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Uncertainty and the Oracle of Market Returns: Evidence from Wavelet Coherence Analysis

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Abstract

Wavelet methodology is employed to investigate the statistical relationship between three well-accepted measures of uncertainty and both market and sector returns. Our primary goal is to determine whether uncertainty is sector specific. Although there are periods when the market works effectively as an oracle capturing uncertainty, we also find sector specific uncertainty. The wavelet equivalent of correlation, coherence, is used to determine the presence of sector specific uncertainty. We find that allowing localized information in the time frequency domain is critical for separating out sector specific uncertainty from market uncertainty.

Keywords: finance, sectors, wavelets, uncertainty, coherence

1. Introduction

Uncertainty shocks call the the market's knowledge-gathering role into question. The equity market as an oracle works well when it provides rapid price discovery that reflects the underlying fundamentals of an economy. But when facing uncertainty shocks the equity market's function as a consensus mechanism that reveals economic reality appears at first glance, poorly suited for the environment it faces. An oracle needs a reliable channel for obtaining information. In the face of uncertainty, the equity market turns into a network of pipes where funds flows in ways that leave many skilled observers of market moves caught off guard. The shock filters through to the inter-temporal trade-offs of investors and makes forecasting more of a bet on imagined scenarios than the result of astute modeling that is carefully tested with historic data.

The relevance of wavelet methodology for examining whether the uncertainty measures are correlated at different scales and frequencies with market and sector returns may be more easily imagined with a metaphor.¹ The uncertainty shock operates as a push from behind that a person strolling down the street experiences. The push may be hard and throw the person completely off his path. He may end up face down and in a panic imagining the worse outcome. The push may also be soft from which the person experiences a quick feeling of panic but quickly recovers and

¹ The use of imagery as a guide to economic understanding has a rich history. See for example, the use of a bicycle imagery by Samuelson to explain how a real economic system is capable of resolving indeterminacy even when the path between present and future is far from smooth [1].

continues his walk. It is not that the person is caught completely off guard. The push comes after a signal such as the sound of feet running from behind or the quiet sound of someone walking at a slightly faster rate to catch-up. The relationship between the signal and push is based on short-lived features of the environment. However, very different outcomes are possible. Wavelet methodology is particularly well-suited for capturing these different outcomes because it is designed to capture short-lived features of the environment. Wavelet methodology provides a snapshot of the outcomes in the form of market and sector returns that result from various shocks.

A defining feature of wavelet methodology that makes it particularly well-suited for capturing the economic effects of uncertainty shocks is that at a given point in time the same signal can be analyzed by different wavelets. Most importantly, it is capable of capturing an uncertainty signal that only lasts for a finite period of time. It can also handle non-stationarity which often characterizes uncertainty shocks. Wavelet coherence plots help us discover whether the measures of the shock provide new information that is not reflected in market and sector returns at various scales.

In this chapter, we investigate the statistical relationship between three well-accepted measures of uncertainty and both market and sector returns. The three measures are Macroeconomic and Financial Uncertainty of Jurado, Ludvigson, Ng (JLN) [2] and Economic Policy Uncertainty by Baker, Bloom and Davis (BBD) [3]. We explore the extent to which the impact of uncertainty is sector specific. Employing the wavelet equivalent of correlation, we observe that in the presence of significant coherence, market returns are anti-phase with all three measures of uncertainty. Between market volatility and financial uncertainty, we also observe very high in-phase coherence at low frequencies for prolonged periods of time. However, this is not the case when considering the volatility of Economic Policy Uncertainty or Macro Uncertainty. For those measures, while there are periods of high coherence, these periods are not as extensive as found with financial uncertainty. One conclusion is that the prolongness of the coherence differs depending on the measure of uncertainty.

Looking at the coherence plots with sector returns and the three measures of uncertainty, we find prolonged high coherence at low frequencies and intermittent coherence at high frequencies. For each coherence plot, we also consider the conditional coherence, after partialing out the effects of the market. By and large, most of the coherence disappears pointing to the question of whether there is any sector-specific uncertainty. Our focus is on six sectors, Telecom, Bus, Equip, Shops, Manufacturing, Energy and Money where each had at least one period of high conditional coherence. For each sector, based on our observation of the conditional coherence plot, we sampled the scales using a Discrete Wavelet Transform (DWT). A DWT is used to run a regression of sector returns against both an uncertainty measure and market returns. A rolling regression is used from which we find the time-pattern of the uncertainty coefficients. It was often the case that the uncertainty had a significant negative impact on sector returns. These snapshots that the wavelet coefficients provide point to the general result that there are significant differences in how uncertainty filters through the sectors that are different from what the market reaction alone tells us.

The remainder of our chapter proceeds 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 [4] 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 [2] develop a measure of uncertainty based on the h-period ahead forecasting error, where $h = 1, 3, \text{ and } 12$ 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 [4], 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 [5] 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 [6] 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.

3. Wavelet analysis

Prior to the work of Ramsey², the use of wavelets in economic and financial analysis was largely non-existent. Today, however, wavelet analysis is a well known, and widely applied tool for any economist who studies time series data.³ The reason for the rapid increase in wavelet based applications is that the wavelet transform yields a localized decomposition in both time and frequency domain. This stands in sharp contrast to the traditional Fourier transform often used by economists that is global in the sense that there is no time component after the

² See for instance, [7].

³ See [8, 9] for an introduction to wavelet methods in economics and finance.

Fourier transform is applied.⁴ Since the wavelet transform yields a decomposition that is in localized frequency and time, it has proven to be particularly useful. A clear application where wavelet methodology benefits the analysis is when applied to investment decisions over different time horizons.⁵

The wavelet transform consists of a father wavelet and a set of mother wavelets. Given a function Φ , the father wavelet for the discrete transform is defined as:

$$\Phi_{J,k} 2^{-\frac{j}{2}} \Phi \frac{t - 2^j * k}{2^j} \quad (1)$$

$$\int \Phi(t) dt = 1 \quad (2)$$

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

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

$$\int \Psi(t) dt = 0 \quad (4)$$

Where J is the number of scales or levels, 2^j is a scale factor, and k is the time domain index. Note that the father and mother wavelets are each indexed by scale and time. The scale parameter is inversely proportional to frequency.⁶ The father wavelet can also be represented as a low pass filter, and the mother wavelets as high pass filters.⁷

Wavelet functions transform a time series, $f(t)$, into a series of wavelet coefficients,

$$S_{J,k} = \int f(t) \Phi_{J,k} \quad (5)$$

and,

$$d_{j,k} = \int f(t) \Psi_{j,k} \quad j = 1, \dots, J \quad (6)$$

Where $S_{J,k}$ are the coefficients for the father wavelet at the maximal scale, 2^J ; These coefficients are often referred to as the smooth coefficients. The $d_{j,k}$, or detailed coefficients, are the coefficients of the mother wavelets at the scales from 1 to 2^J .

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 $[1/128, 1/64]$.

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 $j = 1, \dots, J-1$. At the

⁴ Note that while wavelet transforms are often compared to the Fourier transform are they two differ in a number of fundamental ways. See [10] for a comparison of wavelet versus Fourier transforms.

⁵ For the relevance of horizon effects see, for example, [11].

⁶ See [7] 99–103 for a complete discussion.

⁷ See Ramsey [12].

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.⁸

A time series $f(t)$ can be represented in decomposed form, known as the multi-resolution analysis of $f(t)$, as follows:

$$f(t) = \sum_k s_{j,k} \Phi_{j,k}(t) + \sum_k d_{j,k} \Psi_{j,k}(t) + \dots + \sum_k d_{j,k} \Psi_{j,k}(t) + \dots + \sum_k d_{1,k} \Psi_{1,k}(t) \quad (7)$$

Using a more convenient summary notation,

$$f(t) = S_j + D_j + D_{j-1} + \dots + D_1 \quad (8)$$

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.

In the case of monthly data, as we use in our analysis, decomposing the series into six scales (D1-D6) corresponds to 2–4, 4–8, 8–16, 16–32, 32–64, and 64–128 months. D1 is the shortest scale (highest frequency) component and D6 is the longest scale (lowest frequency) component. The smooth component (S_6) captures the trend of the original series.

The continuous wavelet transform (CWT) is also a useful approach for gaining insight into the localized time-scale decomposition of a time series. One advantage that the CWT has over the DWT is that it produces a powerful visual for detecting time-scale patterns. The CWT, which is based on continuous variations in the scale (λ) and time components (t) is defined as,

$$W(\lambda, t) = \int_{-\infty}^{+\infty} \Psi_{\lambda,t}(u) x(u) du \quad (9)$$

where,

$$\Psi_{\lambda,t}(u) \equiv \frac{1}{\sqrt{\lambda}} \Psi\left(\frac{u-t}{\lambda}\right) \quad (10)$$

The DWT can be viewed as a critical sampling of the CWT with $\lambda = 2^{-j}$ and $t = k2^{-j}$.⁹

The wavelet power spectrum, or squared amplitude, measures the local variance of a time series at different scales. It is defined as $|W(\lambda, t)|^2$, and aids our analysis in terms of understanding how periodic components evolve over time.

In addition to the wavelet power spectrum, we also employ wavelet coherence to measure the co-movement of two time series across time and scale. To define coherence we need to define of two other measures, the cross wavelet transform (XWT), and the cross wavelet power (XWP). The XWT is defined as

$$W_{xy} = W_x(\lambda, t) W_{y*}(\lambda, t) \quad (11)$$

The XWP is the absolute value of the XWT, $|W_{xy}(\lambda, t)|$. It measures the local covariance of 2 series at different time scales. The XWP identifies areas in time-scale space where the two series have high common power.

⁸ The wavelet power is the amplitude squared.

⁹ The DWT can also be derived independently, see [12].

The wavelet coherence, is defined as:

$$R^2(\lambda, t) = \frac{|S(S^{-1}W_{xy}(\lambda, t))|^2}{S(S^{-1}|W_x(\lambda, t)|^2) * S(S^{-1}|W_{xy}(\lambda, t)|^2)} \quad (12)$$

Where S is a smoothing operator in time and scale, and $0 \leq R^2(\lambda, t) \leq 1$. The wavelet coherence is similar to the correlation coefficient, and is typically interpreted as a localized correlation in time-scale space. Note that the coherence between two series may be high even if the XWP is low.

The applicability of wavelet methodology to investigate uncertainty shocks is rooted in the fact that market returns reflect an aggregation of investors' decisions. Investors do not all share the same time horizon. Wavelet methodology is used so that localized information that affects returns is not lost.

4. Data

4.1 Sector returns

The equity return data used for our analysis is from the Kenneth French Data Library (**Table 1**) [13]. 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.

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

Table 1.
Kenneth French 12 Industry Data Set.

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.¹⁰ The sample frequency is monthly, and the sample period is July 1960 to Dec. 2019.¹¹ The sample period includes eight recessions. These are illustrated in **Figure 1**. All but three were less than a year in duration. The 1974–1975 recession was 16 months, this was the time of the first

¹⁰ 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.

¹¹ The starting period of the sample is determined by the starting period of the uncertainty indexes.

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. An examination of the cumulative returns of each sector indicates a high degree of variability across sectors and over time for a given sector. **Figure 2** shows the sectors with cumulative growth that exceeds the market for the sample period. **Figure 3** shows sectors with cumulative growth near or below cumulative market growth. The sector with the highest cumulative growth over the sample period is Consumer Non-durables (NoDur) with growth of almost 6400%, compared with the market as a whole which increased 2378%. The sector with the lowest cumulative returns is Durable Goods (900%). The effect of the technology bubble burst (2000–2001), on Telecom, and BusEq returns is salient. The drop is so precipitous that by the onset of the Great Recession (Dec. 2007), cumulative returns for these sectors was still below peak (March 2000). They did not reach the March 2000 peak until 2016. As a whole, **Figures 2** and **3** indicate a change occurring with the 2001 recession in that when it comes to cumulative returns, sector returns appear to part ways. One result is that some sectors recovered quickly from the 2001 and 2007 recessions and some recovered very slowly.

Figure 4 contains the wavelet power spectrum for market returns. Wavelet power is a measure of variance local to time and scale. The most striking feature of

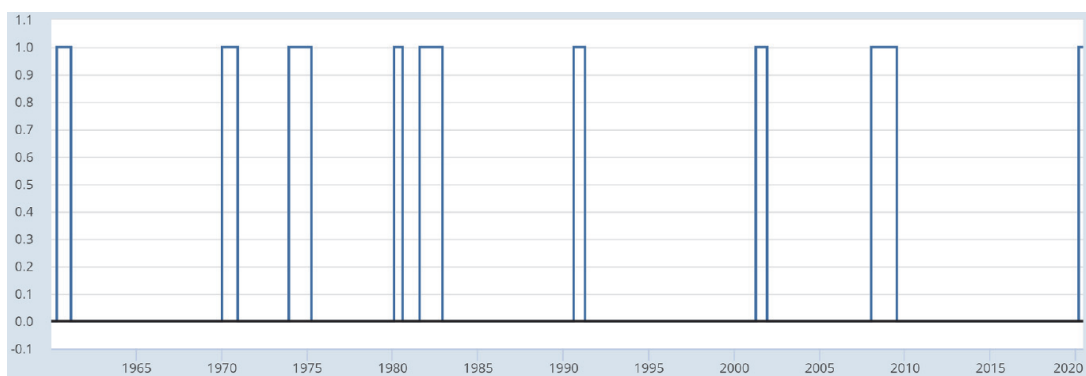


Figure 1.
 US Economic Recessions, 1960–2020 - NBER Dating.

