Interdependence between uncertainty and sector returns: Evidence from wavelet coherence analysis

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Abstract

The relationship between uncertainty and sector returns is investigated by using wavelet coherence of a set of uncertainty measures with sector returns and sector volatility. By capturing changes in the frequency domain over time, we find that the importance of frequency components does not remain stable over time but differs depending on whether the uncertainty reflects a short-lived shock or a long-lived shock. We associate short-lived shocks with market shrugs, and long-lived shocks with market turns. Shrugs are typically sector-specific, while market turns affect most sectors.

1 Introduction

The big question of whether the economy has become less or more uncertain is tackled in many different ways by researchers. Many studies focus on defining and measuring uncertainty that affects real economic variables, as well as, asset returns. Recent research on time-varying macroeconomic uncertainty is found in Jurado et al, (2015) and Ludvigson et al (2017). Their research identifies three "big" episodes (1973-74), (1981-82), and (2007-2009) associated with a high diffusion of uncertainty. Our analysis employs the Ludvigson et al measures of uncertainty and investigates the time/scale nature of the interdependence between uncertainty measures and sector returns. Our motivation for exploring the uncertainty measures in the context of sector returns is that the supply and demand shocks that go hand in hand with well-accepted measures of uncertainty affect sectors at different times or horizons.

Our contributions are rooted in the use of wavelet coherence analysis to investigate uncertainty and sector returns. A key advanatage of wavelet methodology is that the frequency components of dynamic movement can be measured without losing time specific information. We find that scale matters in that the persistent episodes of uncertainty are scale dependent and show with the aid of coherence plots that uncertainty episodes vary in terms of their persistance both across and within sectors. We associate short-lived shocks(low scale) with market shrugs, and long-lived shocks(high or medium scale) with market turns. We find that for the wavelet power of Ludvigson et al macroeconomic uncertainty measure is highest at low frequencies, while the power of their financial uncertainty measure is also high at low frequencies, but for the financial uncertainty measure there are also periods of high power at medium and high frequencies. When it comes to examining comovements, we find that during the Great Recession coherence is high for both measures of uncertainty in most of the sectors. Healthcare and Business Equipment sectors have the lowest coherence with uncertainty measures during the Great Recession. Another period where the comovement is high across sectors for both measures is the late 1960s through the 1970s. During this period Energy, Utility, and Manufacturing sectors see the beginnings of high coherence with Macroeconomic uncertainty at a period of 8 to 12 years that lasts through 2016, We also find that all the sectors have high coherence with macroeconomic uncertainty in the early 1980s. All sectors, but energy and "other" have high level of coherence with both measures of uncertainty at the lowest frequency. The tech bubble burst of 2001 is barely discernable in the coherence plots. As illustrated by the low coherence of health care sector with measures of uncertainty during the Great Recession, and the weak effects of the Tech bubble burst, some episodes of major uncertainty appear as market shrugs either for specific sectors or across sectors. Our results are also consistent with the Great Moderation in that there is little or no coherence for the sectors and the uncertainty measures at periods of 1-4 years from the late 1980s to the Great Recession. Our results provide evidence of important scale dynamics affecting uncertainty measures that should be taken into account for a complete picture of the effects of uncertainty on the economy that should be of concern for both investors and policymakers. The remainder of the paper is organized as follows: Section 2 highlights research based on wavelet analysis in applied

financial economics of particular relevance for our analysis. The important concepts used in wavelet analysis that are applied in our analysis are introduced in Section 3. The data and uncertainty measures are discussed in Section 4. The analysis and results are presented in Section 5. The conclusions follow in Section 6.

2 Literature Review

The modern strain of literature relating to uncertainty, and its effects on the economy, grew out concerns in the post credit crisis era that firms were holding off on investments due to uncertainty about the future. Bloom (2009) shows that a number of cross-sectional measures of uncertainty are correlated with time series measures of volatility. The cross-sectional measures of uncertainty he considers are the standard deviation of pre-tax profit growth, a stock return measure and the standard deviation of total factor productivity. His time series measure of volatility is stock market volatility. In addition, he evaluates the impact of uncertainty on the real economy using a VAR. He finds that a shock to stock market volatility causes a 1 percent drop in industrial production over a 4 month period. He also reports a similar effect on employment. Bloom identifies 17 major instances of uncertainty based on the stock market volatility measure. Baker, Bloom and Davis (2013) develop a measure of policy uncertainty based on newspaper coverage frequency. They find that their index proxies for movements in policy-related economic uncertainty. Specifically, tight presidential elections, Gulf Wars I and II, the 9/11 attacks, the failure of Lehman Brothers, and the 2011 debt-ceiling dispute are associated with spikes in the index. Jurado, Ludvigson and Ng (2015) develop a new measure of uncertainty based on the h-period ahead forecasting error, where h=1,3, and 12 months. Using a comprehensive data set of 132 macroeconomic series they aggregate the forecast errors for each series to create a macroeconomic uncertainty index. In contrast to Bloom (2009), their analysis finds that there are three major episodes of uncertainty in the 1960-2016 period: 1973-1974, and 1981-1982 recessions, and the Great recession of 2007-2009. Bali, Brown and Tang (2014) create an index of macroeconomic uncertainty based on ex-ante measures of cross-sectional dispersion in economic forecasts by the Survey of Professional Forecasters. After controlling for a number of factors, they find a statistically significant negative relationship between their measure of uncertainty and future stock returns. Ludvigson, Ma and Ng (2017) examine the question of whether uncertainty is a source of business cycle fluctuations, or an endogenous response. Their analysis distinguishes macroeconomic uncertainty and uncertainty about real economic activity from financial uncertainty. They find that financial uncertainty is primarily an exogenous shock. In addition they find that higher uncertainty about real economic activity is likely to be endogenous, in response to business cycle fluctuations. The financial and macro uncertainty series developed by Ludvigson, Ma, and Ng(LMN) are used in our paper to evaluate the wavelet coherence of uncertainty and sector returns.

3 Wavelet Analysis

The main feature of wavelet analysis that has broadened its applicability in finance is its capability to decompose a time series into low and high frequency components that correspond to short, medium and long term variation in the series. Both time and frequency components of a series are captured through wavelets that represent a set of basis functions that are classified into father and mother wavelets. The father wavelet captures smooth and low frequency components, while the mother wavelets capture the short-term dynamics or high frequency parts.[1] In contrast to Fourier methods where the basic Fourier transform frequency decomposition is global, the wavelet transform allows for localized decomposition in both frequency and time. This is particularly suitable for an analysis where there are investors with different time horizons.[2]

The transformation is not in terms of trigonometric polynomials, but in terms of wavelets.[3] The wavelet transform is composed of a father wavelet and a set of mother wavelets. Given a function Φ, the father wavelet for the discrete transform is defined as:

$$\Phi_{J,k} 2^{-\frac{J}{2}} \Phi \frac{t-2^J * k}{2^J} \ (2)$$

$$\int \Phi(t) dt = 1$$

The mother wavelets, also in discrete form, are defined as:

$$\Psi_{j,k} \, 2^{-\frac{j}{2}} \Psi \frac{t-2^j * k}{2^j}, j = 1, ..., J \ (3)$$

$$\int \Psi(t) dt = 0$$

Where J is the number of scales or levels,$2^J$is a scale factor and k is the time domain index.

The father and mother wavelets are each indexed by both scale and time. It is precisely this dual indexing that makes wavelet analysis appealing since as a time series, f(t), is represented as a linear combination of wavelet functions that are localized in space and time.

The scale parameter is inversely proportional to frequency.[4] The father and mother wavelet functions may also be represented as filters. In this alternative representation the father wavelet is a low pass filter, and the mother wavelets are high pass filters.[5] We can use the wavelet functions to transform a time series, f(t), into a series of wavelet coefficients,

$$S_{J,k} = \int f(t) \Phi_{J,k} \ (4)$$

and,

$$d_{j,k} = \int f(t) \Psi_{j,k} \text{ j=1,...,J } (5)$$

Where $S_{J,k}$ are the coefficients for the father wavelet at the maximal scale, 2^J, and the $d_{j,k}$, are the coefficients of the mother wavelets at the scales from 1 to 2^J. The $d_{j,k}$ are referred to as the detailed coefficients and the $s_{J,k}$ are referred to as the smooth coefficients. Applying the transforms results in a time series of length k of smooth coefficients at the maximal scale J, and J time series of detailed coefficients each of length k. If there are 6 scales, the frequency of the first scale is associated with the interval [1/4,1/2], and the frequency of scale 6 is associated with the interval [1/128, 1/64]. For a monthly time series decomposing into six scales (D1-D6) corresponds to periods 2-4, 4-8, 8-16, 16-32, 32-64, and 64-128 months. The smooth component (S6) captures the trend of the original series. The high frequency component is associated with the shortest scale D1, while the low frequency component is associated with the longest scale D6.

Given the smooth and detailed coefficients, a time series f(t) can be represented in decomposed form, known as the multi-resolution analysis of f(t), as follows:

[1] See Cowley(2005) for an introduction to wavelet methods in economics and finance, and Gencay, et. al. An Introduction to Wavelets and Other Filtering Methods in Finance and Economics.

[2] For the relevance of horizon effects see for example Kamara, et.al. (2012).

[3] See Strong (1993) for a comparison of wavelet versus Fourier transforms.

[4] See Gencay, et al. 2010, pp. 99-103 for a complete discussion.

[5] See Ramsey (2002).

$$f(t) = \Sigma_k S_{J},_k\ \Phi_{J},_k\ (t) + \Sigma_k d_J, k\Psi_{J},_k\ (t) + ... + \Sigma_k d_{j},_k\ \Psi_{j},_k\ (t) + ... + \Sigma_k d_{1},_k\ \Psi_{1},_k\ (t)\ (6)$$

Or, using summary notation,

$$f(t) = S_J + D_J + D_{J-1} + ... + D_1$$

The discrete wavelet transform decomposes a time series into orthogonal signal components at different scales. S_j is a smooth signal, and each D_j is a signal of higher detail. The number of coefficients differs by scale. If the length of the data series is n, and divisible by 2^J, there are $n/2^j\ d_{j},_k$ coefficients at scale j=1,...,J-1. At the coarsest scale there are $n/2^J\ d_{J},_k$ and $s_{J},_k$ coefficients. The wavelet variance at each scale is captured as the wavelet power of each scale.

The continuous wavelet transform (CWT) is also useful for gaining insight into the time-scale characteristics of a time series. The CWT is defined as,

$$W(\lambda, t) = \int^{+\infty}{}_{-\infty}\ \Psi_{\lambda},_t\ (u)x(u)du\ (7)$$

$$\text{where, } \Psi_{\lambda},_t\ (u) \equiv \frac{1}{\sqrt{\lambda}}\Psi\left(\frac{u-t}{\lambda}\right)$$

As noted by Ramsey, the main difference between the CWT and DWT is that the CWT considers continuous variations in the scale (λ) and time components (t). The discrete wavelet transform can be derived independently of the CWT, but it can also be viewed as a critical sampling of the CWT with $\lambda = 2^{-j}$ and $t = k2^{-j}$.

The wavelet power spectrum which measures the local variance of a time series at different scales is defined as $|W(\lambda, t)^2|$, and aids our analysis in terms of understanding how periodic components evolve over time when applied to the market, as well as, the eleven sectors examined in our analysis. A clear advantage that the CWT has over the discrete transform is that it produces a powerful visual for detecting time-scale patterns. The wavelet power spectrum is helpful for understanding how the power varies with the scaling of the wavelet. But we also need to understand how periodic components evolve jointly over time. The Fourier coherency identifies frequency bands where two time series are related, while the wavelet coherency identifies both frequency bands and time intervals when time series are related. The wavelet coherence of two series, x and y, is a measure of co-movement across time and scale based on the CWT. To define it we need the definition of two other measures, the cross wavelet transform (XWT) and the cross wavelet power (XWP). The XWT is defined as

$$W_{xy} = W_x(\lambda, t)W_{y*}(\lambda, t)\ (8)$$

The XWP is the defined as the absolute value of the XWT, $|W_{xy}(\lambda, t)|$. It measures the local covariance of x and y at different time scales. The XWP identifies areas in time-scale space where the two series have high common power. In addition to identifying the common power of two time series, we are also interested in identifying areas of co-movement in time-scale space, even if the cross wavelet power is low. A measure of co-movement, the wavelet coherence, is defined as:

$$R^2(\lambda, t) = \frac{|S(S^{-1}Wxy(\lambda,t))|^2}{S(S^{-1}|W_x(\lambda,t)|^2)*S(S^{-1}|W_{xy}(\lambda,t)|^2)}\ (9)$$

Where S is a smoothing operator in time and scale, and 0 $\leq R^2(\lambda, t) \geq$ 1. The wavelet coherence is similar to the correlation coefficient, and is typically interpreted as a localized correlation in time-scale space.

