S&P 500 and macro variables

The synchronization of the S&P 500 and macro variables will be calculated by using a rolling-window Spearman rank correlation[1], similar to Jordà, Schularick, Taylor and Ward (2018). They used the Spearman rank correlation coefficients to measure the bilateral co-movement for real and financial cycles internationally. Different to the analysis performed in this thesis, Jordà, Schularick, Taylor and Ward (2018) calculate the co-movement of the same macroeconomic variables over different countries. Here, the method will be used to calculate the synchronization of different variables, being the S&P 500 and real macroeconomic variables, within one country. Due to the availability of monthly data, the rolling window will be set on 12. This might be a relatively short window for a rolling correlation, but if the window would be larger, it could include observations of a shock and the recovery at the same time. This could cause the problem that the effect of the shock would not translate into the correlation as it would be balanced by a quick recovery if the window is too large. Hence, the smaller window should reflect the fluctuations of interest better. The window, defined as W is evenly spread around time t. The sample window sample will therefore be $\left[t-\frac{W}{2}\ ;\ t+\frac{W}{2}\right]$.

[1] The Spearman rank correlation differs to the more classical Pearson correlation coefficient as it can capture monotone relationships and not only linear relationships. The Spearman rank correlation coefficient is calculated on the ranking of the values of the variables instead of the absolute values.

The Spearman rank nnnnnnnn correlation coefficient is constructed as follows:

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \qquad (3)$$

where d_i is the difference in paired ranks and n is the number of cases.

Before performing the rolling Spearman rank correlation coefficient, the cyclical component of the time series must be isolated from the trend. Therefore, after calculating the logarithms of the series, the Hodrick-Prescott filter is performed. The Hodrick-Prescott filter is the most used technique to detrend series and allows to split the time-series y_t into a trend τ_t and a cyclical component ζ_t.

$$y_t = \tau_t + \zeta_t \qquad (4)$$

The variables are calculated by minimizing the following quadratic loss function

$$\min_{\tau_t} \sum_{t}^{T} \zeta_t^2 + \lambda \sum_{t=1}^{T} [(\tau_t - \tau_{t-1}) - (\tau_{t-1} - \tau_{t-2})]^2 . \qquad (5)$$

Because monthly data is used in this analysis, the Hodrick-Prescott smoothing parameter is set at 129,600. This is the common detrending lambda for detrending monthly data (Bloom, 2009) (Hodrick & Prescott, 1997) (Ravn & Uhlig, 2002).

4.2. Structural Vector Autoregression

Studied literature showed that uncertainty is a key element in explaining the relationship between business cycles and stock prices (Ludvigson, Ma, & Ng, 2018) (Bloom, 2009) (Croce, 2014) (Gourio, 2012). Often, researchers used a vector autoregression to evaluate the impact of a shock on macroeconomic variables (Bloom, 2009). VAR models create a dynamic correlation analysis but cannot causally explain the effect the endogenous shock variable has on the responding variables due to the occurring identification problem. The residuals u_t cannot be interpreted as structural economic shocks as they are correlated among each other. This is because the elements of the residual inherit all the contemporaneous relations among the endogenous variables.

Due to the limitations of the VAR, the structural VAR has become a broadly used method for describing macroeconomic time-series. The structural VAR can be seen as a description of the actual structure of the economy and allows for contemporaneous relations among the variables. The structural shocks ε_t analysed in these models are serially uncorrelated and independent of each other, allowing for the causal effect of one shock at the time whereas the residual of a non-structural VAR consists out of all contemporaneous relations among the endogenous variables.

In a short-run SVAR, identification is obtained by placing restrictions on the matrices A and B. Both matrices are assumed to be non-singular, meaning that they have an inverse. Matrix A denotes the restrictions on the contemporaneous relationships of variables. These restrictions are made based on general economic insights and often come in the form of a sign restriction. The B matrix captures the 'impact effect' of the shock variable on the response variable. Across the literature, several identification schemes have been used in order to find the correct B matrix. Common identification schemes in macroeconomics are Zero (recursive) contemporaneous restrictions, as will be used in this thesis, and sign restrictions. An influential paper that used the latter is written by Harald Uhlig (2005). He used sign restrictions to examine the effect of monetary policy on output. Literature showed raising the interest rate has a negative impact on inflation. If a central bank expects an increase in inflation, it could raise the interest rate to slow inflation. When inflation continues to increase, a VAR would conclude that increasing interest rates will have a positive effect on inflation. By setting sign restrictions in matrix A, Uhlig prevented this conclusion. The restrictions introduced in this SVAR model are based on the literature review.

Ludvigson, Ma and Ng (2018) argued that the VAR is not always a satisfactory identification strategy for a study on uncertainty and business cycles because it restricts the timing of the relationship between uncertainty and real activity. As discussed in the literature review, uncertainty is not only an exogenous impulse that drives the business cycles, but it also reacts endogenously to shocks in real activity. Ludvigson, Ma and Ng used an under identified structural VAR to not restrict the recursive interaction of the shock variable uncertainty and the macroeconomic response variables.

In this thesis, an overidentified structural VAR is performed. Herein, this thesis differs in its assumption with respect to Ludvigson, Ma and Ng (2018) and Uhlig (2005). The assumption has been made that financial and macro uncertainty shocks have a contemporaneous relationship and a similar assumption has been made regarding the S&P 500 and the macro variable included within the model. The imposed restrictions can be found in equation (14).

4.2.1. The identified SVAR model

The SVAR models performed in this thesis include $n = 5$ variables. The following variables: macro uncertainty (U_{Ft}), financial uncertainty (U_{Mt}), the calculated Spearman rank correlation coefficients (ρ_{ijt}), the monthly growth rate of the log S&P 500 stock market index ($\Delta SP500_t$) and of the macroeconomic variable included in ρ_{ijt}. Hence, the monthly growth rate of the log Real Personal Consumption ($\Delta Consumption_t$), the log Real Personal Income ($\Delta Income_t$), the log Industrial Production index ($\Delta Production_t$) or the log Unemployment Rate ($\Delta Unemploy_t$).

(7) $$y_t = \begin{bmatrix} U_{Ft} \\ U_{Mt} \\ \Delta SP500_t \\ MacroVar \\ \rho_{ijt} \end{bmatrix}, MacroVar = \begin{Bmatrix} \Delta Consumption_t \\ \Delta Income_t \\ \Delta Production_t \\ \Delta Unemploy_t \end{Bmatrix}$$

The appropriate lag order of the SVAR model will be chosen based on the Akaike Information Criterion (AIC) and Final Prediction Error (FPE) criterion. According to Lütkepohl (2005, p. 152), in small samples, AIC and FPE are more likely to choose the correct lag order because the criteria are designed for minimizing the forecast error variance.

4.2.2. The Model

In creating the model, the AB-Model approach of Lütkepohl (2005) and Antolin Diaz and Rubio-Ramirez (2018) is followed closely in this thesis. First, consider a VAR(p) with the general form

(8) $$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p_t} + u_t.$$

Here, y_t is a $(n \times 1)$ vector of the variables that will be included in the model, the A_j's ($j = 1, \dots, p$) are $(n \times n)$ coefficient matrices and $u_t = (u_{1t}, \dots, u_{nt})$ is a residual that is n-dimensional white noise that is, $E(u_t) = 0$, $E(u_t u'_t) = \sum_u$. The covariance matrix $\sum_u$ is assumed to be non-singular.

Equation (8) can be written in the Wold moving average representation

(9) $$y_t = u_t + \Phi_1 u_{t-1} + \Phi_2 u_{t-2} + \cdots,$$

where

(10) $$\Phi_i = \sum_{j=1}^{i} \Phi_{i-j} A_j, \qquad i = 1,2, \ldots,$$

with $\Phi_0 = \mathrm{I}_n$.

The elements of the Φ_j matrices are the forecast error impulse responses. The elements do not indicate the relationship between the variables correctly since the components of u_t can be correlated directly, meaning that shocks in components of u_t are not likely to be isolated in practice since it inherits all the contemporaneous relations among the endogenous variables. This is the identification problem that occurs when using a VAR(p).