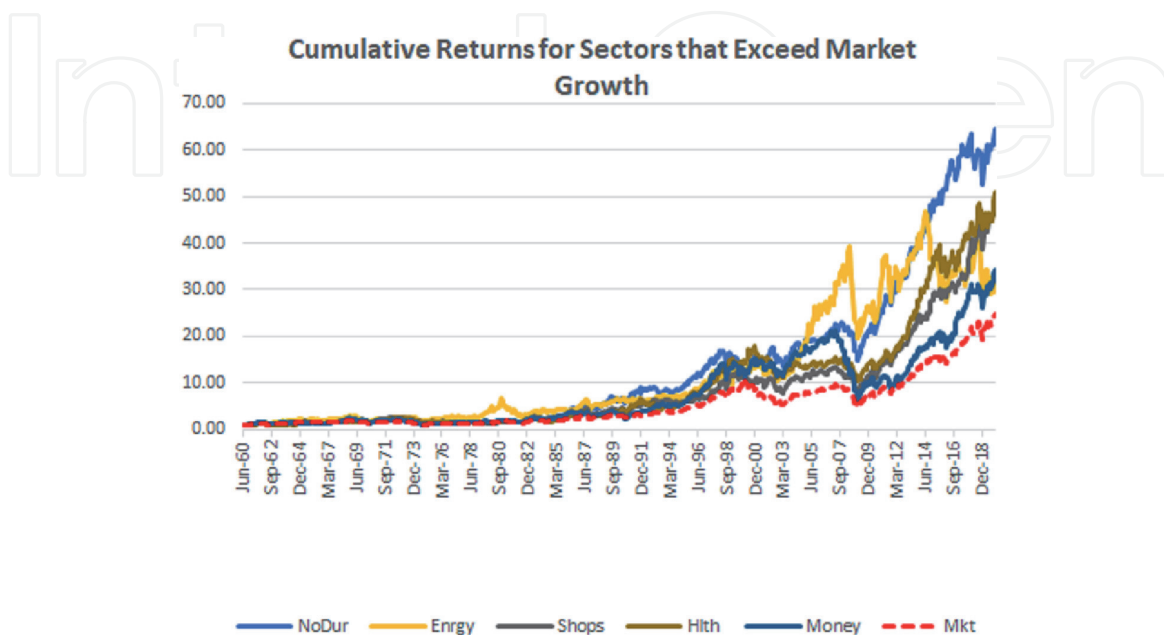


Figure 2.
 Cumulative Returns - High Growth Sectors.

Cumulative Returns for Sectors Near or Below Market Growth

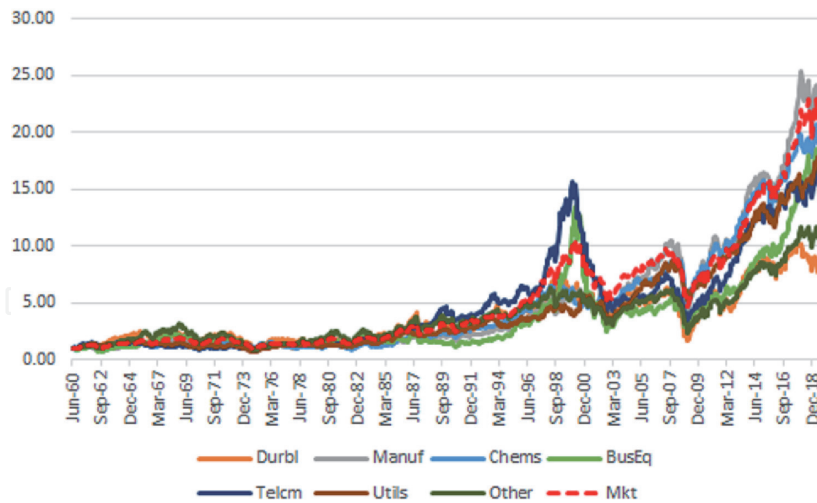


Figure 3. Cumulative Returns - Low Growth Sectors.

U.S. Equity Market

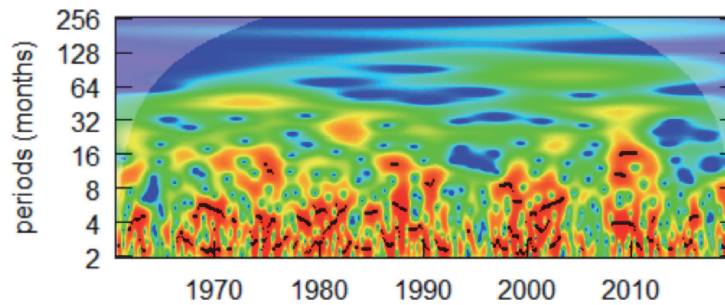


Figure 4. Wavelet Power Spectrum - U.S. Equity Market.

Durable Goods

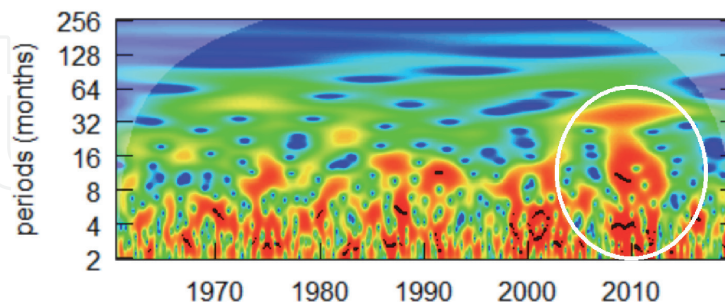


Figure 5. Wavelet Power Spectrum -Durable Goods.

this chart is that most of the power occurs intermittently at high frequencies. The wavelet power spectrum for the Durables sector (the lowest growth sector) is shown in **Figure 5**, and the power spectrum for the Consumer Non-durables sector (the highest growth sector) is shown in **Figure 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. This is outlined in white for expository purposes. Consumer non-durables have relatively high power at the 32–64 month frequency

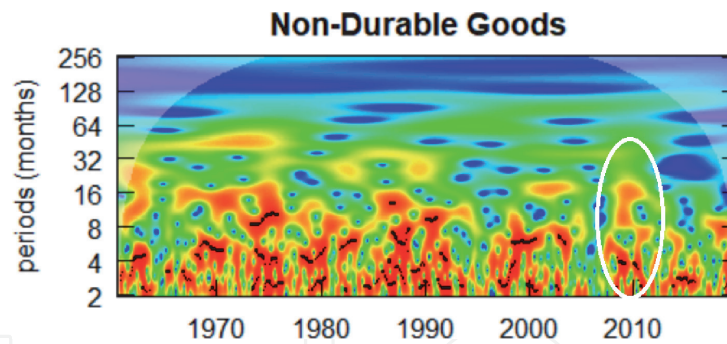


Figure 6.
 Wavelet Power Spectrum - Consumer Non-durables.

during the 1970s, while the Durable Goods sector has less variability associated with this frequency band.¹²

A set of descriptive statistics for the monthly excess returns (%) is reported in **Table 2**. Monthly returns range from a high of 42.6% for Durable goods (Apr. 2009) to a low of minus 32.7% also for Durable goods (Oct. 2008). Skewness is negative for most sectors, the exceptions being except Durable goods (0.13%); 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 4.8 for Durables.

4.2 Uncertainty measures

We use three measures of uncertainty in our analysis, macroeconomic and financial uncertainty from Jurado, Ludvigson, and Ng [2], and economic policy

Sector	Mean	Std Dev	Median	Minimum	Maximum	Skewness	Kurtosis
NoDur	0.68	4.24	0.76	-21.63	18.3	-0.33	2.03
Durbl	0.51	6.15	0.46	-32.71	42.62	0.13	4.77
Manuf	0.59	5.22	0.98	-29.18	21.07	-0.49	2.52
Enrgy	0.63	5.4	0.66	-19.01	23.6	-0.03	1.23
Chems	0.53	4.55	0.74	-25.19	19.71	-0.26	2.11
BusEq	0.63	6.36	0.66	-26.41	20.32	-0.24	1.3
Telcm	0.51	4.59	0.62	-16.43	21.22	-0.18	1.14
Utils	0.49	3.95	0.64	-12.94	18.26	-0.15	1.01
Shops	0.67	5.08	0.75	-28.83	25.28	-0.31	2.4
Hlth	0.67	4.87	0.77	-21.06	29.01	-0.03	2.29
Money	0.64	5.38	0.91	-22.53	20.59	-0.38	1.59
Other	0.49	5.34	0.82	-29.81	18.85	-0.5	2.16

Note: n = 714

Table 2.
 Summary Statistics - Sector Returns.

¹² The highest power level is shown in red, and the lowest is blue. For the U.S. equity market the highest power level is 4. For the Durable goods sector the highest power level is 6.8, and for the non-durable goods sector it is 5.0.

uncertainty from and Baker, Bloom and Davis [3]. These are arguably the most common measures of uncertainty, and they are both updated on a regular basis and available online.¹³ JLN and BBD are different measures of uncertainty constructed using very different methodologies. We summarize both approaches in this section.

JLN define uncertainty for variable y_{jt} as the volatility of the unforecastable part of the future value of y_{jt} .

$$U_{jt}^y(h) \equiv \sqrt{E \left[\left(y_{jt+h} - E \left[y_{jt+h} | I_t \right] \right)^2 | I_t \right]} \quad (13)$$

where, $E(\cdot | I_t)$ is the expectation conditional on information at time t , and h is the number of time periods for the projection. An increase in the squared forecasting error of y_{jt} indicates an increase in uncertainty at time of y_j at t . The JLN methodology computes financial and macroeconomic indexes by aggregating uncertainty measures of the individual economic series.

$$U_t^y(h) = \sum_{j=1}^{N_y} w_j U_{jt}^y(h) \quad (14)$$

where w_j are the aggregation weights.

JLN 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 data set 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 premium, and also a small stock value spread.

JLN 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, denoted as $h = 1$. Their macroeconomic uncertainty series is shown in **Figure 7**. In general the peaks of the series align with the NBER recession dates (shaded areas). The three highest peaks are in the mid-1970's during the first OPEC oil shock, the early 1980's when there were back to back recessions, and the recession of 2008–2009. **Figure 8** shows the wavelet power spectrum for this series. The power is highest for periods of 32 to 128 months. Unlike the time plot of uncertainty which peaks at each recession the power spectrum has two basic clusters of uncertainty. It does not distinguish among the first four recessionary periods, and instead shows one extended period of uncertainty from the early 1970's to the late 1980's. The second period of uncertainty is the Great Recession which is notable for the

¹³ [2] is available at <https://www.sydneyludvigson.com/macro-and-financial-uncertainty-indexes>, and [3] is available at <https://www.policyuncertainty.com/index.html>.

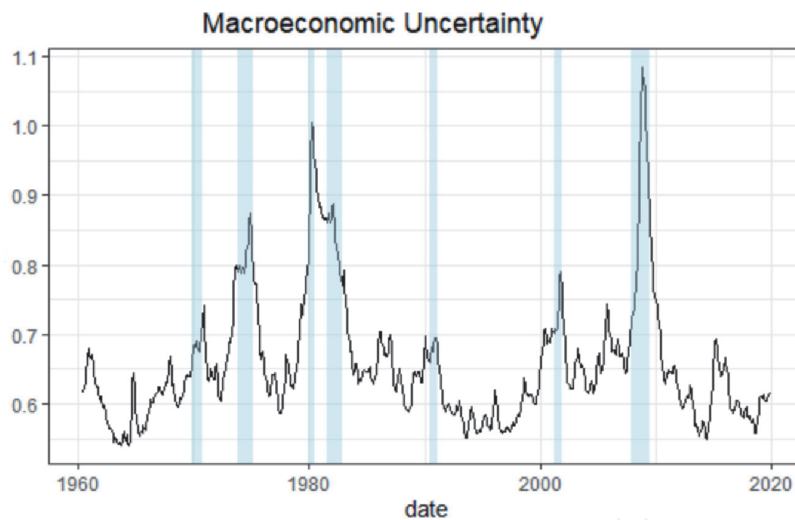


Figure 7.
 Macroeconomic Uncertainty, Jurado, Ludvigson and Ng, (Ph1), horizon = 1 month.

range of scale which is from 8 to 256 months. The Great Moderation in the 1990's (outlined in white) is also apparent as a break in the low frequency power. In contrast power spectrum for the market returns 4 macroeconomic uncertainty tends to have low power at high frequencies.

Figure 9 displays the financial uncertainty series for $h = 1$. The peaks of this series do not align as closely with recessions as does the macroeconomic uncertainty. For instance there is a noteworthy spike in Oct. 1987 (outlined in red) when the equity market dropped, and there was no recession. Events such as the 1997 Asian financial crisis, the 1998 Russian financial crisis and the 2000 Tech. bubble bust are all apparent prior to the 2001 recession. Also, the magnitude of the peaks in the financial uncertainty index are greater than those of the macroeconomic uncertainty index. Alignment of the peaks of the macroeconomic index with recessions, and to a lesser extent the financial uncertainty index, is intuitive as forecasting a turning point is difficult if not impossible. One way useful to think about this is with regard to asset returns which can be written as,

$$r_t = sign * |r_t| \tag{15}$$

It is generally possible to forecast the absolute value of returns but not returns themselves. The reason is that one cannot forecast the sign.

The wavelet power spectrum or variance (**Figure 10**) for financial uncertainty is generally highest at low frequencies. The 1987 stock market crash (outlined in

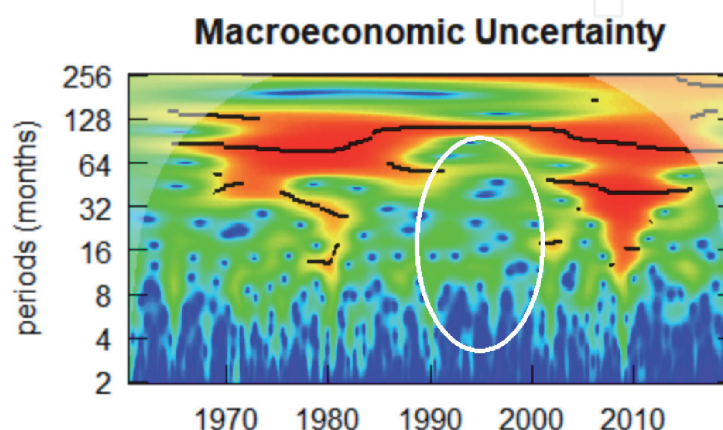


Figure 8.
 Wavelet Power Spectrum - Macroeconomic Uncertainty (EP1).

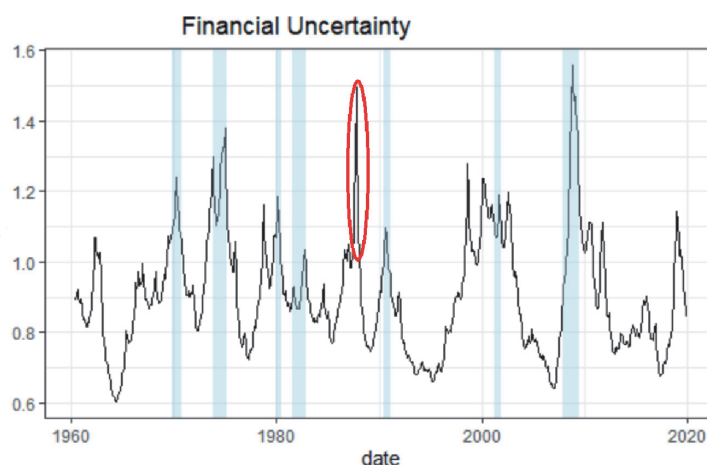


Figure 9.
Financial Uncertainty, Jurado, Ludvigson and Ng, ($Fh1$), (bottom), horizon = 1 month.

