MEASURING UNCERTAINTY IN THE STOCK MARKET

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Abstract

We propose a daily index of time-varying stock market uncertainty. The index is constructed after first removing the common variations in the series, based on recent advances in the literature that emphasize the difference between risk (expected variation) and uncertainty (unexpected variation). To this end, we draw on data from 25 portfolios sorted by size and book-to-market value. This strategy considerably reduces information requirements and modeling design costs, compared to previous proposals. We also compare our index with indicators of macro-uncertainty and estimate the impact of an uncertainty shock on the dynamics of macroeconomic variables.

Key words: Uncertainty, Risk, Factor models, Stock market.

JEL Codes: E00, E44, G10, G14.

1. Introduction

Uncertainty and risk have been primary concerns in economics, and among scientists in general, since the birth of modern science. Indeed, Bernstein (1998) goes as far as to claim that the interest in measuring and mastering the two phenomena marks the threshold separating modern times from the previous thousands of years of history.

In economics, Frank Knight was the first person to postulate the distinction between uncertainty and risk on the grounds that the former cannot be described by means of a probability measure while the latter can. According to both Knight (1921) and Keynes (1921, 1939), economic agents inhabit an environment of pervasive uncertainty and, therefore, there can be little hope of quantifying or forecasting economic variables, or of even taking informed decisions that rely on quantitative measures of economic dynamics (in other words, probabilities are incommensurable).

Today, the distinction between risk and uncertainty remains a lively topic for debate on the academic agenda. Indeed, several recent studies have attempted to explain decision-making under uncertainty, albeit oriented more towards the social conventions than towards the development of rational calculations. Accordingly, in this branch of the literature, there is a clear need to distinguish between the concepts, while measuring what can be measured and not losing sight of what cannot be quantified in probabilistic terms (Nelson and Katzenstein, 2014; Ganegoda and Evans, 2014; Taleb, 2007).

Although of obvious importance in its own right, this extreme *Knightian* differentiation between risk and uncertainty leads to the impossibility of defining a probability space and prevents us from using any variation of the Ergodic Theorem in empirical studies. And this, in turn, leads to the impossibility of conducting any science at all (Hendry, 1980; Petersen, 1996) or, at least, the kind of social science based on 'measurement', as has been fostered by the Cowles Commission for Research in Economics since its foundation[1].

However, confronted by this panorama, the profession has moved from this *Knightian* extreme (fundamental) view of uncertainty and adopted a more promising approach to the concept. In this new strand of the literature, uncertainty has generally been assimilated to a time-varying conditional second moment of the series under study, closely linked to underlying, time- varying, structural shocks, such as terrorist attacks, political events, economic crises, wars and credit crunches. Yet, despite this, the differentiation between risk and uncertainty in most instances is not properly dealt with.

Our contribution can be thought of as an attempt to measure the 'known' and part of the 'unknown', in the popular taxonomy of risk proposed by Gomery (1995). This author differentiates between the 'known', the 'unknown' and the 'unknowable', and highlights a traditional exaggerated focus on the former, while ignoring the other two categories. That bias can lead to misconceptions about the world around us, because the 'known' constitutes only a very small fraction of what we see and face on our daily

[1] 'Science is Measurement' was the original motto of the Cowles Commission (though it would later be changed in 1952 to 'Theory and Measurement'). See Keuzenkamp (2004) and Bjerkholt (2014) for details about the history and methodology of econometrics and the role of the Cowles Commission and the Econometric Society in the transition of economics to a more formally based science.

decisions. Nevertheless, there is still the 'unknowable', which is clearly beyond the scope of this paper, since in this situation even the events defining the probability space cannot be identified in advance as pointed out by Diebold et al. (2010).

In this paper we seek to make three specific contributions to the study of uncertainty. First, we propose a new index for measuring stock market uncertainty on a daily basis (or what we refer to as financial uncertainty).[2] The index considers the inherent differentiation between uncertainty and the common variations between the series (which we identify as risk). Recent advances in the field have identified the methodological tools for performing the task using factor models (Jurado, Ludvigson and Ng, 2015; henceforth JLN). These proposals, however, have tended to focus their attention on the use of macroeconomic variables to construct their indexes, as opposed to financial variables. Therefore, because of the low frequency of macroeconomic series, the proposals lack a desirable property of traditional proxies of uncertainty based on financial returns (such as VXO, VIX or credit-spreads): namely, practitioners and policy makers cannot trace their dynamics in real time.

Our second contribution is to show how our financial uncertainty index can also serve as an indicator of macroeconomic uncertainty. We examine the circumstances under which our index might be thought to capture all the relevant information in the economy as a whole. We exploit the fact that the information contained in hundreds, or even thousands, of economic indicators can be encapsulated by just a few stock market portfolio returns. This circumstance makes the construction of the index easier, in terms of its information requirements, modeling design and computational costs, and it allows us to provide a high frequency uncertainty measure. The construction of our index, based on portfolio returns, for which there are significant and timely data, provides a better basis for analyzing uncertainty compared to other situations, in which this kind of information and frequency are absent. Therefore, the extension of the methodology beyond the stock markets must be approached with caution, since there is little hope to extract the uncertainty components of less timely data, in an accurate fashion.

Finally, we analyze the dynamic relationship between uncertainty and the series of consumption, interest rates, production and stock market prices, among others. This allows us to further our understanding of the role of (financial or macroeconomic) uncertainty, and to determine the dynamics of the economy as a whole. Our empirical model allows us to analyze the extent to which traditional monetary policy can be trusted to manage situations of uncertainty. Thus, on the one hand, we document a significant and negative relationship between uncertainty and real variables such as production, employment and consumption; on the other, we find that the interest rate tends to decrease after an uncertainty shock while uncertainty decreases following a fall in the interest rate. However, this last effect only explains a small proportion of the total variation in the forecasted uncertainty.

The rest of this paper is organized as follows. First, we review theoretical and empirical studies of uncertainty. In section 3 we describe the methodology used to estimate the uncertainty index. Our approach relies on generalized dynamic factor models and stochastic volatility (SV) devices. In section 4 we present our data and in section 5 our main results. We also relate our findings to macroeconomic dynamics by means of a vector autoregressive (VAR) analysis. In the last section we conclude.

[2] The daily index is available on www.ub.edu/rfa/uncertainty-index.

2. Related literature

2.1. Risk, uncertainty, economic decisions and policy intervention

The current paradigm for understanding uncertainty was developed within the framework of irreversible investment, in which a firm's future investment opportunities are treated as real options and the importance of waiting until the uncertainty is resolved is emphasized. Hence, aggregate uncertainty shocks[3] are thought to be followed by a reduction in investment, and possibly in labor, and, consequently, by a deterioration in real activity (Bernanke, 1983; Bertola and Caballero, 1994; Abel and Eberly, 1996; Leahy and Whited, 1996; Caballero and Pindyck, 1996; Bloom et al., 2007; Bachmann and Bayer, 2013). Nevertheless, some studies point out that after the original worsening of the variables, a rebound effect related to a 'volatility over-shoot' may be observed (Bloom, 2009; Bloom et al., 2013). It is worth noting that these original impacts on the macroeconomic variables may be amplified as a result of financial market frictions (Arellano et al., 2012; Christiano et al., 2014; Gilchrist et al., 2014).

The study of uncertainty is not confined to the firm's investment problem. For example, Romer (1990) suggests that consumers may postpone their acquisition of durable goods in episodes of increasing uncertainty. Ramey and Ramey (1995) and Aghion et al. (2010) have studied the negative relationship between volatility and economic growth. The effects of uncertainty on equity prices and other financial variables have also been analyzed. In this stream, Bansal and Yaron (2004) provide a model in which markets dislike uncertainty and worse long-run growth prospects reduce equity prices. In the same line, Bekaert et al. (2009) find that uncertainty plays an important role in the term structure dynamics and that it is the main force behind the counter-cyclical volatility of asset returns.

Additionally, there has been a revival of interest in examining the relationship between uncertainty and policy interventions. However, there is no clear consensus in this resurgent research agenda. Some authors conclude that the optimal monetary policy does not change significantly during episodes of crisis and that uncertainty about crises has relatively little effect on policy transmission (Williams, 2012), but others report that financial uncertainty plays a significant role in monetary policy transmission mechanisms (Baum et al., 2013; Bekaert et al., 2013). Neither is it clear whether a highly responsive or moderate monetary policy scheme is best when facing uncertainty. For instance, Williams (2013), in the same spirit as Brainard (1967), forwards the argument that, once uncertainty is recognized, some moderation in monetary policy might well be optimal. In marked contrast (albeit under a different notion of uncertainty), Fendoğlu (2014) recommends a non-negligible response to uncertainty shocks.