4 Data

4.1 Sector Returns

The equity return data used for our analysis is from the Kenneth French Data Library.[6] The market portfolio (MKT) is a composite portfolio of all stocks traded on the NYSE, AMEX, and NASDAQ. The market is divided into 12 industry groups or sectors defined below. We use the abbreviation associated with each sector throughout the paper.

Table 1: Kenneth French 12 Industry Data Set

1 NoDur Consumer NonDurables – Food, Tobacco, Textiles, Apparel, Leather, Toys
2 Durbl Consumer Durables – Cars, TV's, Furniture, Household Appliances
3 Manuf Manufacturing – Machinery, Trucks, Planes, Off Furn, Paper, Com Printing
4 Enrgy Oil, Gas, and Coal Extraction and Products
5 Chems Chemicals and Allied Products
6 BusEq Business Equipment – Computers, Software, and Electronic Equipment
7 Telcm Telephone and Television Transmission
8 Utils Utilities
9 Shops Wholesale, Retail, and Some Services (Laundries, Repair Shops)
10 Hlth Healthcare, Medical Equipment, and Drugs
11 Money Finance
12 Other Other – Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment

All returns are reported in excess of the risk free rate. The risk-free rate is measured by the yield on the 1-month T-bill.[7]

The sample period includes eight recessions. These are illustrated in Figure 1. All but three were less than a year in duration. The 1974-75 recession was 16 months, this was the time of the first OPEC price shock, when oil prices quadrupled. The recession starting in July 1981 lasted 16 months. This coincided with Fed interest rate tightening which was implemented to reduce inflation. Finally the Great Recession of 2008-2009 had a duration of 18 months.

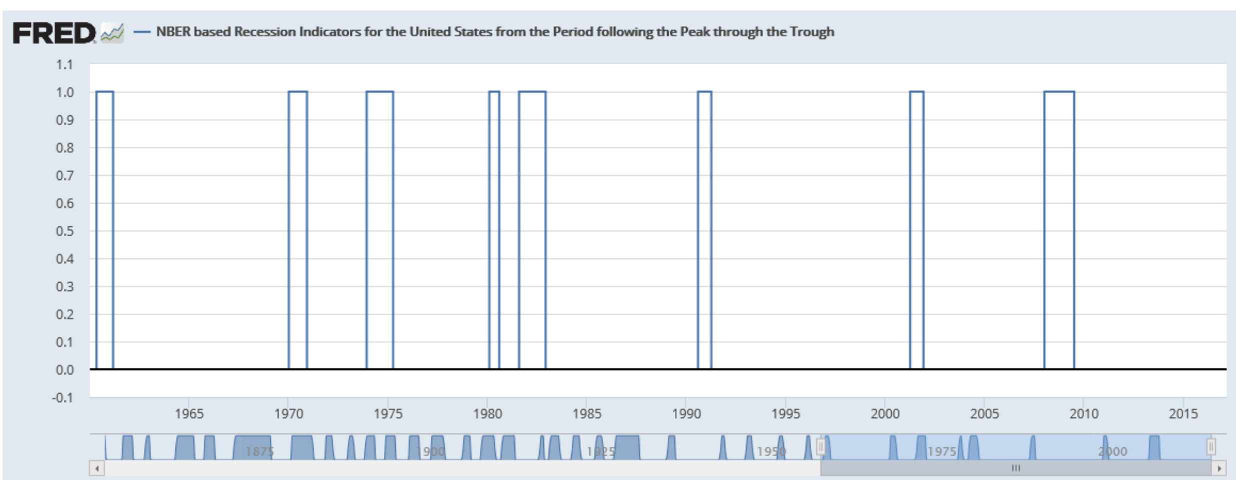


Figure 1: US Recessions - NBER Dating

An analysis of the cumulative returns for each sector indicates a high degree of variability across sectors and over time for a given sector during the sample period. Figure 2 contains the sectors with cumulative

[6] `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

[7] The 1 month T-bill rate used as a risk free rate is calculated by Ibbotson and Associates, and provided by Kenneth French in his Data Library

growth that exceeds the market for the sample period. Figure 3 contains sectors with cumulative growth near or below the market. The sector with the highest cumulative growth over the sample period is Consumer Non-durables (NoDur) with cumulative growth of almost 5400%, compared with the market as a whole which increased 1600 percent. One interesting point about the two charts is that most of the low growth sectors had a large drop in returns following the tech bubble burst (2000-2001), and also experienced another drop during the Great Recession. These sectors are only now getting back to the level of cumulative returns achieved prior to the tech bubble burst. The higher growth sectors had a noticeably less severe downturn following the tech bubble burst.

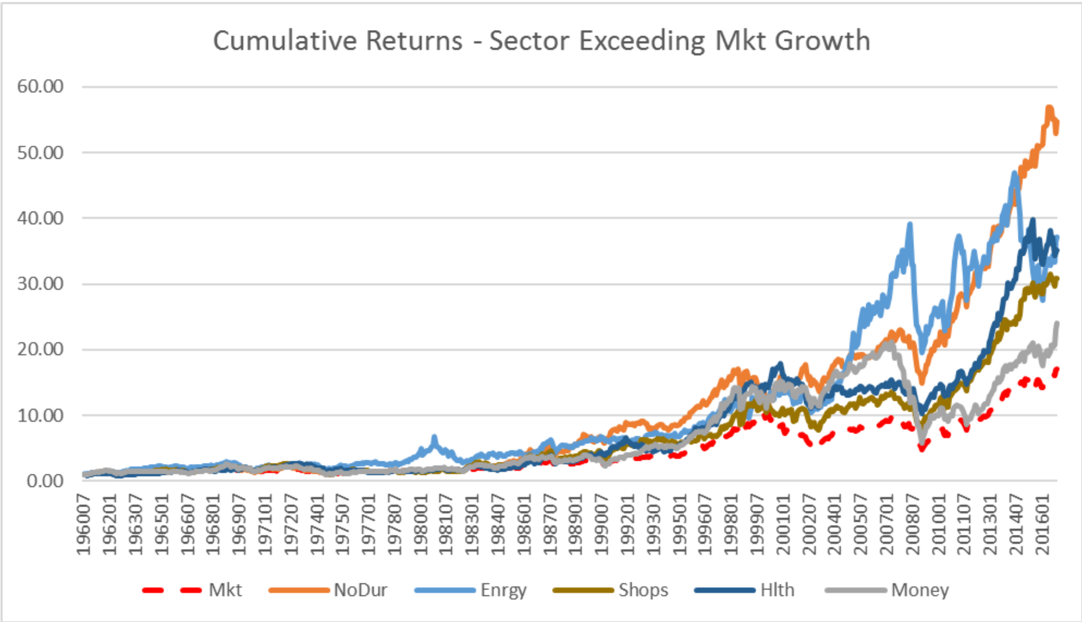


Figure 2: Cumulative Returns - High Growth Sectors

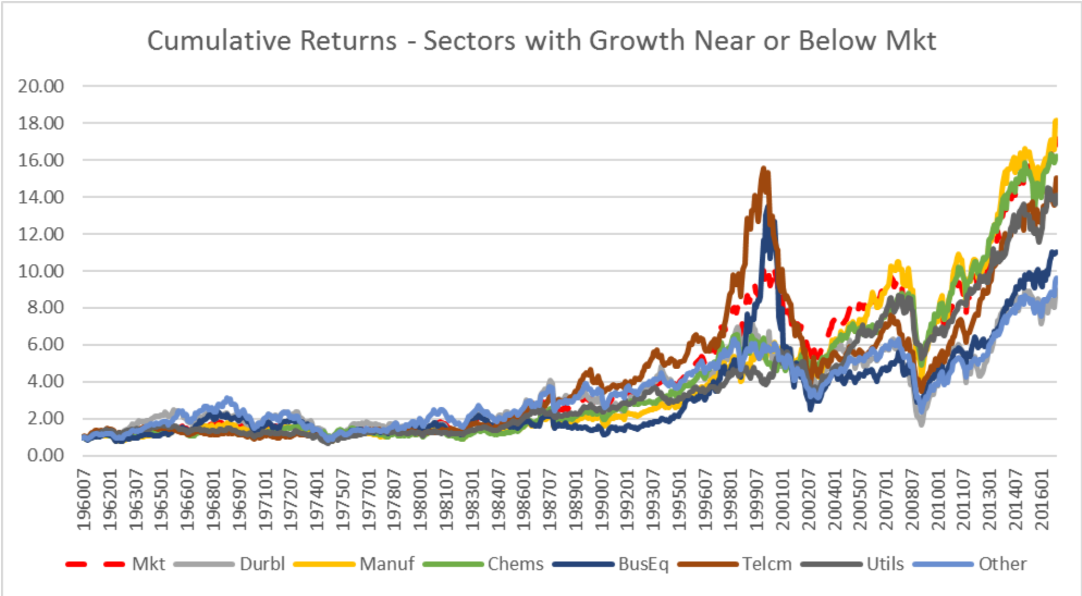


Figure 3: Cumulative Returns - Low Growth Sectors

Figure 4 contains the wavelet power spectrum for market returns. The most striking feature of this chart is that most of the power occurs intermittently at high frequencies, in contrast the Uncertainty measures of Ludvigson et.al. (2017) tend to have high power at low frequencies(Figures 8 and 9). The wavelet power spectrum for the Durables sector (the lowest growth sector) is shown in Figure 5 5, and the power spectrum for the Consumer Non-durables sector (the highest growth sector) is shown in Figure 6 6. Both sectors look similar to the market at high frequencies. At intermediate frequencies (16-32 months) the Durable goods sector shows high power during the Great Recession, but the the Non-durables goods sector does not. Consumer non-durables have relatively high power at the 32-64 month frequency during the 1970's, while the Durable Goods sector has less variability associated with this frequency band.

