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Changes in Global Equity Prices Precede Changes in Global Expressions of Economic Policy Uncertainty

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Abstract

Using global economic policy uncertainty data from 1997-2016 and coincident data from the MSCI World Stock Index, we present empirical evidence that global stock prices change first and expressions of global economic policy uncertainty change subsequently. This contradicts a prevailing assumption that events and related economic policy uncertainty cause price changes in the stock market. Instead, we propose that another variable, natural fluctuations in unconscious social mood, causes changes in equity prices and feelings of uncertainty and subsequently manifests in expressions of economic policy uncertainty, macroeconomic performance and the aggregate tenor and character of social events.

Introduction

Over the past century, from the decade-long Great Depression to the current era of instantaneous global communication, predominant models of economic decision making have evolved and diversified. Important developments range from rational choice to bounded rationality (Simon 1967; Akerlof 1970) to theories that distinguish between financial and economic decision making (Prechter and Parker 2007), to theories that prioritize emotions (Lerner et al. 2015) and human evolution and cognitive biases (Santos and Rosati 2015; Kahneman 2011), to the accelerating and distorting effects of social media on the informational landscape and on financial and other decisions (e.g. Bentley et al. 2014a; Phillips et al. 2017).

Given the evolution of the theoretical, social and technological landscape, we ought to consider how multiple layers of behavioral dynamics contribute to financial decision making. One layer of financial decisions is rational; we traditionally expect stock prices to reflect macroeconomic activity (e.g. Nasseh & Strauss 2000) and, according to the expectations hypothesis, we expect changes in interest rates to inversely affect stock market returns (e.g. Alam & Uddin 2009; Amarasinghe 2015; Çifter and Ozun 2008; Muradoglu et al. 2000; Salimullah 2015; Zafar et al. 2008). There are other layers to financial decisions, however. Another layer is social influence, while yet another is emotional, and the two are likely to be related. In recent decades, new messaging and information technologies have accompanied a vast increase in the number of choices people make on a daily basis (Beinhocker 2006; Bentley and O'Brien 2017; Sela & Berger 2012), implying less time to consider each decision, including financial transactions (Saavedra et al. 2011). In contexts where there is a decrease in time and reliable information by which to make decisions, uncertainty increases, and we could expect other drivers of decisions to become more evident, such as social influence and emotions.

While information and uncertainty about events play a role in decision-making, following the development of the concept of bounded rationality (Akerlof, 1970) and the incompleteness and variation of information among individual decision-makers, the variance in stock returns can be partly explained by a layer of "something other than news about fundamental values" (Cutler et al., 1989). Among the leading candidates is social influence, which is considered a primary driver of human behavior in fields such as anthropology, ecology and sociology (Hoppitt & Laland, 2013) and has come to be viewed as at least as important as objective information in economic decisions (e.g. Durlauf & Young, 2001; Brock & Durlauf, 2007; Bentley et al., 2014a; Young, 2015). On a short time scale, the ubiquity of social media has facilitated the spread of false information that can—through re-Tweeting, for example— spread faster and reach more users than true information (Vosoughi et al. 2018). False rumors on social media have been documented to affect stock prices (Rapoza 2017).

Besides information, emotions are central to decision-making (Lerner et al. 2015; Taquet et al. 2014), including economic and financial decisions (Park and Sela 2018; Loewenstein 2000; Rick & Loewenstein 2008). The emotions of fear versus anger, for example, lead decision-makers to be more versus less risk-averse, respectively (Lerner & Keltner 2001). Research on emotions and decisions has greatly increased through the availability of online texts, as words in different sentiment categories can be counted and their relative frequencies compared to real-world events (e.g., Acerbi et al. 2013; Bentley et al. 2014b; Bollen et al. 2011; Curme et al. 2014; Preis et al. 2013). Fluctuation in unconscious public sentiments, which arise endogenously and imbue societies with feelings ranging from predominant optimism to predominant pessimism, is another candidate for explaining non-mean-reverting dynamism in financial markets. In contrast to economic decisions, in which the law of supply and demand operates among rational valuers to produce equilibrium in the marketplace for utilitarian goods and services, financial decisions are made in contexts of uncertainty about valuations by other market speculators, which induces unconscious, non-rational herding (Prechter and Parker 2007). Aggregate psychological states manifest quickly in financial markets and later become evident across the spectrum of social behavior (Prechter 1999, 2003, 2016; Parker & Prechter 2005, Olson 2006, Casti 2010, & Nofsinger, 2010). Under this view, fluctuations in "social mood" – such as confidence versus fear, amity versus anger, certainty versus uncertainty – influence social actions and events, not vice versa. In other words, natural fluctuations in unconscious social mood cause changes in equity prices and feelings of uncertainty, and subsequently manifest in expressions of economic policy uncertainty, macroeconomic performance and the tenor and character of political and cultural events.

The more predominant alternative to the social psychology view is that events drive feelings of (un)certainty, which subsequently affect equity prices and the economy (Bloom 2009, Baker et al., 2013). If certain dramatic events trigger a recession, for example, the resulting uncertainty further exacerbates the recession (Bloom, 2013). So, policy uncertainty not only increases stock price volatility, but also reduces investment and employment in policy-sensitive sectors (Baker et al., 2015). Under this view, events cause changes in feelings of uncertainty and expressions thereof, and subsequently manifest in changes in equity prices and macroeconomic performance.

We aim to distinguish which of the above two hypotheses more accurately accounts for certain empirical evidence. Our primary goal in this paper is to examine the chronology of changes in expressions of economic policy uncertainty relative to changes in stock prices. Under the socionomic hypothesis, stock price changes should generally precede changes in expressions of economic policy uncertainty, whereas the reverse should occur under the alternative hypothesis—uncertainty should precede the stock market.

How can we measure expressions of economic policy uncertainty and then compare them to trends in equity markets? Measures of changes in public emotional states derived from emotion-related words used online or in news articles, books and other publications have shown promise in the literature. In an influential study, Bollen et al. (2011) found that during a period of about two and a half weeks in December 2008, a model that incorporated the usage of "calm" words on Twitter predicted the direction of daily changes in the Dow Jones Industrial Average with an accuracy of approximately 87%. Subsequently, many other studies (Bordino et al., 2012; Choi & Varian, 2012; Liu et al., 2016) have explored how the use of emotion-laden words can be used to predict financial changes. Other authors have studied the usage of Google search terms to anticipate changes in equity prices. Preis et al. (2013) found that from 2004 to 2011, the three-week trend in Google search volume for "debt" could have been used to predict subsequent changes in the Dow Jones Industrial Average. Over a similar period, 2004 to 2012, Curme et al. (2014) found that increases in Google search volume for political or business topics tend to precede stock market declines. Other approaches have applied neural network algorithms to data—such as Internet search volumes, emotion words and/or social-media buzz— to make short-term predictions of socio-economic phenomena (Bordino et al., 2012; Challet et al., 2014; Dong & Bollen, 2015; Gayo-Avello, 2013; Garcia & Schweitzer, 2015; Yelowitz & Wilson, 2015).

