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Department of Economics Working Paper Series

Effect of Uncertainty on U.S. Stock Returns and Volatility: Evidence from Over Eighty Years of High-Frequency Data

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Working Paper: 2019-42
May 2019

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Effect of Uncertainty on U.S. Stock Returns and Volatility: Evidence from Over Eighty Years of High-Frequency Data

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Abstract

In this paper, we analyse the asymmetric impact of financial uncertainty shocks on stock returns and volatility of the U.S. equity market over the period of 18th March, 1936 to 30th November, 2016, by controlling for impact of monetary policy shocks and recessions. We find that positive growth rates of uncertainty reduce stock returns and increases volatility, while, negative growth rates of uncertainty primarily reduce stock market variance. Further, the impact of changes in uncertainty on volatility is found to be asymmetric in the statistical sense. A rolling window estimation over the period of 30th June, 1954 to 30th November, 2016, shows that there is significant time variation in the impact of uncertainty, though the direction of impact largely confirms with the static case. Our study provides new evidence that the impact of financial uncertainty on the U.S. equity markets is intuitively consistent even in the historical and high-frequency context.

Keywords: Uncertainty, Stock Returns and Volatility, Asymmetry, Rolling Estimation
JEL Codes: C32, G10

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1. Introduction

In the wake of the "Great Recession", which was exacerbated by the "Global Financial Crisis", a large literature has evolved, which aims to measure uncertainty – a latent variable – and empirically evaluate the impact of uncertainty on the macroeconomy and financial markets (see for example, Chuliá et al., (2017a) and Gupta et al., (2019) for literature reviews). As far as quantifying uncertainty is concerned, multiple approaches have been developed (see, Strobel (2015) and Plakandaras et al., (2019) for detailed discussions). Ideally, analysing the impact of uncertainty on fast moving financial market returns and volatility would require measures of uncertainty at a high (for example, daily) frequency. However, most of the measures of uncertainty are only available at lower (monthly and quarterly) frequencies, and if available daily, the sample periods are restricted only going back to 1985 (see, Gupta et al., (2018) for rigorous discussions in this regard). As such, it has been a challenge to estimate the historical impact of uncertainty on financial markets as well as evaluate whether the effect is time varying. However, the recent work of Chuliá et al., (2017b), provides a solution to this issue by developing a daily measure of financial market uncertainty for the United States (U.S.) dating back to 1927.

Given that the equity market is an accepted leading indicator of the overall macroeconomy (Plakandaras et al., 2017), high frequency information indicating the direction of the stock market following shocks is of paramount importance to policymakers. Moreover, historically evaluating previous the results of previous shocks, likely improves the design of policies (for example Bernanke's work on the financial accelerator in the Great Depression greatly influenced the policies used during the 2008 financial crisis). Against this backdrop, unlike the existing literature that is restricted to analysing only 35 years or so of recent data, the objective of this paper is to provide a historical perspective on the evolution of the high-frequency daily impact of uncertainty shocks on the first and second moments of stock returns of the U.S. over 80 years (18th March, 1936 to 30th November, 2016). Even though data on uncertainty is available from the 6th January 1927, given the importance of monetary policy shocks on stock market movements (Bernanke and Kuttner, 2005; Kishor and Marfatia, 2013), we could only start our analysis on 18th of March 1936, which corresponds to the first available date of meeting of the Federal Open Market Committee (FOMC).

Intuitively, uncertainty is expected to negatively affect stock returns and increase volatility, through a decline in the level of the discount rate (and future cash flows), and increases in its volatility, respectively (Pastor and Veronesi, 2012; Arouri et al., 2016; Kaminska and Roberts-Sklar, 2018). The remainder of the paper is organized as follows: Section 2 discusses the data and methodology, while Section 3 presents the results, and Section 4 concludes.