Transforming the VAR(p) model to a structural form model by including the A and the B matrices allows us to impose restrictions on the contemporaneous and lagged matrices of coefficients in order to improve the estimations. The A matrix models the instantaneous relations between the observables directly. The B matrix identifies the structural shocks ε_t from the reduced form residuals u_t. To perform an impulse response analysis, it is necessary to be able to analyse the impact of a shock while all other shocks are fixed. Correlation between the ε_t's implies that shock to one variable is associated with shocks to other variables. Hence, the impulse response cannot be isolate.

The SVAR can be written as

(11) $$\mathrm{A} y_t = A_1^* y_{t-1} + \cdots + A_p^* y_{t-p_t} + \mathrm{B}\varepsilon_t,$$

(12) $$\mathrm{A} u_t = \mathrm{B}\varepsilon_t$$

where $A_j^* = \mathrm{A} A_j$ $(j = 1, \ldots, p)$ and $\varepsilon_t \sim (0, \mathrm{I}_K)$ is the vector of structural shocks. Hence

(13) $$u_t = \mathrm{A}^{-1}\mathrm{B}\varepsilon_t,$$

(14) $$\textstyle\sum_u = \mathrm{A}^{-1}\mathrm{B}\mathrm{B}'\mathrm{A}^{-1\prime}\,.$$

This implies that ε_t will have a diagonal covariance matrix if A is set correctly. The structural form in equation (11) can be written in Wold moving average representation as

$$y_t = \Theta_0 \varepsilon_t + \Theta_1 \varepsilon_{t-1} + \Theta_2 \varepsilon_{t-2} + \cdots. \tag{12}$$

where

$$\Theta_j = \Phi_j \mathrm{A}^{-1} \mathrm{B} \qquad (j = 0,1,2, \ldots), \tag{13}$$

The elements of the Θ_j matrices represent the responses of the variables to the structural ε_t shocks.

In order to identify the unique estimates of A and B from $\sum_u$, $n^2 + n(n-1)/2$ must be placed in the matrices, otherwise, the SVAR is under identified. Since $n = 5$, the number of restrictions must be 35. As mentioned in the previous section, this thesis restricts some entries of A and B to zero or one.

In a recursive structure, the A will be defined as a lower triangular matrix, restricting all entries above the diagonal to 0. If the A matrix is recursively structured, it assumes that y_{1t} may have a direct effect on all other variables y_{nt}, while y_{2t} may have an impact on all variables y_{nt} except y_{1t}, and so on. The impulse response functions (IRFs) that will be constructed will be qualitatively similar to the IRF constructed based on a Cholesky decomposition of the variance-covariance matrix of the reduced form VAR.

In this thesis, a SVAR model is used as it allows to impose additional short-run constraints to improve the estimation of the IRFs. This is called an overidentified SVAR model. By setting $a_{21} = 0$ the assumption is made that a financial uncertainty shock has no direct effect on the macro uncertainty, it only affects it with a lag. So, the relationship between the two types of uncertainty is equal, they both have a similar impact on the other. A comparable assumption is made that the S&P 500 has no direct effect on the macro variables due to rigidities, hence $a_{43} = 0$. Matrix A could be written as

$$\mathrm{A} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 & 0 \\ a_{41} & a_{42} & 0 & 1 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & 1 \end{bmatrix}. \tag{14}$$

The B matrix places restrictions on the error structure. Due to the standard assumption of an expected covariance in the error terms, only the diagonal will be estimated, all other elements are restricted to 0. The B matrix can be written as

$$(15) \qquad B = \begin{bmatrix} b_{11} & 0 & 0 & 0 & 0 \\ 0 & b_{22} & 0 & 0 & 0 \\ 0 & 0 & b_{33} & 0 & 0 \\ 0 & 0 & 0 & b_{44} & 0 \\ 0 & 0 & 0 & 0 & b_{55} \end{bmatrix}.$$

Hence, the AB-model form can be written as

$$(15) \qquad \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 & 0 \\ a_{41} & a_{42} & 0 & 1 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & 1 \end{bmatrix} u_t = \begin{bmatrix} b_{11} & 0 & 0 & 0 & 0 \\ 0 & b_{22} & 0 & 0 & 0 \\ 0 & 0 & b_{33} & 0 & 0 \\ 0 & 0 & 0 & b_{44} & 0 \\ 0 & 0 & 0 & 0 & b_{55} \end{bmatrix} \varepsilon_t.$$

5. Results

In this thesis, two statistical tests are performed. First the synchronization of the S&P 500 and the macro variables real personal income, industrial production, real personal consumption, and the unemployment rate. In this chapter's first section, the correlation coefficients are discussed and explained by the context of the period. The full sample is divided into four different periods, based on the trend of the correlation coefficients. Secondly, the role of uncertainty shocks on the synchronisation of the cycles is regressed.

5.1. Synchronization S&P500 and macro variables

As described in the methodology is the cyclical component isolated from the trend of the five investigated series. First, the correlations of the cyclical components of the full sample, the period 01/1958 until 01/2021, are calculated and shown in table 2.

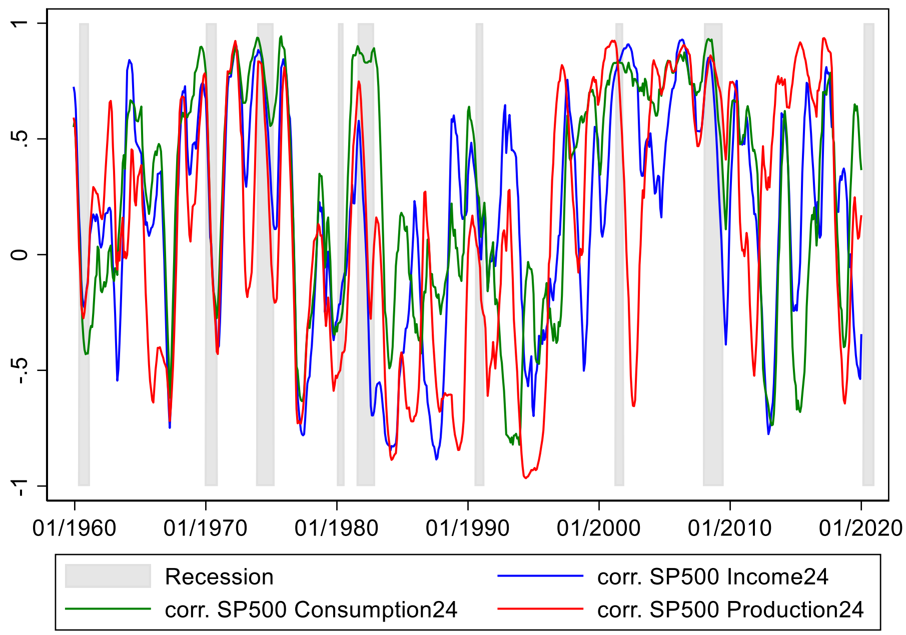
Table 2: Matrix of correlations

Variables	(1)	(2)	(3)	(4)	(5)
(1) hp_SP500	1.000				
(2) hp_Income	0.327	1.000			
(3) hp_Production	0.344	0.653	1.000		
(4) hp_Consumption	0.350	0.661	0.684	1.000	
(5) hp_Unemployment	-0.277	-0.667	-0.861	-0.747	1.000

The table shows a strong positive correlation between the macro variables and a weaker positive correlation around the .340 between the S&P 500 and the macro variables. The coefficients of the unemployment rate are all negative, meaning that unemployment is negatively correlated with the S&P 500 and other macro variables. This was expected since unemployment shrinks during economic growth and grows during times of economic downturn.