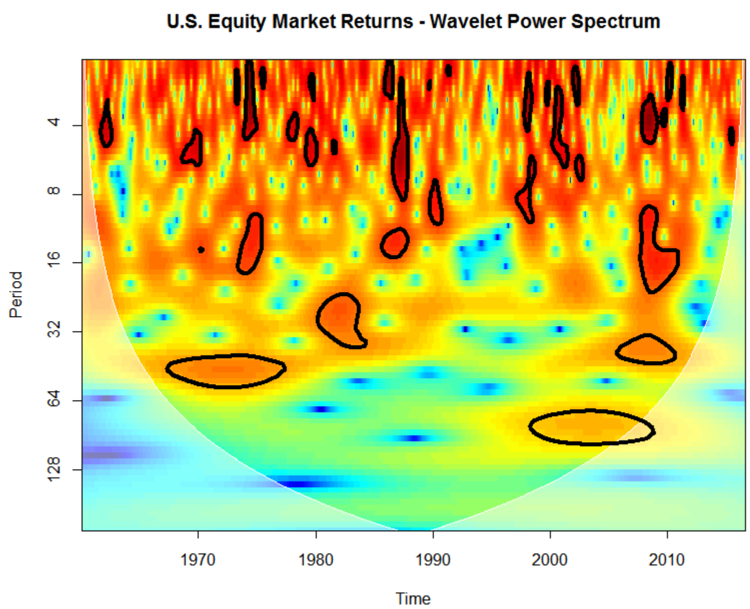


Figure 4: Wavelet Power Spectrum - U.S. Equity Market

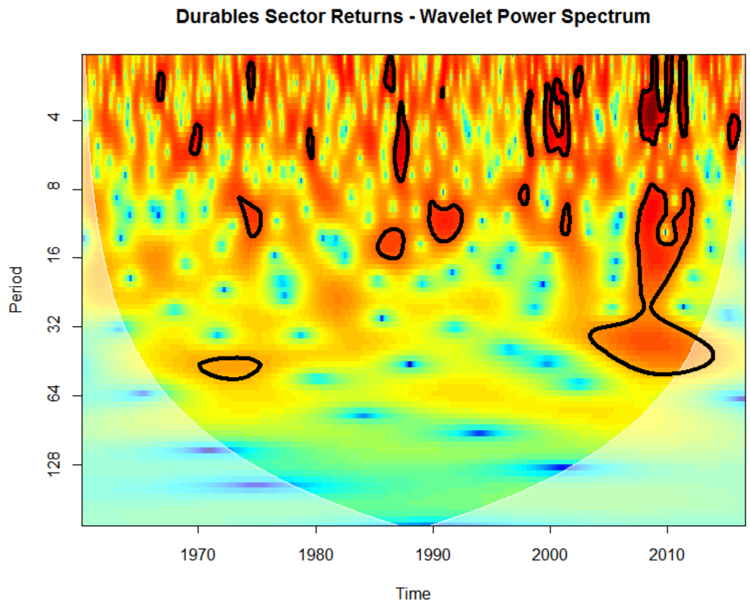


Figure 5: Wavelet Power Spectrum -Durable Goods

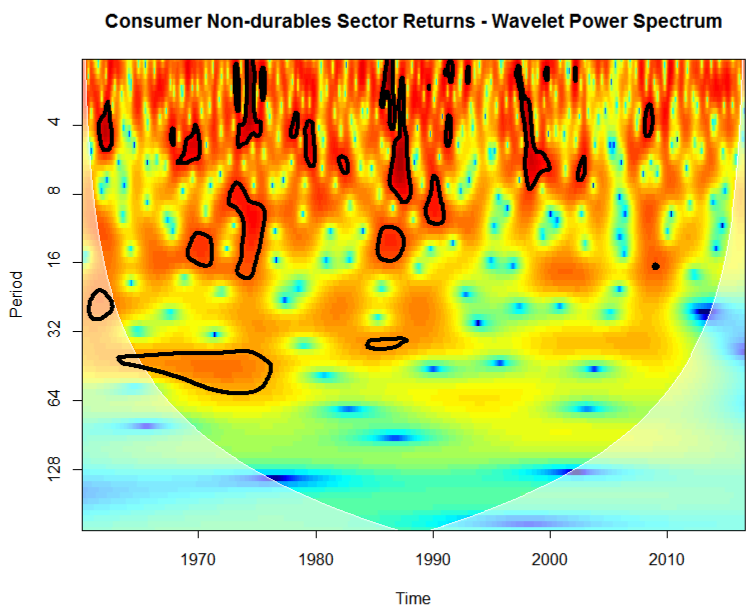


Figure 6: Wavelet Power Spectrum - Consumer Non-durables

A set of descriptive statistics for the monthly excess returns (%) is reported in Table 2 2. Monthly returns range from a high of 42.6% for Durable goods (Apr. 2009) to a low of minus 42.8% also for Durable goods (Oct. 2008). Skewness is negative for most sectors, the exceptions being except Durable goods (0.14%), and 0% for Energy; Excess kurtosis is positive (leptokurtic) for all of the sectors, suggesting that the distribution of returns has fatter tails than a Normal distribution. It ranges from 1.0 for Utilities to 4.9 for Durables.

	Mean	**Std Dev**	**Skewness**	**Kurtosis**	**Minimum**	**Maximum**
Mkt	0.5188	4.4175	-0.5160	1.8694	-23.24	16.10
NoDur	0.6844	4.2831	-0.3110	2.0215	-21.63	18.30
Durbl	0.5167	6.2094	0.1419	4.8716	-32.71	42.62
Manuf	0.5682	5.2395	-0.4746	2.6275	-29.18	21.07
Enrgy	0.6782	5.3622	0.0003	1.3377	-19.00	23.60
Chems	0.5183	4.6092	-0.2351	2.1100	-25.19	19.71
BusEq	0.5643	6.4368	-0.2185	1.2952	-26.45	20.34
Telcm	0.5082	4.6332	-0.1701	1.1563	-16.30	21.20
Utils	0.4714	4.0046	-0.1318	1.0026	-12.94	18.26
Shops	0.6394	5.1282	-0.3032	2.4515	-28.85	25.28
Hlth	0.6469	4.9194	-0.0068	2.3387	-21.06	29.01
Money	0.6188	5.4279	-0.3752	1.6120	-22.53	20.59

Table 2: Summary Statistics - Sector Returns

4.2 Uncertainty Measures

The uncertainty measures we use in our analysis are from Ludvigson et. al. (2017). The method used to develop the uncertainty measures is described in Jurado et. al. (2015). To summarize, Jurado defines $U^y_{jt}(h)$ h-period ahead uncertainty for variable y_{jt} as the squared error of the h-period ahead forecast of y_{jt}.

$$U^y_{jt}(h) \equiv \sqrt{E[(y_{jt+h} - E[y_{jt+h}|I_t])^2|I]}$$

where, $E(.|I_t)$ is the expectation conditional on information at time t.

An increase in the squared forecasting error of y_{jt} indicates an increase in uncertainty at time of y_j at t. The Jurado et. al. methodology computes financial and macroeconomic indexes by aggregating uncertainty measures of individual economic series.

Ludvigson et. al. (2017) used a total of 132 economic series to estimate macroeconomic uncertainty. The series span the following categories: real output and income, employment and hours, real retail, manufacturing and trade sales, consumer spending, housing starts, inventories and inventory sales ratios, orders and unfilled orders, compensation and labor costs, capacity utilization measures, price indexes, bond and stock market indexes, and foreign exchange measures.

The financial uncertainty series is comprised of uncertainty measures for 147 financial series. These series include valuation ratios such as the dividend-price ratio and earnings-price ratio, growth rates of aggregate dividends and prices, default and term spreads, yields on corporate bonds of different ratings grades, yields on Treasuries and yield spreads, and a broad cross-section of industry equity returns. In addition, returns on 100 portfolios of equities sorted into 10 size and 10 book-market categories are included. The dataset also includes excess return on the market, small-minus-big and high-minus-low portfolio returns, a momentum factor, a measure of the bond risk premia, and small stock value spread.

Ludvigson et. al. (2017) provide measures of financial and macroeconomic uncertainty based on 1, 3, and 12 month forecast horizons. Our analysis focuses on the one month horizon series. The two measures of uncertainty are shown in Figure 7 7.

The macroeconomic uncertainty series contains three episodes of high uncertainty, the 1970's during the first OPEC oil shock, the early 1980's, and the great recession of 2008-2009. In contrast, the financial uncertainty series comtains more episodes of high uncertainty.

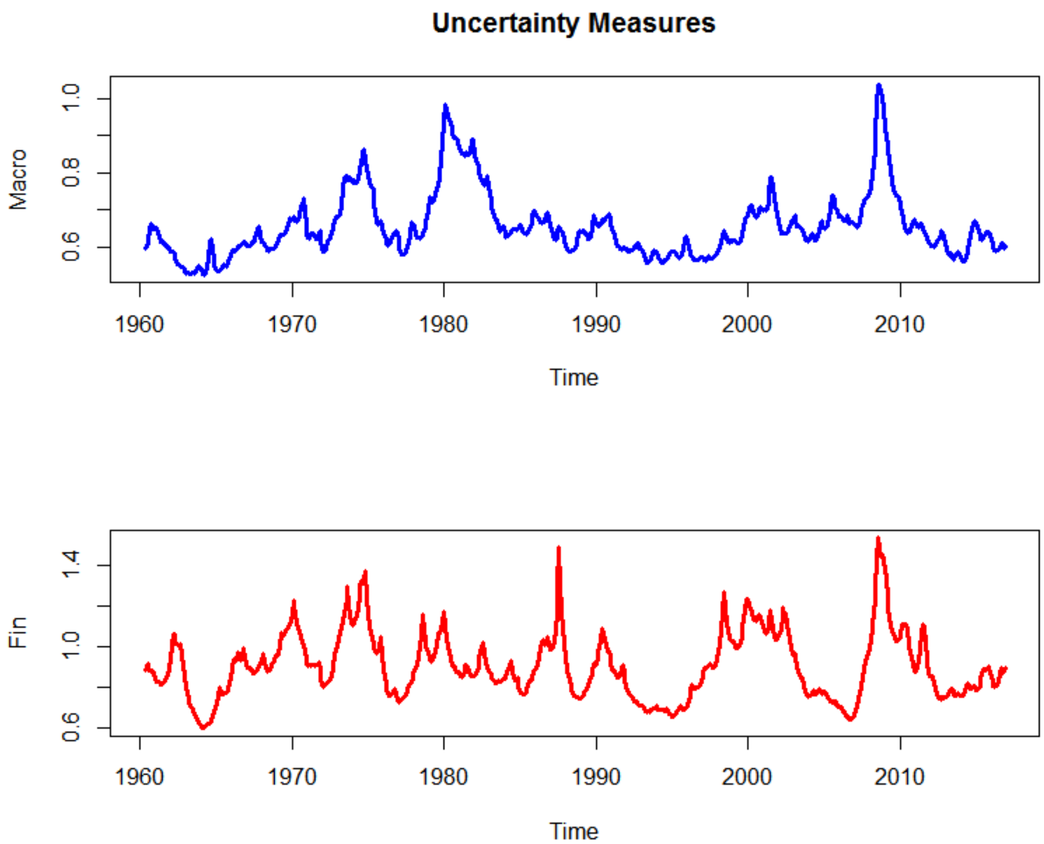


Figure 7: Macroeconomic Uncertainty (Ph1) (top) and Financial Uncertainty (Fh1) (bottom), horizon=1 month
Source: Ludvigson, Mai, Ng (2017)

Figures 8 and 9 8 and 9 contain the wavelet power spectra for the macroeconomic uncertainty and financial uncertainty series for h=1, denoted Ph1 and Fh1, respectively. The power of the macroeconomic series tends to be highest at low frequencies. The power of Financial uncertainty is also high at low frequencies, and also high for some bands at medium and low frequencies. The Great Moderation is apparent in both series. In addition, the frequency of significant power for Financial uncertainty is lower after 1990 and resembles the Macroeconomic uncertainty wavelet power spectrum.

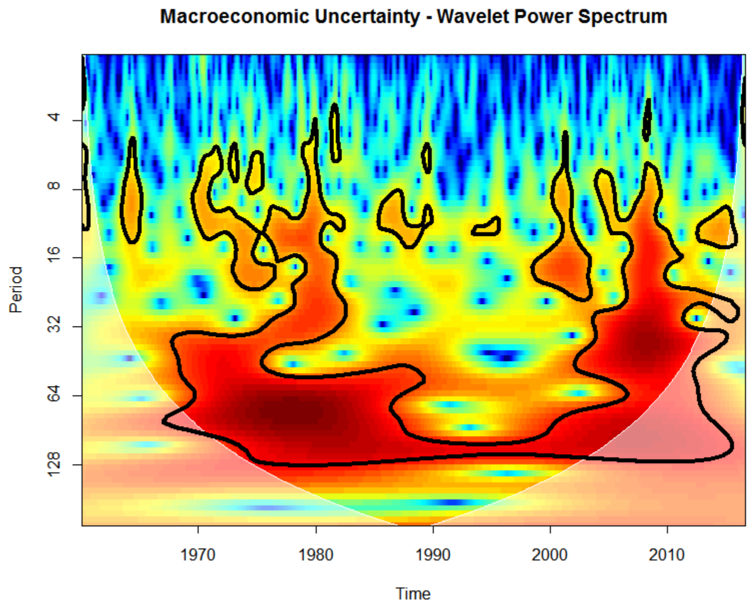


Figure 8: Wavelet Power Spectrum - Macroeconomic Uncertainty (Ph1)

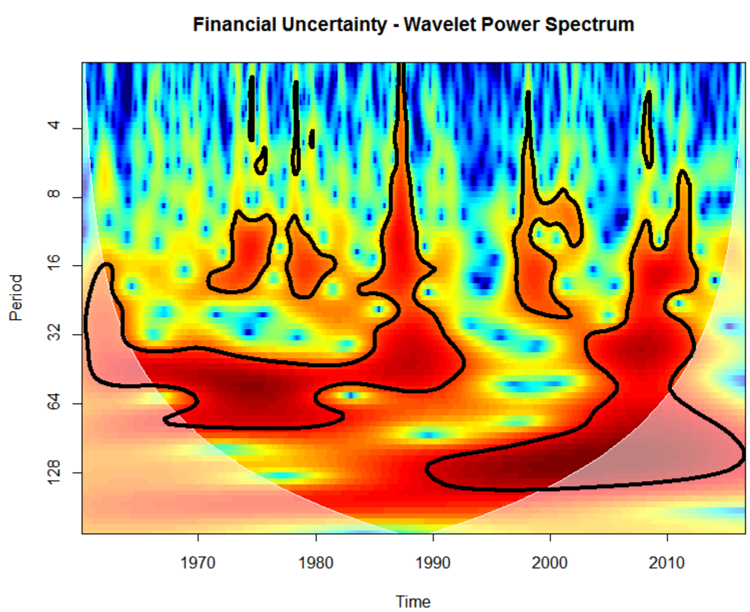


Figure 9: Wavelet Power Spectrum - Financial Uncertainty (Fh1)

5 Analysis & Results

Our analysis investigates the wavelet coherence of the two LMN measures of uncertainty with sector returns. We also examine the coherence of market return with the two LMN measures of uncertainty. Figure 10 contains the coherence of market returns with the macroeconomic uncertainty measure. Note that the frequency is inverted compared with the power spectrum charts. In addition, the coherency charts contain phase arrows which are explained in Table 3.