2.2. Empirical measures of uncertainty

Empirical studies have frequently relied on proxies of uncertainty, most of which have the advantage of being directly observable. Such proxies include stock returns or their implied/realized volatility (i.e., VIX or VXO), the cross-sectional dispersion of firms'

[3] Panousi and Papanikolaou (2012) explain possible sources of inefficiency in the investment process arising from idiosyncratic uncertainty, under high-powered incentives and risk-averse managers. Bachmann and Bayer (2013) also study the impact of idiosyncratic uncertainty shocks on business cycles.

profits (Bloom, 2009), estimated time-varying productivity (Bloom et al., 2013), the cross-sectional dispersion of survey-based forecasts (Dick et al., 2013; Bachmann et al., 2013), credit spreads (Fendoğlu, 2014), and the appearance of 'uncertainty-related' key words in the media (Baker et al., 2016; Alexopoulos and Cohen, 2015).[4]

Although these uncertainty proxies have provided key insights to the comprehension of uncertainty, and have been reliable starting points for the analysis of the economic impacts of uncertainty on economic variables, most of them have come under criticism, most notably from Scotti (2016) and JLN. On the one hand, volatility measures blend uncertainty with other notions (such as risk and risk-aversion), owing to the fact that they do not usually take the forecastable component of the variation into account before calculating uncertainty. On the other, analysts' forecasts are only available for a limited number of series. Moreover, it is not entirely clear whether the responses drawn from these surveys accurately capture the conditional expectations of the economy as a whole. The disagreement reported in survey forecasts could be more of an expression of different opinions than of real uncertainty (Diether et al., 2002) and even if forecasts are unbiased, the disagreement in analysts' point forecasts is not generally equivalent to forecast error uncertainty (Lahiri and Sheng, 2010)[5]. Aimed at overcoming these shortcomings, a new branch of the literature has emerged, which proposes measuring uncertainty only after the forecastable component of the series has been removed (Carriero et al., 2015[6]; Gilchrist et al., 2014; JLN).

Our model takes into account the extraction of the contemporaneously forecastable component of the variation before calculating uncertainty, which is important in order to distinguish satisfactorily between uncertainty and risk. We also aim to construct estimations of uncertainty by deliberately adopting an atheoretical approach, in the same vein as JLN. Our study contributes to the existing literature by providing a *daily* measurement of uncertainty. This is important, because it means the market can be monitored in real time, while enabling the researcher to undertake event studies with greater precision including uncertainty as a variable. The literature notes that estimations of impacts extracted from event studies are much more precise and less noisy as the frequency of the data increases (Fair, 2002; Bomfim, 2003; Chuliá et al., 2010).

3. Methodology

The construction of our uncertainty index consists of two steps. First, we remove the common component of the series under study and calculate their idiosyncratic variation. To do this, we filter the original series using a generalized dynamic factor model (GDFM). Second, we calculate the stochastic volatility of each residual in the previous step using Markov chain Monte Carlo (MCMC) techniques. Then, we average the series, obtaining a single index of uncertainty for the stock market, and possibly for the economy as a whole. In sections 3.1 and 3.2 below, we explain each step in detail.

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[4] Other studies, such as Shi et al. (2016), have used linguistics-based sentiment scores of the news releases to study the dynamics of stock volatility.

[5] Bachmann et al. (2013) and Scotti (2016) acknowledge these problems and address them by using additional proxies for uncertainty. Nevertheless, as noted by JLN, these studies focus on variation in outcomes around subjective survey expectations.

[6] These authors do not address the problem of measuring uncertainty directly, but still they use a closely related methodological approach to the one employed in this strand of the literature.

3.1. Idiosyncratic component extraction

Following Bai and Ng (2008), let N be the number of cross-sectional units and T be the number of time series observations. For $i = 1, \dots, N$ and $t = 1, \dots, T$, the dynamic factor model (DFM) can be defined as:

$$x_{it} = \lambda_i(L) f_t + e_{it}, \tag{1}$$

where $\lambda_i(L) = (1 - \lambda_{i1}L -, \dots, -\lambda_{is}L^S)$ is a vector of dynamic factor loadings of order s. When s is finite, we refer to it as a DFM. In contrast, a GDFM allows s to be infinite. Stock and Watson (2002, 2011) provide examples of the former and Forni and Reichlin (1998) and Forni et al. (2000) introduce the latter. In any case, the (dynamic) factors f_t evolve according to:

$$f_t = C(L)\varepsilon_t, \tag{2}$$

where ε_t are iid errors. The dimension of f_t, denoted q, is the same as that of ε_t and it refers to the number of dynamic or primitive factors (Bai and Ng, 2007).

The model stated in (2) can be rewritten in static form, simply by redefining the vector of factors to contain the dynamic factors and their lags, and the matrix of loads accordingly, as:

$$\underset{(N \times T)}{X} = \underset{(N \times r)(r \times T)}{\Lambda\, F} + \underset{(N \times T)}{e}, \tag{3}$$

where $X = (X_1, \dots, X_N)$ and $F = (F_1, \dots., F_T)$. Clearly, F and Λ are not separately identifiable. For any arbitrary $(r \times r)$ invertible matrix H, $F\Lambda' = FHH^{-1}\Lambda' = F^*\Lambda'^*$, where $F^* = F\Lambda$ and $\Lambda^* = \Lambda H^{-1}$, the factor model is observationally equivalent to $X = F^*\Lambda'^* + e$. Therefore r^2 restrictions are required to uniquely fix F and Λ (Bai and Wang, 2012). Note that the estimation of the factors by principal components (PC) or singular value decomposition (SVD) imposes the normalization that $\frac{\Lambda'\Lambda}{N} = I_r$ and $F'F$ is diagonal, which are sufficient to guarantee identification (up to a column sign variation).

The GDFM is a generalization of the DFM because it allows a richer dynamic structure for the factors. It places smaller weights on variables with larger idiosyncratic (uncertainty) components. So that the idiosyncratic 'error' contained in the linear combination is minimized. In this way we ensure that the uncertainty component is purged from risk-related variations.

Our first step enables us to estimate the idiosyncratic variation of the series $e_{it}^u = X_{it} - \hat{C}_{it}$, where $\hat{C}_{it} = \lambda_i(L) f_t$. This component is primarily related to uncertainty, whereas the common variation (i.e., the variance of $\hat{C}_{it}$) can be referred to as risk.

3.2. Conditional volatility estimation

Once we recover the series of filtered returns, e_{it}^u, a SV model is specified on an individual level, for each $i = 1, \dots N$[7], as:

[7] In what follows we omit the cross-sectional subscript to simplify the notation.

$$e_t^u = e^{h_t/2}\epsilon_t, \tag{4}$$

$$h_t = \mu + \emptyset(h_{t-1} - \mu) + \sigma\eta_t, \tag{5}$$

where ϵ_t and η_t are independent standard normal innovations for all t and s belonging to $\{1, \dots, T\}$. The non-observable process $h = (h_0, h_1, \dots, h_T)$ appearing in equation 5 is the time-varying volatility with initial state distribution $h_0|\mu, \phi, \sigma \sim N\left(\mu, \sigma^2/(1-\phi^2)\right)$. This centered parameterization of the model should be contrasted with the uncentered reparameterization provided by Kastner and Frühwirth-Schnatter (2014):

$$e_t^u \sim N\left(0, e^{\mu+\sigma\tilde{h}_t}\right), \tag{6}$$

$$\tilde{h}_t = \emptyset\tilde{h}_{t-1} + \eta_t,\ \eta_t \sim N(0,1). \tag{7}$$

Whether the first or the second parameterization is preferred for estimation purposes generally depends on the value of the 'true' parameters (Kastner and Frühwirth-Schnatter, 2014). Nevertheless, both of them have intractable likelihoods and, therefore, MCMC sampling techniques are required for Bayesian estimation.

Kastner and Frühwirth-Schnatter (2014) provide a strategy for overcoming the problem of efficiency loss due to an incorrect selection among the representations in applied problems. They propose interweaving (4)-(5) and (6)-(7) using the ancillarity-sufficiency interweaving strategy (ASIS) as introduced by Yu and Meng (2011). Their results indicate that this strategy provides a robustly efficient sampler that always outperforms the more efficient parameterization with respect to all parameters, at little extra cost in terms of design and computation. We follow their advice to estimate the volatilities of the idiosyncratic shocks.