Considering the difficulty of inferring causality from observational data (Clarke, 2005; Freedman, 2004), critics argue that these web-based studies suffer from the dangers of *post-hoc* explanation, lack of a causal theory and multiple hypotheses testing (e.g. Shalizi & Thomas, 2010; Challet and Ayed, 2014). Causality can be hard to identify, as economic choice models that consider social influence explicitly (e.g. Choi et al. 2012) usually face the difficult challenge of identifying and estimating the strength of endogenous social interactions as opposed to correlated unobservables and other identification problems (Brock & Durlauf, 2001, 2007, 2011; Blume et al., 2015). We overcome these critiques by using consistent causal theories to generate *ex ante* accounts of the expected relationship, which we examine empirically using validated measures. We also consider longer time scales than just days or weeks.

News-based uncertainty indices (Baker et al., 2016) offer the opportunity to represent expressions of uncertainty on a broader and longer time scale. To represent media expressions of economic policy uncertainty at the national and global scales, Baker et al. (2016) developed the Economic Policy Uncertainty (EPU) index, which indexes the coverage frequency of uncertainty-related news topics among more than ten thousand newspaper articles aggregated at monthly intervals. Each national EPU index reflects the relative frequency of own-country newspaper articles that contain a trio of terms pertaining to the economy, uncertainty and policy-related matters. These EPU indices have been aggregated into a publicly available (www.policyuncertainty.com/global_monthly.html) version called the Global Economic Policy Uncertainty (GEPU) Index, which is a GDP-weighted average of national EPU indices for 16 countries that account for two-thirds of global output.

Methods

Here we use monthly observations of the GEPU index from January 1997 to August 2016, the entirety of the index's coverage period at the time we gathered the data. To represent monthly equity prices, we use the MSCI World Stock Index (MSCI), a common and publicly accessible index derived from 1,650 large and mid-cap stocks from 23 stock markets of developed countries. The MSCI has been calculated since 1969 and covers approximately 85% of the free-float-adjusted market capitalization in each country.

To examine the temporal relationship between stock prices and expressions of economic policy uncertainty, we compare the time series of monthly MSCI data and GEPU data from January 1997 to August 2016. We look at whether a moving average of past changes or levels in one time series can be used to predict changes or levels in the other time series. We also test correspondences involving the monthly changes in MSCI and GEPU. After observing the relationships between these variables and their moving averages, we then test them more formally using Granger (1969) causality, which, while not a test of true causality, can be used to generate a statement about the incremental predictive value of time series (Geweke, 1984; Bollen et al., 2011; Heckman & Pinto, 2014). Time series *D* is said to "linear Granger cause" time series *U* if past values of *D* and *U* incrementally predict future values of *U* better than past values of *U* alone, using the following bivariate linear autoregressive model:

$$U(t) = \sum_{j=1}^{p} A_{11,j} U(t-j) + \sum_{j=1}^{p} A_{12,j} D(t-j) + \varepsilon_1(\mathrm{t}) \quad (1)$$

$$D(t) = \sum_{j=1}^{p} A_{21,j} U(t-j) + \sum_{j=1}^{p} A_{22,j} D(t-j) + \varepsilon_2(\mathrm{t}) \quad (2)$$

Where p is the maximum number of lagged observations in the model, A is a matrix of coefficients, and $U(t)$ and $D(t)$ are stationary time series representing the uncertainty and stock market indices, respectively. The regression errors ε_1 and ε_2 are assumed to be conditionally independent of the regressors at each time interval t (Greene, 2003, eq. 8.4; Clarke, 2005). We used the function "grangertest" in the statistical package R on four different sets of bivariate series: U versus D, ΔU versus D, U versus ΔD, and ΔU versus ΔD. The function grangertest executes a Wald test of the respective parameters for two possible versions of a Granger causality model. Since the test typically requires the data to be stationary, we performed two additional time series tests for unit root and stationarity on the GEPU and MSCI data series, the Dickey-Fuller test and the augmented Dickey-Fuller test.

In addition to testing the directionality of a possible causal relationship, we incorporate an analysis of generalized autoregressive conditional heteroscedasticity, or linear GARCH model (Engle et al., 1983, Bollerslev 1986; Andersen et al. 2006, sect. 3.2; Greene 2003: Chapter 11) to study volatility clustering in the uncertainty time series data. Here we use GARCH(1,1) tests on the GEPU monthly time series using the tseries package of R. Without testing the full range of more complex non-linear GARCH models (Franses & Van Dijk 1996; Andersen & Bollerslev 1998) and wavelet models (Gallegati 2008; Ismail et al. 2016), for our purposes to characterize volatility clustering in the uncertainty time series, we use the simpler linear GARCH(1,1) model which performs well for stock market data (Gokcan 2000). The linear GARCH (1,1) model assumes a symmetric news impact curve that allows big innovations to produce more volatility than small ones (Engle and Ng, 1993). As variance clustering is likely to occur on daily or intraday time scale (Martens 2002; Xie & Li 2010), we also perform a GARCH(1,1) test on daily EPU data, available for the U.S. As a measure of volatility clustering, a GARCH analysis of daily GEPU data would provide context for our Granger results, as a means of identifying narrow date ranges of clustered volatility that may point to events that could account for sudden spikes in uncertainty expressions, such as 9/11 or the invasion of Iraq in 2003. Unfortunately, daily GEPU data are unavailable, so we substitute daily U.S. EPU data as a proxy.

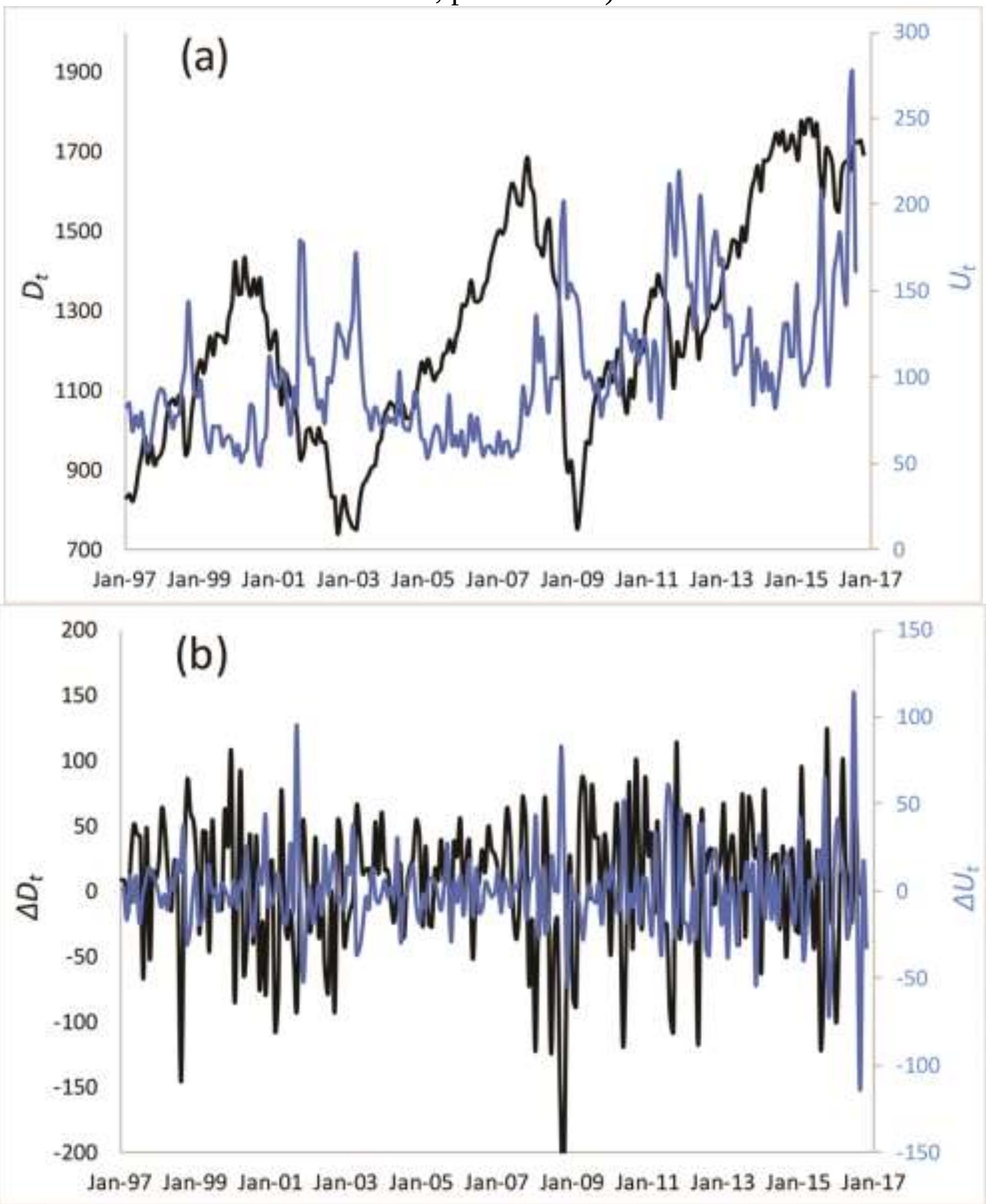
In our results below, we designate the time series for GEPU and MSCI as U and D, respectively, so that subscripts can be used to designate moving averages: for example, D_{12-} for the average of the *past* 12 months of MSCI and U_{12+} for average of the *future* 12 months of GEPU. Changes in GEPU and MSCI from the previous month's value are designated as ΔU and ΔD, respectively, with their moving averages using the same kinds of notation and previously described subscripts.