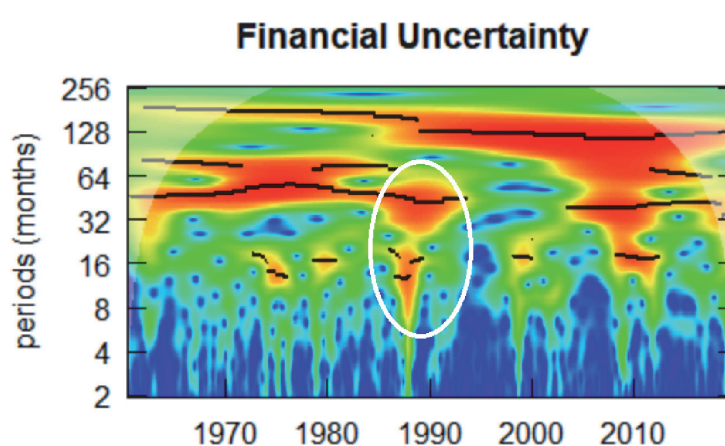


Figure 10.
Wavelet Power Spectrum - Financial Uncertainty ($Fh1$).

white) is one of several instances where high variance can be also be observed at medium (8 to 32 month) frequencies.¹⁴ The scale of uncertainty is lower from 1960 to 1990 (32–64 months) than it is from 1990 to 2020 (up to 128 months). In effect low frequency financial uncertainty exists through the sample period.

Baker, Bloom and Davis (BBD) construct a measure of economic policy uncertainty using three major components. For the first component, they search ten major newspapers and create an index based on the volume of news relating to economic policy uncertainty. The second component, which is designed to capture uncertainty in the federal tax code, is derived from Congressional Budget Office reports on temporary tax code due to expire over the next ten years. The third component uses the dispersion of opinions among professional forecasters regarding the future of the Consumer Price Index, Federal expenditures and, State and Local Government Expenditures. The forecasts are from the Philadelphia Federal Reserves Survey of Professional Forecasters.¹⁵ These three components are combined to create the Index of Economic Policy Uncertainty. The index is shown in **Figure 11**. Unfortunately the series starts in 1985, so we are unable to study this series over the same sample period as the JLN uncertainty indices. The BBD index shown in **Figure 11**, appears to have a local maxima during each of the 3 recessions,

¹⁴ The Wavelet power and coherence analysis was done using MatLab 2020B.

¹⁵ <https://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/historical-data/individual-forecasts>.

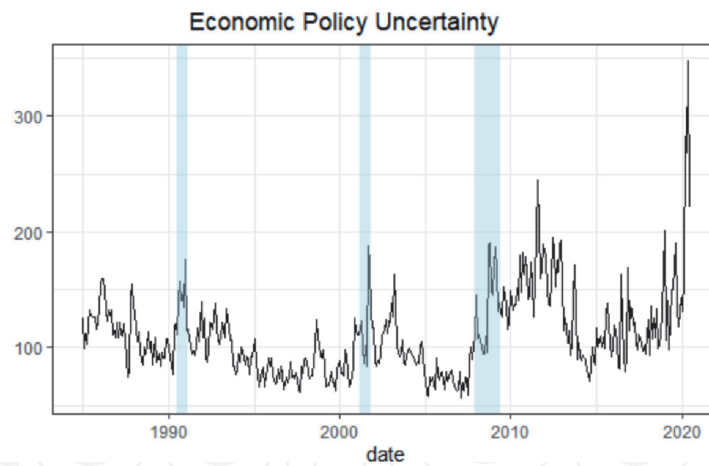


Figure 11.
Economic Policy Uncertainty Index - Baker, Bloom and Davis (EC1).

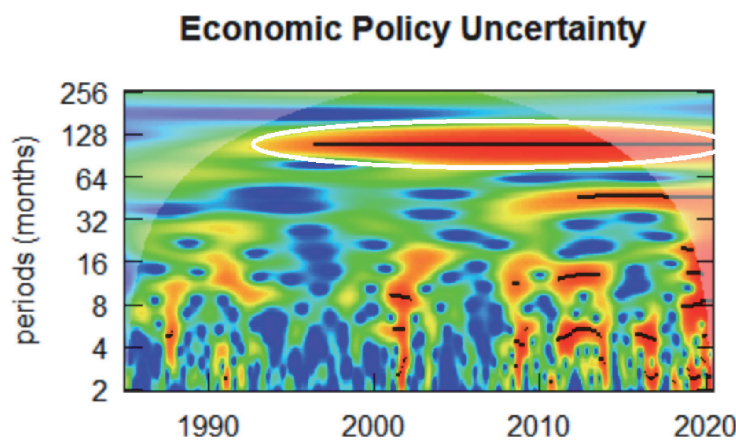


Figure 12.
Wavelet Power Spectrum - Economic Policy Uncertainty.

but it tends to be volatile with peaks at other important dates such as the two Gulf wars (1991, and 2003), the debt ceiling debates (2011–2012), the fiscal cliff (2013), the government shutdowns (1995,2013,2018), and the election of Trump (2016).¹⁶ The wavelet power spectrum for the BBD series is shown in **Figure 12**. High power is found at the 128 month scale from the mid-1990's to the present (outlined in white). There are also a series of high frequency (2–16 months) spikes in the wavelet power which are not present in the other two uncertainty indices.

5. Uncertainty & the market portfolio

We begin our analysis by examining the relationship between the three measures of uncertainty, and the market portfolio. **Figure 13** shows the coherence between macroeconomic uncertainty and excess market returns. Red indicates high coherence and blue indicate no coherence. Coherence is a measure of co-movement between the two series, similar to a correlation. Note that high coherence does imply high power. The heavy black lines around the outside of the red areas indicates statistical significance at the 95% level of confidence. The frequency is inverted in the coherence

¹⁶ [3] provide an annotated version of the index at https://www.policyuncertainty.com/media/US_Annotated_Series.pdf

charts compared with the power spectrum charts. The coherency charts also contain phase arrows which are explained in **Table 3**. There are two basic categories of coherence in **Figure 13**. Sporadic high coherence at the 8 to 64 month scale, and prolonged coherence at the 64–128 month scale. The high coherence at the 64–128 month scales lasts from 1960 until the mid-1980s, breaks for about 15 years (outlined in white), and reoccurs from 2000 to 2019. The period of the break in coherence is shorter than the typical time frame known as the Great Moderation (mid-1980's to 2007). The phase arrows are pointing left indicating that the two series are out of phase. The sporadic high coherence at the 16 to 32 month scales occurs in the middle 1970s, and to a much greater extent during the Great Recession. The phase arrows indicate that the two series are in anti-phase.

In addition to the monthly returns, we also examine coherence of uncertainty with the absolute value of market returns that we use as a measure of market volatility. **Figure 14** shows the coherence plot for the absolute value of market returns with macroeconomic uncertainty. As was the case in **Figure 13** there are two periods of high coherence at a low frequency, but in this instance the scale is lower (32–64 month), the break (outlined in white) begins in the early 1990s and lasts for about 5 years. During the Great Recession, uncertainty and market volatility are in phase.¹⁷

Figure 15 shows the coherence of the market returns with the financial uncertainty. Coherence occurs at lower scales than the coherence of the market with the

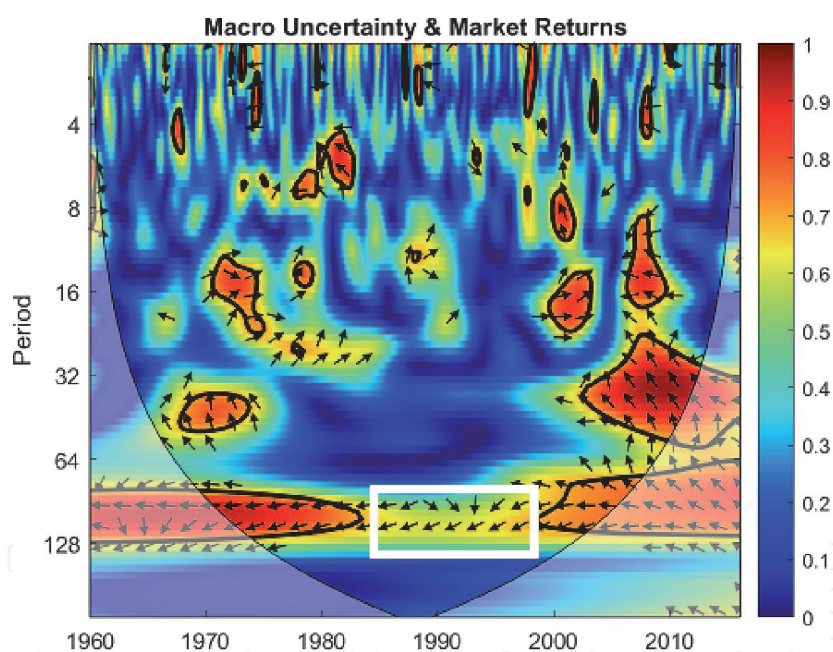


Figure 13.
Wavelet Coherence - Macroeconomic Uncertainty and U.S. Equity Market Returns.

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.

¹⁷ 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).

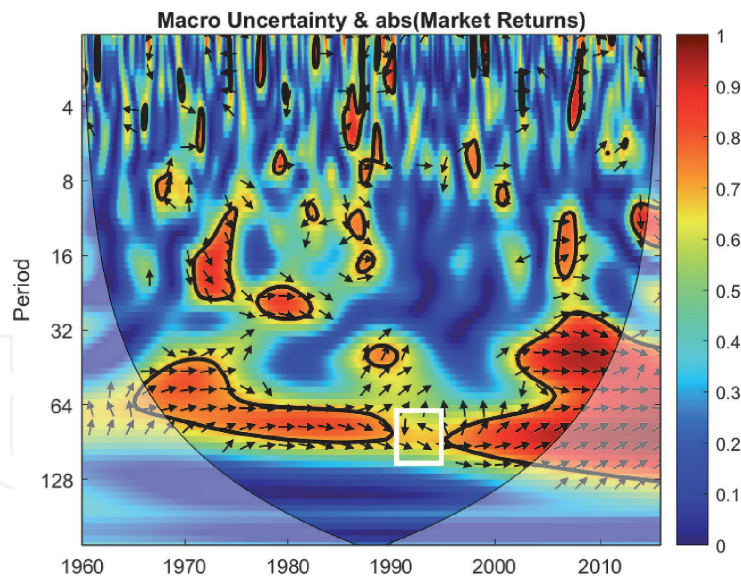


Figure 14.
Wavelet Coherence - Macroeconomic Uncertainty and Absolute Value of U.S. Equity Market Returns.

macroeconomic uncertainty. There is a high degree of coherence in the 1960s and 1970s at the 16–32 month scale, then there is a break (outlined in white) of 20 years when coherence at these scales is non-existent. Beginning in 2000, coherence is high once again at the 16–32 month scales. The two series are out of phase during these periods of high coherence.

The coherence of financial uncertainty and market volatility is shown in **Figure 16**. The coherence is high and in-phase throughout the entire sample period for scales above 32 months. There also are numerous low scale periods when the two series are in phase and have high coherence.

As shown in **Figure 17** the coherence of economic policy uncertainty and market returns generally occurs at a lower scale than coherence of the two BLN indices. Statistically significant coherence never exceeds the 64 month scale, but it is high and nearly continuous at the 8 to 16 month scale from 1993 to 2003 (outlined in white). These periods of high coherence at lower scales appear to coincide with financial crises. During the Great Recession there is a very clear distinction in coherence between the 8–16 month scales (2008–2012), and the coherence at the

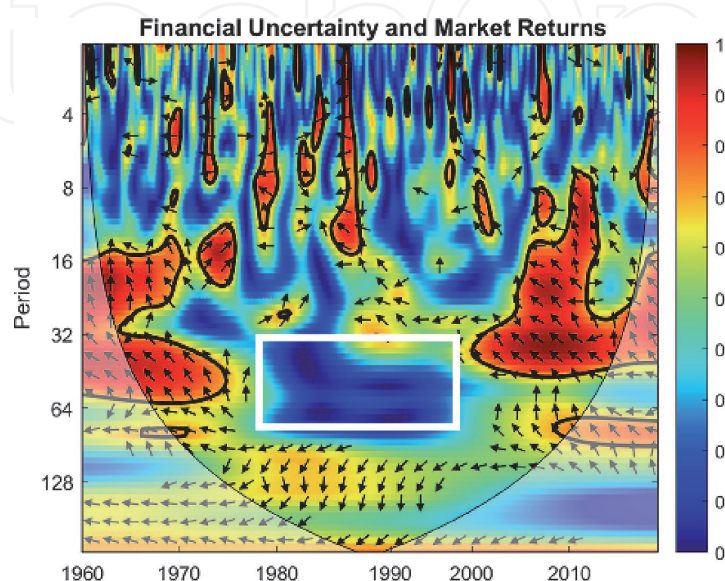


Figure 15.
Wavelet Coherence - Financial Uncertainty and U.S. Equity Market Returns.

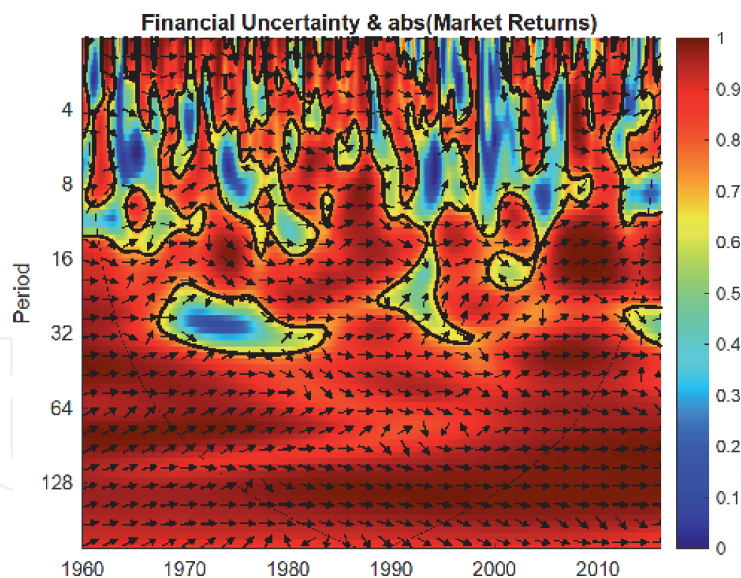


Figure 16.
Wavelet Coherence - Financial Uncertainty and Absolute Value of U.S. Equity Market Returns).