Once the idiosyncratic stochastic volatility measures have been constructed, we are able to estimate the uncertainty index in the stock market as the simple average of the individual volatilities:

$$U_t = \frac{\sum_{i=1}^{N} h_{it}}{N}. \tag{8}$$

This scheme corresponds to the equally weighted average, with $\sum_{i=1}^{N} w_i h_{it} \xrightarrow{p} E(U_t)$, where $w = 1/N$. Alternatives, such as using the first PC to aggregate the series of variances, are possible but have no grounding in econometric theory to guarantee their consistency in the estimation process (Jurado et al., 2013; JLN). Unlike the previously referenced studies by JLN, here we only use information from portfolio returns organized by different factor criteria; thus, there is no *ex ante* reason to weight each portfolio return using different loads. In principle, any firm might belong to any portfolio, and all of them are equally important in the estimation of the aggregate shock. Hence, it is natural to favor the equally-weighted scheme over other asymmetric alternatives, but note that the asymmetric scheme would be more appropriate when macro-variables are blended with financial or other kind of variables.

4. Data

In our empirical exercise we use 25 portfolios of stocks belonging to the NYSE, AMEX, and NASDAQ, sorted according to size and their book-to-market value, as provided by Kenneth French on his website[8]. Those portfolios have been widely used in the literature examining multi-factor asset pricing models (Cochrane, 2005), and can be seen as a good summary of whole market dynamics. Moreover, Sentana (2004) justifies the use of portfolios for extracting the subjacent factors by proving that many portfolios converge to the factors as the number of assets increases. Clearly this does not rule out the fact that other possibilities might be explored in future research, such as the use of less well-known portfolios constructed on an industry sector basis, or using different factors to organize the series.

Our data set spans from 1 July 1926 to 30 September 2014, which gives a total of 23,321 observations. More details on the portfolio formation are provided in Davis, Fama and French (2000) and on Kenneth French's web page.

In section 5.3 we estimate a vector autoregressive (VAR) model. The data for this exercise were taken from the web page of the Federal Reserve Saint Louis (FRED: http://research.stlouisfed.org/). Specifically, we use the Industrial Production Index; the total number of employees in the non-farm sector; Real Personal Consumption Expenditures in 2009 prices; the Personal Consumption Expenditures Price Index; the New Orders Index known as NAPM-NOI; Average Weekly Hours of Production and Nonsupervisory Employees for the Manufacturing sector (the all-sector index is not available from the beginning of our sample); Effective Federal Funds Rate; M2 Money Stock in billions of dollars and Standard and Poor's 500 index. Each series was taken seasonally adjusted where necessary, and the sample spans from February 1959 to September 2014, which is the longest period possible using these series.

5. Results

In this section we present our uncertainty index (section 5.1); we compare it with some of the main macro-uncertainty indicators (section 5.2); we analyze the relationship between our proposal and some real and financial variables, including policy variables (section 5.3); and, we perform several robustness exercises (section 5.4).

5.1. Uncertainty index

We estimate the GDFM using six static factors and one dynamic factor, which are optimal following the criteria proposed by Bai and Ng (2002) and Bai and Ng (2007), respectively. Based on these estimates we construct the uncertainty index by aggregating the conditional volatilities of the idiosyncratic residual series as explained in section 3.

The daily uncertainty index is presented in Figure 1, together with the recession dates in the United States, as indicated by the NBER on its web site. The index peaks coincide with well-documented episodes of uncertainty in the financial markets and the real economy, including the Great Depression, the recession of 1937-38 in the US, Black Monday in October 1987, the bursting of the dot-com bubble and the Great Recession 2007-2009.

Recession dates, such as August 1929 to March 1933, May 1937 to June 1938 and December 2007 to June 2009, clearly correlate with the amount of uncertainty in the market, although interestingly, not all recessionary episodes are preceded or followed

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

by a notable uncertainty shock. For example, the uncertainty peak in the index corresponding to March 2000 appears one year before the economic contraction in March 2001. Likewise, several recessions during the decades of the 40s, 50s and 60s do not seem to be associated with episodes of high or even increasing uncertainty.

More importantly, uncertainty in the stock markets appears to correlate not only with the volatility of fundamentals (i.e., recessions), but also with episodes of over-valuation or bubbles in the market, as discussed for example in Yuhn et al. (2015), namely, those of 1987 (Black Monday), 2000 (information technology boom) and 2007 (housing market boom). Indeed, these episodes may well be the main drivers of uncertainty (even more so than the recessions), at least in the last part of our sample. Many such episodes have been identified in the recent literature and they constitute a particularly active area of current research within the financial econometrics field (Phillips and Yu, 2011; Phillips et al., 2011; Homm and Breitung, 2012; Phillips et al., 2015; Anderson and Brooks, 2014) and even outside economics, especially in the application of statistical mechanics tools to financial problems (see Zhou and Sornette (2003), Sornette and Zhou (2004), Sornette et al. (2009), Budinski-Petković et al. (2014) and references therein).

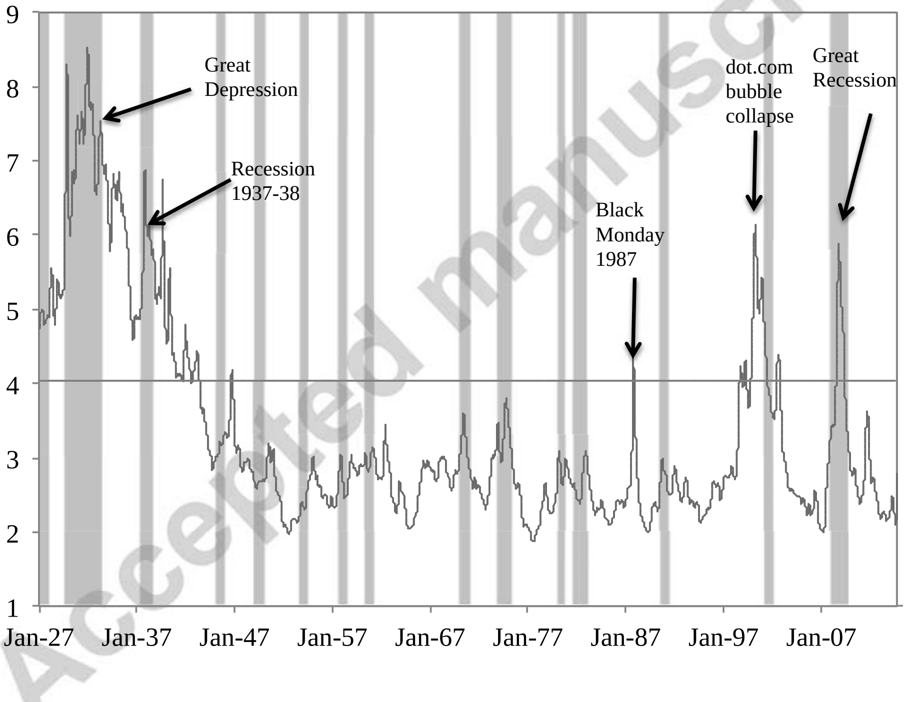


Figure 1: Uncertainty Index: Jan-06-27 to Sept-30-14. The first 153 observations have been discarded and the last 153 have been replaced by calculations using a (scaled) one-sided filter version of the GDFM (Forni et al., 2005). The reason for doing this is that original GDFM are biased at the beginning and at the end of the sample, because they make use of the estimation of the variance- covariance matrices of order $\sqrt{T}$. Grey areas correspond to NBER recession dates (peak-to-trough), including the peaks and troughs. The horizontal line corresponds to the 95 percentile of the empirical distribution of the index from Jan-40 onwards. The original measure is rescaled by a factor of 100 in the plot.

The observation above can be rationalized under a framework of agents with heterogeneous beliefs and bounded rationality as the one proposed by Hommes and Wagener (2009). In their model, there is an endogenous switching mechanism, governing the proportion of financial investors who follow a ‘perfect foresight’ forecasting rule (driven by market fundamentals), or alternative linear heuristics, such as 'biased beliefs' and 'past trends'. Instabilities may follow after an increasing in the number of non-fundamentalist traders in the market and hence, produce the apparition of persistent bubbles. Uncertainty, as measured by our index, is naturally related to this possibility. That is, in high uncertainty regimes more agents may choose to switch to a non-fundamentalist rule of prediction, driving the prices away from their fundamental path.