2. Data and Methodology

Our analysis involves daily information on the Center for Research in Security Prices (CRSP) stock returns, uncertainty, monetary policy shocks and the recession dummy, over the period of 18th March, 1936 to 30th November, 2016. The CRSP stock returns (*r*) is obtained from the data library of Professor Kenneth R. French,[1] while the daily recession dummy (*rec*) comes from the FRED database of the Federal Reserve Bank of St. Louis. To compute the exogenous monetary policy shocks, we use the first-difference of the appropriate interest rate variable on the FOMC dates

[1] The data is downloadable from: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

(and zero otherwise),[2] and then regress it on the recession dummy and recover the residual. The positive residuals are identified as a contractionary shock (mps^{pos}), and the negative ones as an expansionary shock (mps^{neg}).[3] As far as the interest rate variable is concerned, we use the 3-month Treasury bill rate over the period of 17th March, 1936 till 30th June, 1954, the effective Federal funds rate from July 1st, 1954 to 15th December, 2008 and then from 16th December 2015 to 30th November, 2016, with data derived from the FRED database. For the time period of 16th December, 2008 till 15th December, 2015, which corresponds to the zero lower bond (ZLB) scenario, we used the shadow short rate developed by Krippner (2013) based on models of term-structure.[4] The yield curve-based framework developed by Krippner (2013) essentially removes the effect that the option to invest in physical currency (at an interest rate of zero) has on yield curves. This results in a hypothetical "shadow yield curve" that would exist if the physical currency were not available.[5]

Finally, financial market uncertainty is measured using the metric developed by Chuliá et al., (2017b), who uses 25 portfolios of stocks belonging to the NYSE, AMEX, and NASDAQ, which comprises the CRSP stock index, sorted according to size and their book-to-market value. These authors follow a two-step process for the construction of their uncertainty index. First, they remove the common component of the series under study and calculate their idiosyncratic variation by filtering the original series using a generalized dynamic factor model (GDFM). Second, these authors calculate the stochastic volatility of each residual in the previous step using Markov chain Monte Carlo (MCMC) techniques. Then, Chuliá et al., (2017b) obtain a single index of uncertainty for the stock market by average the series.[6] As with the monetary policy, to capture possible asymmetric effects of increases and decreases in uncertainty changes (shocks), we work with the positive (unc^{pos}) and negative (unc^{neg}) growth rates of this financial market uncertainty index.[7]

Having defined the data, we now turn our attention to the econometric framework. Note that, one empirical observation associated with equity markets is that, the impact of negative price moves on future volatility is different from that of positive ones. The Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model of Nelson (1991) captures this feature by its design of the volatility process. Formally, the EGARCH model used in this paper can be described as follows:

$$r_t = \mu_0 + \mu_1 mps_t^{pos} + \mu_2 mps_t^{neg} + \mu_3 unc_t^{pos} + \mu_4 unc_t^{pos} + \mu_5 rec_t + \sigma_t \varepsilon_t \tag{1}$$

where, ε_t is a sequence of $N(0, 1)$ *i.i.d.* random variables, and

$$\ln(\sigma_t^2) = \alpha_0 + \frac{\alpha_1 a_{t-1} + \gamma \mid a_{t-1} \mid}{\sigma_{t-1}} + \beta \ln(\sigma_{t-1}^2) + \theta_1 mps_t^{pos} + \theta_2 mps_t^{neg} + \theta_3 unc_t^{pos} + \theta_4 unc_t^{pos} + \theta_5 rec_t \tag{2}$$

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2 The historical FOMC dates are available at: https://www.federalreserve.gov/monetarypolicy/fomc_historical_year.htm.

3 Our results were qualitatively similar, if we just used the changes in the interest rate on FOMC dates without filtering the recessionary impact. Complete details are available upon request from the authors.

4 The data is available for download from: https://www.rbnz.govt.nz/research-and-publications/research-programme/additional-research/measures-of-the-stance-of-united-states-monetary-policy.

5 The process allows one to answer the question: "What policy rate would generate the observed yield curve if the policy rate could be taken as negative?" The shadow policy rate generated in this manner, therefore, provides a measure of the monetary policy stance after the actual policy rate reaches zero.