We also test the expectations hypothesis by examining the correspondence between MSCI and the U.S. Federal Reserve's Effective Federal Funds Rate, the interest rate at which banks and other depository institutions lend money to each other. And, we use Bayesian structural time-series models to infer causality between GEPU and MSCI. We report the results below.

Results

We first compare the time series of 235 monthly values for both GEPU, U, and MSCI, D, dating from January 1997 to August 2016. A key finding is that the relationship between MSCI data and subsequent GEPU data is far stronger than the relationship between GEPU data and subsequent MSCI data. Figure I shows four relevant plots as described below.

Figure I. Four illustrative comparisons of time series (1997 to 2016) and their moving averages, for global uncertainty, *U*, and MSCI index, *D*, as well as their respective changes, ΔU and ΔD. **(a)** Values of *D*, versus *U*, in real time with no significant correspondence (*D* vs. *U*: r = 0.093, *p* = 0.153). **(b)** Comparison of changes, ΔU, versus ΔD, in real time (r = 0.350, p < 0.0000001). **(c)** MSCI index, *D*, versus ΔU_{12+}, the moving average of monthly changes in uncertainty in the subsequent twelve months (r = 0.394, p < 0.00001). **(d)** Change in MSCI over the previous 12 months, ΔD_{12-}, versus the negative value of uncertainty index, -*U* (r = 0.427, p < 0.00001).



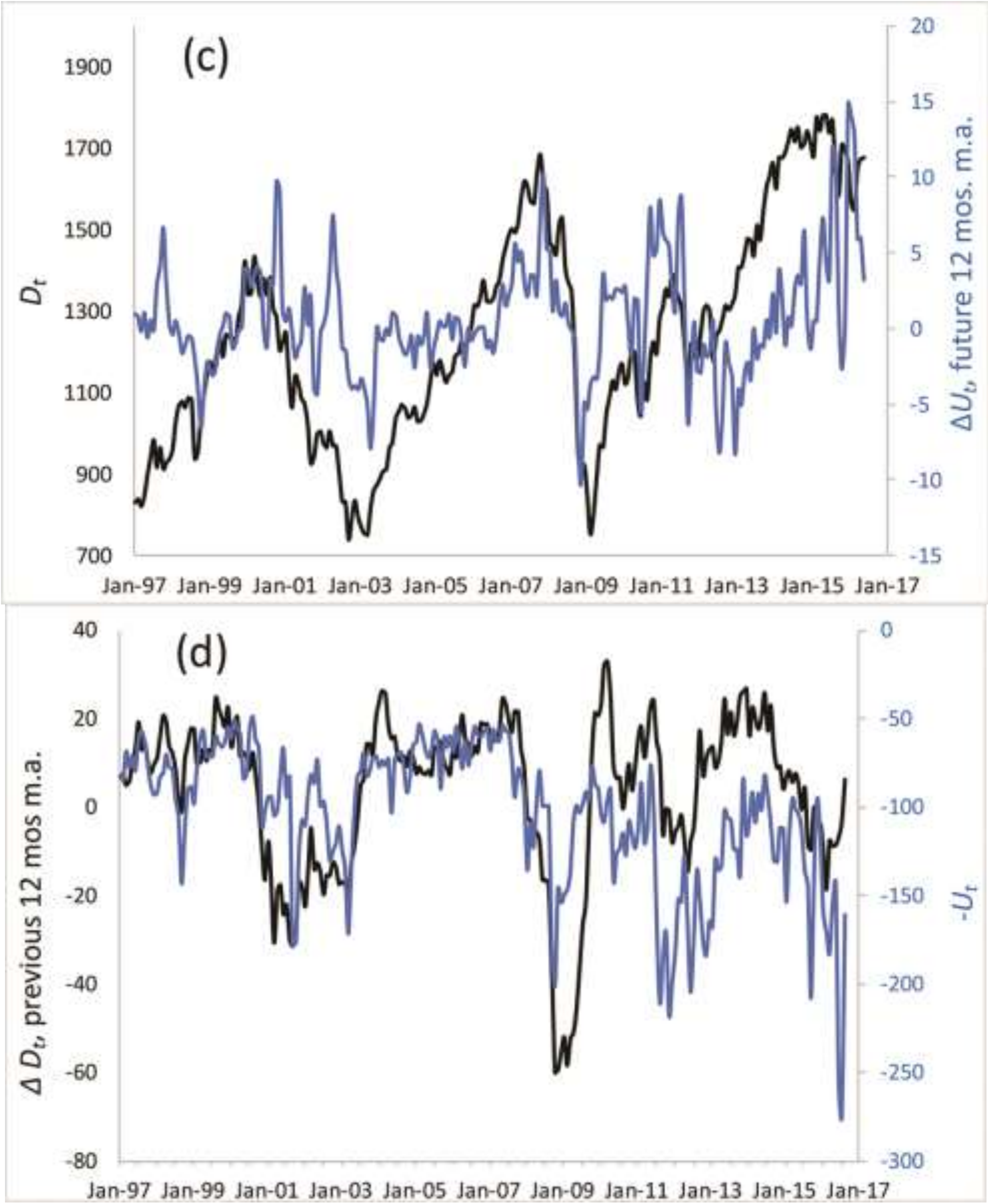
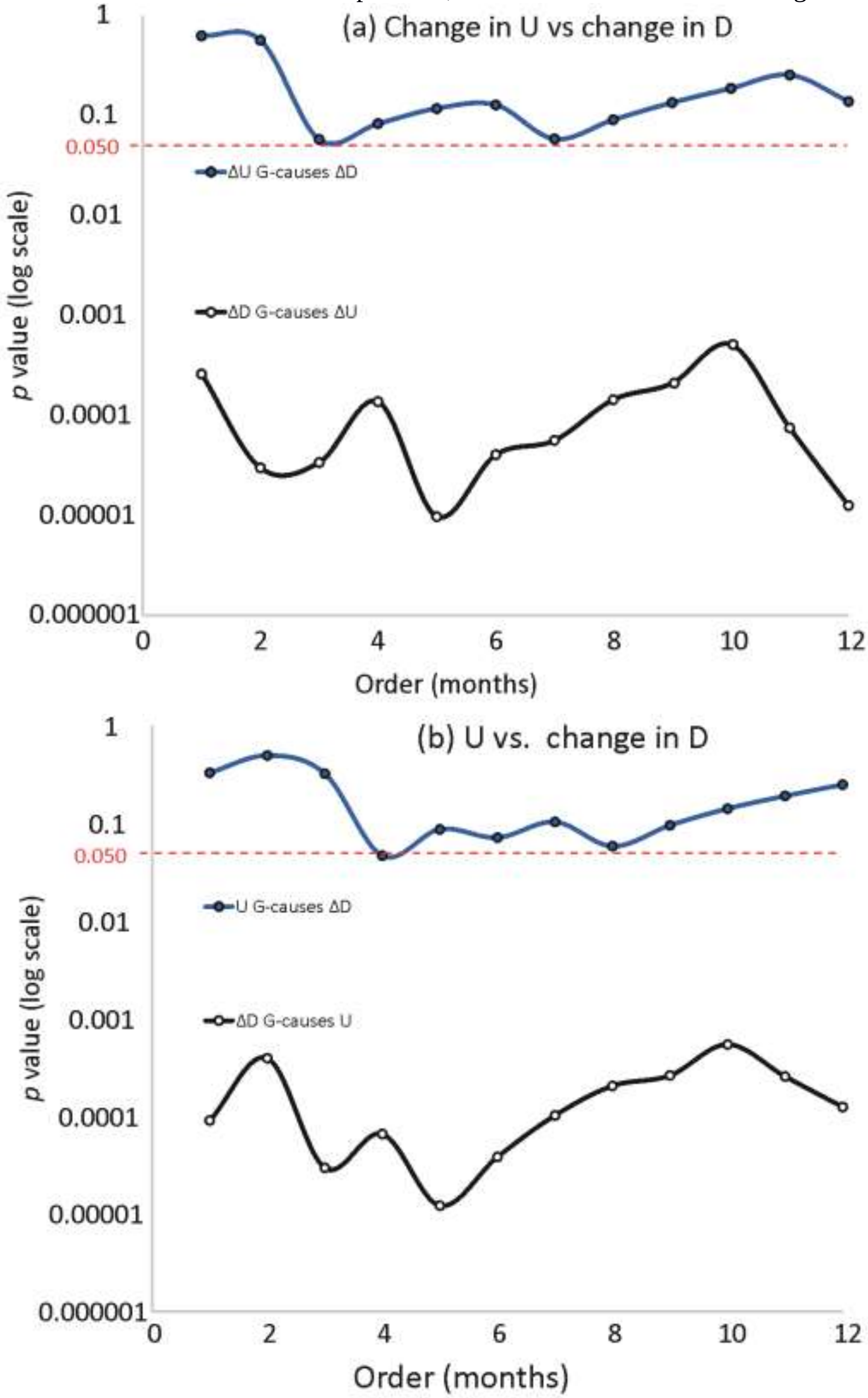