Left arrow: anti-phase
Right arrow: in-phase
Down arrow: X leading Y by 90deg
Up arrow: Y leading X by 90deg

Table 3: Phase Arrow Definitions

[8]

Figure 10 10 shows the coherence between macroeconomic uncertainty and Market Returns. There is high coherence at both high and low frequencies. There is strong coherency at the 2 to 4 year period during the 1960's and early 1970's, and also during the Great Recession. There is also a very strong coherence at the highest periods, though much of this is outside the cone of inference. The two series are never in phase.

Fig 11 11 shows the coherence between macroeconomic uncertainty and the absolute value of returns for the market. In effect, a comparison of two measures of uncertainty. The coherency of these two series is similar to those in Figure 10 though there tends to be greater coherence at the s to 8 year periods for the absolute value of returns and macroeconomic uncertainty. Also the there a greater tendency for the series in Figure 11 to be in phase.

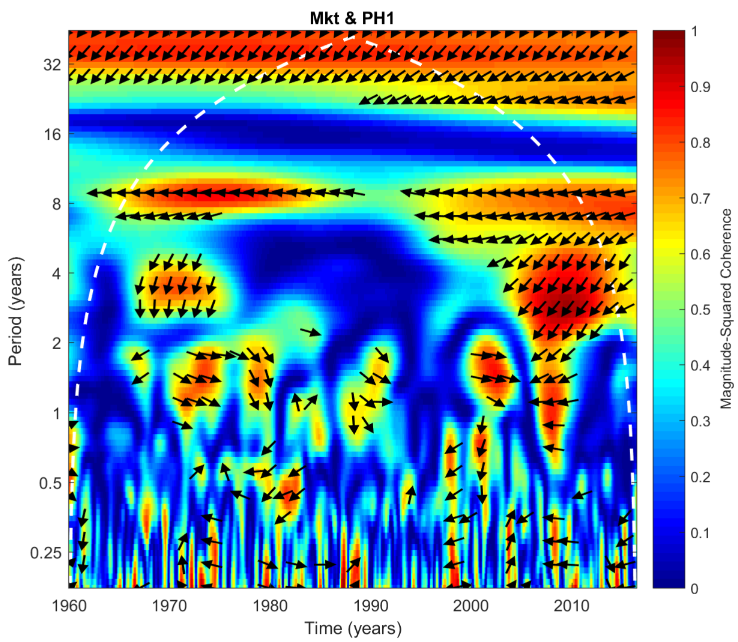


Figure 10: Wavelet Coherence - Macroeconomic Uncertainty and U.S. Equity Market Returns

[8]Note: interpreting the phase as a lead(/lag) should always be done with care. A lead of 90 degrees can also be interpreted as a lag of 270 degrees or a lag of 90 degrees relative to the anti-phase (opposite sign).

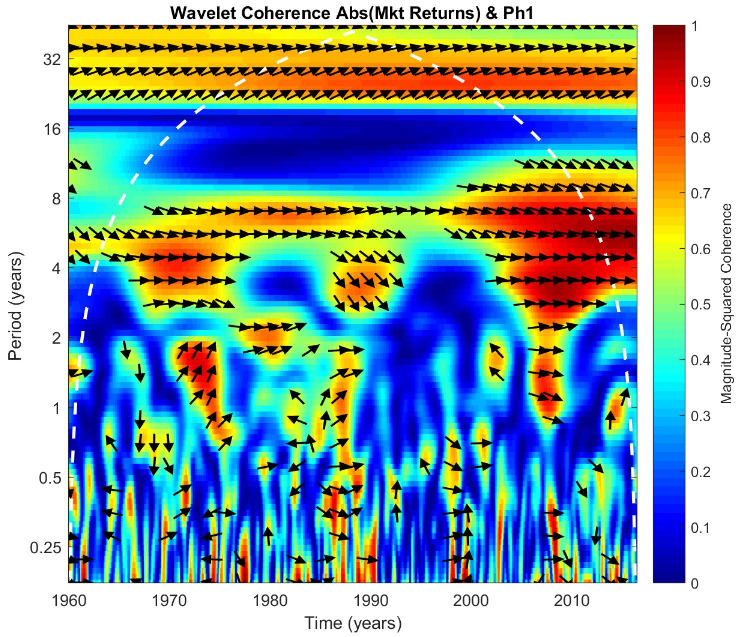


Figure 11: Wavelet Coherence - Macroeconomic Uncertainty and the Absolute Value of U.S. Equity Market Returns

Figure 1212 shows the coherence of the market with the financial uncertainty. The coherence is generally higher than the coherence of the market with the macroeconomic uncertainty. Both series have a high level of coherence at the lowest frequency (16-32 years), but the coherence is strong for financial uncertainty. The two series are in anti-phase at the lowest frequency. At the higher frequencies there appears to be a lead/lag relationship, the charts are not able to say which series is the lead.

Figure 13 13 shows that the coherence between the absolute value of market returns and financial uncertainty is very high, especially for period greater then a year. Also, the two series are in phase at all scales for the entire time span of the sample.

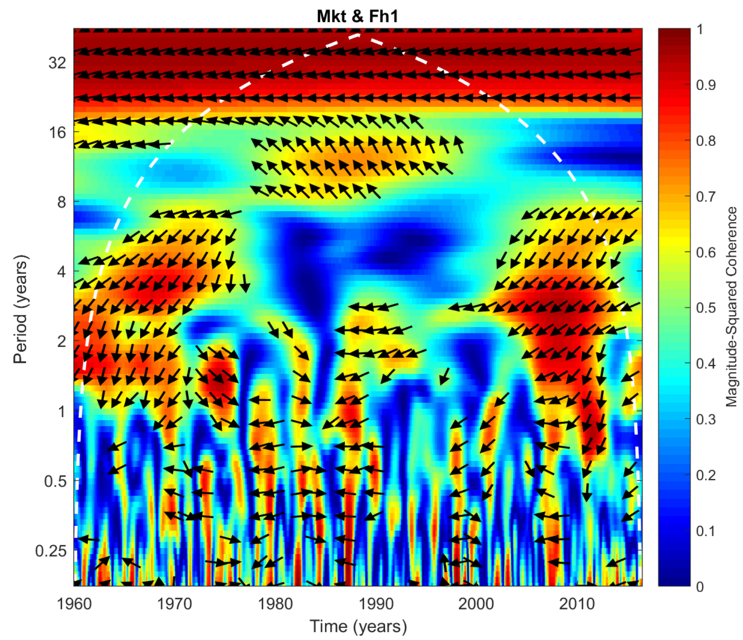


Figure 12: Wavelet Coherence - Financial Uncertainty and U.S. Equity Market Returns

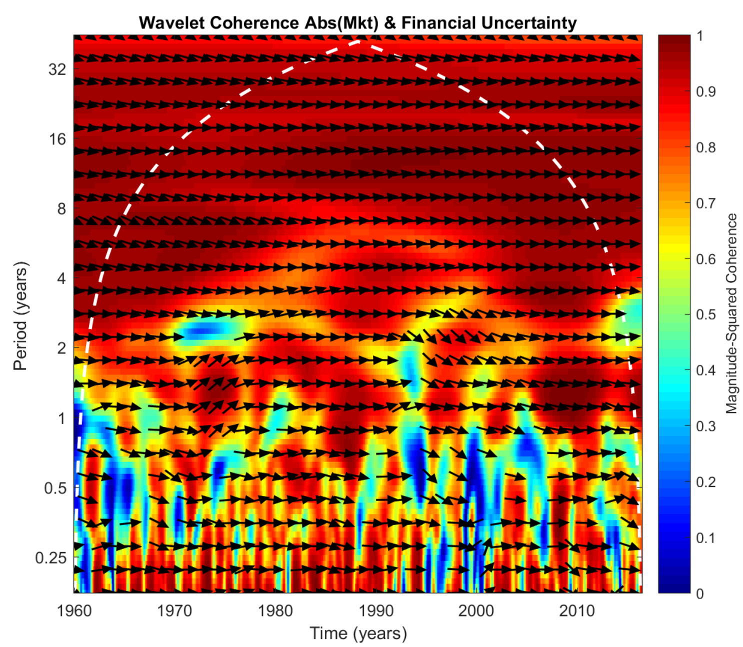


Figure 13: Wavelet Coherence - Financial Uncertainty and the Absolute Value of U.S. Equity Market Returns

5.1 Uncertainty and Sector Returns

In this section we examine the coherence between sector returns and the two measures of economic uncertainty. A side by side comparison of the coherence of sector returns with uncertainty allows us to examine the difference in the effects on returns. It should be noted that the macroeconomic uncertainty index contains a set of financial variables, so that differences cannot be attributed solely to real economic effects.

In the Figures below, the left hand side figure is the wavelet coherence of sector returns with macroeconomic uncertainty and the right hand side is the coherence of sector returns with Financial Uncertainty. (Standard spectral coherence is presented in Appendix A.)

5.1.1 Market Turning Events or Long Lived Shocks

An examination of the plots reveals several distinctions and commonalities between the two measures of uncertainty and how they cohere with the returns of the individual sectors. First, coherence during the the Great Recession is high for both measures of uncertainty in most of the sectors. The coherence is highest for periods from 1 to 8 years. Also, the sector returns and uncertainty are always in a lead-lag relationship, though it is impossible to determine from the charts which series leads. The Healthcare, and Business Equipment sectors have the lowest coherence with uncertainty during the Great Recession.

The second period when coherence is highest across scales for both measures of uncertainty is the late 1960's through the 1970's. This is a period of high inflation, an OPEC oil price shock, and political uncertainty relating to the Vietnam War and Watergate. The sectors with the lowest coherence during this time period are Business Equipment, Chemicals, and Money. Also, during this time period the Energy, Utility, and Manufacturing sectors see the beginning of a high coherence with macroeconomic uncertainty at a period of 8 to 12 years that lasts through 2016.

Coherence with macroeconomic uncertainty is also high in the early 1980's. This is the period right after the second OPEC shock, when the Federal Reserve dramatically raised interest rates to stop inflation (see Figure 7). However, a consistent pattern of high levels of coherence for either measure of uncertainty with sector returns is less apparent during this period.

To some degree the coherence charts also show the so called period of 'Great Moderation' in that there tends to be a period of little or no coherence at periods of 1 to 4 years from the late 1980's until the Great Recession, though the paatern is not consistent across sectors.

Finally, With the exception of the energy sector and the sector called 'Other', both measures of uncertainty have high coherence with sector returns at the lowest frequencies.

5.1.2 Market Shrugs or Short Lived Shocks

The effects of the stock market crash in October 1987 show up in the financial uncertainty charts as a high level of coherence for periods of 0.25 to 2 years, and lasting several months. It is apparent in all sector except Utilities. It is less pronounced in the macroeconomic coherence charts.

The tech bubble burst is barely discernable in the charts. There is a small level of intensity in the macroeconomic uncertainty chart for BusEq at a period of 1 to 2 years, and the two series are in phase. Other sectors also show a similar pattern of intensity at this time most likely due to the 2001 recession that follows the bubble burst. The coherence intensity for Telcm at this time begins at the 2 year period and continues (and expands) through to the present.

Interestingly, for the Healthcare sector the Great Recession was essentially a market shrug. The level of coherence was high for about a year , and was primarily in the 2 to 4 year period. To a lesser extent the same was true of the Energy industry.

5.2 Sector Returns and Scale

In this section we decompose the monthly sector returns into 8 scales using a Discrete Wavelet Transform(DWT). Then, we have applied mean-variance efficient portfolio optimization to analyze the periodical performance of mean-var efficient portfolio allocations that minimize the covariance matrix of the 12 monthly return series as well as the respective scales. We applied a rolling window approach, rebalanced the portfolio every month, and tracked the out-of-sample returns.