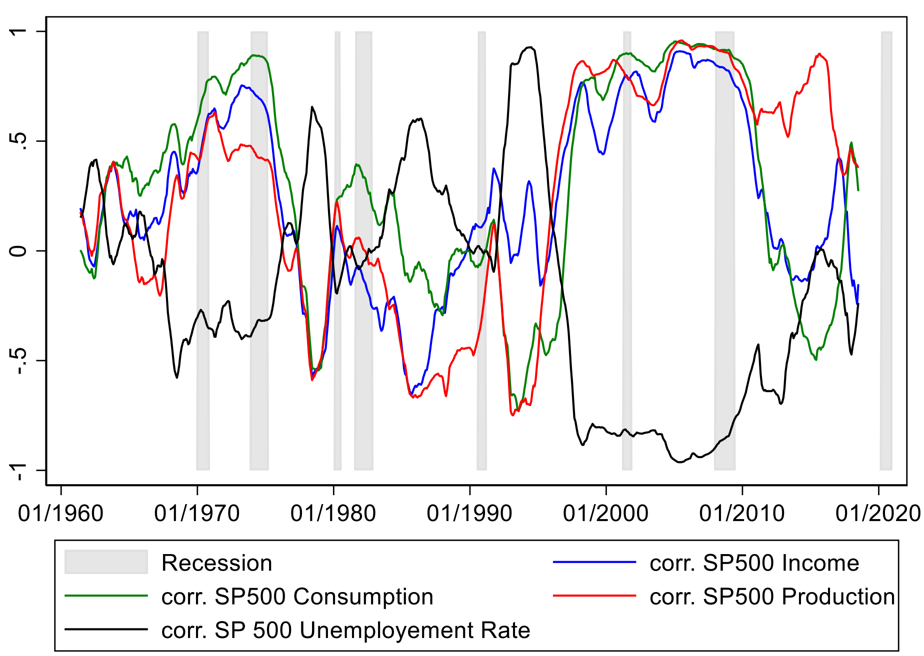
Secondly, the correlations of the cyclical components of the S&P500 and the macro variables are calculated over a rolling window of 12 months and over 24 months. The constructed correlations are highly volatile over time as displayed in figure 3 and figure 4. Yet, the figure shows strong similarities in the correlation of the S&P 500 with income, consumption, and production. The correlation of the S&P500 and the unemployment rate is not included in figure 3 as it has the opposite path, it can be found in the appendix. The calculated Spearman correlation coefficients do not show a linear growth over time and have more of a cyclical pattern. By broadening the window further, the calculated correlations become less volatile, and the trend becomes better observable

Figure 3: 24-month rolling correlation



Notes: All series were detrended with a Hodrick-Prescott filter with smoothing variable 129600. Then, the Spearman rank correlation coefficient is calculated over a 24-month rolling window.

Figure 4: 60-month rolling correlation



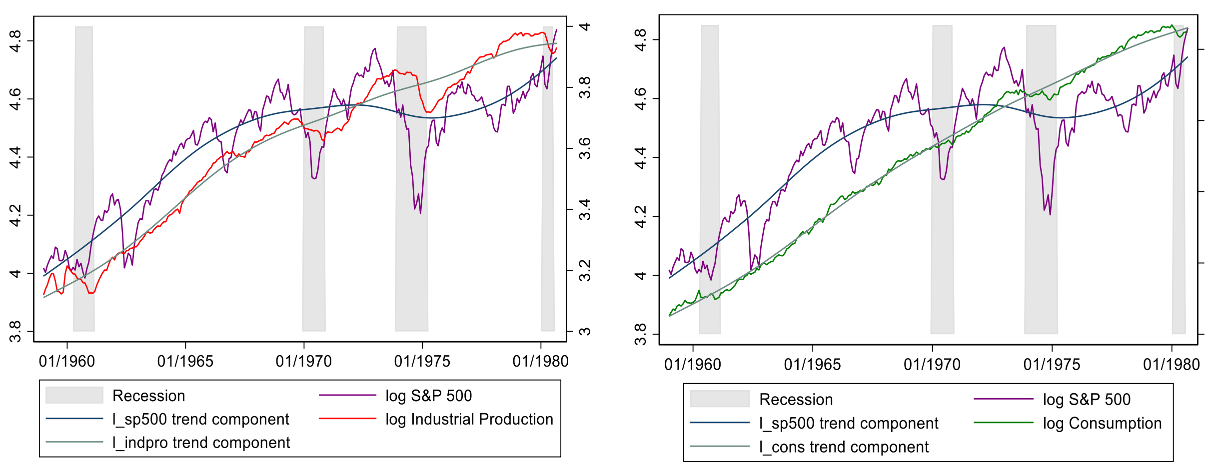
Notes: All series were detrended with a Hodrick-Prescott filter with smoothing variable 129600. Then, the Spearman rank correlation coefficient is calculated over a 60-month rolling window.

and easier to interpret. The downside is that shocks are not directly visible within the calculated correlation. Therefore, for further calculations within this thesis, the correlation calculated over 12 months is used. In figure 4, the correlations are shown calculated with a window of 5 years.

It shows that the correlations are positive for several periods, meaning that the S&P 500 and the macro variables move in the same direction, they grow or shrink together. The first period of positive correlation from 1959 until the recession of 11/1973 until 03/1975. During that recession, the unemployment rate increased with 3.8 percent point, the industrial production falls with 14.8%, the consumption falls only 1% and the real personal income shrinks with 2.7%. The turning point of the S&P 500 cycle dated earlier. The peak of the cycle was at 01/1971 and the through was 09/1974, during this period the S&P 500 lost 42,5% of its value. The recovery of the S&P 500 was slow, 70 months after the through, the S&P 500 reached a similar level to the peak of 01/1971. Figure 5 shows that from 1971 the S&P 500 and the macro variables industrial production and consumption started moving in a different direction. Industrial production is earlier at its pre-recession level and even though the recession had an impact, the trend remained positive. The consumption was hardly impacted by the recession. Due to the impact of the recession on especially the S&P 500, both cycles became negatively correlated after a long period of parallel movement.

In the period that followed, from 1975 until 1995, the S&P 500 grew explosively while the growth of the macro variables become more volatile. Hence, the synchronisation of the cyclical components was limited. There are several possible explanations for the dismantlement of the S&P 500 and the real economy. During the early 1980s, the U.S. faced severe economic recessions

Figure 5: Comparison of logs and trends components in 1960 – 1980



Notes: All series were detrended with a Hodrick-Prescott filter with smoothing variable 129600.

resulting in a historically high effective federal fund rate and inflation. In these years, the cyclical component of the macro variables was relatively high as the administration diminished economic regulations and export of agricultural products was restricted. As figure 3 shows, the correlation tended to be negative but did imply not much strength as it was close to 0. Over this period, the correlation between the S&P 500- and income was -0.085, and production -0.207, and consumption 0.092 and unemployment rate 0.138. The correlations between the macro variables remained positive and large.

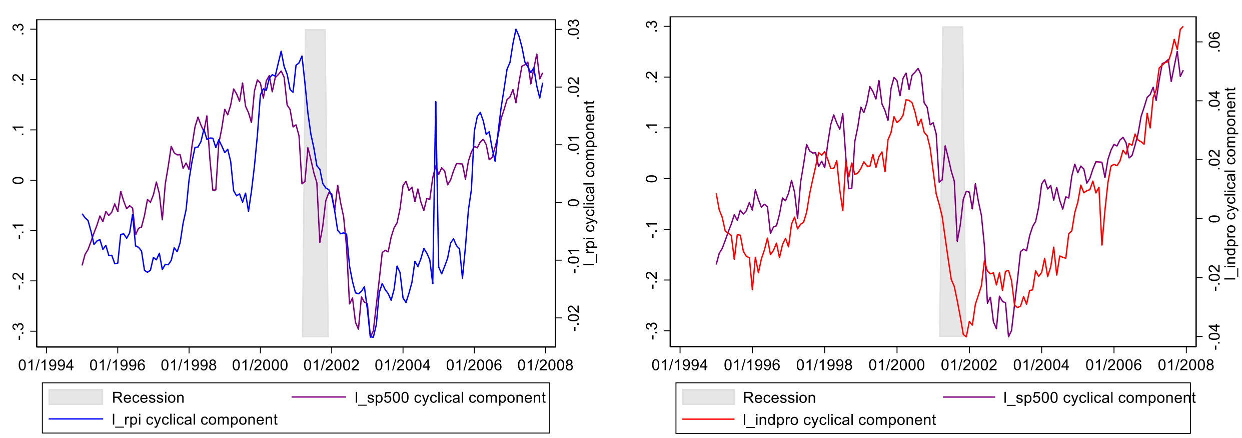
The second extensive period of positive correlation starts around 1995 and is abruptly ended by the financial crisis of 2007-2008. After a period wherein the S&P 500 grew explosively and was far more volatile than the macro variables, the synchronization of the S&P 500 and the macro variables started to synchronize to an unprecedented level within this sample from 1995 onwards. This can be accounted to the steady growth of both the S&P 500 and the macro variables. As is clearly feasible in figure 6, the movement of the cyclical component of the S&P 500 is very similar to the movement of the cyclical component of the personal income and the industrial production, the cycles seem to be timed evenly. The most noticeable economic event during this period is the dotcom bubble. This eventually led to a sharp fall of the S&P 500 and a burst period in the real economy. After the through of the business cycle in 2002, a long period of relatively consistent growth started until 2008.