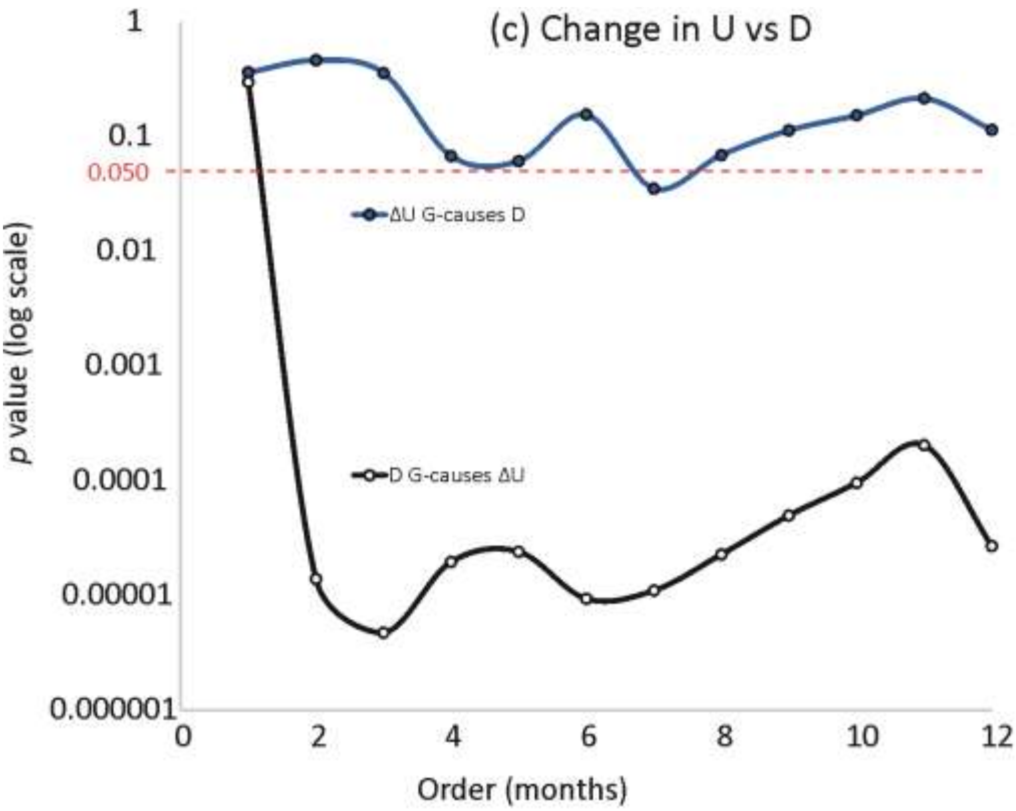
Figure I (a) shows the MSCI data, *D*, versus the uncertainty index, *U*, in contemporaneous months *t*, yielding no significant correspondence (*D* vs. *U*: r = 0.093, p = 0.153). The correspondence is significant, however, when we compare change in these phenomena, rather than their levels. Figure I (b) shows the correlation between contemporaneous changes in each, ΔU versus ΔD (r = -0.350, $p < 0.0000001$). In Figure I (c), we show the significant correspondence (r = 0.394, $p < 0.00001$) between the MSCI index, *D*, versus the average change in GEPU in the subsequent 12 months, ΔU_{12+}. Finally, Figure I (d) shows the average change in MSCI over the previous 12 months, ΔD_{12-}, versus "certainty", -*U* (we change the sign of *U* so the correspondence can be easily seen); the correlation (r = 0.427, $p < 0.00001$) is the strongest of the four panels in Figure I.