Statistics that describe the out-of-sample performance of each strategy are presented in the Table **??**. The column labeled ?monthly data? describes the out-of-sample performance for the portfolio that takes the covariance matrix of monthly returns of the 12 segments into account. Column ?Scale 1? describes the performance of the portfolio that exclusively takes the covariance matrix of short-run fluctations (1-2 mos.) into account. Similarly for, Scale 2 (2-4 mos.) to scale 8 (124-256 mos.).

Both the average out-of-sample return and the variance increase with scale. Interestingly, the Sharpe Ratio increases as well, therefore the results indicate that, scale 6 might comprise the adequate information for periodical portfolio management.

	Total	**Scale 1**	**Scale 2**	**Scale 3**	**Scale 4**	**Scale 5**	**Scale 6**	**Scale 7**	**Scale 8**
mean	0.57%	0.59%	0.60%	0.56%	0.62%	0.67%	0.76%	0.62%	0.66%
min	-14.64%	-16.97%	-13.87%	-17.45%	-18.09%	-14.75%	-15.18%	-19.55%	-18.38%
max	15.22%	16.41%	20.38%	21.17%	15.47%	12.46%	12.17%	12.55%	11.13%
variance	0.13%	0.14%	0.14%	0.14%	0.15%	0.15%	0.16%	0.14%	0.16%
sharpe	0.1565	0.1587	0.1629	0.1479	0.1576	0.1724	0.1886	0.1628	0.1646

Table 4: Mean-Variance Portfolio Performance: Full Sample

5.2.1 Partial Wavelet Coherence

Appendix B contains partial coherence charts for each sector. Each chart shows the coherence of financial uncertainty with sector returns after partialing out the effect of macroeconomic uncertainty. Note that the macroeconomic uncertainty measure contains a set of financial measures, so these charts do not completely separate the non-financial from the financial effects. The coherence pattern after removing macroeconomic uncertainty is relatively similar across sectors. At the high frequencies (less than 1 year) there are periodic episodes of short lived high intensity coherence. At the low frequency (64 months) there tend to be two major episodes of high coherence, the 1970's and the Great Recession.

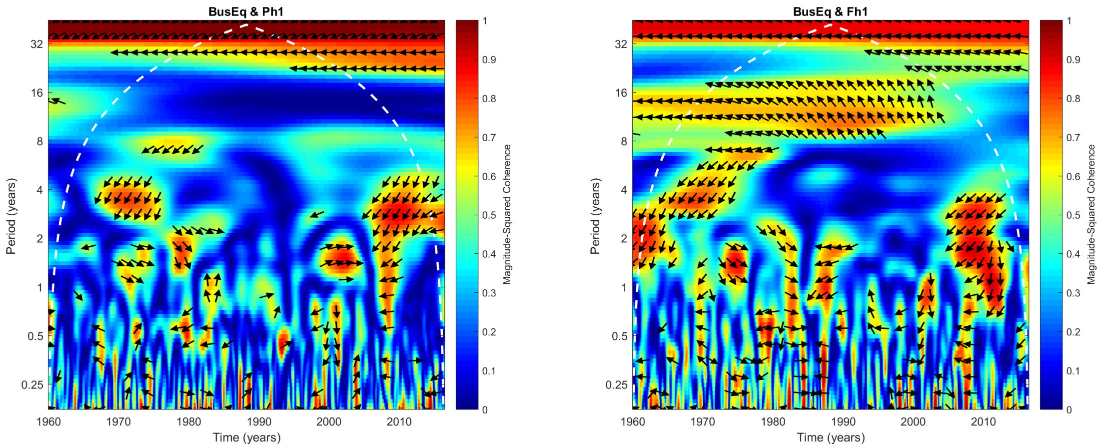


Figure 14: Wavelet Coherence of Business Equipment Returns and Uncertainty; Macroeconomic Uncertainty (Ph1, left); Financial Uncertainty(Fh1)

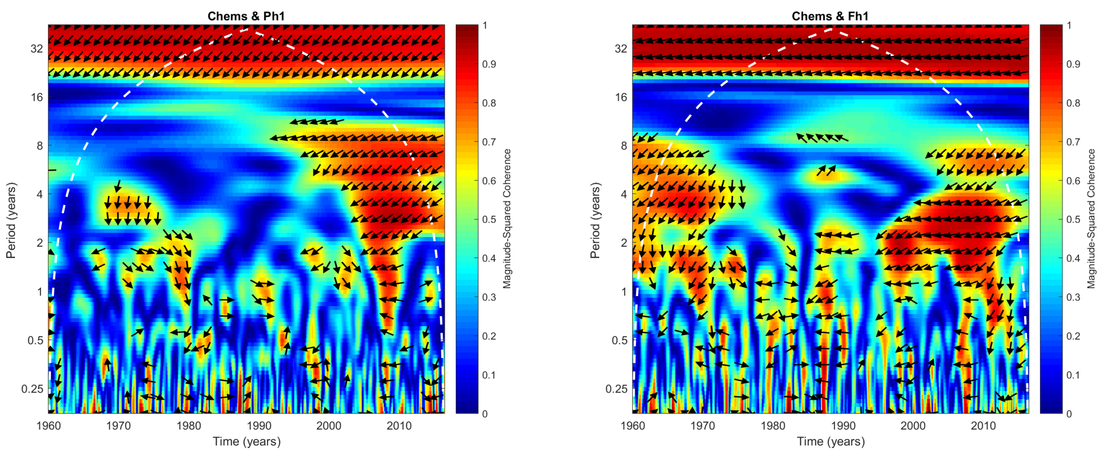


Figure 15: Wavelet Coherence of Chemicals Returns and Uncertainty; Macroeconomic Uncertainty (Ph1, left); Financial Uncertainty(Fh1)

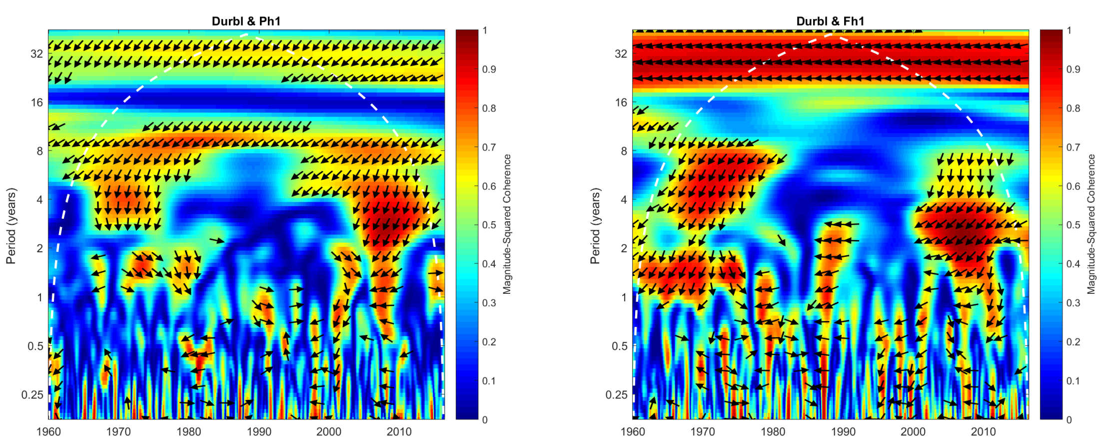


Figure 16: Wavelet Coherence of Durables Returns and Uncertainty; Macroeconomic Uncertainty (Ph1, left); Financial Uncertainty(Fh1)

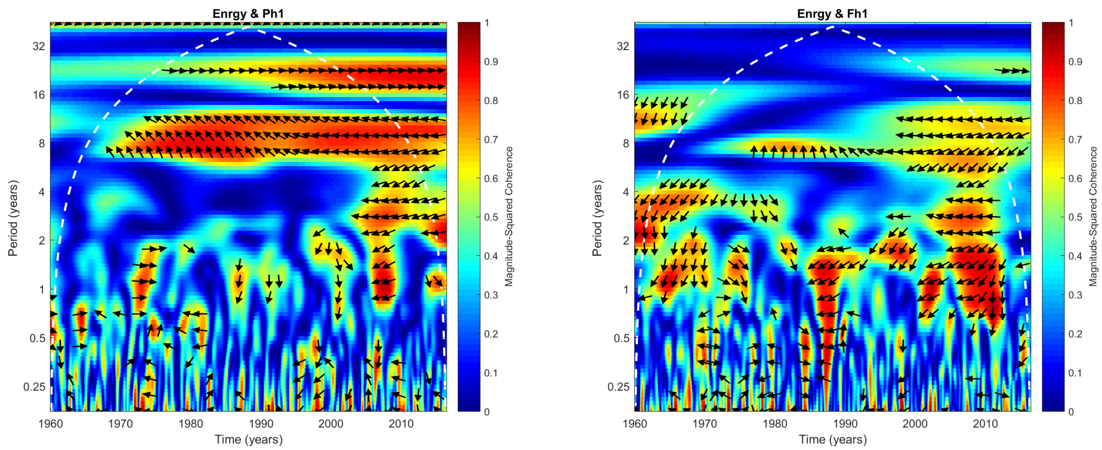


Figure 17: Wavelet Coherence of Energy Returns and Uncertainty; Macroeconomic Uncertainty (Ph1, left); Financial Uncertainty(Fh1)

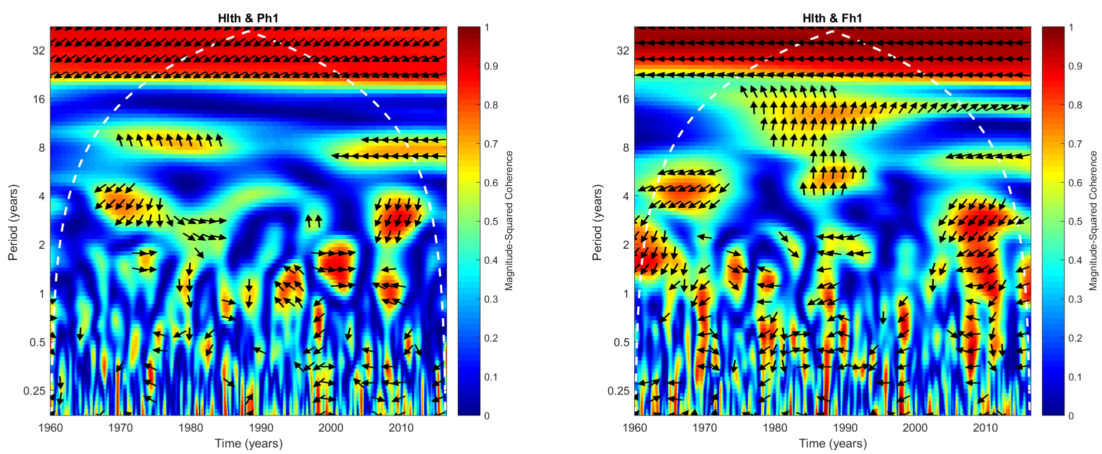


Figure 18: Wavelet Coherence of Healthcare Returns and Uncertainty; Macroeconomic Uncertainty (Ph1, left); Financial Uncertainty(Fh1)