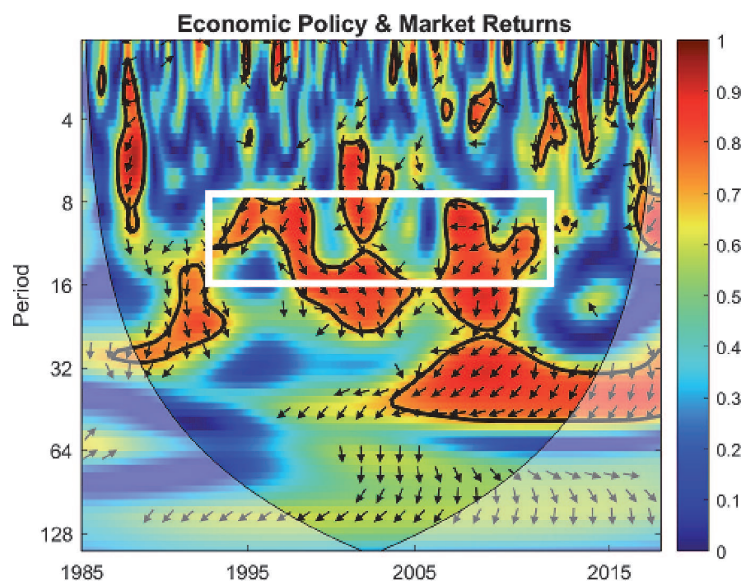


Figure 17.
Wavelet Coherence -Economic Policy Uncertainty and U.S. Equity Market Returns.

32 months scale from 2003 to 2018. The phase arrows generally point upwards indicating a lead-lag relationship.

Figure 18 shows the coherence between economic policy uncertainty and the absolute value of market returns. Coherence is generally quite low, except for the 128 month scale beginning in the mid -1990s and going to 2019.

5.1 Uncertainty and sector returns

In the previous section, we showed that regardless of the uncertainty measure employed, there is evidence of high coherence between market returns and uncertainty, and also market volatility and uncertainty. In this section, we examine the coherence between sector returns and the three measures of uncertainty. Our goal is to characterize the extent to which uncertainty has impacted individual sectors. To do this we examine the coherence of each measure of uncertainty with sector returns. However, uncertainty affects the market and we want to find the

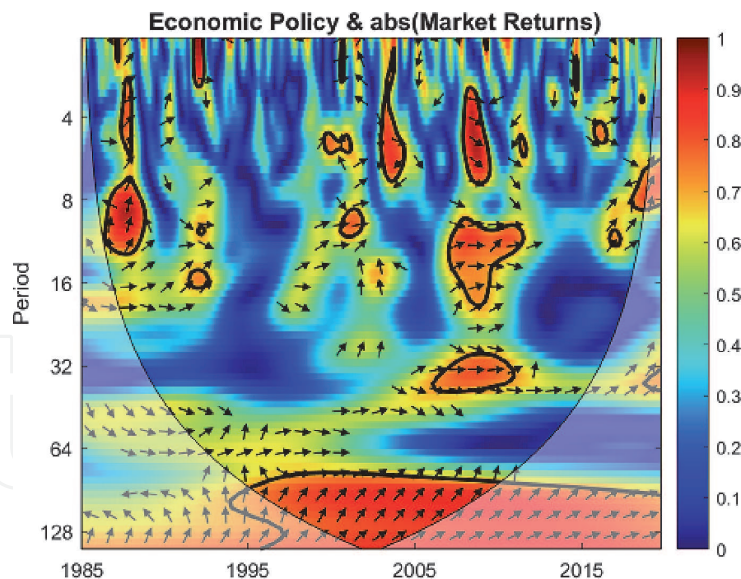


Figure 18.
 Wavelet Coherence -Economic Policy Uncertainty and absolute Value of U.S. Equity Market Returns).

relationship between uncertainty and sector returns after removing the relationship of uncertainty with the market. In order to accomplish this, there is a “before and after.” We refer to the “after” as the conditional coherence. Conditional coherence is the coherence of sector returns with uncertainty conditional on the market returns.¹⁸ In addition, to further illustrate the extent to which uncertainty impacts a sector independently of the impact it has vis-a-vis the market portfolio, we estimate a rolling regression. The rolling regression is of sector returns against the market return and the uncertainty index for one or more scales using the discrete wavelet transform.¹⁹ Selection of the scales was based on high conditional coherence of sector returns and uncertainty measures. The functional form of the regression is,

$$r_{sector,t}^s = \beta_{0,t}^s + \beta_{1,t}^s * r_{mkt,t}^s + \beta_{2,t}^s * U_{i,t}^s \quad (16)$$

where $U_{i,t}$ for $i = 1, 2, \text{ or } 3$ is a measure of uncertainty, and $s = 1, \dots, 6$ is the scale. The estimation window is 60 months.

As there are three measures of uncertainty and 12 sectors, it would be cumbersome to show all of the coherence plots for the 12 sectors. Instead, we have chosen to discuss a subset consisting of six sectors where each sector has at least one period of high coherence with one measure of uncertainty. While the other sectors may also have periods of high coherence, including them would add little to our analysis.²⁰

5.1.1 Financial sector returns and uncertainty

The first sector examined is the financial sector. **Figures 19–21** show the coherence of the financial sector with all three types of uncertainty both before and after the market has been partialled out. Most of the coherence with all three types of uncertainty is subsumed by the market. However, financial uncertainty is one measure of uncertainty that does matter. As shown, in **Figure 20** the right hand side chart shows several areas of significant conditional coherence. Conditional

¹⁸ The partial CWT was estimated using code from [14] updated to run on MatLab 2020B.

¹⁹ The rolling regressions were estimated using R. DWT was estimated using the Waveslim package [15] in R.

²⁰ The other sectors are available from the authors upon request.

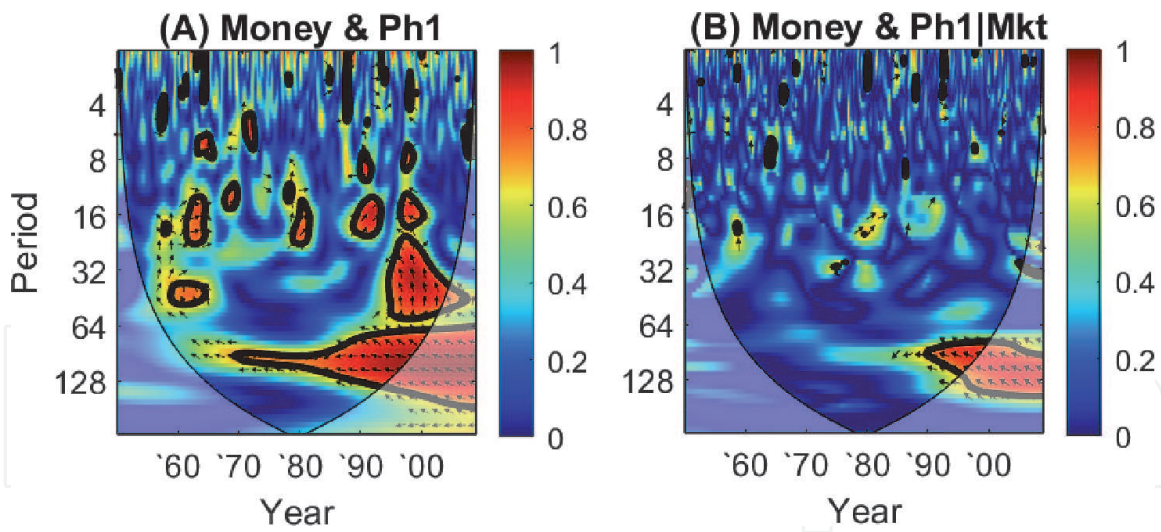


Figure 19.
Wavelet Coherence - Macroeconomic Uncertainty and the Money Sector.

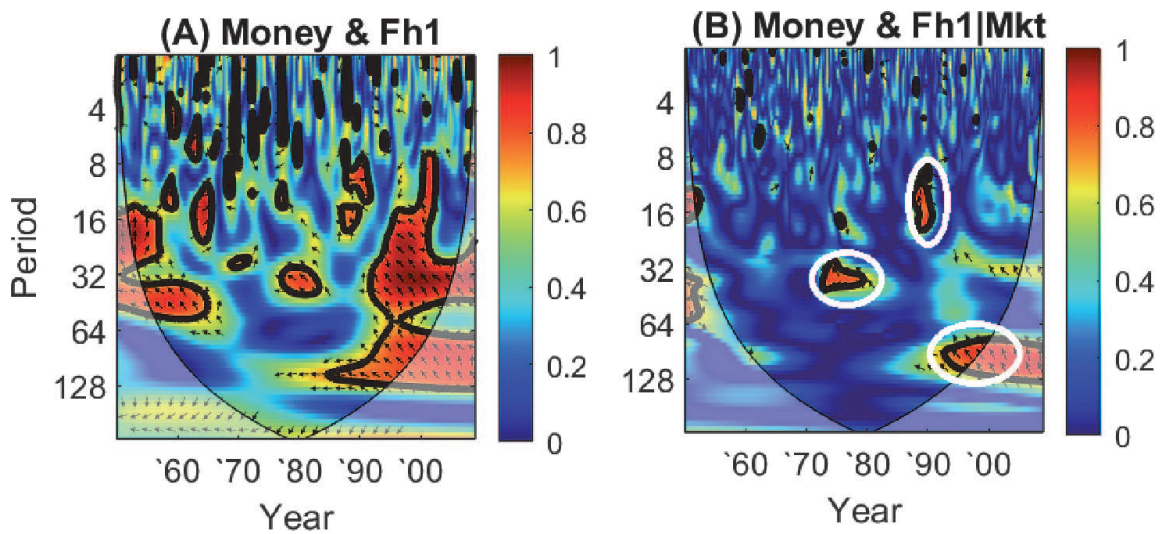


Figure 20.
Wavelet Coherence - Financial Uncertainty and the Money Sector.

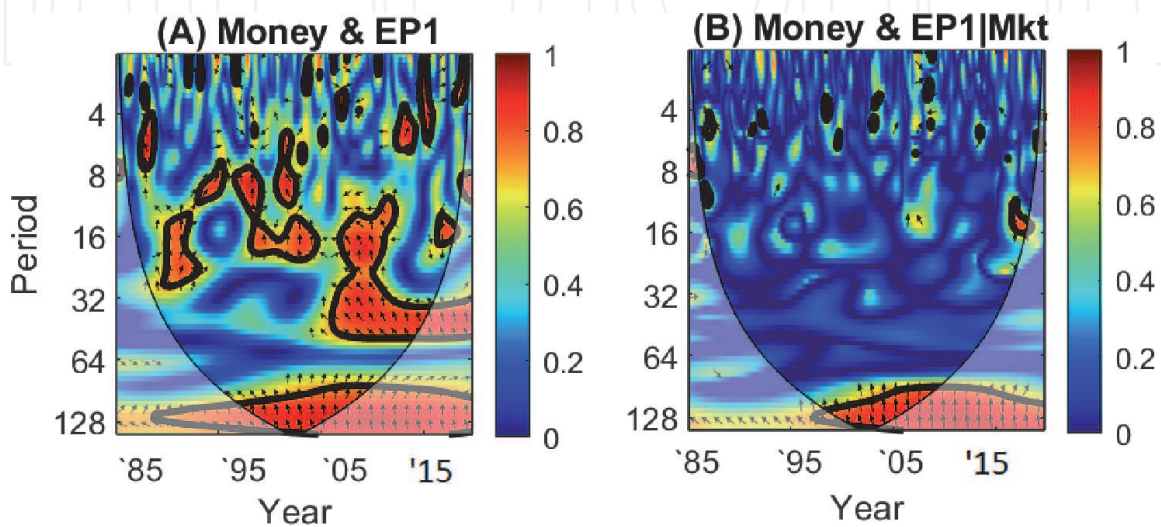


Figure 21.
Wavelet Coherence - Economic Policy Uncertainty and the Money Sector.

coherence exists for the 32 month scale in the 1970s (circled in white). There is also a small area of conditional coherence around 1990 at the 16 month scale and it is also present at the 64–128 month scale beginning around in the mid 1990s. It is interesting to note that there is no apparent conditional coherence with Economic Policy Uncertainty in 2010 when Dodd-Frank was passed.

Figure 22 shows the financial uncertainty coefficient estimates (top) and corresponding t-statistics (bottom) for scales 4 and 5 using the rolling window regression given in Eq. (16). The scales were chosen based on the conditional coherence charts. Scales 4 and 5 for financial uncertainty suggest by the presence of red hot spots that there would be significance for the uncertainty measure. The dashed lines in the t-stat chart indicate ± 2 . Although both scales are presented, scale 5 stands out. Scale 5 (32 months) is negative and statistically significant for three segments of time beginning in the late 1970s. The longest of these three periods begins in the late 1990s and ends in 2010. Given the large number of shocks all of which effected equity values, it is interesting to find that the financial uncertainty index had significance in a rolling window regression that includes both the market and the uncertainty index. Some of the important financial events include the Asian financial crisis (1997), the Russian financial crisis (1998), the collapse of Long Term Capital Management (1998), the repeal of the Glass-Steagall Act (1999), the 2001 recession, and the 2008 recession. The significant negative coefficients for this time period are an indication that there was sector specific uncertainty over and above that which impacted the market as a whole.