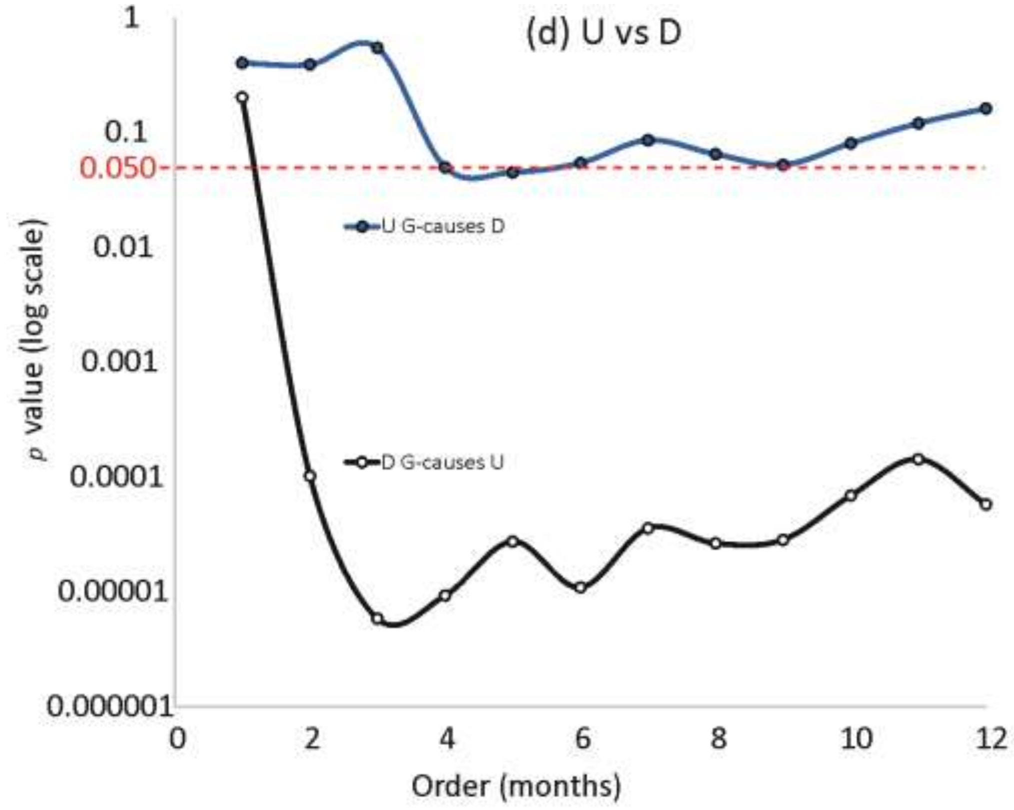
Given this evidence that changes in global stock market prices, *D*, precede those in expressions of economic policy uncertainty, *U*, we then tested the reverse, whether *U* can be used to predict *D*. We find no significant association between the past twelve months of GEPU, U_{12-}, and either *D* (r = 0.060, p = 0.37) or ΔD (r = 0.051, p = 0.45). Averaging fewer months of GEPU only reduced the Pearson correlation further. Similarly, there was no association between changes in GEPU and subsequent changes in MSCI. For moving averages of ΔU between one and twelve months, we find no significant relationship with D (max $r = 0.042$, $p = 0.52$ for D vs. ΔU_5). Overall, there was very little evidence that changes in expressions of global economic policy uncertainty, U, can be used to predict changes in global stock market prices, D.

Following this overall comparison, our next step was to test temporal relationships more formally through Granger causality analysis. We first confirm the stationarity of the data through an augmented Dickey-Fuller test for unit root (n = 239, Z(t) = -10.77, p < 10-4) and the Dickey-Fuller test for unit root (n = 248, Z(t) = -17.24, p < 10-4). We then made Granger causality tests on four different sets of bivariate series: U versus D, ΔU versus D, U versus ΔD, and ΔU versus ΔD. For the example *D~U*, in which *U* is designated as the Granger causal variable, the Granger test is of the model in which *D* is explained by the lags (up to a specified order, in months) of both *D* and *U*, versus a null model, in which *D* is only explained by the lags of itself, *D*.

Figure II. Several illustrative comparisons of Granger analysis results. For reference only, the red line in each chart indicates p = 0.05, a conventional threshold for significance.



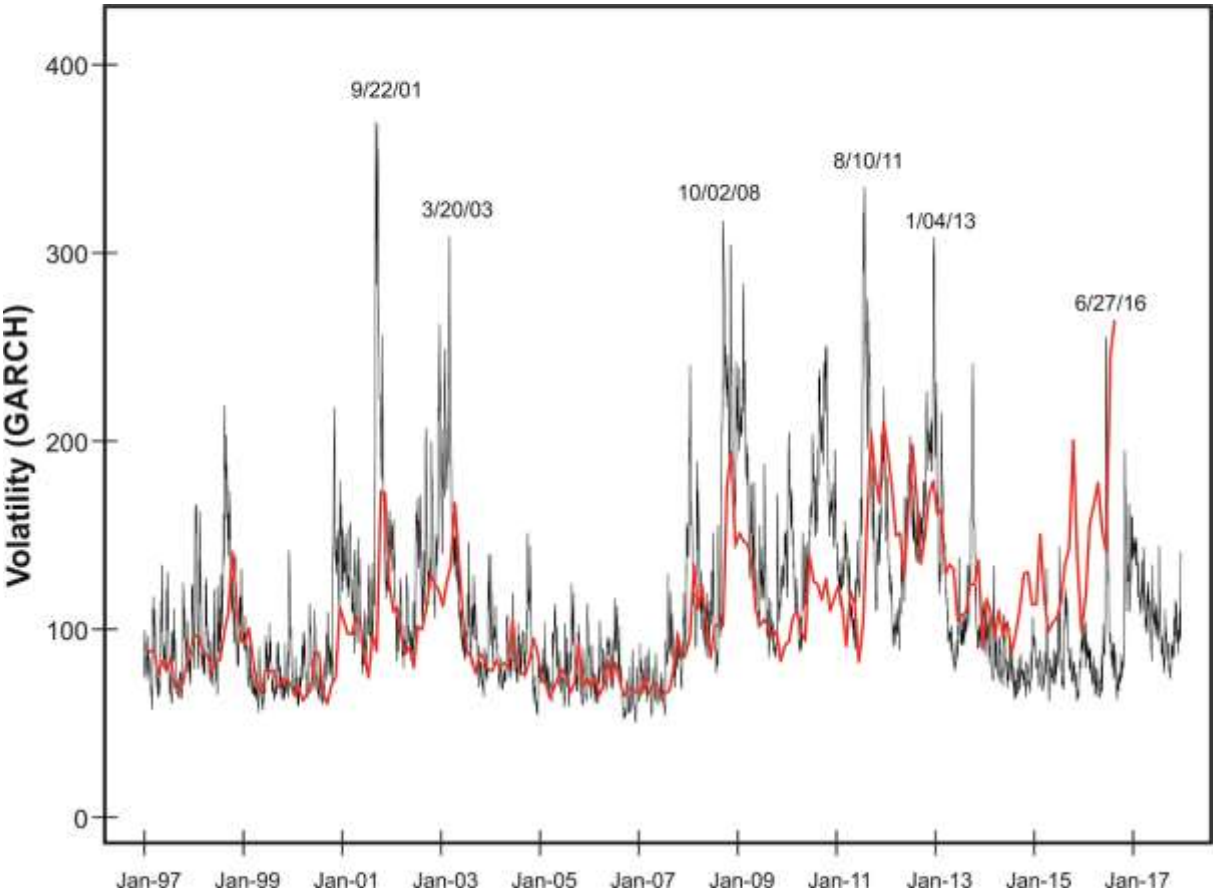




The results of these Granger tests (Figure II) show that the stock variable (*D*) or its change Granger-causes the economic policy uncertainty variable (*U*) or its change. In the tests using *D* as the causal variable, the most significant results ($p \leq 0.00001$) were observed at order 3 (i.e. up to 3 months lag) using *D* and at order 5 using Δ*D*. When *U* was tested as the causal variable, however, the results were insignificant at all orders in one of the tests