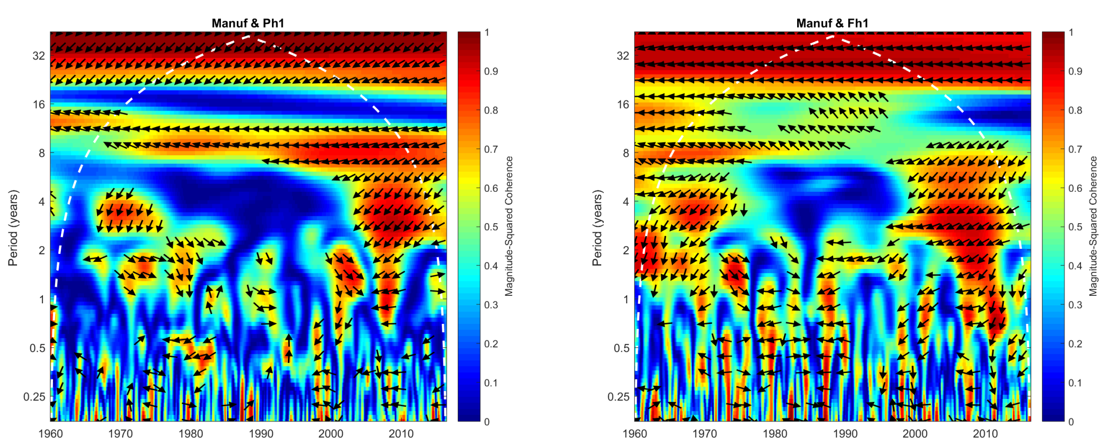
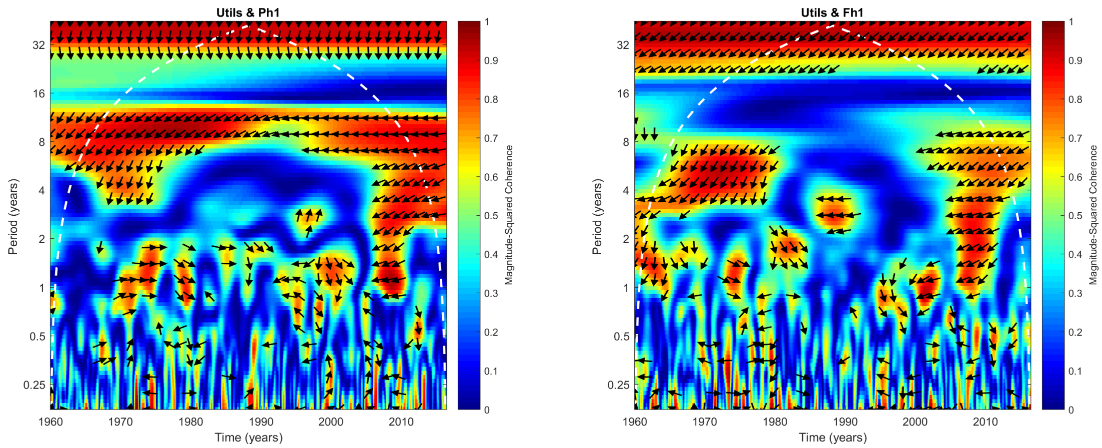


Figure 19: Wavelet Coherence of Manufacturing Returns and Uncertainty; Macroeconomic Uncertainty (Ph1, left); Financial Uncertainty(Fh1)



(a) (b)

Figure 23: Wavelet Coherence of Utility Returns and Uncertainty; Macroeconomic Uncertainty (Ph1, left); Financial Uncertainty(Fh1)

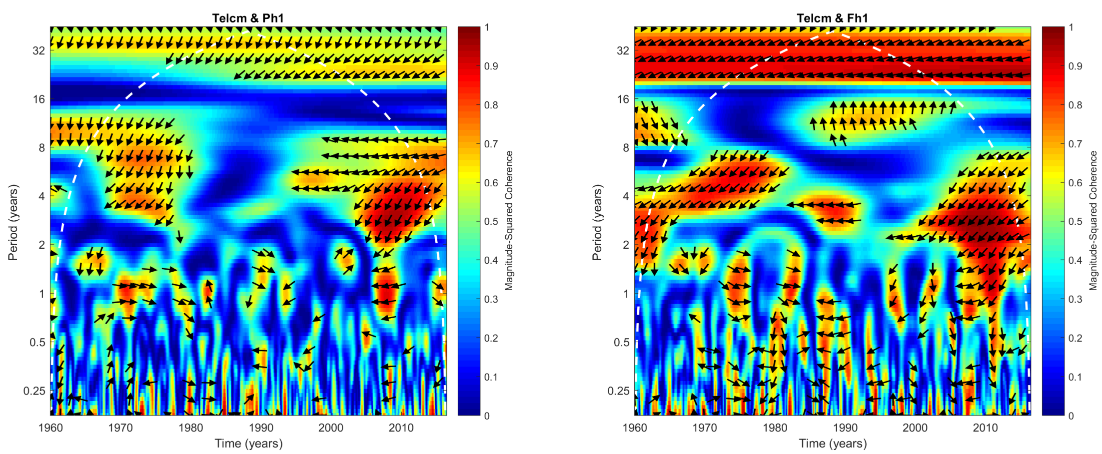


Figure 24: Wavelet Coherence of Telecommunication Returns and Uncertainty; Macroeconomic Uncertainty (Ph1, left); Financial Uncertainty(Fh1)

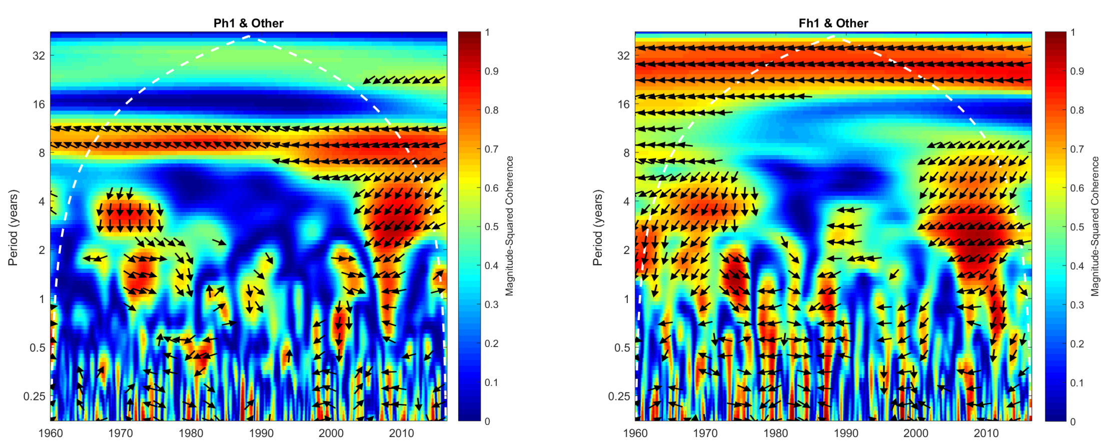
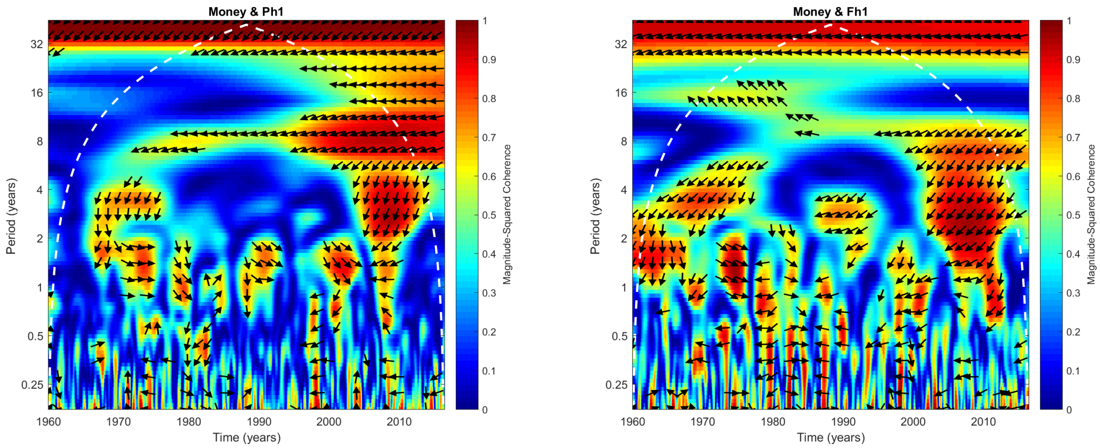


Figure 25: Wavelet Coherence of Other Returns and Uncertainty; Macroeconomic Uncertainty (Ph1, left); Financial Uncertainty(Fh1)



(a) (b)

Figure 20: Wavelet Coherence of Money Returns and Uncertainty; Macroeconomic Uncertainty (Ph1, left); Financial Uncertainty(Fh1)

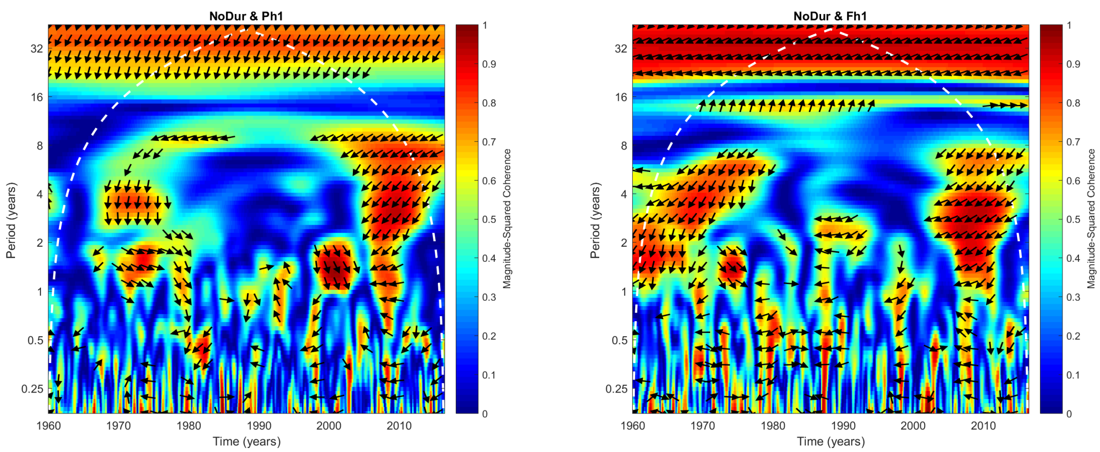


Figure 21: Wavelet Coherence of Non-Durables Returns and Uncertainty; Macroeconomic Uncertainty (Ph1, left); Financial Uncertainty(Fh1)

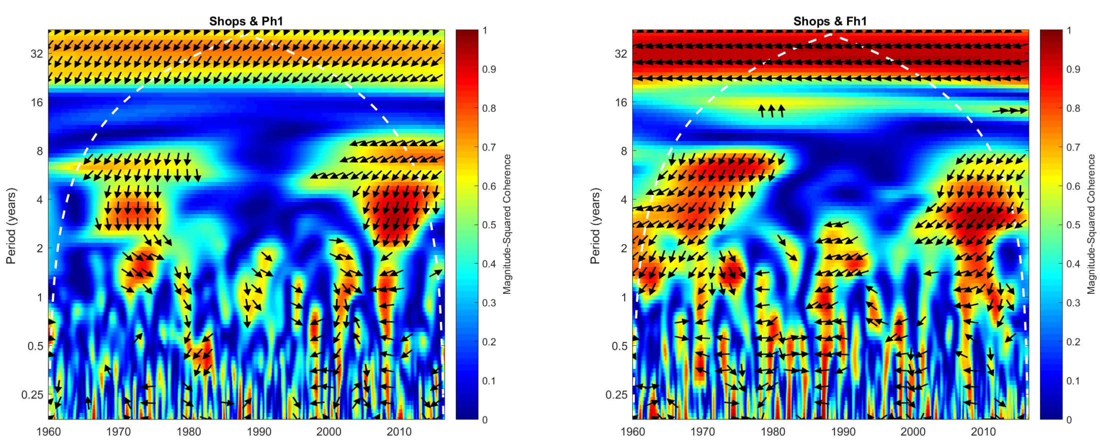


Figure 22: Wavelet Coherence of Shops Returns and Uncertainty; Macroeconomic Uncertainty (Ph1, left); Financial Uncertainty(Fh1)

6 Conclusion

In our paper, we investigate the interdependence between LMN's two measures of uncertainty and sector returns. The two uncertainty measures were estimated by Ludvigson et.al. (2017), and consist of a comprehensive measure of macroeconomic uncertainty and financial uncertainty. Using wavelet analysis we examine changes in coherence between each uncertainty measure and the returns of each sector. We find that the importance of frequency components does not remain stable over time but differs depending on whether the uncertainty reflects a short-lived shock or a long-lived shock. Our analysis supports the conclusion of Jurado et al (2015) that for this sample period (1960-2016) there are essentially three majors periods of uncertainty: the 1970's, the early 1980's and the Great Recession. We find that uncertainty during these time periods has high coherence with sector returns at low frequencies (2 to 8 years) for extended lengths of time. In addition, we find that certain events typically identified with uncertainty, such as the 1987 stock market crash and the 2000 tech bubble burst are revealed as short lived burst of intense coherence at relatively high powers. Our main conclusion is scale matters for measures of uncertainty in that major episodes of uncertainty do not affect all sectors equally. Our finding that there are episodes of uncertainty when there is increased comovements across frequency and over time for specific sectors should be of concern to investors and policymakers, and helps paint a more complete picture of how uncertainty affects the economy through its transmission across sectors.