6 The data can be downloaded from the website of Professor Jorge M. Uribe at: http://www.ub.edu/rfa/uncertainty-index/.

7 To construct the uncertainty shocks, we define a dummy variable which takes the value of one when the growth in uncertainty is positive (negative) and zero otherwise, and then multiply the growth in the uncertainty variable with this dummy to get the corresponding positive (negative) innovation in uncertainty.

where $a_t = \sigma_t \varepsilon_t$. Notice that there is an asymmetric effect between positive and negative returns. Also, to avoid the possibility of a negative variance, the model is an *AR*(1) on $\ln(\sigma_t^2)$ rather than σ_t^2. Based on our discussion in the introduction, we allow both monetary policy and uncertainty shocks, as well as recessions (see for example, Hamilton and Lin (1996) and Atanasov (2018)), to affect both stock returns and its volatility.

3. Empirical Findings

The estimation results for equations (1) and (2) have been reported in Table 1. As can be seen from the table, the leverage effect, as suggested by a negative and statistically significant estimate of α_1, is clearly visible. This clearly supports our modelling strategy. Evaluating the impact of monetary policy, we find that contractionary monetary policy (mps^{pos}) reduces stock returns in a statistically significant manner at the 5% level with no impact on volatility. However, expansionary monetary policy (mps^{neg}) increases volatility significantly but does not impact returns. Recessions are found to increase volatility at the 1% level of significance. As far as uncertainties are concerned, unc^{pos} reduces stock returns at the 1% level of significance, while a decline in the uncertainty growth (unc^{neg}) enhances stock returns weakly at the 10% level of significance. Both these measures however, have a statistically significant impact on volatility, with unc^{pos} increasing volatility and unc^{neg} reducing the same at the 1% level of significance. But the impact of unc^{pos} is much stronger than that of unc^{neg} in terms of its impact on the risk associated with the U.S. stock returns, as suggested by the rejection of the null of equality ($\theta_3=\theta_4$) under a Wald test at the highest possible level of significance. In general, our results are in line with common intuition. Negative news, i.e., increases in uncertainty, has a stronger impact on financial markets, than positive news, i.e., a decline in the growth of uncertainty (Hatemi-J, 2012). In addition, uncertainty is found to influence the second moment more strongly than the first moment, a result in line with general findings associated with stock market movements and uncertainty, since uncertainty affects the variance of financial markets through volatility jumps (Gupta et al., 2018).[8] In sum, the effect of uncertainty on stock market is found to be theoretically consistent, with increases in uncertainty reducing returns and enhancing volatility.

Table 1. Estimation Results of EGARCH Model (18th March, 1936 - 30th November, 2016)

Parameter	Estimate	Std. Error	z-Statistic	Prob.
		Mean Eq.		
μ_0	0.0598	0.0068	8.7984	0.0000
μ_1	-0.1774	0.0896	-1.9786	0.0479
μ_2	0.0342	0.0618	0.5538	0.5797
μ_3	-4.2402	1.5505	-2.7347	0.0062
μ_4	2.8767	1.4843	1.9381	0.0526
μ_5	0.0027	0.0163	0.1662	0.8680

[8] While, FOMC meeting dates are not available prior to 18th March, 1936, daily data on interest rates (i.e., the risk-free rate), is indeed available from Professor French's data library for the period of 6th January, 1927 till 17th March, 1936, as are the other variables of interest from their respective sources. Given this, we take first-difference of the risk-free rate over this additional period as monetary policy shocks, and merge with our existing data set, and then re-conduct the analysis again. The results have been now reported in Table A1 in the Appendix of the paper. As can be seen, our results are qualitatively similar to those reported in Table 1 (except now mps^{pos} does not have a significant negative effect on stock returns, but reduces volatility significantly). In other words, the effect of uncertainty shocks is robust, irrespective of how monetary shocks are measured.