(ΔD~ΔU, minimum $p = 0.06$ at order 3), and insignificant ($p > 0.05$) at all orders except one in the other three tests: at order 4 for ΔD~U ($p = 0.047$), at order 7 for D~ΔU ($p = 0.035$) and at order 5 for D~U ($p = 0.046$). Each of the panels in Figure II show far stronger and more significant Granger-causal results when using the stock index as the causal variable. As a backup analysis, we also used the tests of Toda and Yamamoto (1995), which confirm that time series *D* predicts time series *U* with the following p-values from Wald tests: (*U*) -> (*D*) 0.86; (*D*) -> (*U*) 0.008. As introduced earlier and discussed further in the next section, our theoretical model is *not* that the stock market is causing the changes in economic policy uncertainty, but rather that a hidden variable, social mood, is regulating changes in both series.

Figure III. GARCH(1,1) models of volatility for daily US uncertainty data (black) and the monthly global uncertainty data (red) since 1997. For the daily case, the GARCH model is scaled by sqrt(252), based on 252 trading days per year, whereas the results for the monthly GARCH model are scaled by sqrt(12). All coefficients and residuals of both GARCH models (monthly and daily data) are significant at $p< 0.00001$.



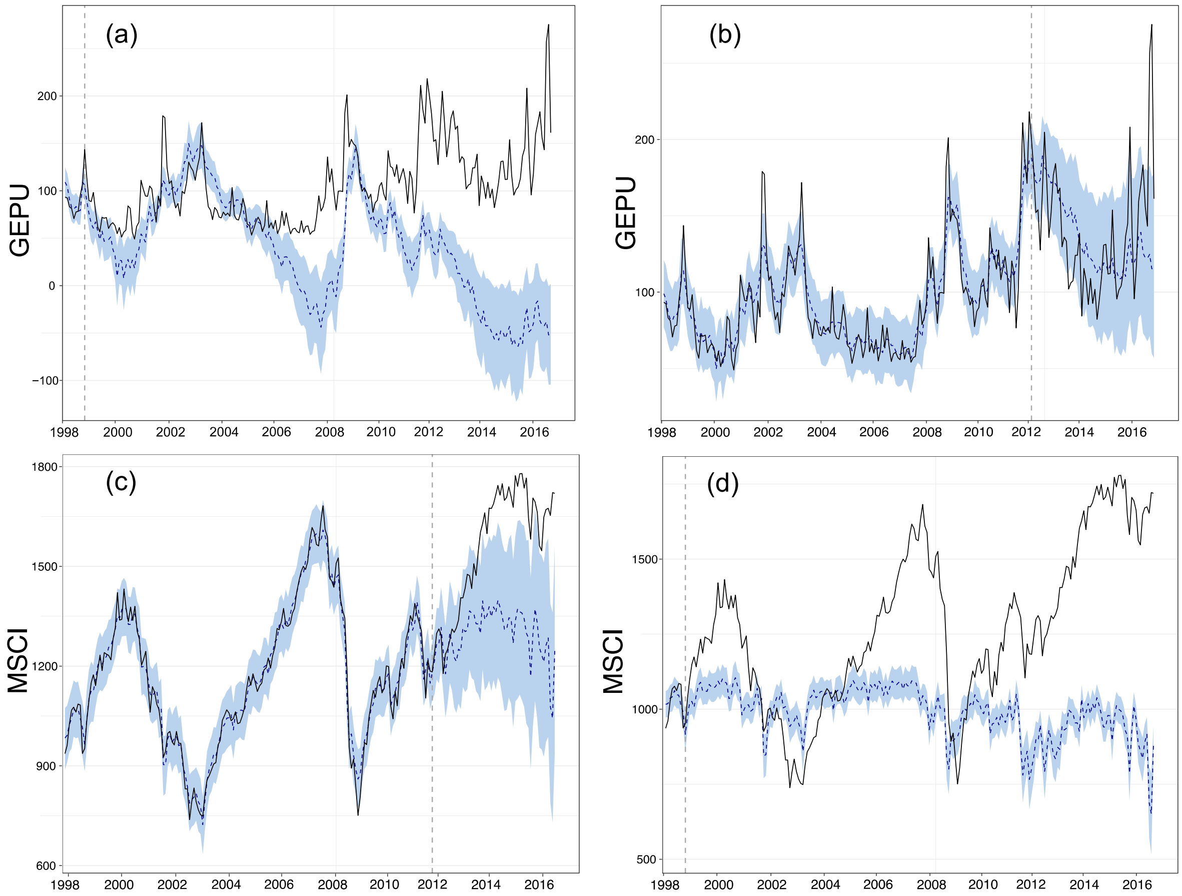
Our next test was to perform a GARCH(1,1) analysis on both the monthly global uncertainty data (GEPU), as well as on a daily EPU data set compiled for the United States.

As indicated in Figure III, the GARCH(1,1) models reveal a number of spikes in volatility clustering, the peaks of which occur on the following days: (1) September 22, 2001, (2) March 20, 2003, (3) October 2, 2008, (4) August 10, 2011, (5) January 4th 2013 and (6) June 27, 2016. Each of these peaks follows an internationally-known event, including (1) the terrorist attacks of September 11, 2001, (2) the U.S.-led invasion of Iraq on March 20, 2003 with global protests earlier that month, (3) the turmoil leading up to the bailout of the U.S. financial system (Emergency Economic Stabilization Act) on October 3, 2008, (4) the riots in England from August 6-11, 2011, (5) the U.S. budgetary "fiscal cliff" feared on January 1, 2013, and (6) the Brexit vote in the U.K. on June 23, 2016. We note how rare and short-lived each spike has been – just six noticeable spikes since 1997. With the reasonable assumption that these volatility clusters in uncertainty were associated with these events, the take-away message is how rare and large these events have had to be to affect volatility of the uncertainty index and how short-lived the effects of those events are in terms of uncertainty. Socionomic theory allows for short-term emotional reactions to exogenous events (Prechter 2016).

Next, we test one prominent alternative, the expectations hypothesis, which holds that changes in interest rates caused changes in stock market activity. We tested this with Granger tests on 234 monthly values for both the global stock index (MSCI) and the U.S. Federal Reserve's Effective Federal Funds Rate. The result revealed that the most significant relation was the MSCI predicting the Fed's interest rate changes four months later (df = 230): F = 3.7198, $p = 0.006$. Lagging the MSCI more than 4 months gave significant results, but always worse than lagging by four months. Lagging the MSCI by one or two months did not give significant results.

Finally, we use Bayesian structural time-series models to infer causality (Brodersen et al. 2015). The four plots in Figure IV show Bayesian predictions of one variable given the other, for MSCI and GEPU monthly data from 1998 to late 2017. In Figure IVa, we use the first ten months of MSCI data to "train" a model of the monthly uncertainty data. The plot in Figure IVb has it vice-versa: using the first ten months of the GEPU data to train a model of the MSCI data. In both plots, the blue shows the 95% confidence interval on the prediction. It is considerably better to use MSCI to predict GEPU (Figure IVa) than the other way round.