The last period separated in this thesis is the post-2007 period. This period is characterized by two crises: the financial crisis and the COVID-pandemic. The financial crisis first impacted S&P 500 in July 2007, the real economy peaked later, December 2007 was the first month of contraction. The S&P 500 reached its through in March 2009 while the real economic variables started slowly recovering in June 2009. From peak to trough, the S&P 500 lost 50.21% of its value. For macro variables the relative loss was smaller but still large, consumption lost 2.11%, income shrunk 3.73%, production fell 17.35% and unemployment increased 112.76%. Due to this crisis, the covariance of the S&P 500 and the macro variables loses its strength. The spearman rank correlation coefficient is significantly lower than it was in the previous period, only the correlation coefficient of the S&P500 and production remains around 0.5 after the crisis. Especially during the period of 01/2012 until 08/2015 the macro variables are in a different cyclical phase as the S&P

500. As shown in figure 7, the S&P 500 and the industrial production do move synchronized during this period.

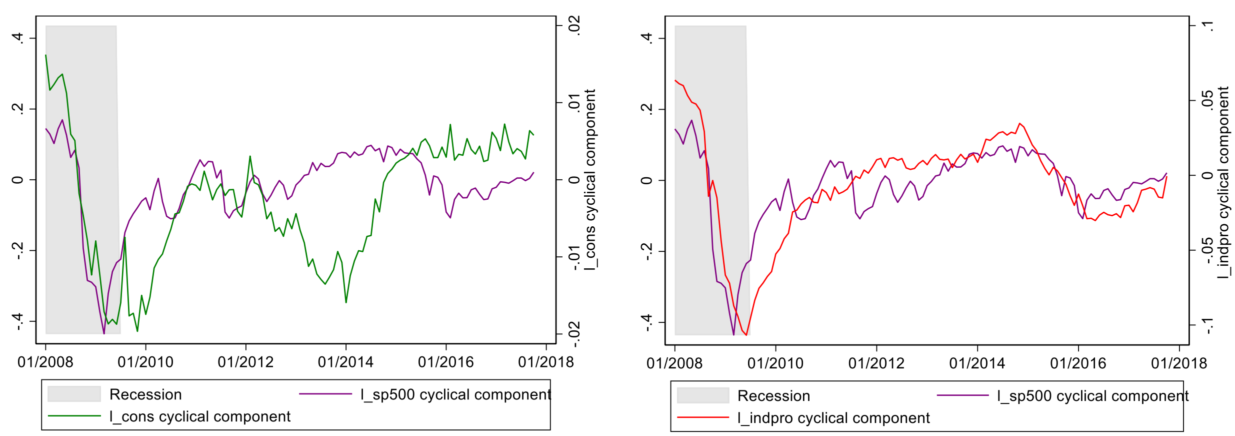
Due to the rolling window of 12 months used in the calculation of the correlation coefficients, the coefficients have only been calculated until 07/2020. Therefore, it remains hard to quantify the effect of the COVID-pandemic on the synchronization of the cycles for a longer period. The best correlation coefficient to assess the COVID-pandemic is the coefficient of 07/2020 since it is calculated over the period 01/2020 – 01/2021. The data correlation has only included one pre-COVID observation. Remarkably, the calculated correlations are positive and strong. The correlation of the S&P500- and consumption is 0.776, production 0.755, the unemployment rate -0.531. Only for income, a weak negative correlation coefficient is calculated: -0.196. Three of the

Figure 6 Comparison of the cyclical component in 1995 - 2008



Notes: All series were detrended with a Hodrick-Prescott filter with smoothing variable 129600.

Figure 7 Comparison of the cyclical component in 2008 - 2018



Notes: All series were detrended with a Hodrick-Prescott filter with smoothing variable 129600.

coefficients indicate that the COVID-pandemic did not result in desynchronization of the equity cycle and the macro variables. The logs of the variables show a relatively similar path during the COVID-pandemic. The S&P500 fell and recovered earlier and in a larger proportion than the macro variables, but they followed rather soon. Table 4 in the appendix shows the calculated Spearman rank correlation coefficients of the 4 periods discussed in this section.

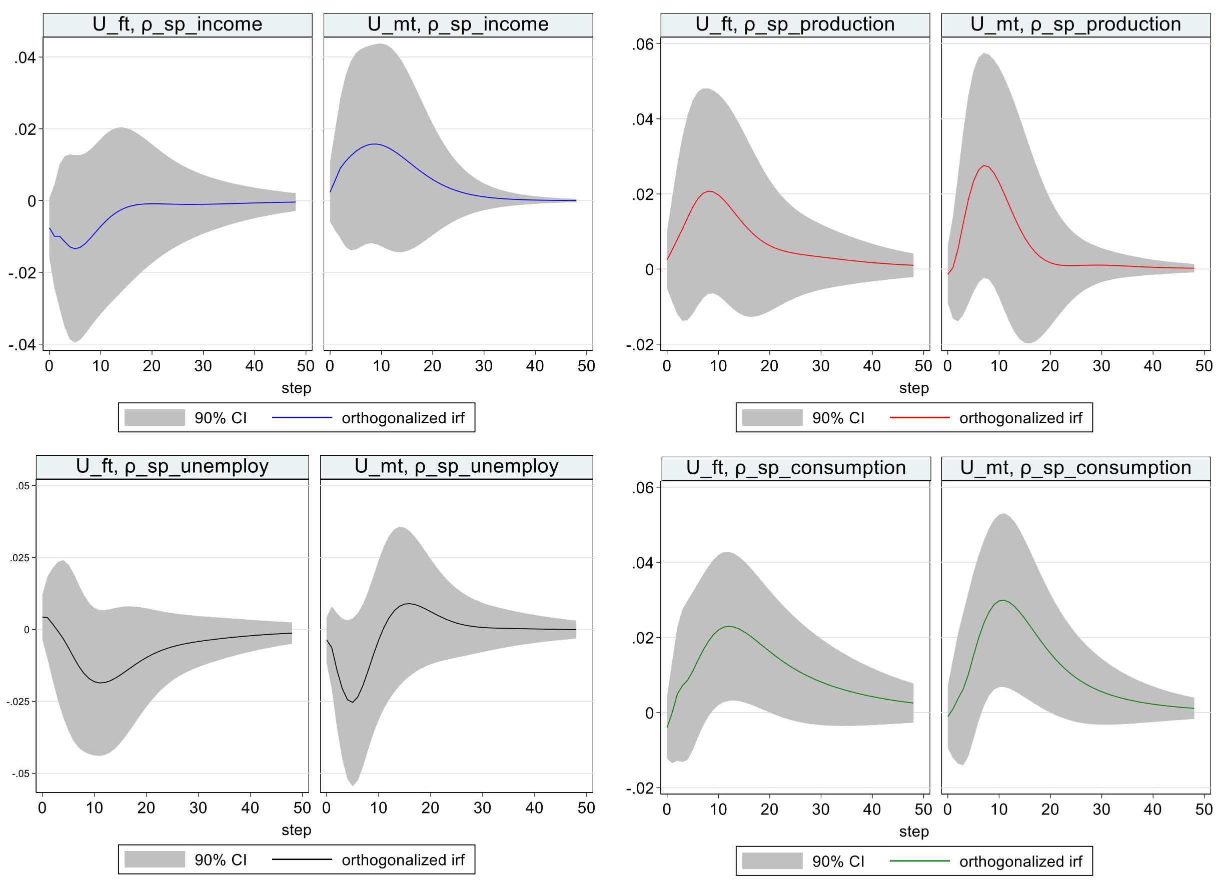
5.2. Vector Autoregression

In this thesis, four SVAR models are constructed. The models differ in the macro variable and the Spearman rank correlation coefficient ρ_{ijt} that is included in y_t. Before setting up the model, the appropriate number of lags is determined using the AIC and the FPE. In most models, $p = 2$ was the best number of lags to include. Only in the model that included $\rho_{sp,unemploy}$ and $Unemploy_t$, three lags were optimal.