In Table 1 we report descriptive statistics for a monthly (end-of-the-month) version of the uncertainty index. We construct this monthly index to facilitate comparisons with other macro-uncertainty proxies. The skewness, kurtosis, persistence and half-life of the shocks for the full sample and for two sub-samples are presented (January 1927 to March 1940 and April 1940 to September 2014). This break date was chosen after testing for multiple breaks (Bai and Perron, 1998, 2003) in the autoregressive model of the shocks persistence (AR(1) with drift)[9].

Table 1. Summary statistics of the uncertainty index in two sub-samples

Statistic	Sample period: Jan 1927-Sept 2014	Jan 1927-Mar 1940	Apr 1940-Sept 2014
Skewness	1.60	0.32	1.70
Kurtosis	4.74	1.97	6.62
Persistence, AR(1)	0.993	0.963	0.978
Half-life: months (years)	101 (8.42)	18.3 (1.53)	31.9 (2.65)

Table 1 shows that using the full sample to calculate persistence can lead to a spurious estimation of the summary statistics. Indeed, the sample distribution of the uncertainty index in the two sub-samples looks quite distinct. In the first part of the sample, persistence is smaller and, therefore, the 'shocks' disappear in a shorter period of time (1.53 years) than is the case in the second sub-sample (2.65 years). There are fewer observations distant from the mean and, lastly, the distribution presents a slightly asymmetric behavior (skewness equal to 0.32). In contrast, even when the second part of the estimation presents shocks of a smaller magnitude (Figure 1), the distribution that characterizes them tends to generate a higher number of 'outliers' (kurtosis equal to 6.92) and they are more likely to be above than below the mean (1.7 is the asymmetric coefficient). This behavior may be interpreted as uncertainty showing some degree of inconsistency across time, which is related to the knightian framework, in which uncertainty is indeed understood as a non-predictable state.

Our estimations of persistence of macro-uncertainty are lower than those reported elsewhere, for example, those provided by JLN. The latter estimate a persistence of 53.58 months, while in the second part of our sample our estimation is of 31.9 months (41.2 months from Jan. 1960 to Sept. 2014). This could be interpreted as evidence that financial-uncertainty shocks are not as persistent as macro-uncertainty shocks. Nevertheless, it should be noted that JLN also report the persistence and half-lives of frequently used proxies for uncertainty, including the VXO and the cross-sectional standard deviation of the returns. They show that these uncertainty-related measures are far less persistent than are macro-uncertainty shocks (with half-lives of 4.13 and 1.92 months). Thus, the half-life and persistence of our uncertainty measure are more similar

[9] See Perron (2006) for a survey of this literature.

to those of the macro-uncertainty shocks than to those derived from the volatility measures.

5.2. Correlations with macro-uncertainty indexes

The closest measure of uncertainty to ours, methodologically speaking, is the uncertainty index proposed by JLN, although their proposal might be interpreted more directly as a 'macro-uncertainty' indicator, given its emphasis on economic variables as opposed to purely financial ones. Given these circumstances, it seems to be a good candidate with which to compare our index while seeking to identify any convergent and divergent paths. In order to compare the indexes, we first reduce our sample to fit theirs. Our resampled data start in January 1960 and end in May 2013[10]. After so doing, we recalculate our uncertainty index by aiming to use the same dates as those employed by JLN. Second, we take the end-of-the-month value of our index, to resemble their index frequency (monthly).

The results are reported in Figure 2. The shaded areas in the plot correspond to periods of 'high' correlation. The Pearson's correlation for the full sample between the indexes is barely above 22%, which could be interpreted, at first glance, to indicate that different forces lie behind the macro-uncertainty and the financial-uncertainty. However, this correlation seems very volatile. We also calculate moving-window correlations of five years during the sample and here our findings are more informative than the static correlation. The correlation remains above 50% for most of the period (left panel). Moreover, for the last part of the sample (from around February 2009 to May 2013), this correlation remained above 90%, revealing practically no difference in the indexes' dynamics. Even higher values were reached during the 70s and we observe correlations between 40 and 80% in the period from May 1994 to February 2003 (right panel). There are also two periods in which this correlation became negative, specifically from January 1992 to August 1993 and December 2005 to September 2007. After these short phases, the indexes started to move in the same direction once again, and in both cases with a stronger impetus than before.

Finally, an analysis of the levels of the uncertainty indexes shows them to be particularly different during the periods from March 1979 to May 1983 and July 1998 to January 2003. Our intuition regarding the explanation for these divergent paths during these periods is that while uncertainty in the financial markets is driven significantly by bubble episodes, such episodes are not always the drivers of the recessions in the real economy and, therefore, cannot be related on a one-to-one basis with macro-uncertainty. Thus, the financial-uncertainty index highlights uncertainty associated with bubble episodes (for instance, during the dot.com collapse) that did not materialize as strong recessionary phases in the real economy and which, therefore, are not captured by the JLN-uncertainty index. In the same vein, recessionary episodes not directly related to the financial market (such as those from 1979 to 1983) are not especially pronounced in our financial-uncertainty indicator.

[10] The JLN-index is publicly available for this period on Sidney Ludvigson's web page: http://www.econ.nyu.edu/user/ludvigsons/

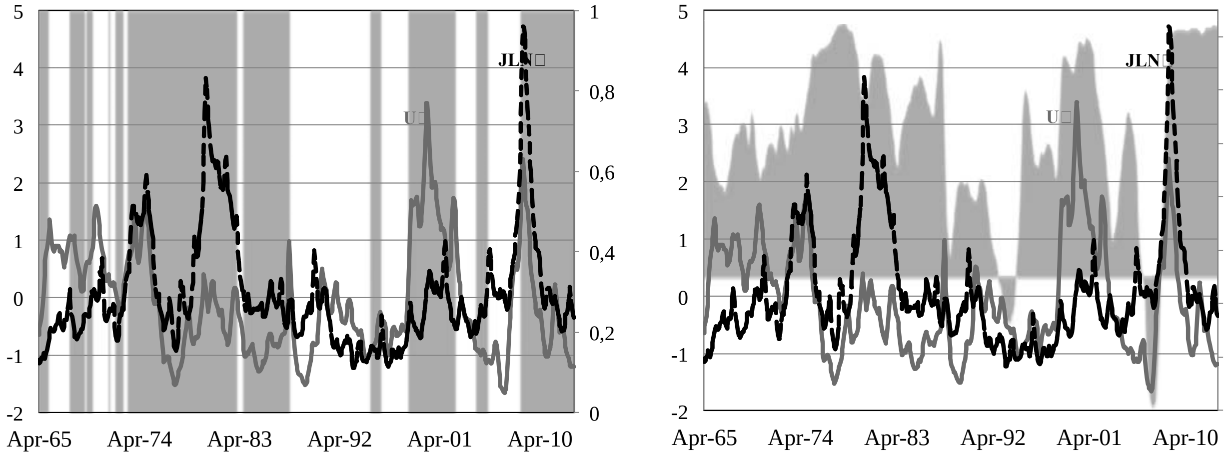


Figure 2: Uncertainty Comparisons I. The solid line represents our Uncertainty Index (U), while the dotted line represents the Jurado-Ludvigson-Ng's Index (JLN) with forecast horizon $h = 1$, both from Apr-65 to May-13. In the panel on the left, the shaded areas correspond to correlation periods above 0.5. In the panel on the right, the shaded areas are the actual correlations. Correlations are measured on the right axis of each panel. Correlations were calculated using rolling, moving windows of five years, starting from January 1960.

We also compare our index with the VIX, another frequent proxy for macro- and financial-uncertainty (Figure 3), but which is only available after January 1990. We found a correlation of 65.2% using the full sample. The dynamics of the VIX and the uncertainty index appear to be largely similar with a correlation above 70% for the last ten years of the sample. However, these dynamics are considerably different (considering the correlation levels) for the first ten years of the sample. Here again, the results could be linked to the fact that volatility as a risk measure is inversely related to the presence of over-valuation in the stock markets, whereas over-valuation appears to be positively related to uncertainty.