5.1.2 Energy sector returns and uncertainty

Figures 23–25 contain the coherence of the Energy sector returns with all three type of uncertainty before (left) and after (right) the market returns are partialled out. Each of the three right hand side charts display several short periods of high conditional coherence indicating uncertainty specific to the energy sector. The longest period of conditional coherence is at scale 6 (64 months) for the Macroeconomic Uncertainty Index (circled in white). There are two small period of high

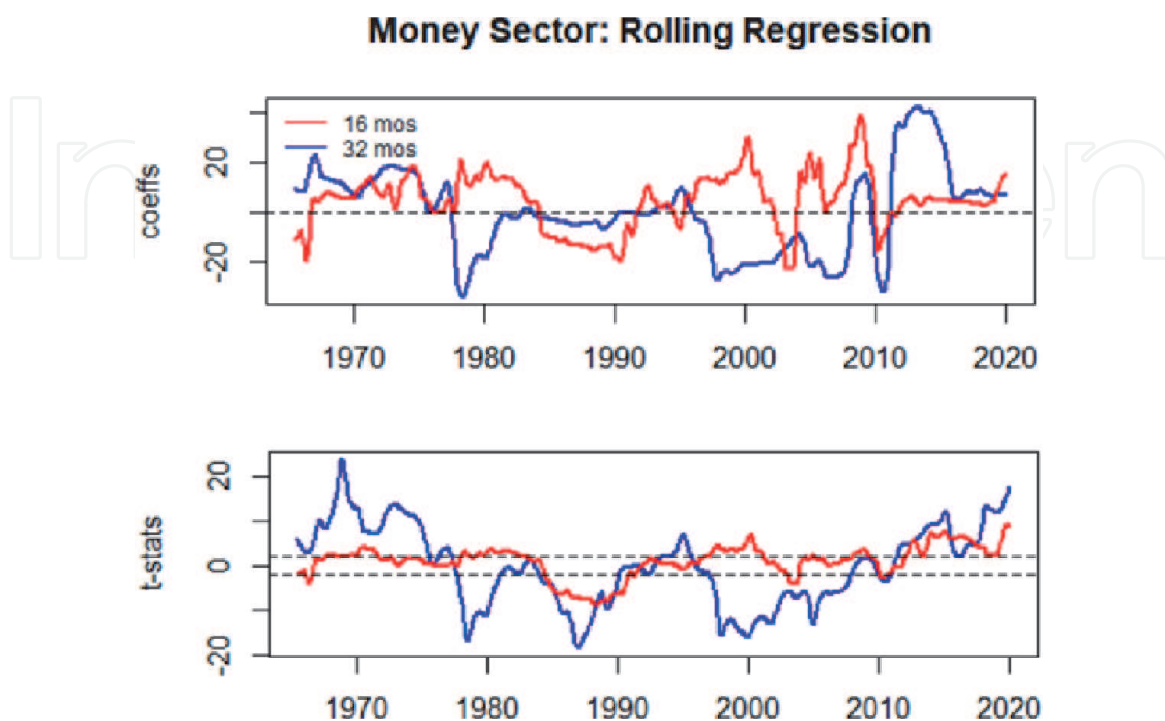


Figure 22.
Rolling Regression Coefficients -Financial Uncertainty and the Money Sector.

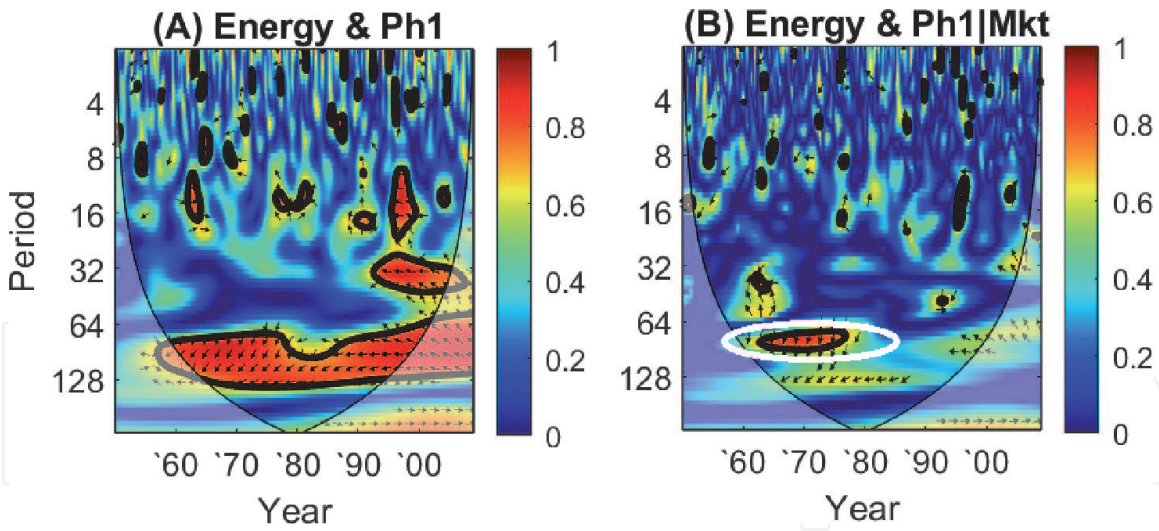


Figure 23.
Wavelet Coherence - Macroeconomic Uncertainty and the Energy Sector.

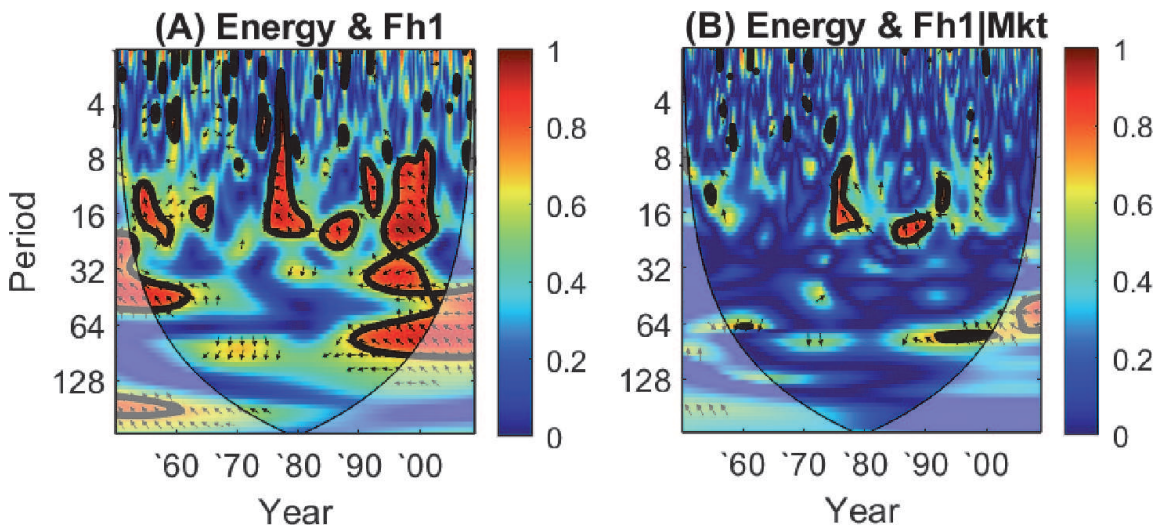


Figure 24.
Wavelet Coherence - Financial Uncertainty and the Energy Sector.

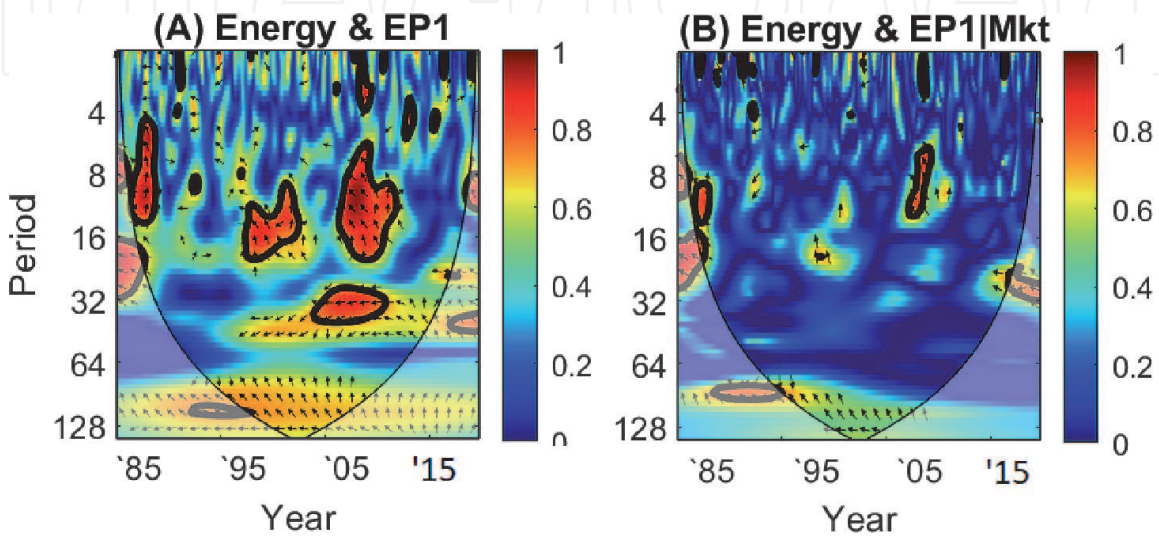


Figure 25.
Wavelet Coherence - Economic Policy Uncertainty and the Energy Sector.

conditional coherence at the 16 month scale with financial uncertainty. There is moderate conditional coherence with policy uncertainty from the mid-1980s until the mid-1990s, but the scale (128 months) is almost completely outside the cone of influence (COI) and is not statistically significant. The 2014 oil glut that led to a steep decline in oil prices has a very small area of significance in the conditional coherence charts. Note also that there is little or no sign of the boom in hydraulic fracking which began in the mid 1990s, nor the environmental backlash that began in 2013–2014 in the conditional coherence charts.

Figure 26 shows rolling window regression coefficients at scales 5 (32 months) and 6 (64 months) for macroeconomic uncertainty. Again, the scales were chosen based on observations from the conditional coherence charts. Scale 6 is negative and statistically significant from the mid-1960s until the mid-1970s and clearly shows the impact of the 1973 OPEC embargo. The uncertainty coefficients for scale 6 are also negative and statistically significant from 2010 to 2015 and may reflect the environmental backlash to fracking.

In summary, although the conditional coherence charts show surprisingly little sector specific uncertainty relating to the OPEC II (1979) oil shocks or the 2014 oil glut, the DWT regression shows a strong negative sector specific impact.

5.1.3 Telecommunications sector returns and uncertainty

Over the course of the sample period, the Telecommunications Industry evolved from a heavily regulated monopoly to a more competitive industry with at least six large firms. In addition, technological changes in communications broadened the scope of services offered by the industry. This resulted in redefining communications providers as content providers and making cell phone usage an imperative for the vast majority of adults. An examination of the coherence charts (**Figures 27–29**) does show some periods of sector specific uncertainty. The conditional coherence chart for financial uncertainty shows high coherence at the 32 months scale throughout the 1980s (highlighted with white) which is coincident with the restructuring of AT&T. The conditional economic policy chart shows four high

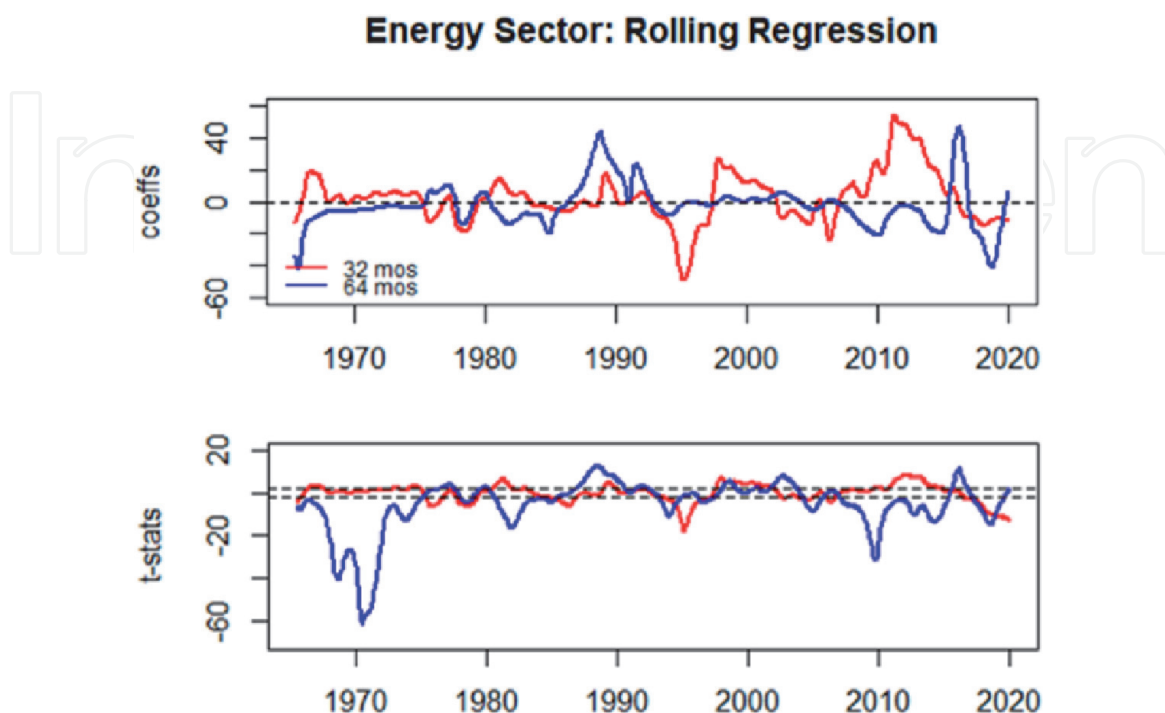


Figure 26.
Rolling Regression Coefficients - Macroeconomic Uncertainty and the Energy Sector.

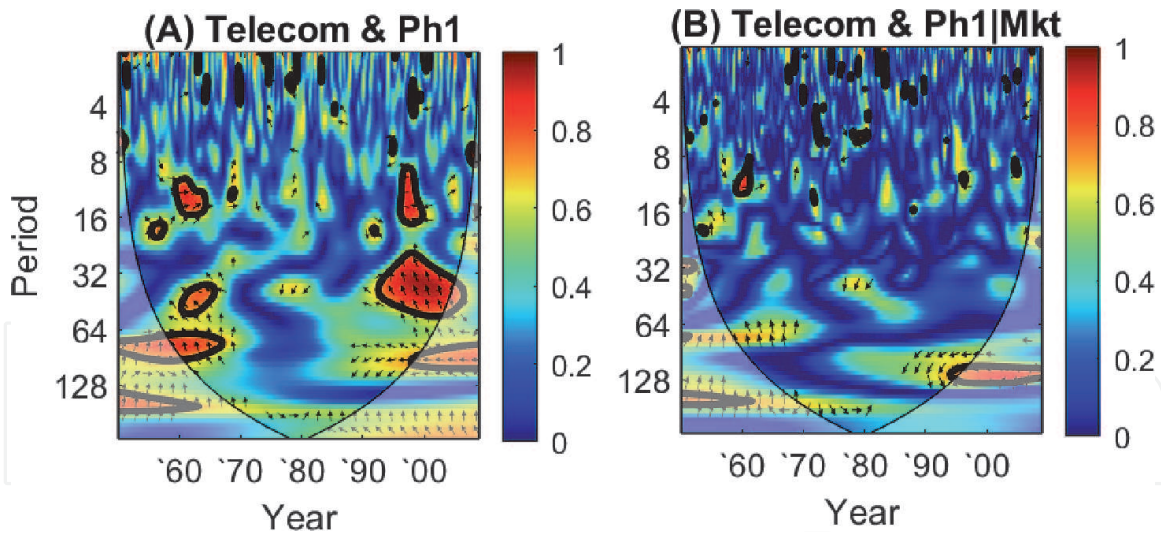


Figure 27.
Wavelet Coherence -Macroeconomic Uncertainty and the Telecom. Sector.