Variance Eq.				
α_0	-0.1040	0.0032	-32.3967	0.0000
α_1	-0.0631	0.0021	-30.0341	0.0000
γ	0.1111	0.0034	32.9180	0.0000
β	0.9798	0.0010	967.1584	0.0000
θ_1	-0.0021	0.0595	-0.0347	0.9723
θ_2	0.0915	0.0404	2.2661	0.0234
θ_3	-0.8974	0.1692	-5.3033	0.0000
θ_4	3.2338	0.1346	24.0307	0.0000
θ_5	0.0051	0.0018	2.8232	0.0048
Log-Likelihood	-24037.30	AIC		2.3007

Note: The estimates correspond to the following EGARCH model: $r_t = \mu_0 + \mu_1 mps_t^{pos} + \mu_2 mps_t^{neg} + \mu_3 unc_t^{pos} + \mu_4 unc_t^{pos} + \mu_5 rec_t + \sigma_t \varepsilon_t$ (Mean Eq.), and

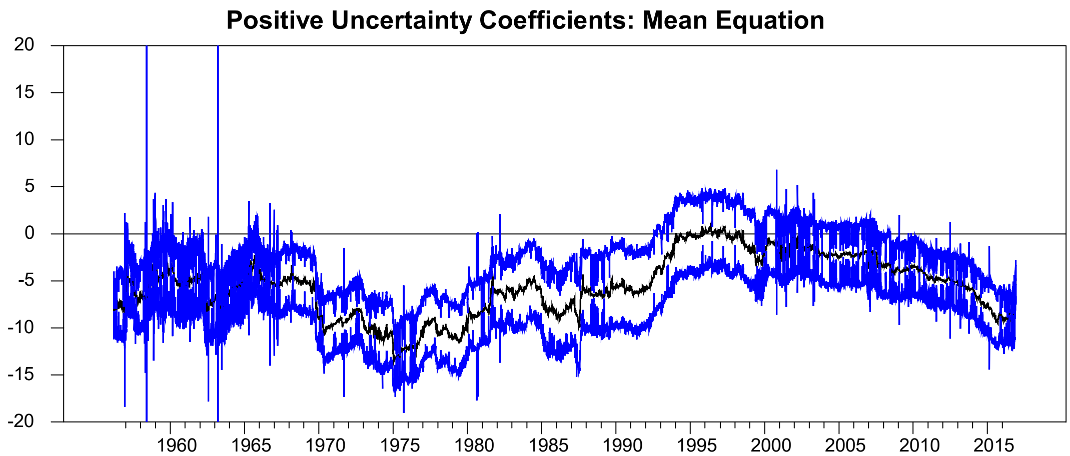
$$\ln(\sigma_t^2) = \alpha_0 + \frac{\alpha_1 a_{t-1} + \gamma \,|\, a_{t-1} \,|}{\sigma_{t-1}} + \beta \ln(\sigma_{t-1}^2) + \theta_1 mps_t^{pos} + \theta_2 mps_t^{neg} + \theta_3 unc_t^{pos} + \theta_4 unc_t^{pos} + \theta_5 rec_t$$

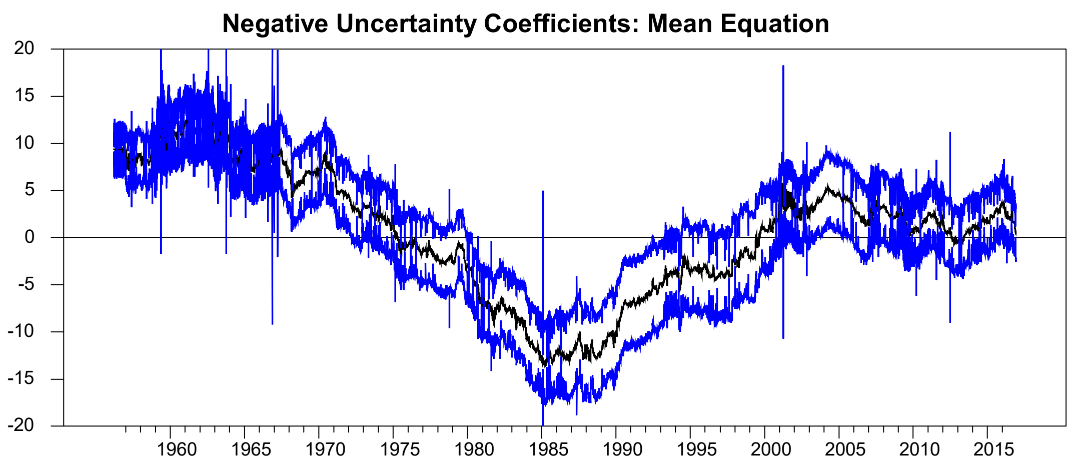
(Variance Eq.).