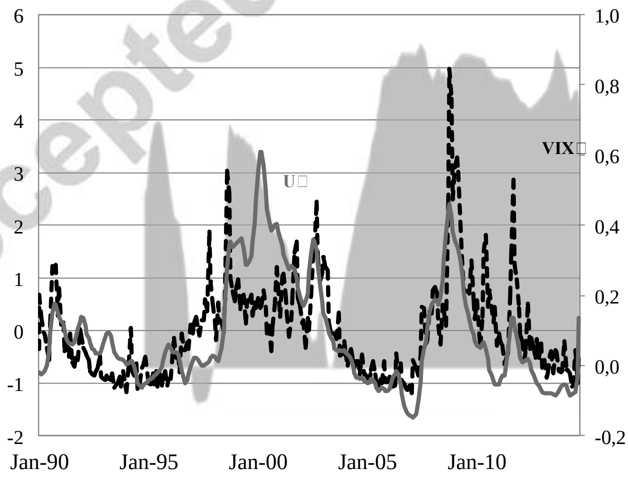


Figure 3: Uncertainty Comparisons II. The solid line represents our uncertainty index (U), while the dotted line represents the VIX, both from Jan-90 to Sept-14. Shaded areas correspond to the five-year rolling correlations and, therefore, start only after Jan-95. Correlations are measured along the right axis.

5.3. VAR dynamics: Uncertainty, economic activity and policy variables

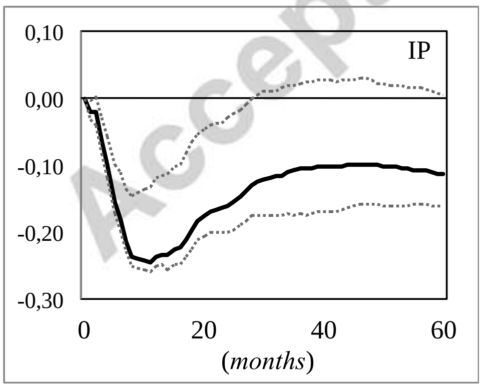
In this section, we explore the dynamic relationship between our uncertainty index and some macroeconomic and financial variables. To do so, we use the model proposed by

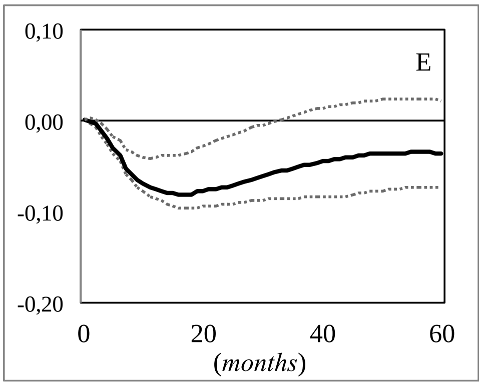
Christiano et al. (2005). This model has been widely studied in the literature and is, therefore, useful for comparing our uncertainty estimates. The model is given in reduced form by:

$$Y_t = A(L)Y_{t-1} + e_t, \tag{9}$$

where, $Y_t = [Y_{1t}\ , R\ , Y_{2t}, U\ ]'$ is a matrix $(T \times N)$ containing the N column-vectors of the model. Y_{1t} contains slow-moving variables which do not react contemporaneously to a monetary policy shock: Production, Employment, Consumption, Inflation, New Orders, Wages and Labor. R refers to the Federal Funds Rate, understood as the monetary policy instrument. Y_{2t} refers to the fastest variables, which are assumed to respond contemporaneously to the policy innovation, such as: the Stock Market Index and M2. Finally, we place our Uncertainty Index U in last position (as do JLN and Bloom, 2009)[11]. We estimate a VAR with 12 lags, as opposed to the four quarters used in Christiano et al. (2005) to cover the same time-span. All the variables enter in log-levels, with the exceptions of the Federal Funds Rate and Uncertainty, which enter in original units, and M2, which enters in growth rates. We recover the structural innovations by means of a Cholesky factorization of the variance-covariance matrix. As is well known, the Cholesky decomposition implies a certain ordering of the set of variables, depending on whether they react or not to other variables contemporaneously. Following Christiano et al. (2005), the variables are sorted from more exogenous to more endogenous as stated above. The impulse response functions are presented in Figure 4.

The reactions of Production and Employment to uncertainty shocks have been studied elsewhere, for example in JLN and Bloom (2009). The former report very similar results to ours even when using their uncertainty index, which requires considerably more information, processing time and modeling design than are required by our index (see also section 5.4). Production reacts negatively to uncertainty increments and the persistence of the shock extends beyond the two-year horizon. In the sixth months after the innovation, 10.5% of the forecast error of the production series is explained by the uncertainty shock, and up to 23.8% is explained 12 months on[12].





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11 See section 4 for a more detailed description of the data used in this section.

12 See Table 2 in the Appendix.

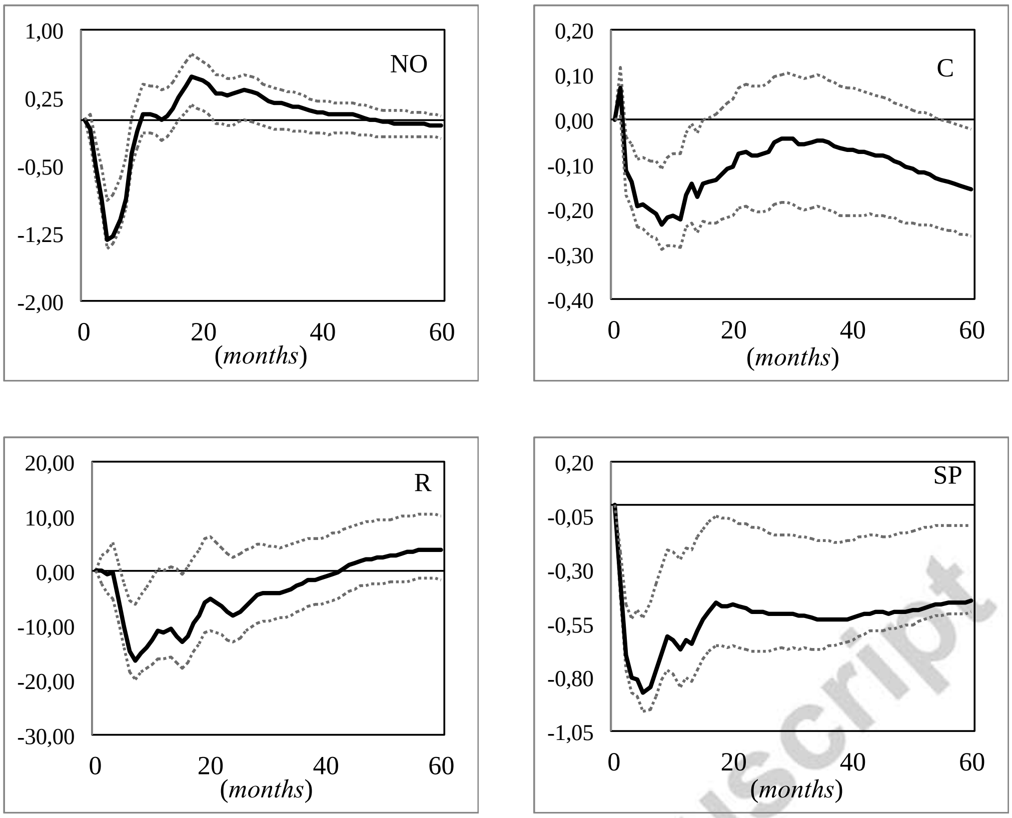


Figure 4: Economic Dynamics under Uncertainty. We use a VAR (12) comprising 11 variables. The axes are in percentages but the Federal Funds Rate is in basic points. The figure shows the reaction of the variables to an unexpected increment of uncertainty. The estimation period runs from February 1959 to September 2014. Confidence bands (86%) are calculated using bootstrapping techniques as explained in Efron and Tibshirani (1993). The variables are defined as: IP: Industrial Production Index, E: Employment, NO: New Orders, C: Consumption, R: Federal Funds Rate, SP: Standard and Poor's 500.

Analogously, although at a smaller magnitude, employment decreases following a positive uncertainty shock and the impact persists for two and a half years (that is, six months more than in the case of production)[13]. Neither we nor JLN find any evidence supporting the 'rebound' effect proposed by Bloom (2009) in the case of production. However, the rebound effect is evident when analyzing the New Orders variable, which is a better proxy for current investment. First, new orders decrease in the face of uncertainty – a negative impact that lasts approximately eight months, but there is a statistically significant rebound effect in months 16 to 19. The reason why a similar effect is not detected in the production dynamics could be that following the original uncertainty shocks, negative feedback is obtained from consumption and expected demand.