Figure IV. Bayesian structural time-series models using the R package CausalImpact (Brodersen et al. 2015). (a) Training a model on 10 months of MSCI data (up to dashed line) to predict GEPU data from months 11 to 225. (b) Training the model on 10 months of GEPU data (up to dashed line) to predict MSCI for months 11 to 225 (c) Training a model on 169 months of MSCI data (up to dashed line) to predict GEPU data from months 170 to 225. The prediction of MSCI is not significantly different from the uncertainty data (p = 0.47) (d) Training the model on 169 months of GEPU data (up to dashed line) to predict MSCI for months 170 to 225, The prediction of the GEPU data at alpha = 0.4 is significantly different from the MSCI data (p = 0.03). In all plots the shaded region around the prediction corresponds to alpha = 0.2.



This does not mean that markets necessarily cause the uncertainty, as the information may arrive via MSCI first, such that MSCI can be used to predict GEPU. It does mean that, in the past twenty years, changes in global stock market prices have preceded changes in global economic policy uncertainty. If we train the respective models instead for 170 months, from 1998 to 2012, the MSCI predicts GEPU well (Figure IVc), such that the prediction is not significantly different than the data ($p = 0.47$), but GEPU does not predict the MSCI (Figure IVd).

Discussion and Conclusions

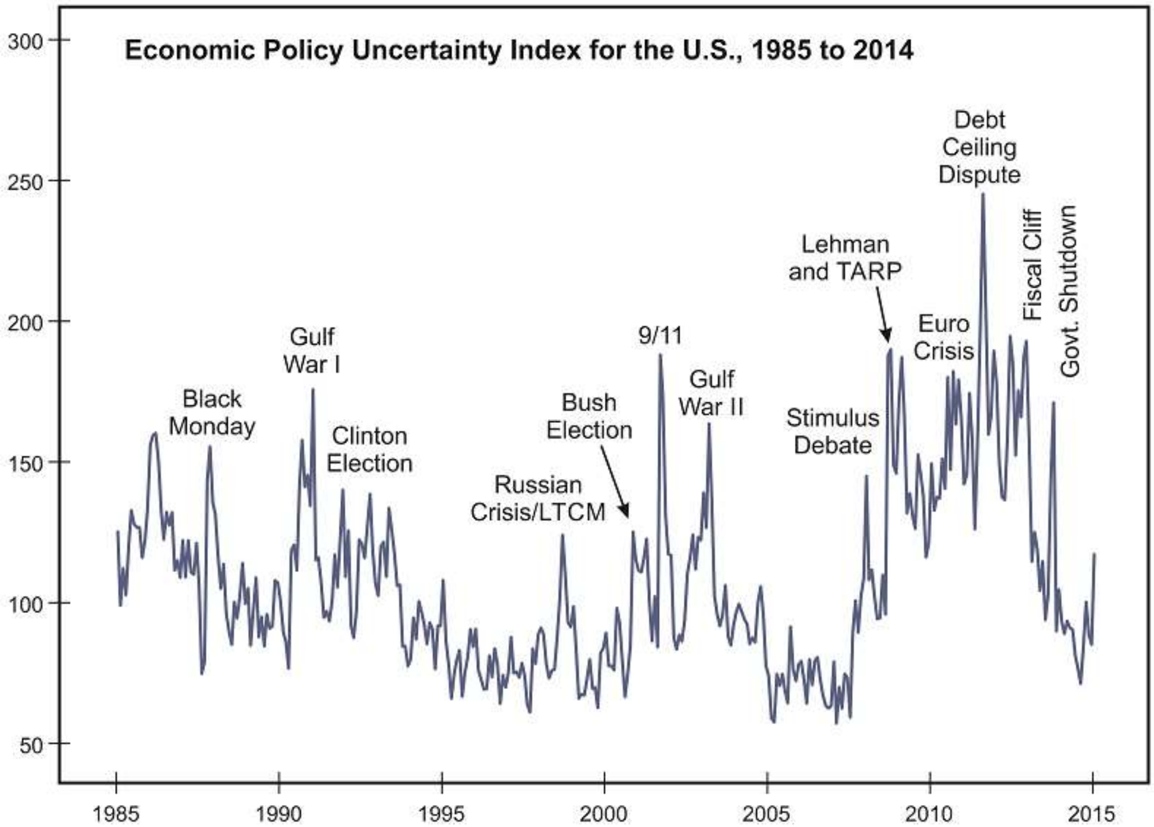
Our primary aim was to evaluate two hypotheses regarding stock prices and economic policy uncertainty. A prevailing view is that feelings of uncertainty are forward-looking, such that that economic policy uncertainty should precede changes in stock prices. In this view, network effects make the system more uncertain by giving rise to multiple equilibria and/or cascading effects that hinder the estimation of systemic risk (e.g. Caccioli et al. 2009; Haldane and May 2011; Acemoglu et al., 2015; Roukny et al. 2017). Our results, however, support the alternative hypothesis, that changes in stock prices should generally precede changes in expressions of economic policy uncertainty. Although this is not identification of causality, the temporal ordering of changes in stock prices before changes in expressions of uncertainty tends to undermine the hypothesis that changes in global economic policy uncertainty cause subsequent changes in global stock index prices.

Our results imply that global equity price changes precede changes in global expressions of economic policy uncertainty. We have modeled and charted how changes in the MSCI World Stock Index can be used to predict changes in the Global Economic Policy Uncertainty Index, in marked contrast to how poorly the Global Economic Policy Uncertainty Index or its changes can be used to predict the MSCI World Stock Index. The strongest correlation is between GEPU and the average of the previous twelve monthly changes in the MSCI. Generally, we find that the most significant correspondences involve the monthly *changes* in these data series rather than their levels.

How might one account for our results? One possibility is that feelings of uncertainty, and hence their expression, are fundamentally backward-looking. Both the stock market and GEPU could be responding to external events, with equity prices responding faster than expressions of economic policy uncertainty. Such backward-looking explanations are consistent with Bayesian approaches to behavior, in which human decision making, planning, learning, causal and abstract reasoning are drawn from evidence accumulated cumulatively through past experiences (Lee, 2006; Perfors et al., 2010; Steyvers et al., 2003; Xu & Tenebaum, 2007). In this view, human decisions are guided by individualistic models of the world based on personal observations, such that individuals continually update their models rationally using the new evidence. Certain models prioritize the most recent observations by discounting the past (Gureckis & Goldstone, 2009; Rendell et al., 2010; Lewandowsky et al., 2009a), whereas others take a moving average of past observations or events (Bentley et al., 2014b, 2015; Lewandowsky et al., 2009b).

Another explanation, generated from socionomic theory, posits that both stock prices and expressions of uncertainty are manifestations of unconscious social mood. Under this hypothesis, it makes sense that textual expressions of uncertainty would lag the stock market, because investors can buy and sell stocks slightly faster than news organizations can print stories that contain textual indications of uncertainty. Stock transactions also occur far faster than business actions and macroeconomic changes, which can take months to produce results. Long-term trends toward negative social mood first produce stock market declines and elevated uncertainty, and then expressions of that uncertainty, macroeconomic contraction, adverse public health outcomes (Hall et al., 2017; McKee-Ryan, 2005; Murphy & Athanasou, 1999; Paul & Moser 2009; Sullivan & von Wachter 2009; van Lenthe et al. 2005) and other cultural expressions. The inverse relationship that our tests identified between the MSCI World Stock Index and the Global Economic Policy Uncertainty Index is consistent with this account. The positive relationship between the MSCI index and the average change in GEPU in the subsequent 12 months (Figure I (c)) is also consistent with the premise that stock market declines occur, as responses to social mood, before the associated expressions of uncertainty.

