MEASURING UNCERTAINTY IN THE STOCK MARKET

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Abstract

We propose a real-time index of time-varying uncertainty in the stock market. The index is constructed after removing the common variations of the series, taking into account recent advances in the literature, emphasizing the difference between risk (expected variation) and uncertainty (unexpected variation). To this end, we use data from 1926 to 2014 of 25 portfolios sorted by size and book-to-market value, which lowers considerably the information requirements and the modeling design costs, compared to previous proposals in the literature. Results show that, even when our estimates should be thought of as an uncertainty measure of the stock market (i.e. financial uncertainty), they perform very well addressing the uncertainty of the economy as a whole. This is apparent from comparisons with macro-uncertainty indicators and from estimations of the economy's dynamics, after facing an uncertainty shock, measured by our index.

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

JEL Codes: E00, E03, E44, G14.

1. Introduction

Uncertainty and risk have been main concerns for the economics profession and in general for scientists, since the earliest years in the history of modern science. Even more, interest in measuring and mastering risk and uncertainty, could be identified as a threshold separating modern times from all other previous thousands of years in the history of humanity, as argued by Bernstein (1996).

In economics it was Frank Knight the first one in postulating a difference between uncertainty and risk, arguing that the former cannot be described by means of a probability measure while the latter can. According to Knight (1921) and Keynes (1921, 1939), the economic agents inhabit in an environment of pervasive uncertainty and therefore little can be done about quantifying and forecasting economic variables, or even taking decisions relying on some quantitative measure of the economic dynamics (i.e. probabilities can be 'incommensurable').

Currently, that original distinction between risk and uncertainty is still a vivid topic of the academic agenda and some recent works have focused on explaining decision making under uncertainty, which seems to be more oriented to social conventions and less driven by rational calculations. Accordingly, in this branch of the literature there is a requirement

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of differencing the concepts, while measuring what is possible to measure, keeping an eye on what cannot quantified in probabilistic terms (Nelson and Katzenstein, 2014; Ganegoda and Evans, 2014; Taleb, 2007).

Although important in its own right, this *knightian* differentiation between risk and uncertainty, taking to the extreme, leads to the impossibility of defining a probability space and restrain us from using any variation of the Ergodic Theorem in empirical studies. Therefore, it conduces to the impossibility of doing any science at all (Hendry, 1980; Petersen, 1996), or at least the kind of social science based on 'measurement', as fostered by the Cowles Commission for Research in Economics, since its origins[2].

Facing this obscure panorama, the profession has moved from the *knightian* extreme view of uncertainty, to a more promising approach to the topic. Nowadays it is commonly accepted that uncertainty can (and must) be measured, because it is related importantly to many economic phenomena. In this new strand of the literature, uncertainty has been generally assimilated to a time-varying conditional second moment of the series under study, linked to time varying underlying structural shocks, such as terrorist attacks, political events, economic crises, wars, credit crunches, among others.

In this paper we seek to make three contributions to the study of uncertainty. First, we propose a new index to measure uncertainty in the stock market (what we call financial uncertainty). The index takes into account the inherent differentiation between uncertainty and the common variations among the series (which we identify as risk). Recent advances in the field (Jurado, Ludvigson and Ng, 2015; Gilchrist, Sim and Zakrajsek, 2014) have highlighted this indispensable differentiation and have pointed out methodological tools to perform the task, by the means of dynamic factor models. Those previous proposals have focused on macroeconomic variables, instead of financial ones. Consequently, given the low frequency of macroeconomic series, they lack a desirable property of the traditional proxies of uncertainty based on financial returns such as VXO, VIX or credit-spreads: practitioners and policy makers cannot trace their dynamics on a real time basis.

Our second contribution is that we motivate the financial uncertainty index as a macroeconomic uncertainty indicator too. We discuss under which circumstances our index can 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 thousands of economic indicators can be encapsulated by few stock-market portfolios' returns. The latter facilities the construction of the index, in terms of information requirements, modeling design, computational costs, and allows us to provide an uncertainty measure on a daily frequency, as stated before.

Lastly, we analyze the dynamic relationship between uncertainty and the series of consumption, interest rate, production and stock market prices, which allow us to advance one step forward in the comprehension of the role of uncertainty (either financial or

[2] 'Science is Measurement' was the original motto of the Cowles Commission, changed in 1952 to 'Theory and Measurement'. See Keuzenkamp (2004) and Bjerkholt (2014) for 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 oriented subject..

macroeconomic), determining the dynamics of the economy as a whole. Our empirical model allow us to explore to what extent we can trust on traditional monetary policy to manage uncertainty situations. We find that uncertainty indeed react to policy interventions, but in a minor magnitude.

This document is organized as follows. First we revise theoretical and empirical literature related to uncertainty. In Section 3 the methodology to estimate the uncertainty index is described. Our approach relies on Generalized Dynamic Factor Models and Stochastic Volatility devices. In Section 4 we describe how the Efficient Market Hypothesis provides a theoretical basis to interpret the financial uncertainty index as a macroeconomic uncertainty indicator. We also discuss there, under which circumstances we can expect the two measures to behave similarly. In Section 5 we present our data and main results, and we relate our findings to macroeconomic dynamics by means of a Vector Autorregressive (VAR) analysis. In the last section we conclude.