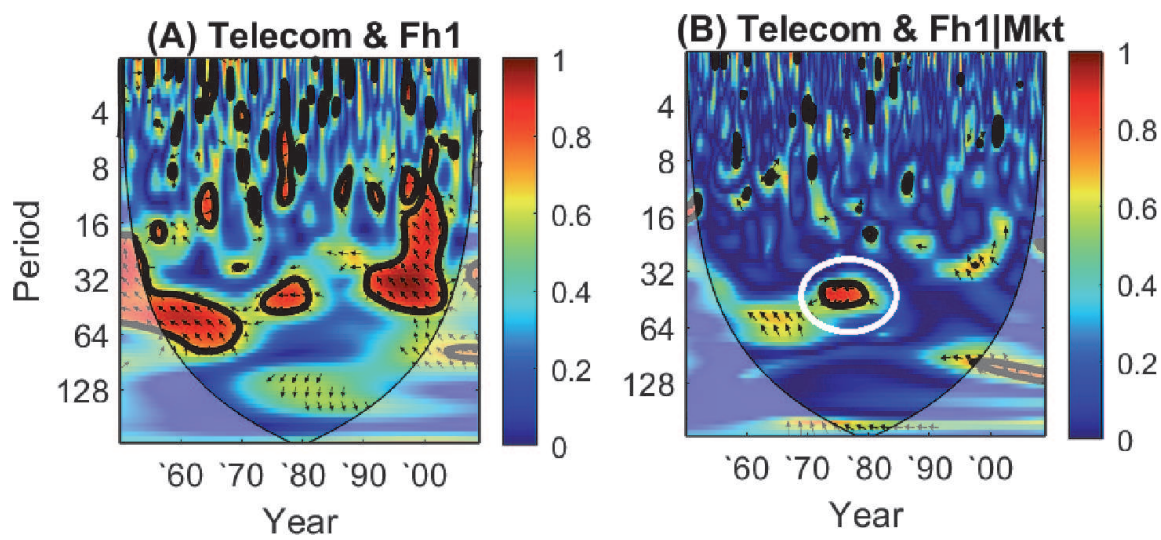


Figure 28.
Wavelet Coherence - Financial Uncertainty and the Telecom. Sector.

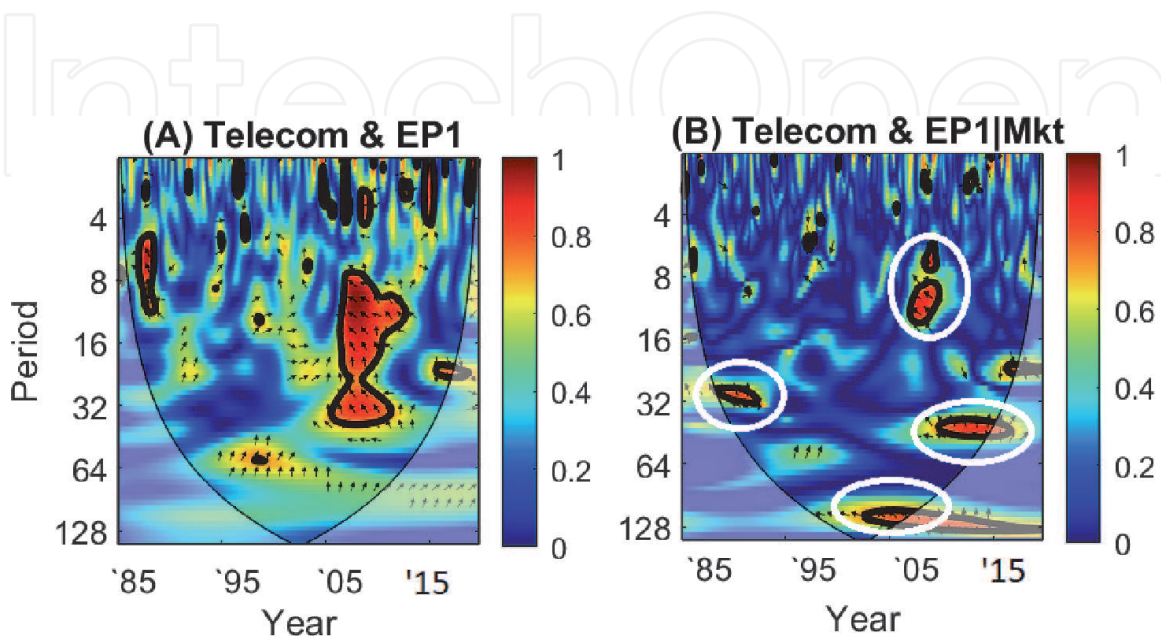


Figure 29.
Wavelet Coherence -Economic Policy Uncertainty and the Telecom. Sector.

periods of coherence. Two are at the 32 month scale, one in the early 1990s and the second starting in 2010. There is also high coherence during the Great Recession at the 8 to 16 month scale. The fourth period of high coherence is at the 64 to 128 month scale beginning in 2005 and ending in 2010.

Based on the conditional coherence charts, rolling regressions were run for both Economic Policy Uncertainty and Financial Uncertainty indices. Significant coefficients were found for both indices. **Figure 30** shows the uncertainty coefficient estimates and t-statistics for the regression of sector returns against market returns and Economic Policy Uncertainty for scales 16 and 32 months. Policy Uncertainty at scale 32 is negative and statistically significant from 1995 to 2000, and from 2007 to 2015. The Telecommunications Act of 1996 may be partially responsible for the large drop in the 32 month coefficient in 1996–1997.

Coefficient estimates for Financial Uncertainty at 16 and 32 month scales are shown in **Figure 31**. This is a longer time series than the policy uncertainty index and it shows a modest negative impact in the 1980s at the 32 month scale. There is a much larger negative impact at the 32 month scale starting in the late 1990s and extending until 2018. The significance coefficients are consistent with the explanation that the Telecommunications Sector exhibits sector specific uncertainty.

5.1.4 Business equipment sector returns and uncertainty

Coherence plots for the business equipment sector, which is comprised of computer, electronic and software firms are shown in **Figures 32–34**. There appears to be very little conditional coherence for Macroeconomic Uncertainty. The 32 month scale for Financial Uncertainty shows some coherence in the early 1990's and from 2000 to 2010. Conditional coherence with Economic Policy Uncertainty is low except in the 2018–2019 period at the 8 month scale (highlighted in white). This may be the result of the policy change in favor of repealing net neutrality on the part of the Trump Administration.

Figure 35 shows the coefficient estimates for Economic Policy Uncertainty at the 8 and 16 month scales. The coefficients for the 16 month scale are negative and

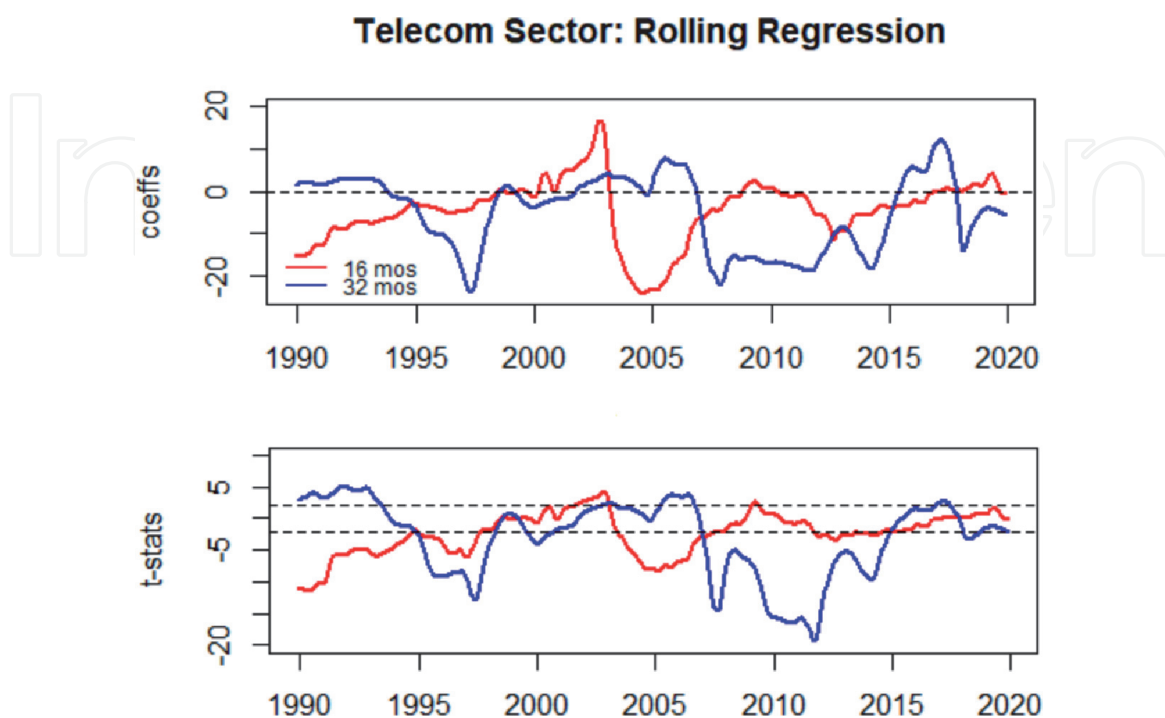


Figure 30.
Rolling Regression Coefficients-Economic Policy Uncertainty and the Telecom. Sector.

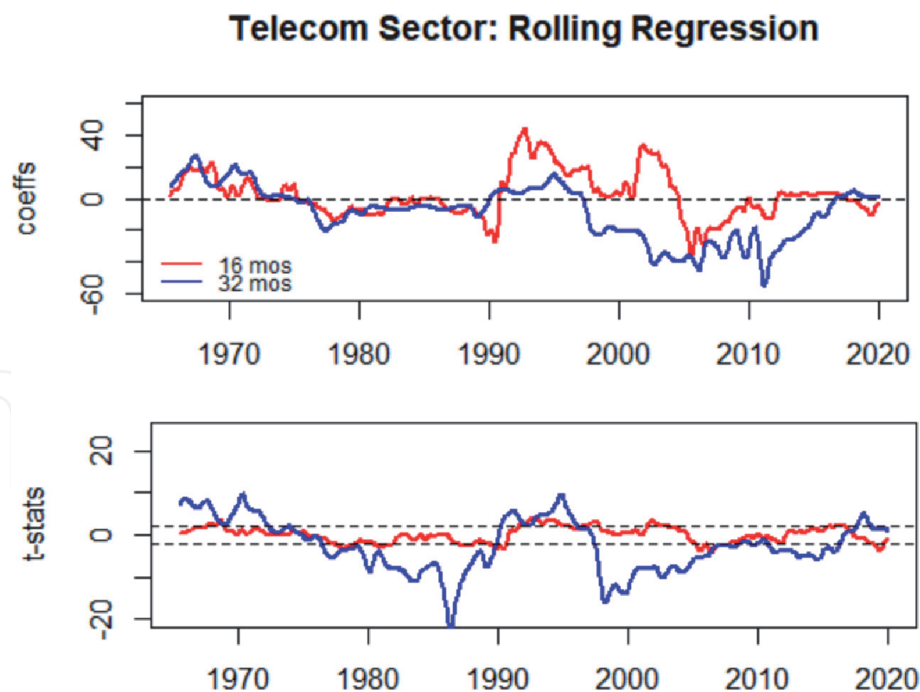


Figure 31.
Rolling Regression Coefficients-Financial Uncertainty and the Telecom. Sector.

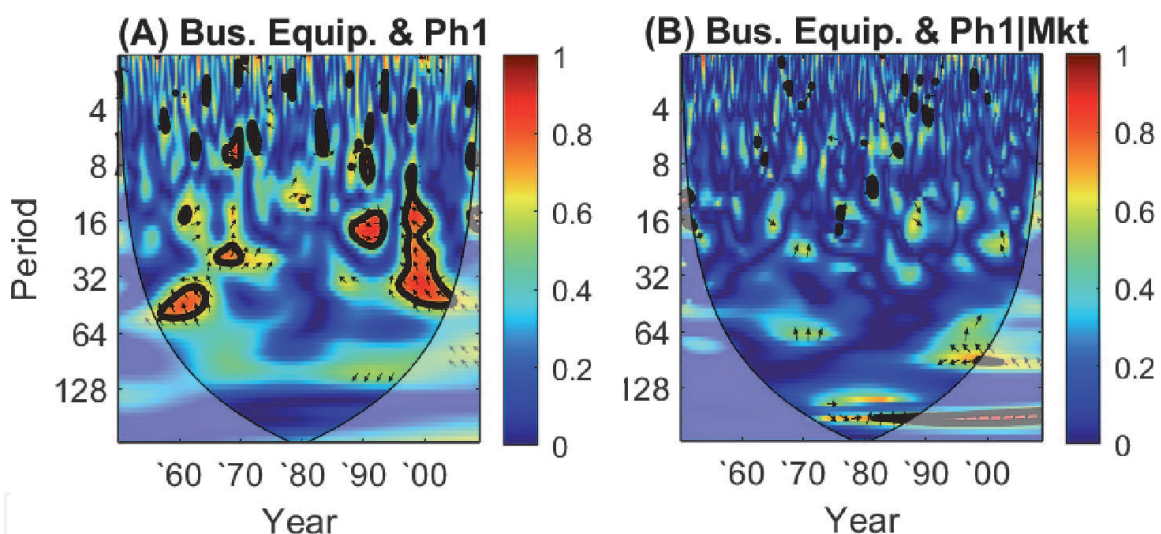


Figure 32.
Wavelet Coherence -Macroeconomic Uncertainty and the Business Equipment Sector.

significant from the late 1990s until 2008. This is a time of rapid growth for the internet. The tech bubble burst after partialing out the market effect clearly has a stand alone component. The significant coefficients are consistent with difficulties encountered when introducing a new technology.