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8 Appendix A

This section presents the squared coherence of returns for each sector with each of the two measures of uncertainty, Macroeconomic (Ph1) and Financial (Fh1). The blue dotted lines are the 05% confidential interval.

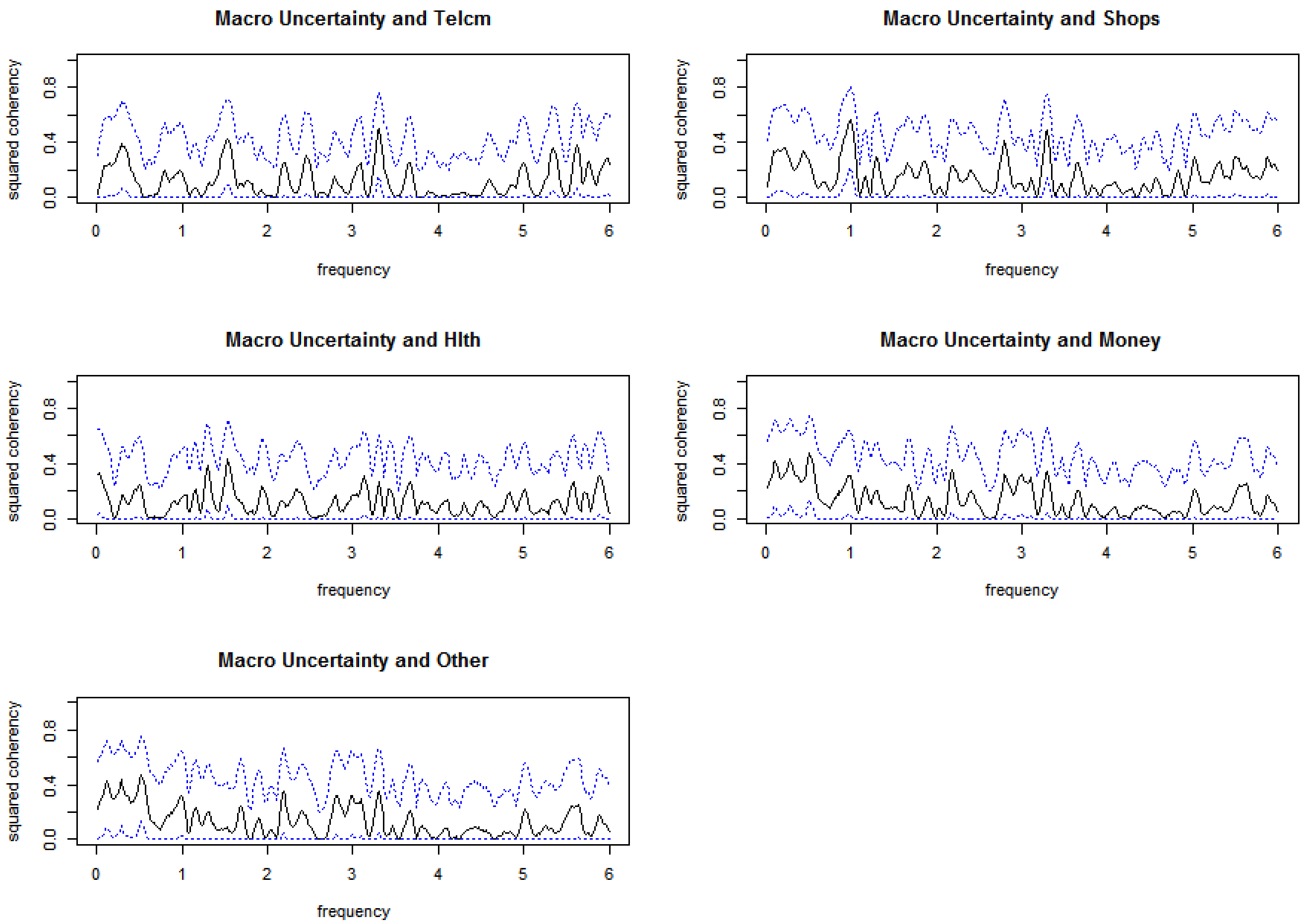

Figure 26: Squared Coherence - Macroeconomic Uncertainty and Sector Returns

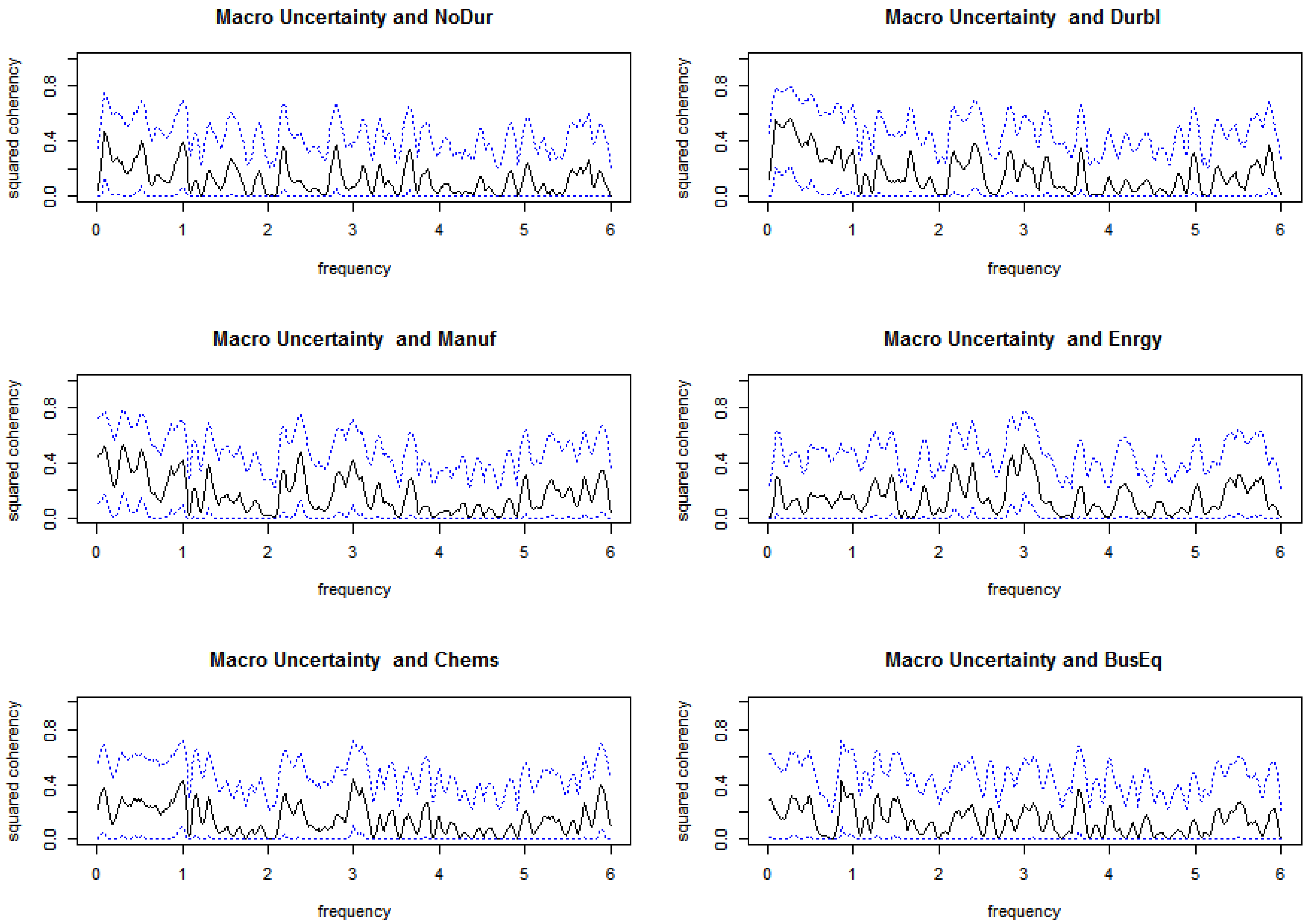

Figure 27: Squared Coherence - Macroeconomic Uncertainty and Sector Returns

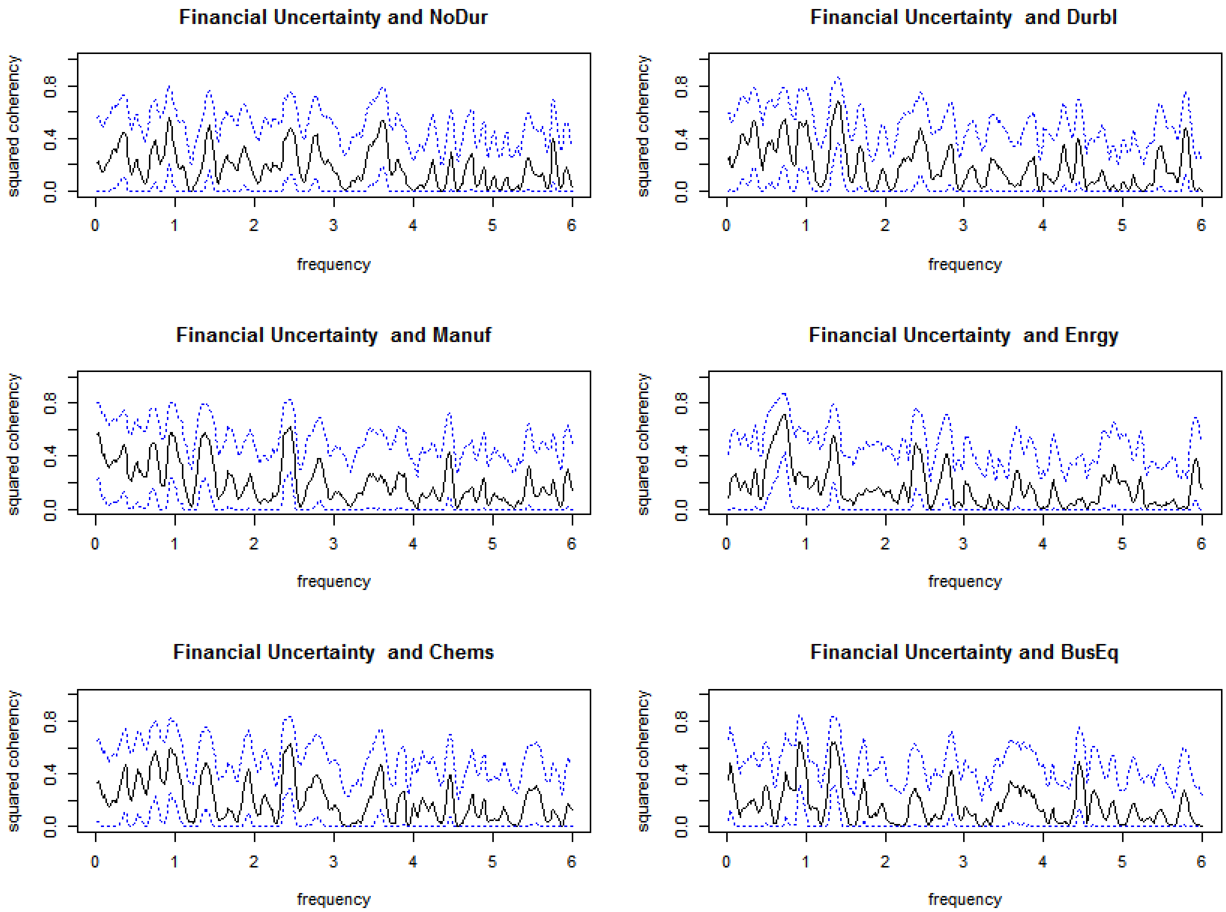

Figure 28: Squared Coherence - Financial Uncertainty and Sector Returns

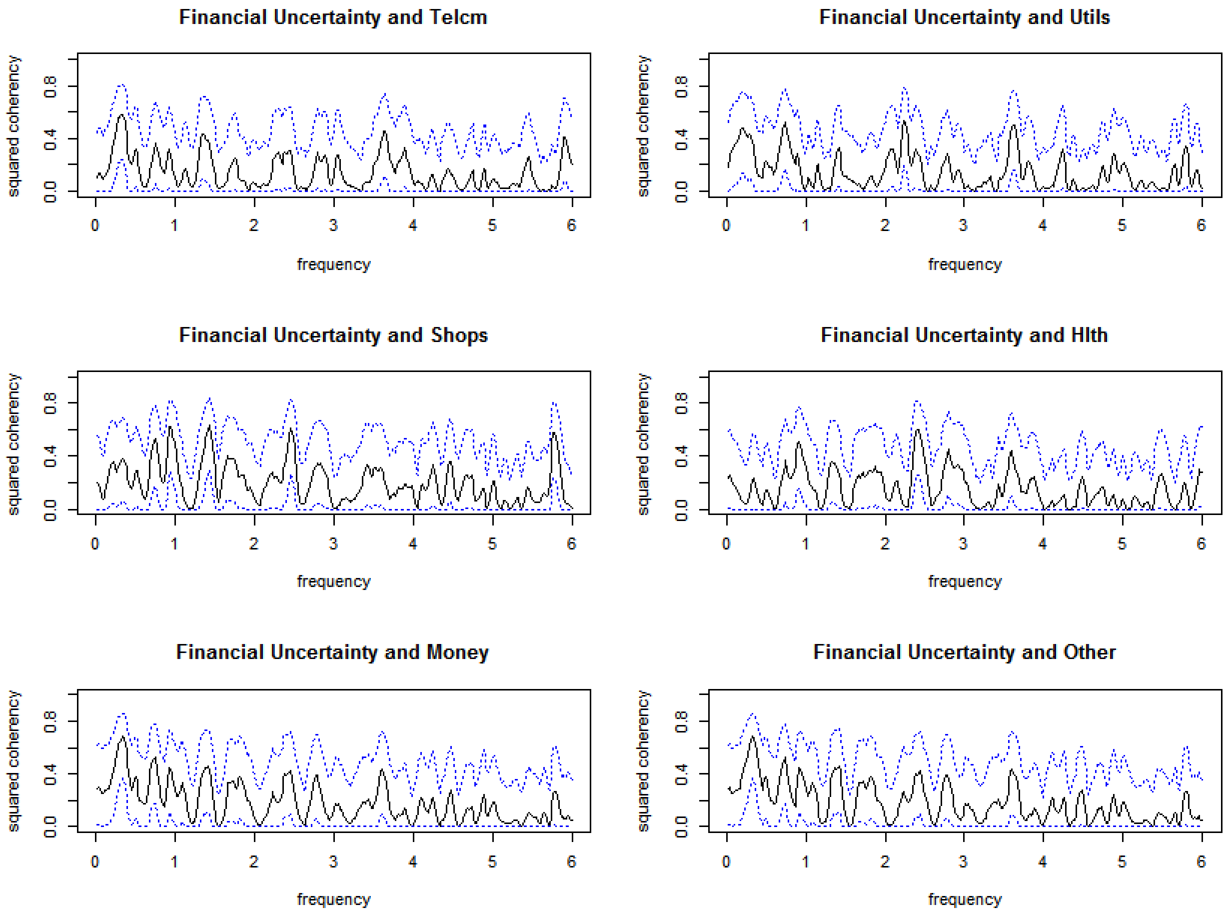

Figure 29: Squared Coherence - Financial Uncertainty and Sector Returns

9 Appendix B

This section presents the partial wavelet coherence of financial uncertainty with sector returns after partialing out macroeconomic uncertainty. Note that the scale in inverted, with the highest periods at the bottom. Also, the periods are measured in months.

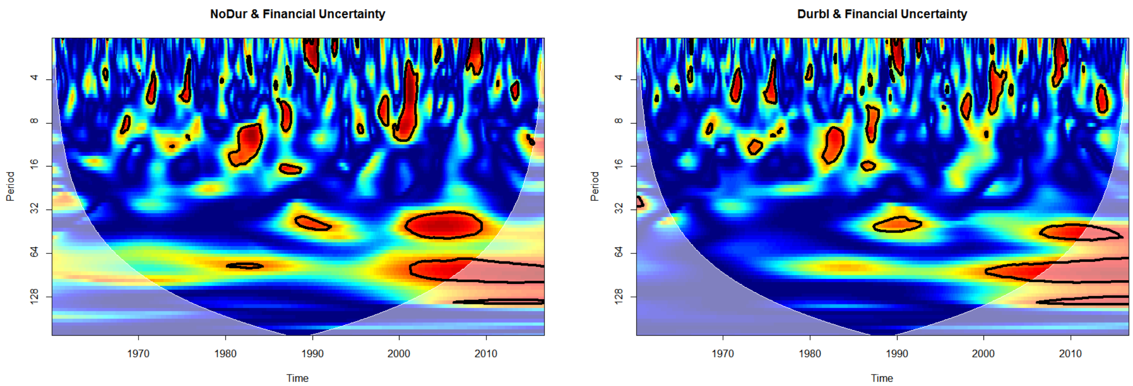