Although there are theoretical claims explicitly linking uncertainty shocks and consumption (see, for instance, Romer, 1990), little empirical evidence has been presented to document this relationship. Here, we find that after an increment in uncertainty, consumption is severely affected (indeed, more or less in the same

[13] JLN report an impact of their uncertainty shock on production that persists for more than 60 months. We also find that the IRF tends to stabilize at a lower level following a shock, as can be seen in Figure 4, although this is only true for the average level. Note that the bootstrapped confidence intervals of our exercise prevent us from fixing the effects beyond three years as statistically different from zero.

proportion as production, and more so than employment). However, the shock tends to disappear more quickly (1.3 years before the upper confidence band reaches zero), but it is also apparent that it causes the series to stabilize at a lower level relative to that of the production series.

In line with the theory, financial prices, such as the stock market index, are significantly affected by uncertainty in the financial markets. Indeed, the marked fall in the market index in the face of uncertainty, and the stabilization of the sequence at a lower level, is consistent with the theoretical discussion in Bansal and Yaron (2004). Basically, the intuition is tied to the fact that markets do not like uncertainty and after an increase in uncertainty, the discount of the expected cash flows is greater, causing the market to reduce the price of the stock.

As can be seen from Table 2 in the Appendix, a variance decomposition of the forecast errors of the series confirms the importance of uncertainty as a driver of the economy's dynamics. One year after the original structural innovation, it accounts for 23.8% of the variance in production, 19.5% of new orders, 13.2% of employment and 15.9% of the stock market prices. In all cases, it is the second or third largest source of variation. It also affects other series, albeit to a lesser degree, including consumption (7.6%) and Federal Funds (4.7%), being in these cases the fourth or fifth cause of variation among the eleven variables considered.

Lastly, the Federal Funds Rate also seems to be sensitive to uncertainty. In the face of an uncertainty shock the Federal Reserve tends to reduce the interest rate (thereby confirming that the reduction in equity prices is due to uncertainty and not to possible confounding interest movements). The reduction is particularly persistent during the first year before it begins to disappear. Nevertheless, the uncertainty shock only accounts for between 4 and 5% of the total variation in the Fed rate according to the variance decomposition.

The Cholesky identification strategy allows us to distinguish the effect in the reverse direction; in other words, it enables us to answer the question: Does an expansionary monetary policy decrease uncertainty? As can be observed in Figure 5, a loosening monetary policy does affect uncertainty. The effects are expected to occur with a lag of one year, to last for a further year, and after this period, to disappear. This finding is in line with similar effects documented by Bekaert et al. (2013), although they use non-corrected uncertainty measures and an alternative strategy to differentiate it from risk. Our results in this direction add to the research field by exploring the relationship between policy intervention and uncertainty. However, the effects are small in magnitude (see Table 2 in the Appendix), with between 2 and 6% being due to the monetary policy innovations.

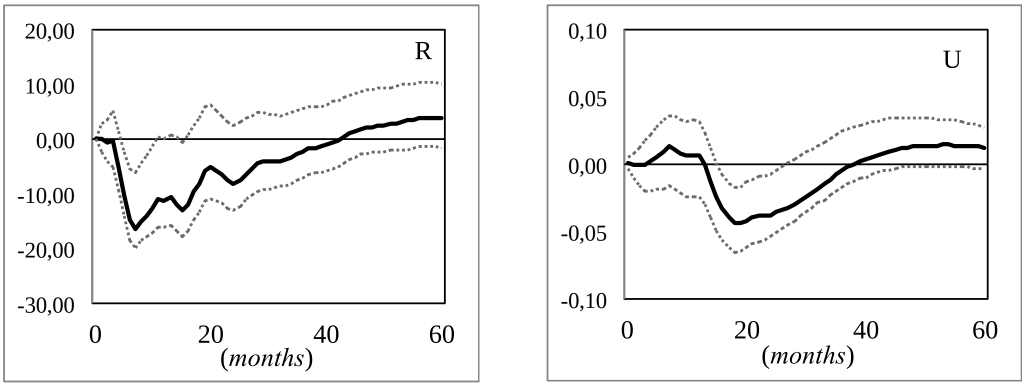
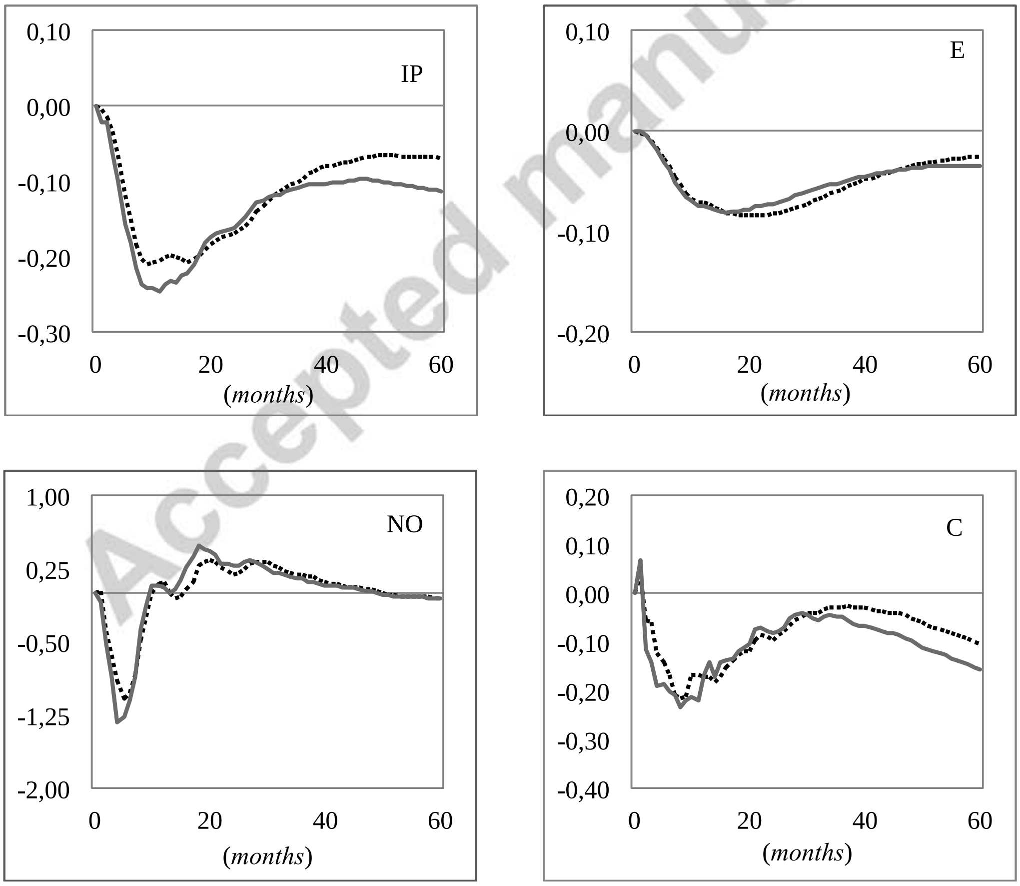


Figure 5: Policy intervention and uncertainty. We use a VAR (12) comprising 11 variables. The axes are in basic points and units, respectively. We replicate the left panel from Figure 5 and we multiply by minus one the response to an increase in the Federal Funds Rate, to be consistent with the text. The estimation period runs from February 1959 to September 2014. Confidence bands (86%) are calculated using bootstrapping techniques as explained in Efron and Tibshirani (1993).

Finally, in Figure 6, using our proposed index and JLN's index, we compare the responses of the variables facing uncertainty. However, the qualitative and quantitative results reported above do not vary significantly depending on the uncertainty measure used.