5.1.5 Shops sector returns and uncertainty

There are several instances of significant conditional coherence for the shops sector (**Figures 36–38**). Notable is the coherence with Macroeconomic Uncertainty, and to a lesser extent Financial Uncertainty, at the 64 month scale from the mid 1970s to the late 1980s. The Shops sector, which consists of Wholesale, Retail, and Some Services, shows very little conditional coherence with the JLN indices after the late 1980s. This is consistent with the rise and expansion of big box retailers such as Walmart and Target and the demise of small Mom & Pop stores. Big Guns

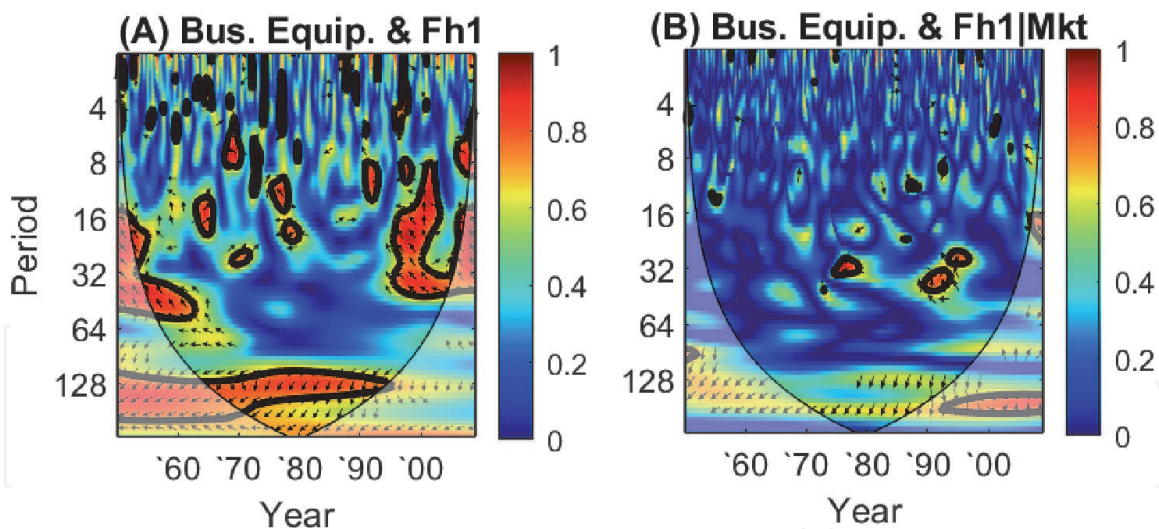


Figure 33.
 Wavelet Coherence - Financial Uncertainty and the Business Equipment Sector.

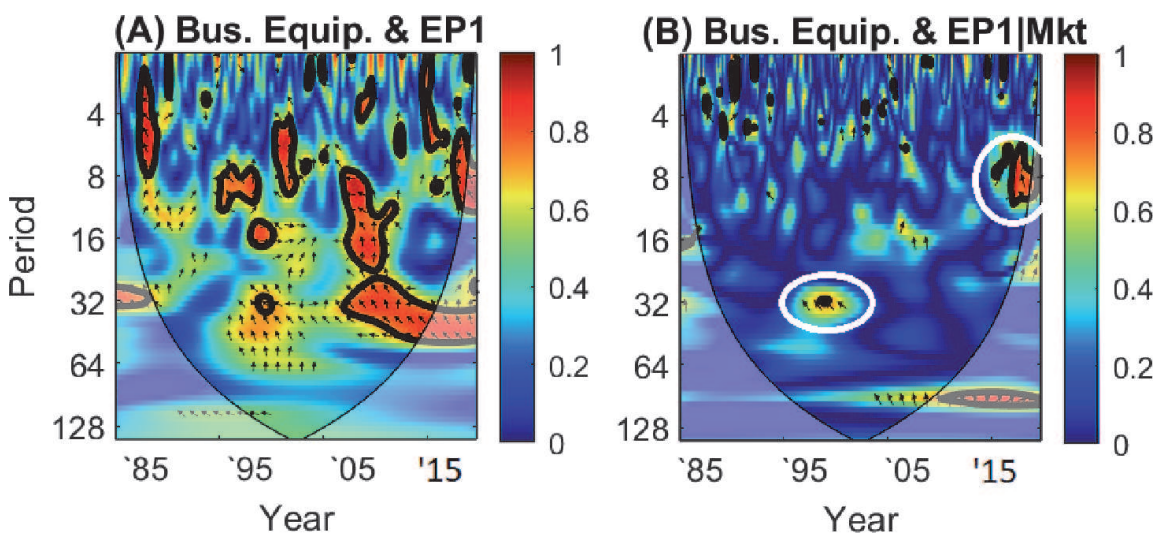


Figure 34.
 Wavelet Coherence - Economic Policy Uncertainty and the Business Equipment Sector.

are better able to weather uncertainty storms. The rise of internet retail captured by Amazon's IPO in 1997 does show up in the conditional coherence for Economic Policy (highlighted in white). This is suggestive that policy treatment regarding internet retail mattered, especially considering taxes.

The rolling regression coefficients for the shops sector with economic policy uncertainty are shown in **Figure 39** for 8 and 16 month scales. The uncertainty coefficients for the 16 month scale are negative starting in 1996 and remain negative until 2015. This seems consistent with the war between internet shopping and brick and mortar retail businesses.

5.1.6 Manufacturing sector returns and uncertainty

Coherence plots for the manufacturing sector are shown in **Figures 40-42**. There is high conditional coherence with Macroeconomic Uncertainty from 1990 to 2019 at the 128 month scale (highlighted in white). However, at least half of this coherence is outside the cone of influence (COI). The onset of this uncertainty coincides with the signing of NAFTA in 1994. There appears to be less conditional coherence with Financial Uncertainty, although there is a significant patch at the

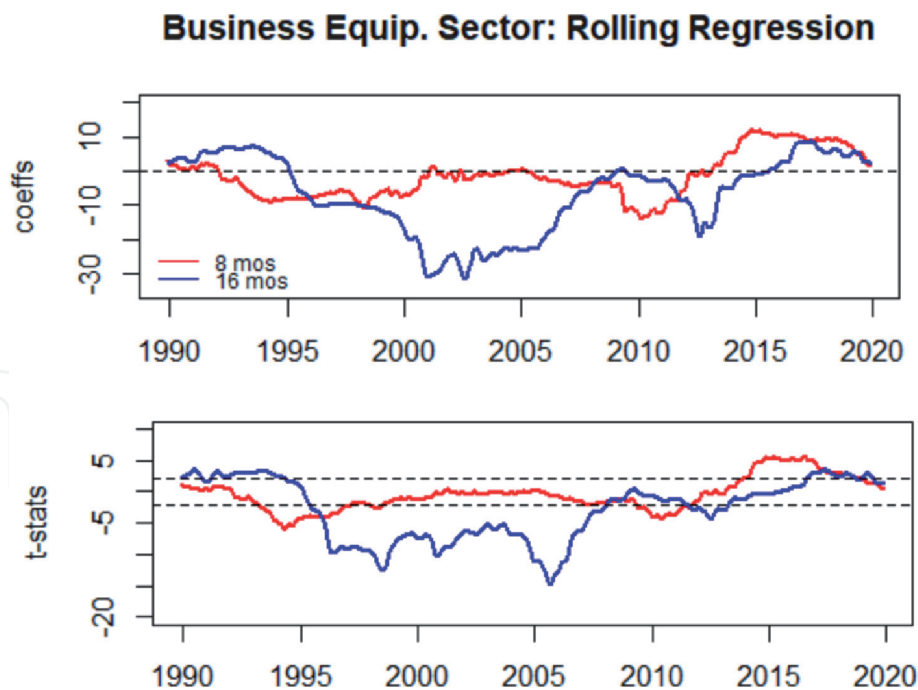


Figure 35.
Rolling Regression Coefficients - Economic Policy Uncertainty and the Business Equipment Sector.

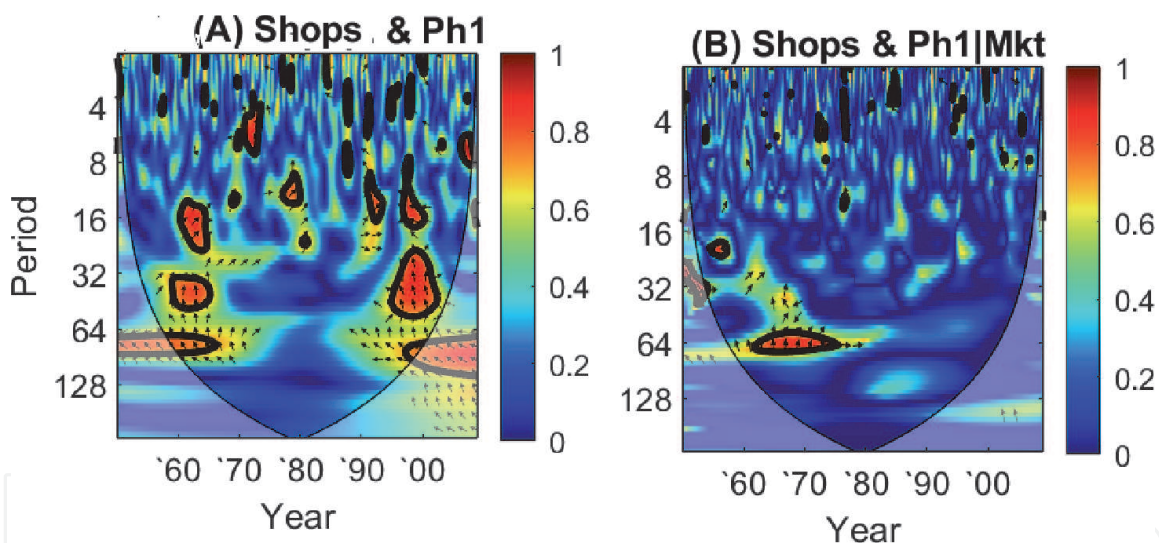


Figure 36.
Wavelet Coherence - Macroeconomic Uncertainty and the Shops Sector.

64 month scale during the Great Recession. Conditional coherence with Economic Policy Uncertainty occurs in the mid to late 1990s at the 8 to 16 month scale (highlighted in white). These findings suggest that the market bears the risk to manufacturing captured by the indices of Macroeconomic and Financial Uncertainty. However, since Economic Policy Uncertainty is showing some hot spots of conditional coherence this suggests that the market responded to news and information regarding this sector, especially the effects of trade on manufacturing. The stand alone uncertainty that is captured may be associated with policy uncertainty regarding trade.

Figure 43 shows the rolling regression coefficients for Macroeconomic Uncertainty at the 64 and 128 month scale. The 128 month scale coefficients are negative and significant throughout the 1970s and 1980s, and from 2000 to 2010. **Figure 44** shows the coefficients for Economic Policy Uncertainty at the 8 and 16 month

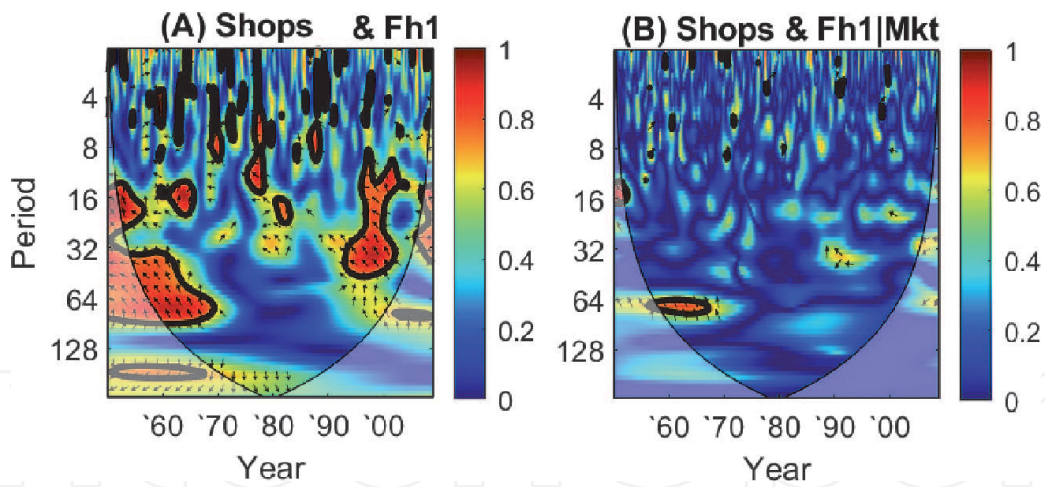


Figure 37.
 Wavelet Coherence - Financial Uncertainty and the Shops Sector.

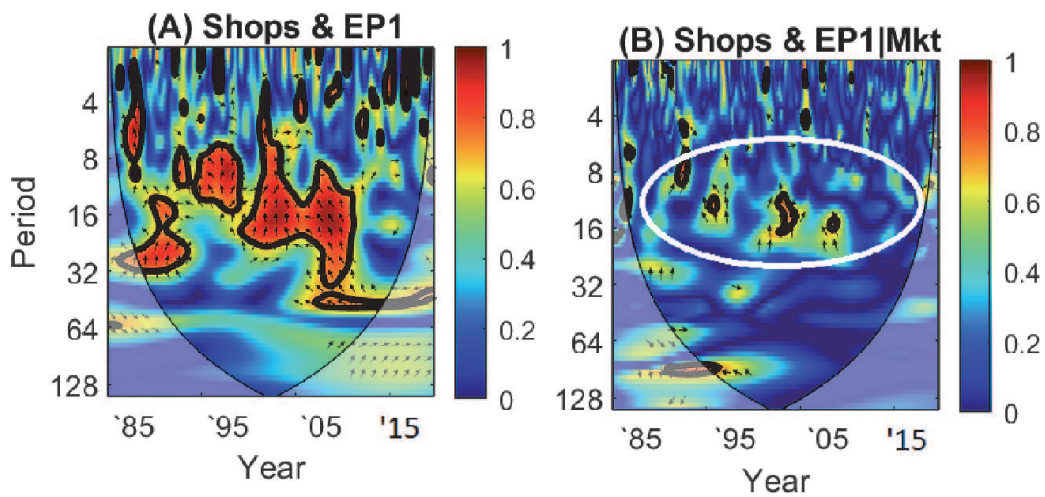


Figure 38.
 Wavelet Coherence -Economic Policy Uncertainty and the Shops Sector.