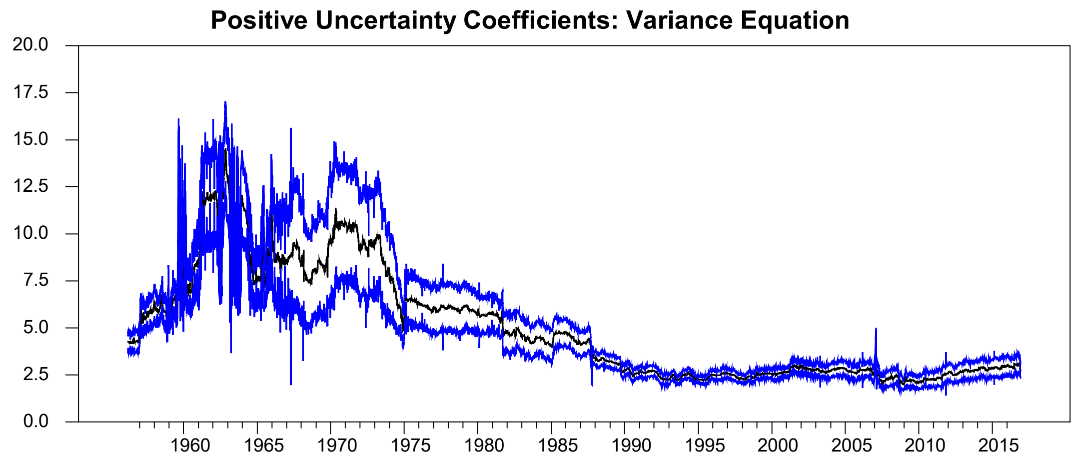
Unlike time spans analysed in existing literature, we analyse a long span of daily frequency data (i.e., more than 80 years). It is therefore likely that effects of uncertainty on the financial markets has changed over time. We now focus on the rolling coefficients (μ_3, μ_4, θ_3, and θ_4) of unc^{pos} and unc^{neg} in both the returns and volatility equation to capture the time-varying impact of uncertainties. For our purpose, we use a rolling window covering the period of 17th March, 1936 till 30th June, 1954, i.e., 5267 observations. The idea is to begin the time-varying estimates of these coefficients from the date on which the effective Federal funds rate data is available, which in turn corresponds to the actual measure of monetary policy shocks for the U.S.[9] The rolling estimates of the coefficients, along with their 95% confidence bands, are reported in Figure 1. As can be seen, the impact of positive growth of uncertainty always tends to reduce returns and increase volatility. as Also, negative growth rates in uncertainty tend to increase equity returns and reduce volatility, barring the 1980s till mid-1990s, when the impact on stock returns is negative in a statistically significant manner, and from late 1980s to early 2000s, when volatility is statistically increased. The decade of 1980 can be associated with monetary policy uncertainty due to high interest rates aimed at curbing double digit inflation. This was also the period that witness interest rate volatility (Friedman, 1988) as well as financial market liberalization. So possibly, even when uncertainty growth was negative, high interest rate and volatility was driving the vulnerability of the stock market during the 1980s by outweighing falls in uncertainty growth. In contrast, the 1990s period witnessed rapid growth in the stock market due to sound monetary policy and technological innovation, which in turn could have led to higher trading volumes and hence volatility even when financial market uncertainty was possibly low, until the dot com bubble in 2001 led to a crash of the U.S. equity market (Jermann and Quadrini, 2006; 2007).