Figure 30: Partial Wavelet Coherence of Financial Uncertainty and Sector Returns after removing Macroeconomic Uncertainty (NoDur, left and Durbl, right);

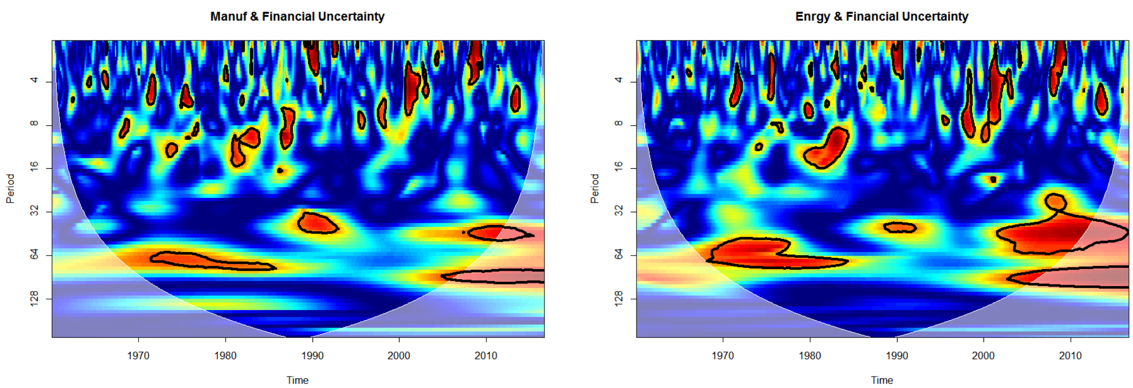

Figure 31: Partial Wavelet Coherence of Financial Uncertainty and Sector Returns after removing Macroeconomic Uncertainty (Manuf, left and Enrgy, right);

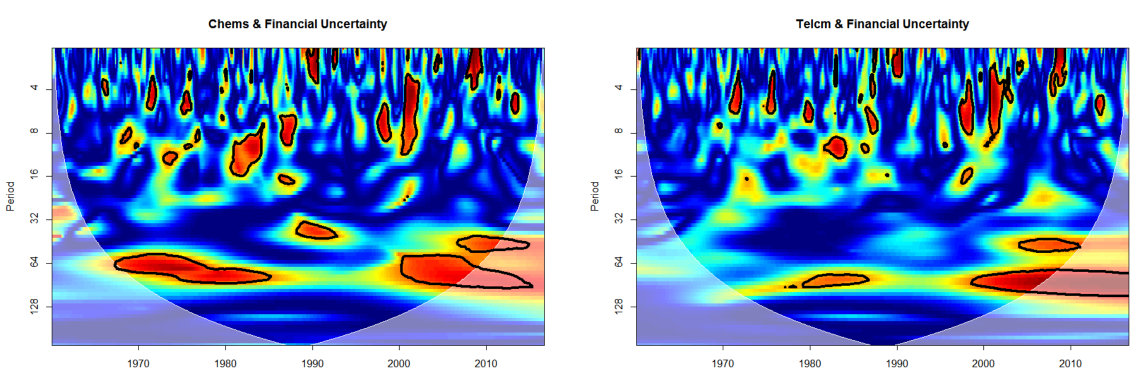

Figure 32: Partial Wavelet Coherence of Financial Uncertainty and Sector Returns after removing Macroeconomic Uncertainty (Chems, left and Telcm, right);

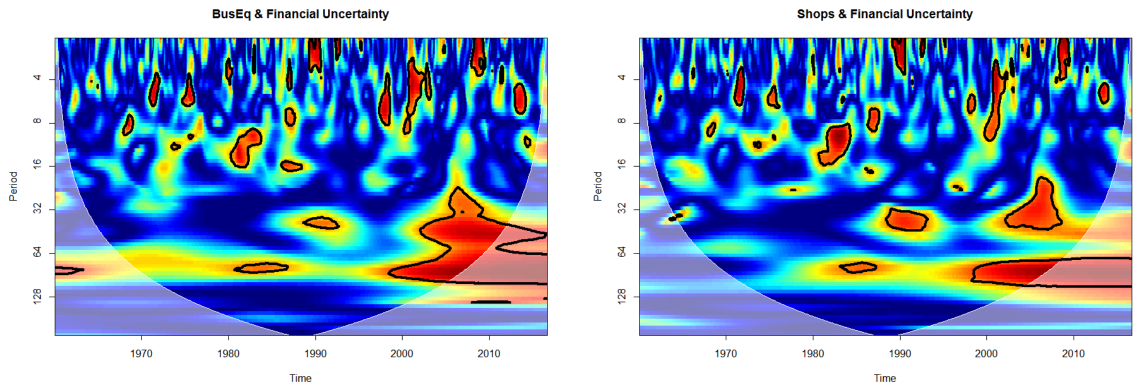

Figure 33: Partial Wavelet Coherence of Financial Uncertainty and Sector Returns after removing Macroeconomic Uncertainty (BusEq, left and Shops, right);

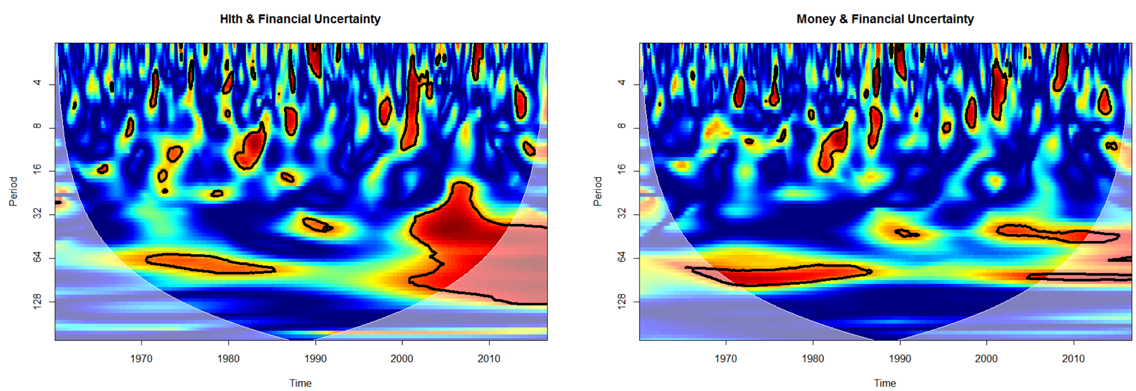

Figure 34: Partial Wavelet Coherence of Financial Uncertainty and sector Returns after removing Macroeconomic Uncertainty (Hlth, left and Money, right);

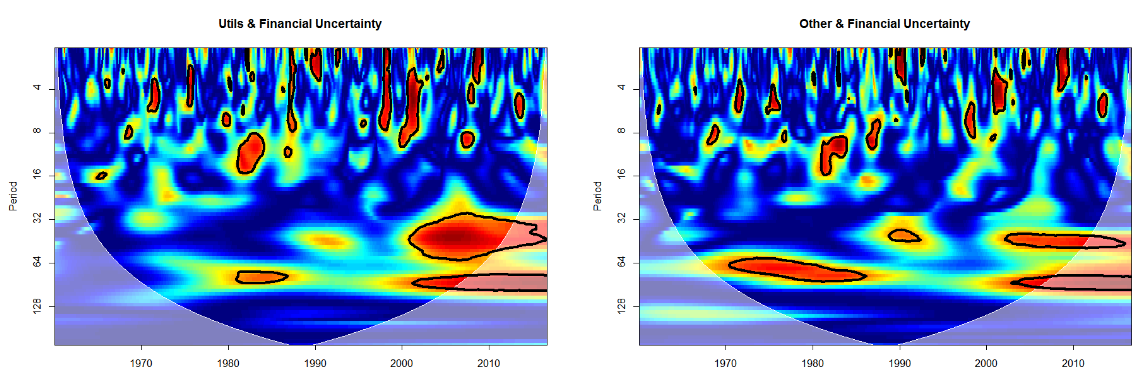

Figure 35: Partial Wavelet Coherence of Financial Uncertainty and sector Returns after removing Macroeconomic Uncertainty (Utils, left and Other, right);