The impulse response functions constructed from the SVAR(p) model displays how one endogenous variable reacts to a shock in an exogenous variable. In the constructed models, the shock variables are the financial- and macro uncertainty indicators, the response variables are the macro variables and the in section 5.1. constructed Spearman rank correlation coefficients. Figure 8 shows the main results of the thesis, the impulse response of the Spearman rank correlation coefficients on the uncertainty shocks. Figure 9 shows the impulse response function of the S&P 500 and the macro variables to the uncertainty shocks. The 90% confidence interval surrounds the estimated response in both figures. The x-axis of the figures shows the number of months after the shock and the y-axis shows the response compared to the pre-shock value of the response variable.

When analysing the impulse response function of the Spearman rank correlation coefficients ρ_{ijt} in figure 9, all functions show a long-lasting effect of the shock on the synchronization of the S&P 500 and the macro variables. The x-axis shows up to 48 months after the shock. Most ρ_{ijt} return to their original level after four years, meaning that the synchronisation is affected by a financial or macro uncertainty shock until then. As can be observed in the first graphs of figure 9, $\rho_{sp,income}$ is the only covariance that seems to react differently to a financial shock than to a macroeconomic shock. The IRF suggest that a financial shock will have a negative impact on the synchronisation of the S&P 500 and the real personal income, but after 26 months, the synchronisation is expected to be mostly recovered to its pre-shock value. The macro uncertainty shock is expected to have and increase the correlation coefficient by 2.8% after eight months. The macro uncertainty shock has a less persistent effect on $\rho_{sp,income}$ since it recovers faster. Since the effect of the shocks on income and consumption are comparable, the same occurs for the effect on $\rho_{sp,production}$ and $\rho_{sp,consumption}$. The IRFs of both correlation coefficients have a comparable path and impact. Correlation $\rho_{sp,production}$ peaks at month 8 after a financial shock and month 7 after a macroeconomic shock. The maximal responses are positive 2.1% and 2.8%. While the peak response is expected to be higher after a macro uncertainty shock, the $\rho_{sp,production}$ tend to recover faster. However, the confidence intervals show that none of the discussed results is significant at a 90% level. Regarding $\rho_{sp,consumption}$, a similar movement is observed. The maximal response is higher, but less persistent after the macroeconomic shock than a financial shock, respectively 2.3% and 3.0%. The correlation coefficient $\rho_{sp,unemploy}$ is the only coefficient negatively impacted by both shocks. Just as the previously discussed correlation coefficient, the impact of the monetary

Figure 8 Impulse response functions of the Spearman Rank correlations coefficients



Notes: The impulse response functions are displayed over 48 months. The titles of the figures first show the impulse variable and followed by the responding variable. The steps are in months after the shock.

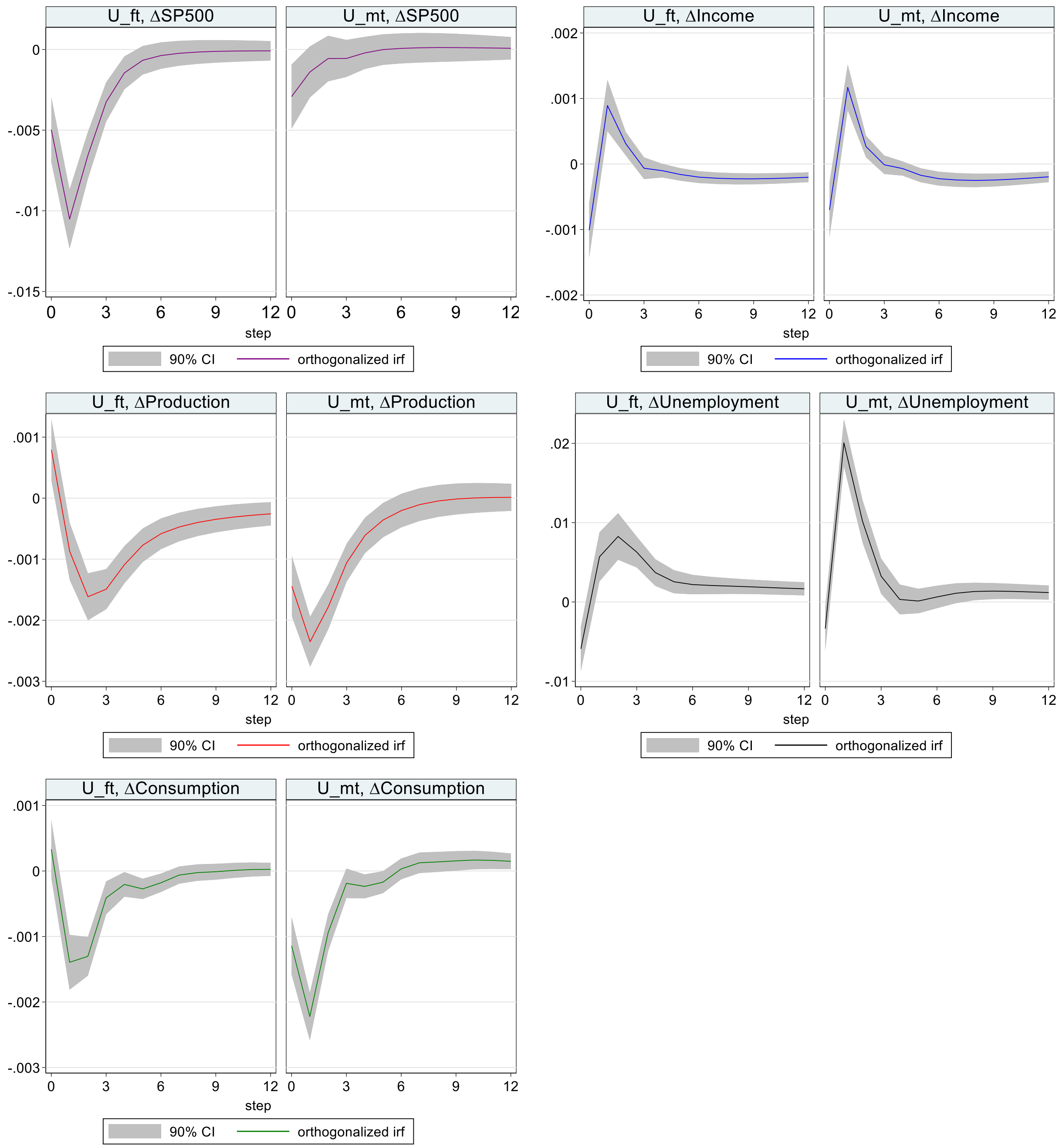
shock is larger but less persistent. The maximum impact of the shocks is -1,9% and -2.5%. Opposed to the other correlation coefficients, both $\rho_{sp,consumption}$ IRFs show a significant, positive effect of shocks on the synchronisation of the S&P 500 and consumption. A financial uncertainty shock positively affects the $\rho_{sp,consumption}$ from 9 until 20 months after the shock. A monetary uncertainty shock has a significant positive impact from 7 to 19 months after the uncertainty shock.

Because the ρ_{ijt}'s are constructed on the values of the S&P500 and the macro variables, the impulse response of these variables are also analysed. As figure 9 displays, the expected difference of the S&P 500's reaction to financial or macro uncertainty is directly visible. The S&P 500 has dropped 10.5 basis point after the first month before it starts its recovery. The majority of the recovery happens almost directly after the first crash. In the second month, the S&P 500 is expected to have recovered 3.9 basis point from the crash. Considering the 90% confidence interval, the financial uncertainty shock has a significant impact within the first 4 months after the impact before the S&P is close to recovery from the crash. The effect of a macro shock on the value of the S&P 500 is a lot smaller. The drop after a macro shock is 1.3 basis point and recovery start immediately. After 1 month, the S&P is already close to full recovery of the macro uncertainty shock and the shock has no longer a significant impact.