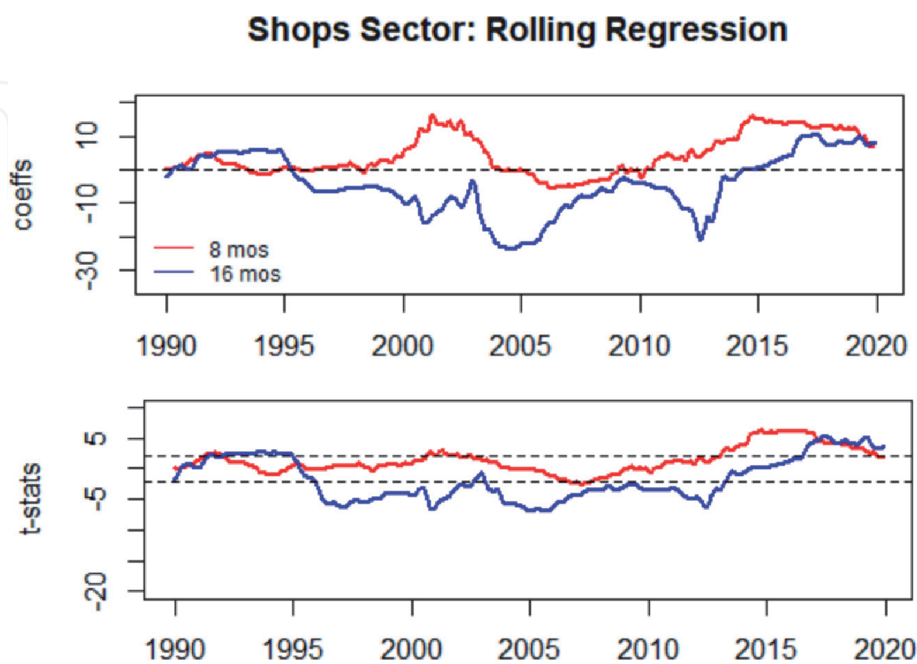


Figure 39.
 Rolling Regression Coefficients - Economic Policy Uncertainty and the shops Sector.

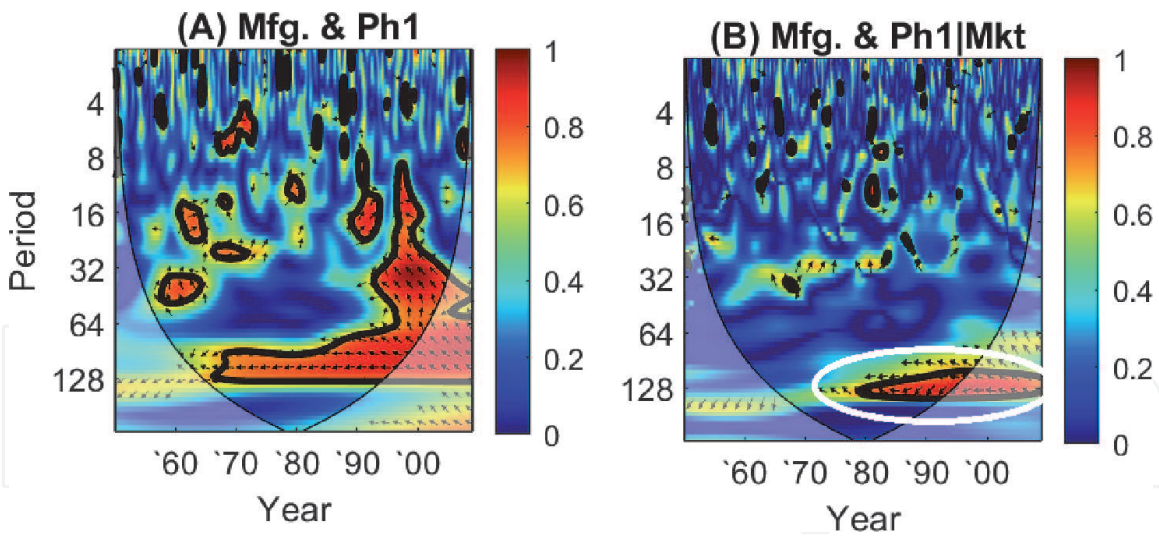


Figure 40.
Wavelet Coherence - Macroeconomic Uncertainty and the Manufacturing Sector.

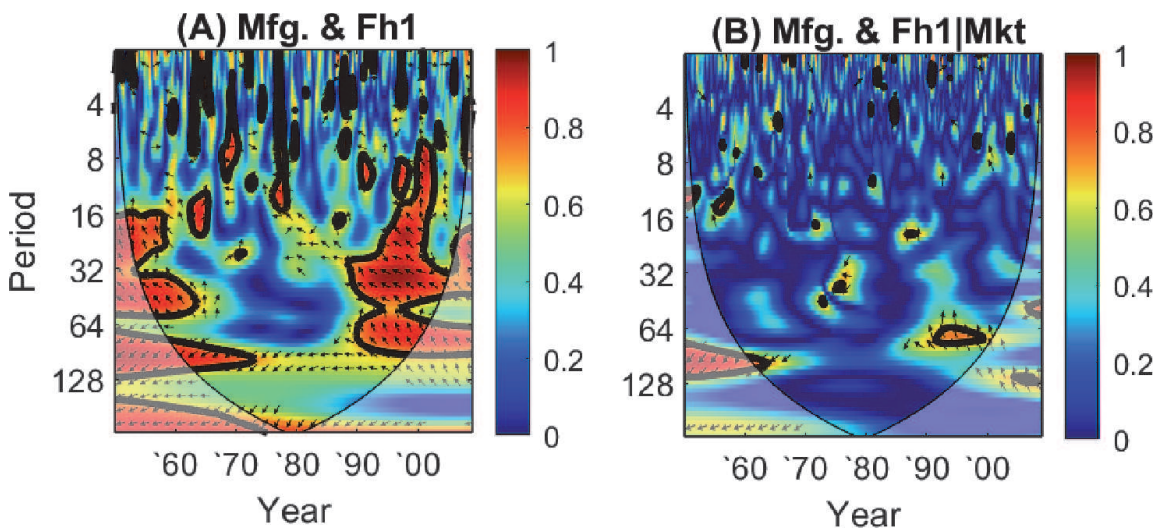


Figure 41.
Wavelet Coherence - Financial Uncertainty and the Manufacturing Sector.

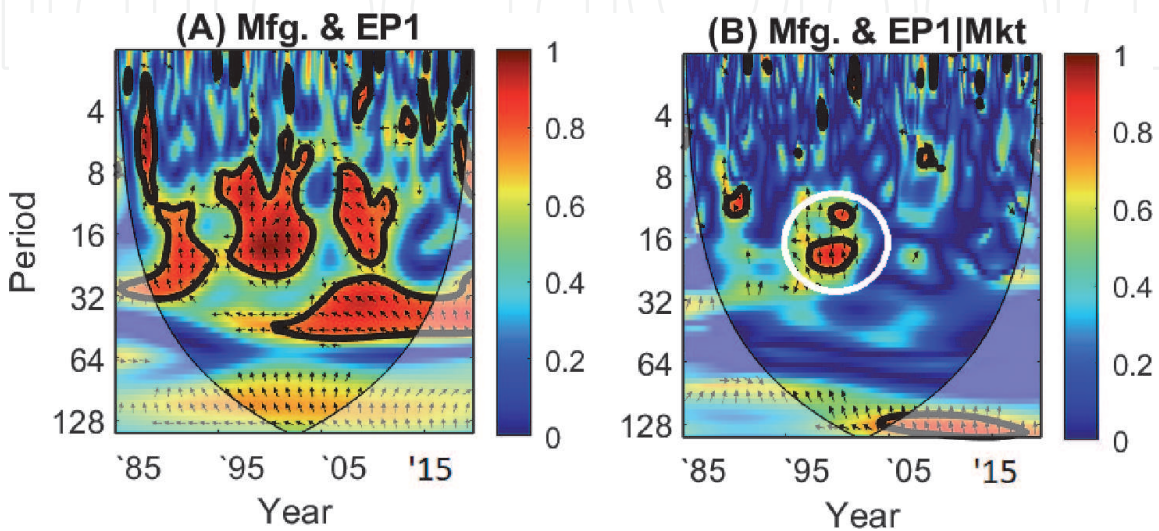


Figure 42.
Wavelet Coherence - Economic Policy Uncertainty and the Manufacturing Sector.

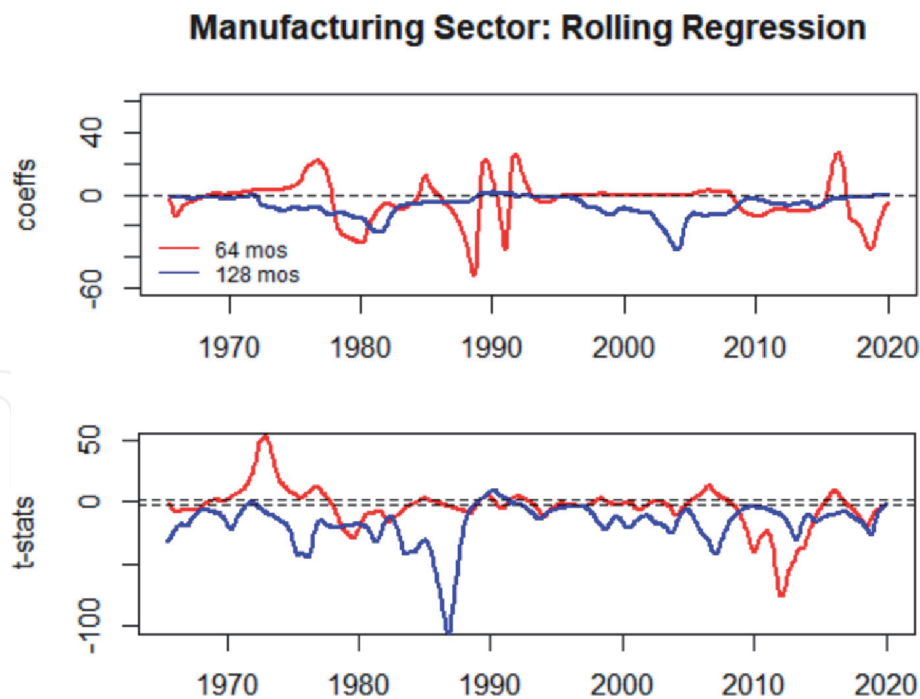


Figure 43.
Rolling Regression Coefficients - Macroeconomic Uncertainty and the Mfg Sector.

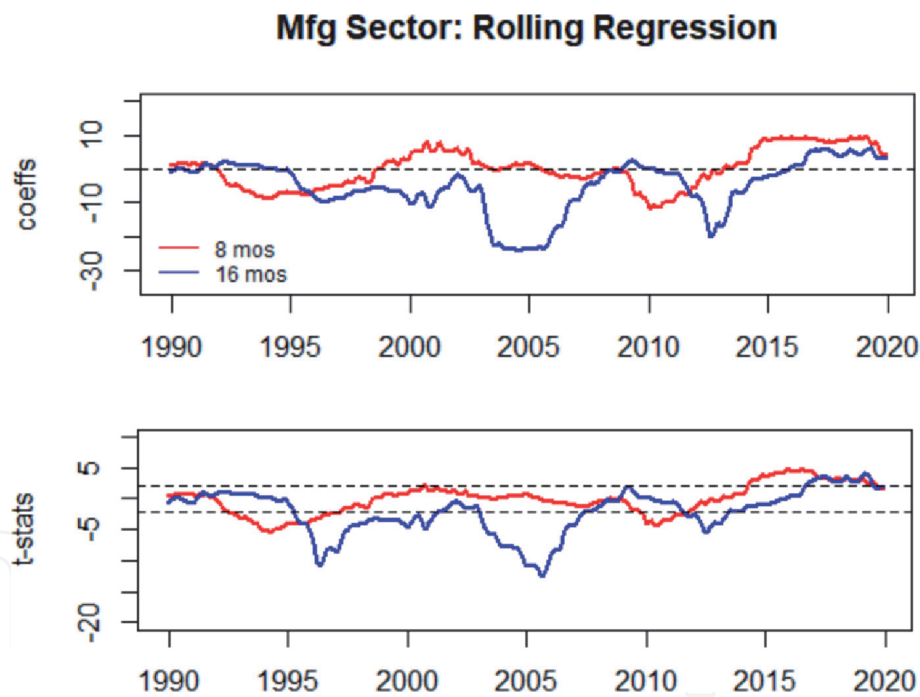


Figure 44.
Rolling Regression Coefficients - Economic Policy Uncertainty and the Mfg Sector.

scales. The impact of concerns about NAFTA is apparent at the 16 month scale with negative coefficients in 1996 and ending in 1998.

6. Conclusions

Wavelet methodology, by allowing local features of the environment to be captured took the lead in our exploration of uncertainty shocks. We examine changes in coherence between each uncertainty measure and the returns of each sector both before and after partialing out the coherence of uncertainty with the

market portfolio. Rolling regressions were used to identify sector-specific uncertainty that is not captured by the overall market. Such uncertainty was found for the Money Sector, Energy sector, Telecommunications sector, and Manufacturing sector. These findings suggest that there are periods when the market reaction to shocks is not reflecting all the information captured by the uncertainty indices. One interpretation of our results is that an industry like Telecommunications, Money, Energy, and Manufacturing undergoing significant technological or regulatory changes will have a great reaction to shocks than the overall market response captures. These sectors have a greater sensitivity to uncertainty shocks when the design of the uncertainty metric is largely macro in orientation.

Our finding that there are episodes of uncertainty when there is increased comovements across frequency and over time for specific sectors helps paint a more complete picture of how uncertainty affects the economy through its transmission across sectors. When local features of the return environment are considered, we conclude that in the face of uncertainty shocks the market's knowledge-gathering role could be improved by introducing uncertainty measures that in terms of information-gathering are less global and more local. Localized or micro measures of uncertainty shocks should be of direct relevance to traders and portfolio managers who must respond to such shocks in a ways that are wealth-preserving for their clients.

Conflict of interest

“The authors declare no conflict of interest.”

Disclaimer

The material presented in this Chapter gives the views of the author, and not necessarily Queens College or the Bank of America.

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