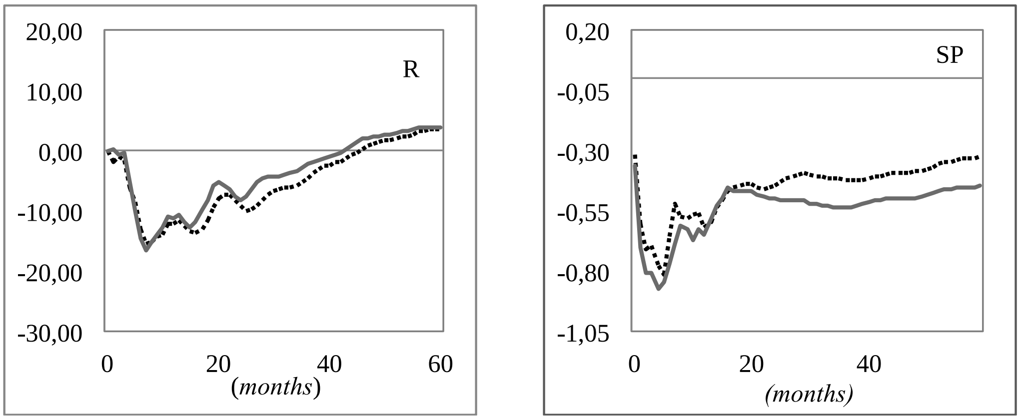
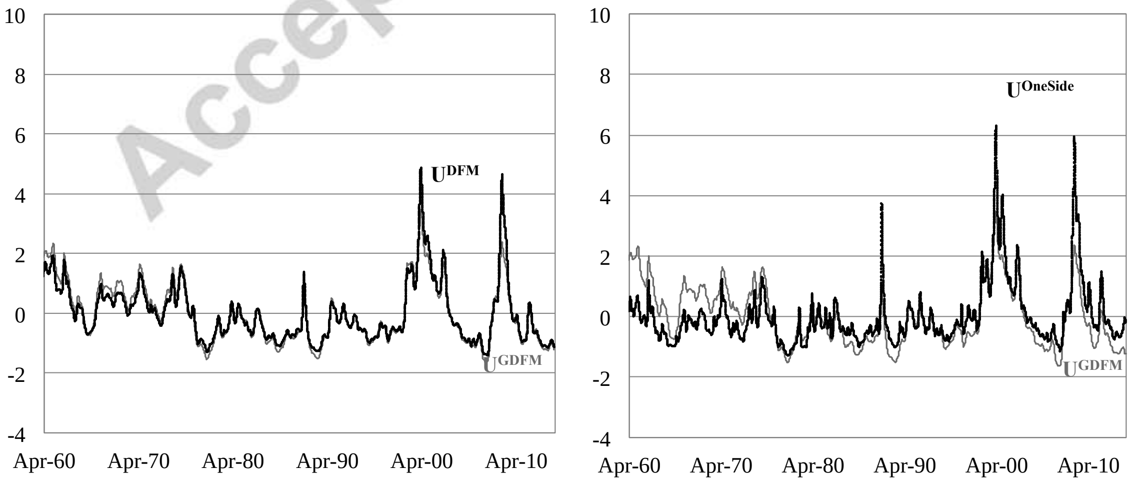


Figure 6: Economic Dynamics under Uncertainty. Comparison of the JLN and U Indexes. We use a VAR (12) comprising 11 variables. The figure displays the reaction of the variables to an unexpected increment in two standardized uncertainty measures, the U index (solid line) and the JLN index (dotted line). The estimation period for the U index runs from February 1959 to September 2014 whereas the JLN index is only publicly available from July 1960 to May 2013 on one of its author's web pages; therefore, we use this latter period to estimate the IRFs in this case. The variables are defined as: IP: Industrial Production Index, E: Employment, NO: New Orders, C: Consumption, R: Federal Funds Rate, SP: Standard and Poor's 500.

5.4. Robustness

We perform several robustness exercises varying the econometric methodology employed to extract the idiosyncratic component. We estimate the uncertainty index using DFM instead of GDFM; we also use the 'one-sided' filter version of the GDFM proposed by Forni et al. (2005) as opposed to the two-sided original GDFM, for the full sample; we estimate the index as the stochastic volatility without using any factor model to extract the idiosyncratic component and, finally, we estimate the idiosyncratic component in a recursive fashion, recalculating each model with rolling windows of 80 days (approx. one quarter). The latter approach speaks directly about parameter stability. The main results are summarized in Figure 7.



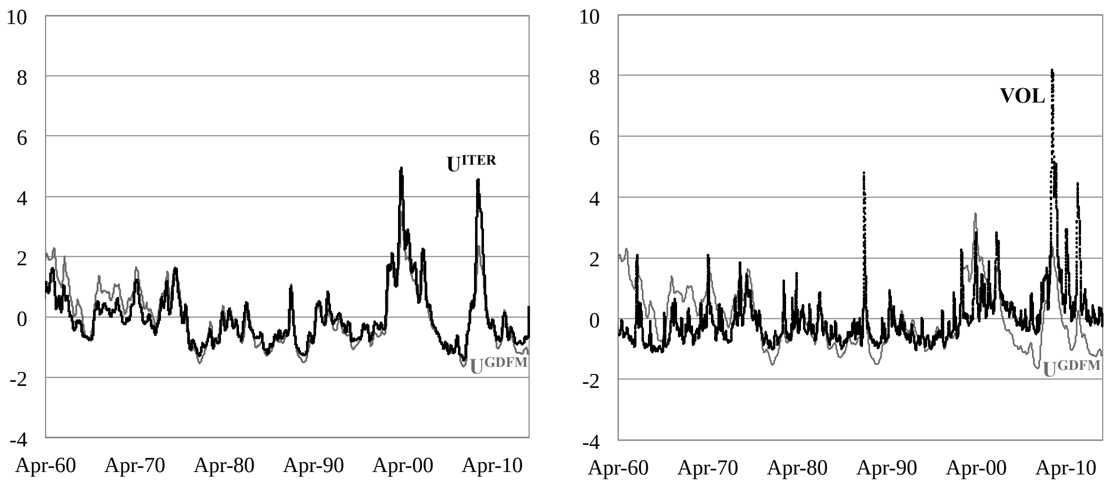


Figure 7: Robustness exercises. The uncertainty index using GDFM (solid line) is compared with different alternatives: a DFM (top left), a one-sided filter version of the GDFM (top right), a recursive algorithm (bottom left) and a conditional volatility measure of the original series (bottom right). All the indexes have been standardized to make proper comparisons.

In general the uncertainty index behaves in a very similar fashion, regardless of the factor methodology used to extract the idiosyncratic components of the series. Nor does it change when we use recursive estimations. Nevertheless, its behavior is considerably different to that of the stochastic volatility of the original series. This, however, is not surprising and is indeed in-line with previous findings in the literature. Volatility measures tend to overestimate the uncertainty of the economy because they confuse uncertainty with risk or risk aversion.

6. Conclusions

We propose an index of time-varying financial uncertainty. The construction of this index is relatively simple as it does not rely on excessive data mining devices nor does it have to satisfy demanding information requirements. We construct the index on a daily basis, for the United States' economy between 1927 and 2014. As such, the index can be used to perform event studies, that is, to evaluate the impact of policy treatments on economic uncertainty, thanks to the higher frequency it offers compared to other proposals.

Our estimations allow us to identify several periods of uncertainty, some of which coincide with well-documented episodes, including major recessions, wars, and political upheavals. Others, especially those occurring in more recent decades, are more closely associated with bubble regimes in the stock market. We also document a change in the persistence of uncertainty between 1940 and 2014 compared to that recorded between 1927 and 1940. Current uncertainty is more persistent and is plagued with more extreme observations, although current periods tend to be smaller in magnitude than earlier periods.

We discuss the circumstances under which our index is a better measure of financial uncertainty and when it is in agreement with measures available elsewhere. We conclude that significant departures between macro-uncertainty and financial uncertainty can be expected during bubble episodes and we present evidence of this.

However, the economic dynamics that we document here (using a VAR model) are consistent with theoretical expectations and previous empirical studies (when available). For example, we find that after an uncertainty shock, production and employment react negatively and the effects of the shock tend to disappear slowly. We also present novel empirical evidence regarding the negative effect of uncertainty on consumption, inventory investment (including overshooting) and stock market prices.

Finally, we explore the relationship between uncertainty and policy variables. We find that there is indeed a relation between the reference interest rate in the economy and uncertainty. The interest rate tends to decrease in the face of an uncertainty shock, while the uncertainty shock decreases following a loosening of the monetary policy position, with a lag of one-year. However, this latter effect is very small in terms of accounting for the total variation of the forecast errors of the uncertainty variable. This result raises questions regarding the capability of the central banks to combat uncertainty by means of traditional monetary policy.