While looking at the macro variables, the impulse response functions of industrial production, consumption and, mirrored, the unemployment rate seem the react in a similar fashion to the financial and macro uncertainty shocks. After a financial uncertainty shock, consumption drops around 1.4 basis point and starts recovering after the first month. Production is expected to fall 1.6 basis point after 2 months before it starts its recovery. Consumption recovers after 7 months, while industrial production is after 12 months still not fully recovered. Both variables are more sensitive to macro uncertainty shocks than financial uncertainty shocks. The throughs are deeper as consumption and production are expected to fall 2.2 and 2.3 basis point after a month. The recovery of both variables is surprisingly fast, the impact has no significant effect after 5 months. The impulse response of the unemployment rate is, as expected, mirrored to consumption and production. A financial uncertainty shock leads to a 2 percent increase in unemployment. The recovery tends to be rather quick, after a month half of the increase in unemployment is recovered. After four months, the lost jobs are expected to be recovered. The reaction towards financial uncertainty shock is expected to be smaller but more persistent. The forecasted increase of unemployment is 8.3 basis point after three months, but the unemployment is not expected to fully recover within a year. The only macro variable that reacts surprisingly is the real personal income. Even though the initial reaction of income after a financial uncertainty shock is negative, the shock invokes an 8.9 basis point increase after the first month. Income is expected to return to its pre-shock value in the third month. Comparable to the other macro variables, the reaction to macro uncertainty exceeds the described reaction to financial uncertainty. Income is expected to increase 1.1% in the first month before returning to its original value in the third month after the shock.

Where the impact of the shocks on the S&P 500 and the macro variables are significant and mostly in line with the literature, the responses of the correlation coefficients $\rho_{sp,production}$, $\rho_{sp,unemploy}$ and $\rho_{sp,income}$ are not significant as the correlation the 90% confidence interval is never completely above or under zero. Hence, even though most IRF hint at a positive impact of uncertainty shocks on the synchronisation of the S&P 500 and the real economic variable, this cannot be concluded for these covariances. The only covariance that is significantly impacted by a financial- and a macro uncertainty shock is the $\rho_{sp,consumption}$. As figure 9 has shown, the reaction of consumption and production may be comparable in terms of throughs, but both differ in their recovery. The recovery of consumption is more similar to the S&P 500's response as both are expected to return to their pre-shock value quickly. The increased correlation of the S&P 500 and consumption 9 until 20 months after the shock indicates a harmonized recovery of shocks after a time of high uncertainty. When the uncertainty starts to dimmish, both S&P 500 and consumption are in the upward phase of their cycles. The economic explanation could be precautionary savings during high uncertainty. As mentioned in Gourio (2012), uncertainty causes an increase in savings. Hence, if uncertainty falls and consumers have more faith in their future income, they will increase their consumption and investments by spending the income they saved during periods of high uncertainty. Hence, the rigidity of consumption could be smaller than the rigidities of the other macro variables. If production plants went bankrupt after uncertainty shocks, it takes longer to reopen the factors and employ the labour force. Another explanation is the wealth effect, meaning that increasing asset prices have a positive effect on consumption. However, since not every consumer owns assets, the increased consumption must also be caused by other factors.

Figure 9 Impulse Respond Functions of uncertainty shocks to the macro variables



Notes: The impulse response functions are displayed over 12 months. The titles of the figures first show the impulse variable and followed by the responding variable. The steps are in months after the shock.

6. Limitations

The methodology of this thesis has some limitations. First, by quantifying the synchronisation of the S&P 500 and the macro variables, the trade-off between a wider rolling window with more observation and hence a better statistical basis due to an increased number of observations, and a narrower window that reflects that certain point of time better occurred. In widening the window, it becomes more likely to capture multiple phases of the cycles at the same time. Hence, contrasting periods of synchronisation could be captured within the same window and cancel each other out. Therefore, a smaller window is set. The downside of a smaller window is that the correlation is calculated over a shorter period. This has affected the statistical significance of some of the constructed ρ_{ijt}'s used in the SVAR. A second limitation is that the assumption that the S&P 500 and the macro variables did not affect the financial and macro uncertainty had to be made. Hence, in the A matrix of the SVAR model, a_{13}, a_{14}, a_{23}, a_{24} were al assumed to be zero. This assumption had to be made as it was not possible to perform an under identified SVAR in STATA. Therefore, it could not be tested whether uncertainty shocks were endogenous or exogenous as was done in Ludvigson, Ma, and Ng (2018).

7. Conclusion

The literature review of this thesis showed the important role that uncertainty has on the S&P 500 value and the macro variable. According to Ludvigson, Ma, & Ng (2018), financial uncertainty can invoke recessions and where macro uncertainty seems to amplify economic downturns rather than creating them. Others find similar relations between financial or macro uncertainty and economic downturns. Bloom (2009) and Gourio (2012) describe financial uncertainty shock as a likely cause for a recession while Croce (2014) finds that macro uncertainty can lead to an economic downturn.

The synchronisation of the S&P 500 and the macro variables is measured by constructing Spearman rank correlation coefficients over a 12-month rolling window. It showed that the synchronization was high in the periods 1960 – 1975 and 1995 – 2007 and fell after recessions. During the period 1975 – 1995, the correlation of the S&P 500 and the macro variables was mostly negative and close to zero. Hence, in this period of economic recession and recovery, the S&P and the real economy was not synchronised. The SVAR model performed in the thesis simulated the response of these correlation coefficients, the S&P 500 and the macroeconomic variables to a shock in financial or macro uncertainty. The SVAR models hint at a positive impulse response of most correlation coefficients to the financial and macro uncertainty shocks. Unfortunately, these results are not significant for the macro variables income, production and unemployment. Therefore, it cannot be concluded that uncertainty affects the synchronisation of the S&P 500 and these macro variables. However, the financial and macro uncertainty shocks have a significant positive impact on the harmonization of the S&P 500 and consumption 9 until 20 months after the shock. A possible explanation of this significant increase in the correlation could be the quick recovery of both variables after an uncertainty shock. The impulse responses of the S&P 500 and all macro variables were significant. The negative impact that the uncertainty shocks had on the S&P 500, consumption and production, and the positive impact on unemployment were in line with expectations. The significant positive response of income after the shocks was an unforeseen result.

Within the macro-finance literature, the effect of a financial indicator on a macro indicator or vice versa is often tested, but, quantifying the synchronisation of the equity cycle and the real economic cycle has, to the best of my knowledge, not been done before. Hence, this thesis is the first to empirically test shocks to the synchronisation of the S&P 500 and macro indicators. For further research, I would recommend looking into other methods of quantifying the synchronisation of the

S&P 500 and the macroeconomic variable. I presume that the trade-off discussed in the limitations section has had an impact on the significance level of the impulse response function constructed in section 5.2. The finding that the synchronisation of the S&P 500 and the macro variables is relatively low during the period 1975 – 1995 is worthy of research on its own. Within this thesis, clarification of the underlying economic development has been sheared to a certain extent. However, it could be interesting to focus solely on this period to create a better understanding of the economic dynamics. A third suggestion would be to conduct more extensive research on the positive impulse response of income towards an uncertainty shock. This thesis does not present a possible clarification of this surprising result.