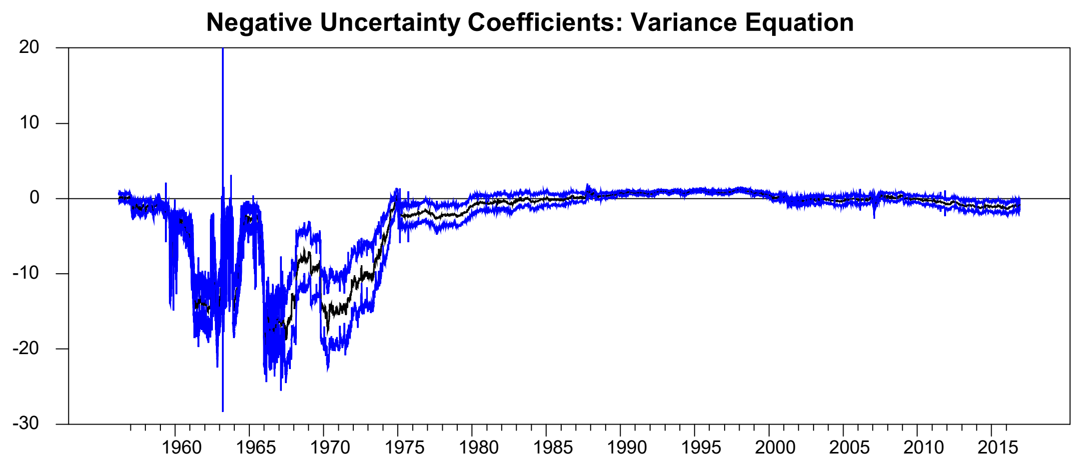
Figure 1. Time Varying Impact of Positive and Negative Uncertainty Growth on Stock Returns and Volatility

[9] However, our results are qualitatively similar to a bigger size of the rolling window involving 10 years of data. Complete details of these results are available upon request from the authors.


Positive Uncertainty Coefficients: Mean Equation
20
15
10
5
0
-5
-10
-15
-20
1960
1965
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015


Negative Uncertainty Coefficients: Mean Equation
20
15
10
5
0
-5
-10
-15
-20
1960
1965
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015





4. Conclusion

In this paper, we analyse the impact of financial uncertainty shocks on stock returns and volatility of the U.S. equity market over the period of 18th March, 1936 to 30th November, 2016. Controlling for impact of monetary policy shocks and recessions, we consider the possible asymmetries in the impact of uncertainty shocks. We find that expansionary monetary policy and recessions increase volatility, while contractionary shocks reduce stock returns. In addition, turning to the main focus of the paper, we observe that positive growth rates of uncertainty reduce stock returns and increases volatility, while negative growth rates of uncertainty primarily reduce stock market variance. A rolling window estimation over the period of 30th June, 1954 to 30th November, 2016 clearly show that the magnitude of financial market's response to uncertainty shocks has greatly varied over the last eight decades. However, the direction of impact is largely in conformity with the static case, with some exceptions associated with negative growth rates of uncertainty for the decades of 1980s and 1990s. Our study essentially confirms that financial market uncertainty has historically impacted the risk profile of the U.S. equity market, with increases in uncertainty having a stronger impact than decreases of the same.

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APPENDIX

Table A1. Estimation Results of EGARCH Model (6th January, 1927 - 30th November, 2016)

Parameter	Estimate	Std. Error	*z*-Statistic	*p*-value
		Mean Eq.		
μ_0	0.0589	0.0066	8.9698	0.0000
μ_1	-0.0197	0.0138	-1.4329	0.1519
μ_2	0.0015	0.0162	0.0915	0.9271
μ_3	-3.6501	1.3779	-2.6491	0.0081
μ_4	1.4853	1.3164	1.1283	0.2592
μ_5	0.0026	0.0141	0.1808	0.8565
		Variance Eq.		
α_0	-0.1088	0.0029	-38.1904	0.0000
α_1	-0.0614	0.0019	-32.2449	0.0000
γ	0.1253	0.0032	39.0688	0.0000
β	0.9826	0.0008	1204.2060	0.0000
θ_1	-0.0251	0.0075	-3.3571	0.0008
θ_2	0.0102	0.0070	1.4731	0.1407
θ_3	-0.6711	0.1501	-4.4719	0.0000
θ_4	2.7224	0.1141	23.8603	0.0000
θ_5	0.0054	0.0015	3.6148	0.0003
Log-Likelihood	-28634.43	AIC		2.4235

Note: See Notes to Table 1.