Acknowledgements

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APPENDIX

In the estimations we make use of some routines from the web page of Serena Ng (http://www.columbia.edu/~sn2294/) to estimate the DFM, and to select the optimal number of static and dynamic factors. To estimate the GDFM, both, one-side and two-sides filters, we use codes from the web page of Mario Forni. (http://morgana.unimore.it/forni_mario/matlab.htm). To estimate stochastic volatilities we use the r-package 'stochvol' (Kastner, 2016), to estimate structural breaks in the index we employ the r-package 'strucchange' and to estimate the VAR model the r-package 'vars' was used.

Table 2: Variance Decomposition of the Forecast Errors

	Industrial Production					
Period	**1**	**6**	**12**	**24**	**48**	**Max**
Ind. Production	95.2%	68.2%	41.8%	23.7%	16.8%	95.2%
Employment	0.7%	3.6%	3.2%	2.1%	5.3%	7.1%
Consumption	0.1%	0.2%	1.0%	0.8%	1.7%	2.2%
Inflation	0.3%	0.2%	2.4%	15.4%	17.0%	18.7%
New Orders	2.5%	8.1%	4.6%	4.9%	3.6%	8.2%
Wage	0.0%	0.1%	0.2%	0.5%	1.0%	1.1%
Hours	0.8%	0.6%	0.4%	0.7%	0.4%	0.9%
R	0.0%	1.6%	4.5%	12.8%	26.0%	26.3%
S&P500	0.0%	5.0%	11.8%	9.8%	6.8%	13.7%
M2	0.0%	1.8%	6.3%	7.7%	7.7%	7.9%
Uncertainty	0.3%	10.5%	23.8%	21.7%	13.7%	25.3%

	New Orders					
Period	**1**	**6**	**12**	**24**	**48**	**Max**
Ind. Production	10.9%	7.5%	8.4%	7.7%	7.3%	10.9%
Employment	3.1%	5.3%	5.9%	5.4%	5.0%	6.1%
Consumption	2.9%	1.9%	1.8%	1.5%	1.4%	3.1%
Inflation	1.9%	2.7%	9.2%	12.6%	12.6%	12.8%
New Orders	78.7%	48.2%	39.9%	33.8%	31.5%	78.7%
Wage	0.0%	0.3%	0.4%	0.5%	0.5%	0.5%
Hours	0.5%	0.8%	1.7%	1.5%	1.5%	1.7%
R	0.0%	5.7%	7.2%	8.8%	9.7%	10.5%
S&P500	1.6%	4.9%	4.5%	10.5%	12.7%	13.3%
M2	0.2%	1.2%	1.5%	1.4%	1.4%	1.6%
Uncertainty	0.1%	21.5%	19.5%	16.4%	16.4%	22.6%

	Consumption					
Period	**1**	**6**	**12**	**24**	**48**	**Max**
Ind. Production	2.9%	5.3%	3.9%	2.1%	1.7%	6.7%
Employment	0.7%	4.8%	3.5%	1.8%	3.4%	5.3%
Consumption	93.8%	62.7%	45.0%	31.9%	25.4%	93.8%
Inflation	0.6%	6.4%	14.4%	24.3%	25.4%	26.1%
New Orders	0.3%	0.8%	2.1%	5.0%	4.8%	5.2%
Wage	0.0%	0.3%	0.4%	0.3%	0.4%	0.4%
Hours	0.0%	0.8%	1.0%	0.9%	0.7%	1.1%
R	0.5%	7.4%	12.1%	19.0%	23.6%	23.8%
S&P500	0.7%	3.9%	4.8%	3.3%	2.1%	5.0%
M2	0.2%	2.3%	5.1%	6.6%	9.5%	10.8%
Uncertainty	0.3%	5.3%	7.6%	4.7%	3.1%	7.8%

	Employment					
Period	**1**	**6**	**12**	**24**	**48**	**Max**
Ind. Production	32.8%	29.5%	19.1%	11.8%	8.8%	35.1%
Employment	66.1%	53.2%	42.5%	26.3%	11.5%	66.1%
Consumption	0.1%	0.6%	0.4%	0.5%	0.3%	0.8%
Inflation	0.0%	0.1%	0.8%	9.0%	13.3%	14.1%
New Orders	0.7%	4.4%	2.3%	1.9%	2.0%	4.5%
Wage	0.1%	0.1%	0.3%	0.8%	1.4%	1.4%
Hours	0.1%	0.1%	0.4%	1.8%	2.2%	2.3%
R	0.0%	2.5%	7.4%	19.6%	41.4%	44.5%
S&P500	0.1%	3.9%	10.4%	9.2%	7.5%	12.5%
M2	0.0%	0.9%	3.3%	4.2%	3.4%	4.2%
Uncertainty	0.0%	4.6%	13.2%	14.7%	8.2%	15.5%

	Standard & Poor's 500					
Period	**1**	**6**	**12**	**24**	**48**	**Max**
Ind. Production	0.3%	0.5%	0.4%	0.5%	1.2%	1.2%
Employment	0.1%	1.3%	2.7%	4.1%	5.6%	6.2%
Consumption	0.3%	0.9%	1.8%	1.8%	1.6%	1.8%
Inflation	0.5%	0.4%	4.0%	6.9%	5.8%	6.9%
New Orders	0.3%	1.3%	3.8%	5.7%	4.6%	5.7%
Wage	0.0%	0.2%	2.2%	4.3%	8.0%	9.0%
Hours	0.6%	1.0%	0.8%	0.9%	1.0%	1.0%
R	1.0%	1.5%	1.1%	1.2%	2.1%	2.1%
S&P500	94.5%	73.6%	63.6%	54.1%	44.7%	94.5%
M2	0.2%	3.4%	3.6%	3.9%	3.7%	4.0%
Uncertainty	2.2%	15.9%	15.9%	16.7%	21.7%	23.4%

	Federal Funds -R					
Period	**1**	**6**	**12**	**24**	**48**	**Max**
Ind. Production	0.0%	6.4%	5.4%	4.9%	6.2%	6.5%
Employment	0.0%	1.7%	6.5%	8.6%	8.2%	9.1%
Consumption	0.0%	0.5%	2.5%	3.3%	8.5%	11.0%
Inflation	0.0%	2.2%	3.7%	3.5%	4.0%	4.0%
New Orders	0.0%	10.6%	11.2%	9.2%	7.6%	11.2%
Wage	0.0%	0.8%	0.7%	0.8%	0.8%	0.9%
Hours	0.0%	1.0%	1.1%	1.1%	1.3%	1.3%
R	0.0%	72.8%	55.9%	47.8%	42.2%	91.7%
S&P500	0.0%	1.7%	6.8%	13.3%	14.4%	16.9%
M2	0.0%	0.5%	1.6%	1.7%	1.5%	1.7%
Uncertainty	0.0%	1.9%	4.7%	5.9%	5.4%	6.1%

	Uncertainty					
Period	**1**	**6**	**12**	**24**	**48**	**Max**
Ind. Production	0.5%	1.9%	2.4%	2.0%	2.2%	2.4%
Employment	0.1%	0.8%	1.0%	1.4%	1.2%	1.5%
Consumption	0.0%	0.5%	1.6%	1.3%	1.1%	1.6%
Inflation	0.4%	2.6%	5.9%	4.8%	5.6%	6.0%
New Orders	0.1%	0.3%	0.4%	1.0%	2.0%	2.1%
Wage	0.0%	0.7%	3.7%	3.5%	3.3%	4.3%
Hours	0.0%	0.7%	1.4%	1.9%	2.2%	2.2%
R	0.0%	0.1%	0.2%	4.0%	4.8%	5.0%
S&P500	1.3%	3.8%	7.1%	22.6%	28.2%	28.6%
M2	1.8%	3.1%	3.1%	2.6%	3.3%	3.4%
Uncertainty	95.7%	85.6%	73.2%	54.9%	46.1%	95.7%

NOTE: We use a VAR (12) comprising 11 variables, in the following Cholesky-order from contemporaneously exogenous to contemporaneously endogenous: Production, Employment, Consumption, Inflation, New Orders, Wages, Labor, R (Federal Funds Rate), Stock Market Index, M2 and the Uncertainty Index. All the variables are in logs except the Fed rate in percentage, the uncertainty index in units and M2 in growth rates.

Highlights

- A daily index of time-varying stock market uncertainty is proposed.
- Stock market uncertainty reacts to economic recessions, but also to bubble episodes.
- Uncertainty impacts negatively investment, consumption, production and employment.
- The impact of uncertainty on stock prices is negative and persistent.