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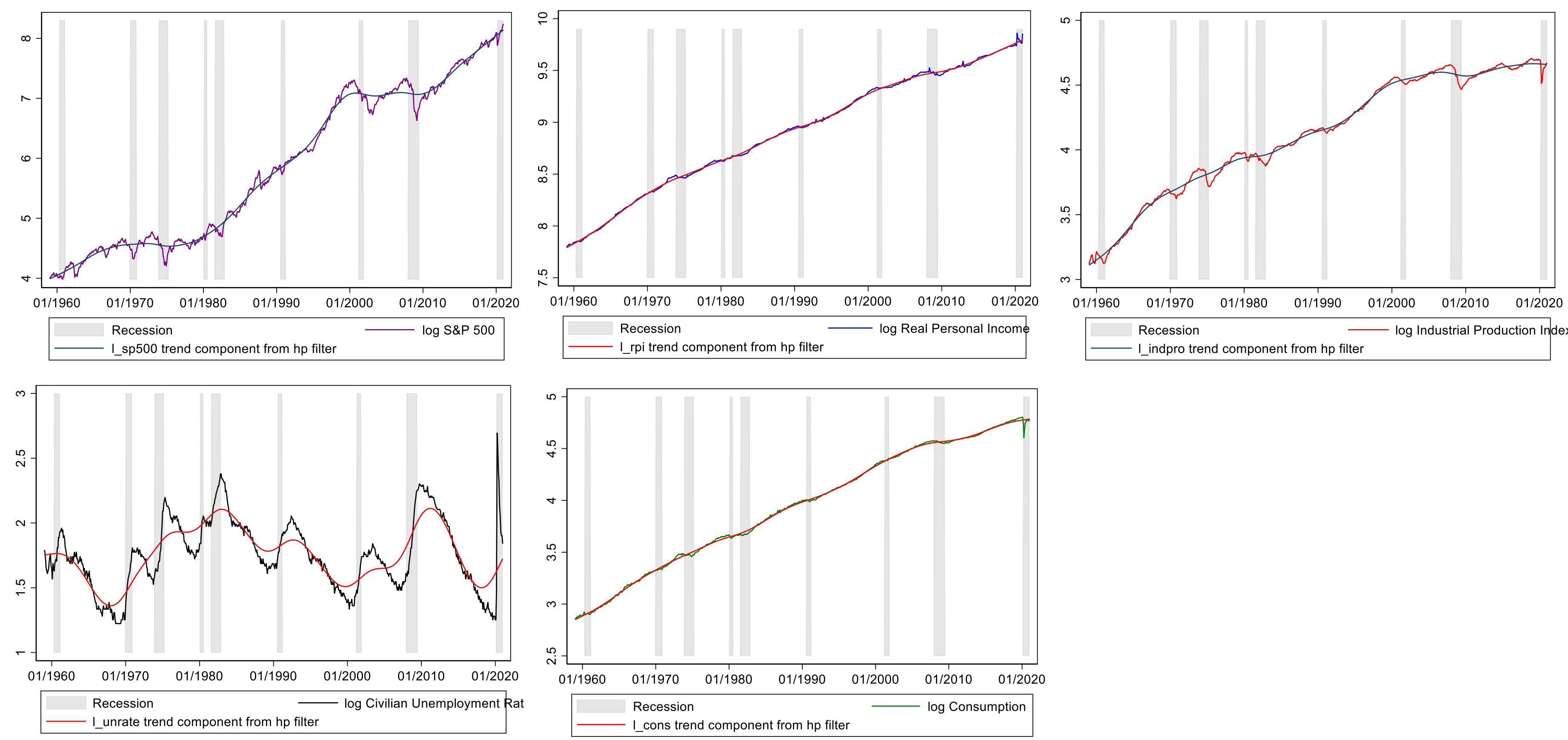
9. Appendices

Table 3: Descriptive Statistics

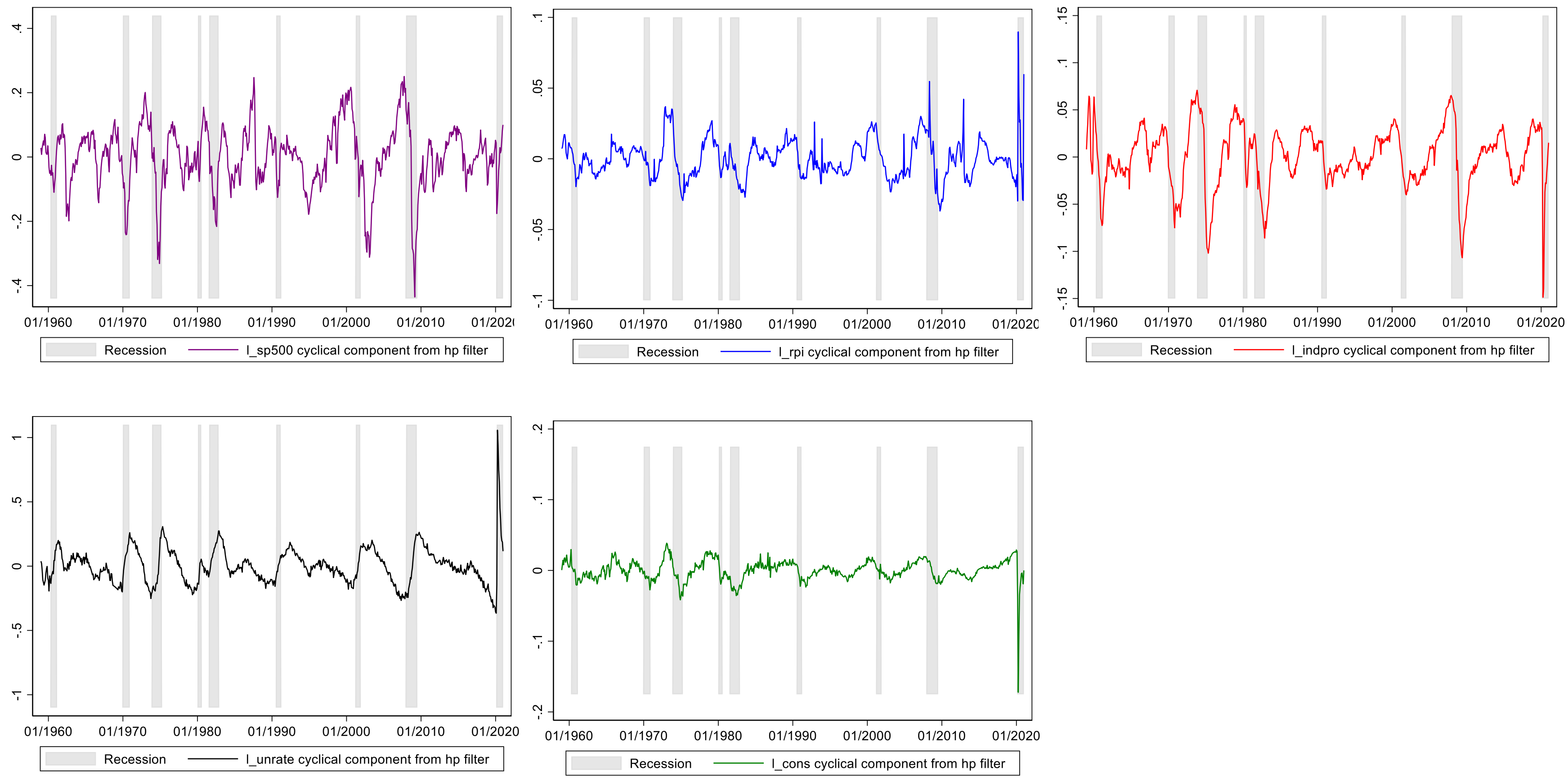
Variable	Obs	Mean	Std.Dev.	Min	Max
Income	745	8481.692	4340.931	2437.296	19152.78
Consumption	745	60.285	31.458	17.302	121.894
Production	745	67.67	27.26	22.625	110.552
Unemployment rate	745	5.992	1.667	3.4	14.8
S&P 500	745	730.769	811.553	53.73	3793.75
l_sp500	745	5.864	1.284	3.984	8.241
l_income	745	8.9	.559	7.799	9.86
l_consumption	745	3.947	.573	2.851	4.803
l_unemployment	745	1.754	.268	1.224	2.695
l_production	745	4.121	.453	3.119	4.705
U_ft1	726	.899	.167	.594	1.546
U_mt1	726	.647	.103	.523	1.219
g_sp500	744	.006	.036	-.228	.114
g_income	744	.003	.008	-.05	.122
g_production	744	.002	.01	-.136	.06
g_consumption	744	.003	.008	-.131	.082
hp_sp	745	0	.099	-.435	.251
t_sp	745	5.864	1.278	3.99	8.141
hp_income	745	0	.014	-.037	.09
t_income	745	8.9	.559	7.791	9.796
hp_production	745	0	.032	-.149	.071
t_production	745	4.121	.451	3.111	4.665
hp_consumption	745	0	.015	-.172	.039
t_consumption	745	3.947	.572	2.85	4.784
hp_unemployment	745	0	.139	-.366	1.057
t_unemployment	745	1.754	.199	1.362	2.113
Recession	745	.140	.347	0	1
Rho_sp_consumption_12	734	.235	.448	-.86	.986
Rho_sp_production _12	734	.103	.567	-.986	.979
Rho_sp_income_12	734	.13	.522	-.958	.958
Rho_sp_unemploy_12	734	-.077	.543	-.972	.965