Figure V. U.S. Policy Uncertainty Index and events listed by Baker et al. (2016).

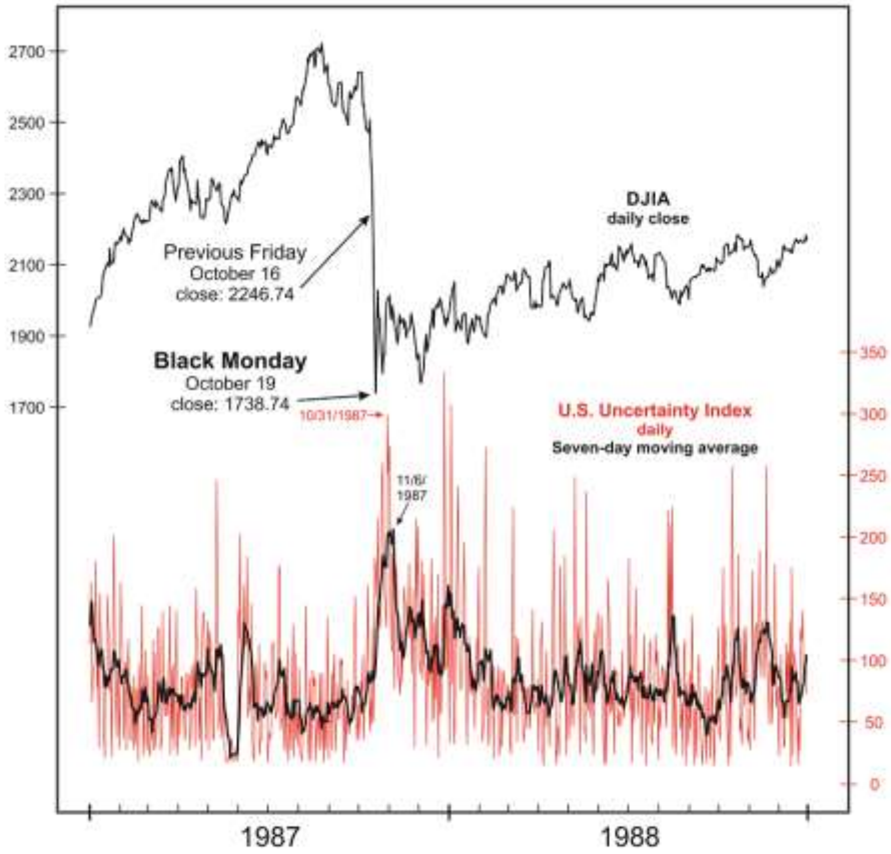


The results are also contextualizable with reference to the Efficient Market Hypothesis (EMH). EMH would assume that current stock prices adjust rapidly to the release of all new public information, such that the stock market responds to information before it is incorporated in the global uncertainty index. Unlike the socionomic view, however, EMH presumes that events, news and other information are principally responsible for stock price fluctuation. Thus EMH would expect major events to precede changes in both stock prices and expressions of uncertainty. Future studies with these time series can be used to test the hypothesis that particular events are the drivers of changes in uncertainty expressions (Baker et al., 2016; Bloom, 2009) and stock prices. As a prelude to this avenue of study, we show the U.S. Economic Policy Uncertainty Index from Baker et al. (2016), in monthly intervals from 1985 to 2014, including events that Baker et al. (2016) attribute as causes of changes in uncertainty expressions (Figure V). Numerous events listed in Figure V occurred at or near significant stock market lows, which often coincide with peaks in expression of uncertainty. This chronology suggests the events did not cause the stock declines. Furthermore, while some events may be associated with brief spikes in economic policy uncertainty expressions, we've shown evidence that changes in the stock market can account for the overall trends in economic policy uncertainty expressions, as measured via moving averages of EPU changes.

Proponents of the hypothesis that events cause stock prices to change might expect that the disastrous Tōhoku earthquake and tsunami of March 11, 2011 affected the Japanese stock market. The Tōhoku earthquake had little effect, however, on the trend of Japan's stock market. On February 28, 2011, the Nikkei 225 Index (charts are available online) stood at 10,624. On December 30, 2011, the Nikkei marked a low that has not been exceeded since, at 8,455, a 20% decline over 10 months. The tsunami disaster was monumental, but the subsequent stock decline was far smaller than several others, including the declines in 1990, 1992, 2000-2003 and June 2007-February 2009, none of which were preceded by exogenous disasters. Wikipedia's information timeline of the Fukushima Daiichi nuclear disaster, arguably one of the worst outcomes of the event, has continued through 2017, with many serious events occurring in 2013 and 2014. Yet, from the December 2011 low, the Nikkei rallied to 20,563 on May 29, 2015, a 143% gain over 41 months. Another of numerous similar examples is the spectacular terrorist attack of September 11, 2001. U.S. stocks declined for 20 months before the attacks, fell for only five days after the attacks, and then rallied strongly for six months. These chronologies suggest the events did not cause stock declines.

Consider also the infamous "Black Monday" stock market crash in October 1987, a market collapse for which there is no consensus explanation with regard to exogenous causal events (Prechter 2016). If we plot two years of daily DJIA data against the U.S. Daily News-based Economic Policy Uncertainty Index, we see that the Dow peak of August 25, 1987 coincided with low levels in the uncertainty index (Figure VI). Daily expressions of uncertainty increased as the DJIA declined, and the uncertainty index peaked 12 days after Black Monday. The seven-day moving average of the uncertainty index peaked 19 days after Black Monday, rather than before Black Monday.

Figure VI. Investors were more certain before Black Monday than after. The plot shows two years of daily data for the Dow Jones Industrial Average plotted against the U.S. Daily News-based Economic Policy Uncertainty Index (www.policyuncertainty.com/us_daily.html).



Our main findings, presented in Figures I, II, III and IV support the interpretation that both stock prices and expressions of uncertainty are responses to unconscious social mood that occur at different time lags, with textual expressions of uncertainty lagging those of the stock market. The socionomic view of stock markets as indicators of trends in collective psychology, i.e. social mood, better explains these data. Socionomic theory allows for short-term, transient emotional responses to events but holds that these responses will have no bearing on the long-term trends of the stock market or feelings of uncertainty. For more on this theme, see chapters 1, 2 and 8 of Prechter (2016).

Future work on these sorts of data may employ approaches such as exogeneity testing (Engle et al., 1983; Ericsson, 1992; Geweke, 1984) or time-series directional-causality testing (Eichler, 2007). Future work could also examine the prevailing assumption that events regulate changes in social mood, stock prices and GEPU vs. the socionomic hypothesis that fluctuations in unconscious social mood regulate changes in stock prices, GEPU and the aggregate tenor and character of events (Prechter, 2003).

In conclusion, we suggest that our main findings, that changes in stock prices precede changes in expressions of uncertainty, result from both phenomena being responses to unconscious social mood that occur at different time lags, with textual expressions of uncertainty lagging those of the stock market. This interpretation views stock markets as indicators of trends in collective psychology, i.e. social mood, while short-term, transient emotional responses to events have negligible bearing on the long-term trends of the stock market or feelings of uncertainty.

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