Figure 10: Logarithms and HP trend component



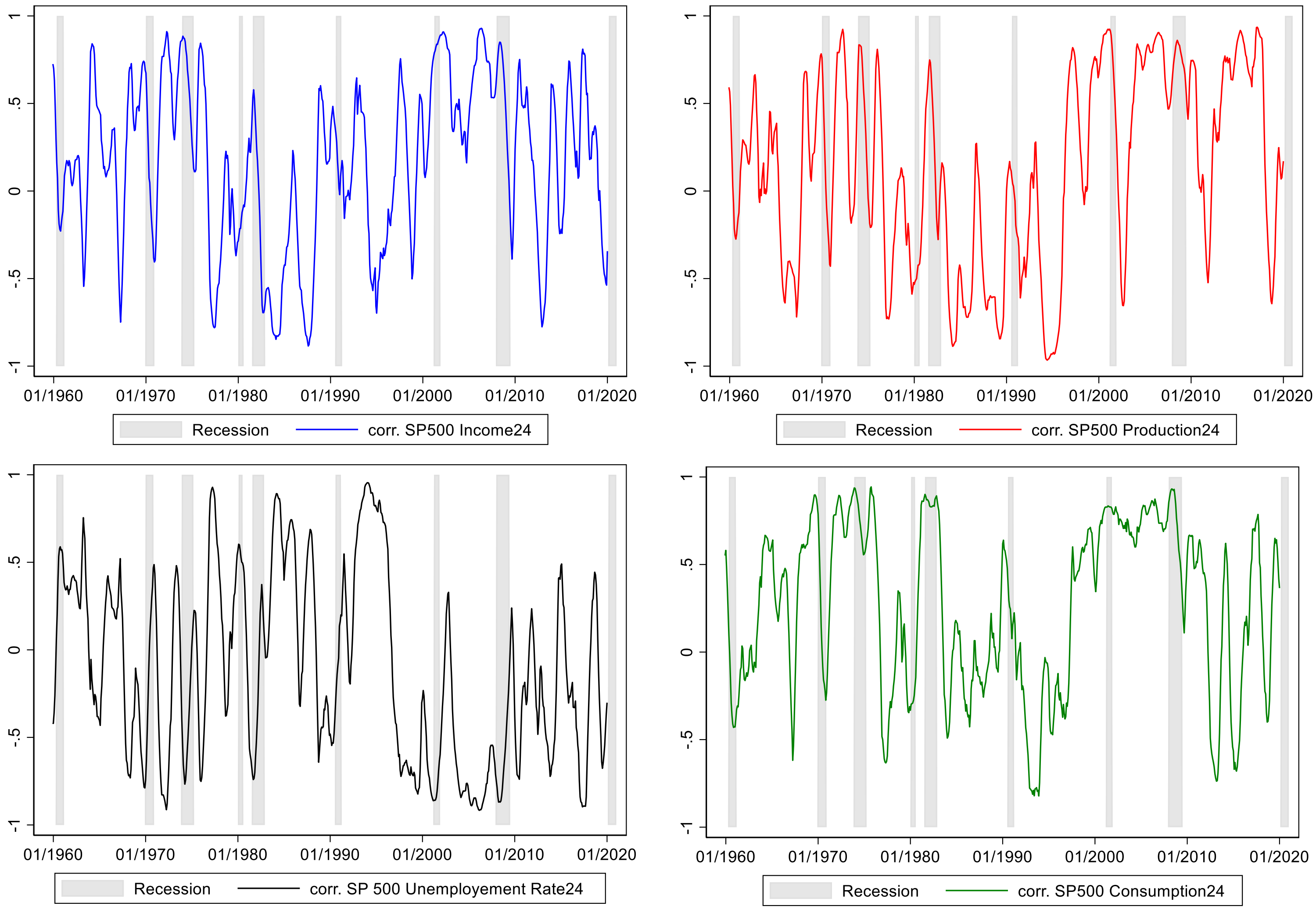
Notes: All trend components are calculated using the Hodrick-Prescott filter with smoothing variable 129600.

Figure 11: Hodrick-Prescott filtered cyclical component



Notes: All series are detrended with a Hodrick-Prescott filter with smoothing variable 129600.

Figure 12: 24-month rolling window Spearman rank correlation coefficient



Notes: All series were detrended with a Hodrick-Prescott filter with smoothing variable 129600. Then, the Spearman rank correlation coefficient is calculated over a 24-month rolling window

Table 4: Matrix of correlations

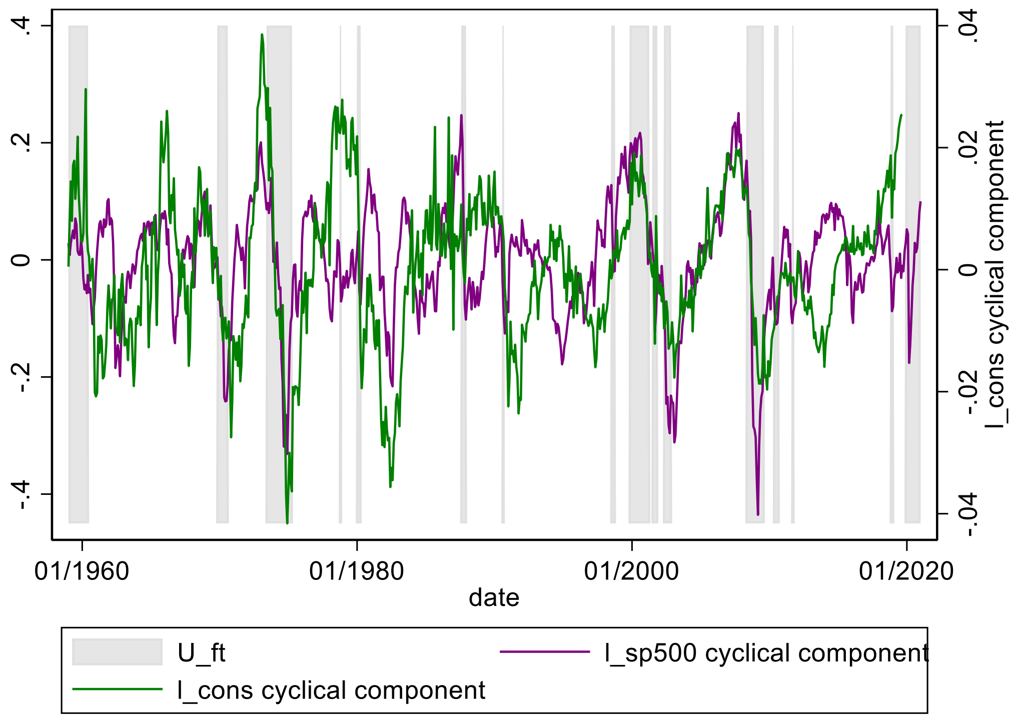
1959 – 1975					Obs = 192
Variables	(1)	(2)	(3)	(4)	(5)
(1) hp_SP	1.000				
(2) hp_Income	0.401	1.000			
(3) hp_Production	0.287	0.804	1.000		
(4) hp_Consumption	0.501	0.835	0.688	1.000	
(5) hp_Unemploy	-0.133	-0.769	-0.863	-0.640	1.000

1975 – 1995					Obs = 240
Variables	(1)	(2)	(3)	(4)	(5)
(1) hp_SP	1.000				
(2) hp_Income	-0.086	1.000			
(3) hp_Production	-0.167	0.793	1.000		
(4) hp_Consumption	0.055	0.726	0.730	1.000	
(5) hp_Unemploy	0.123	-0.802	-0.915	-0.768	1.000

1995 – 2008					Obs = 156
Variables	(1)	(2)	(3)	(4)	(5)
(1) hp_SP	1.000				
(2) hp_Income	0.773	1.000			
(3) hp_Production	0.862	0.744	1.000		
(4) hp_Consumption	0.7618	0.794	0.750	1.000	
(5) hp_Unemploy	-0.8253	-0.825	-0.909	-0.824	1.000

2008 – 2021					Obs = 157
Variables	(1)	(2)	(3)	(4)	(5)
(1) hp_SP	1.000				
(2) hp_Income	0.251	1.000			
(3) hp_Production	0.637	0.210	1.000		
(4) hp_Consumption	0.290	0.319	0.541	1.000	
(5) hp_Unemploy	-0.407	-0.268	-0.713	-0.834	1.000

Figure 13: Synchronisation of the cyclical component of the S&P 500 and consumption



Notes: All series were detrended with a Hodrick-Prescott filter with smoothing variable 129600. The grey areas represent periods of high financial uncertainty where U_{Ft} is at least one standard deviation above mean.