2. Related Literature

2.1. Risk, Uncertainty, Economic Decisions and Policy Intervention

The current paradigm developed to improve our understanding of uncertainty was born under the frame of irreversible investment. Within this framework, firm's future investment opportunities are treated as real options and, the importance of waiting until uncertainty is resolved before proceeding to actual investment is emphasized. Therefore, aggregated uncertainty shocks[3] are thought to be followed by a reduction in investment and possibly labor and, consequently, by a real-activity deterioration together with an increase in unemployment (Bernake, 1983; Bertola and Caballero, 1994; Abel and Eberly, 1994; Leahy and Whited, 1996; Caballero and Pindick, 1996; Bachmann and Bayer, 2013; Bloom, Bond and Van Reenen, 2007). Nevertheless, some studies have addressed the fact that after the original worsening of the variables a rebound effect related to a volatility over-shooting could be observed. Thus, some evidence has been provided pointing out that after those early impacts, economic recovery and increments in labor and investment could be expected (Bloom, 2009; Bloom, Floetotto, Jaimovich, Saporta-Eksen and Terry, 2014).

Another branch of the literature, regarding the topic of investment under uncertainty, has studied the role of financial market frictions as an additional channel through which volatility fluctuations can impact macroeconomic outcomes (Arellano, Bai and Kehoe, 2012; Christiano, Motto and Rostagno 2014; Gilchrist, Sim and Zakrajsek, 2014). For instance, Gilchrist et al. (2014) found that, as in the standard framework, investment irreversibilities cause firms to adopt a 'wait-and-see' strategy facing an uncertainty shock. Moreover, in the case of costly default, the implied illiquidity of capital assets reduces the firms' debt capacity because the liquidation of capital depresses the recovery value of corporate debt claims. In this way, the negative effects of uncertainty over the cycles of variables such as output or employment are amplified due to financial frictions.

[3] Panousi and Papanikolau (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 the business cycles. They find non-significant impacts at an aggregated level.

The study of uncertainty is not confined to the firm's investment problem. For example, Romer (1990) proposes that consumers may postpone their acquisition of durable goods in episodes of increasing uncertainty such as the collapse of stock prices in October 1929. In a different vein, Ramey and Ramey (1995) and Aghion, Angeleton, Abhijit and Manova (2010) have studied the negative relationship between uncertainty (or risk in our terms) and economic growth. Using panel data from dozens of economies around the world, they find favorable evidence to this negative relation.

Some other authors have addressed the effects of uncertainty on equity prices and other financial variables. In this stream, Bansal and Yaron (2004) provide a mechanism through which some asset pricing puzzles could be potentially solved, decomposing dividend and consumption growth rates into a small long-run predictable component and fluctuating economic uncertainty. Essentially, in their model, markets dislike uncertainty and worse long-run growth prospects deteriorate equity prices. From a different perspective, Bekaert, Engstrom, and Xing (2009) model the impact of risk aversion and the volatility of the fundamentals (what they call uncertainty) on the determination of the term structure, equity prices and risk premiums. They found that whereas the variation in dividend yields and the equity risk premium is primarily driven by risk aversion changes, uncertainty plays an important role in the dynamics of the term structure and it is the main force behind the counter-cyclical volatility of asset returns.

Additionally, there has been a reviving interest in accessing the relationship between uncertainty and policy interventions. Uncertainty may be understood, for example, over the effectiveness of monetary policy in the style of Brainard (1965), or about the economic environment in which monetary policy operates, which in turn can affect the policy's transmission mechanism. In this latter strand, one may be even interested in accessing the effects of monetary policy on the uncertainty itself. However, there is not a clear consensus in this resurgent research agenda. Some authors conclude that optimal monetary policy does not change significantly during crises episodes and that uncertainty about crises has relatively little effect on the policy transmission (Williams, 2012), but others have found that financial uncertainty has an important and significant role in the monetary policy transmission mechanism (Baum, Caglayan and Ozkan, 2013). Moreover, a lax monetary policy decreases both risk aversion and uncertainty (Bekaert, Hoerova and Lo Duca, 2013).

Neither it is clear whether a highly responsive or moderate monetary policy scheme is better facing uncertainty. For instance, Williams (2013) makes the argument that, once uncertainty is recognized (related to the effects of monetary policy on economic dynamics), some moderation in monetary policy might well be optimal, in the same spirit than Brainard (1965). On the contrary, although under a different notion of uncertainty understood as the time variation in cross-sectional dispersion of firms' productive performance, Fendoğlu (2014) recommends a non-negligible response to uncertainty shocks[4]. His results suggest that the optimal policy is to dampen the strength of financial amplification by responding to uncertainty. Following this author the planner achieves so by reducing the sensitivity of external finance premium to borrowers' leverage, effectively increasing the efficiency of financial intermediation that would otherwise occur in a

[4] He uses credit spreads as a measure for uncertainty.

decentralized economy. Fendoğlu (2014) extracts his conclusions from a New-Keynessian model with financial market imperfections. In his model uncertainty has two direct effects on credit market conditions. First, it affects the number of borrowers that will go bankrupt. Second, it impacts the worth that will be retained by borrowers, and hence the quality of balance sheet of these borrowers.

2.2. Measures of Uncertainty

As highlighted by Jurado, Ludvigson and Ng (2015, JLN hereafter) empirical measures of uncertainty are still in their infancy. This empirical branch has relied frequently on proxies of uncertainty, most of which have the advantage of being directly observable. Such proxies include: the stock returns or their implied/realized volatility, the cross-sectional dispersion of firm's profits, estimated time-varying productivity, the cross-sectional dispersion of survey-based forecasts, credit spreads, or the appearance of 'uncertainty-related' key words in the media. More recently, some studies have started to recognize that in order to measure uncertainty accurately, it is necessary first to remove the common or forecastable component of the variation, and only then proceed to the computation of the uncertainty indicator (JLN and Gilchrist et al. (2014) among them).

Conditional volatility estimations are very common proxies for uncertainty. Thus implied volatility indexes such as VXO, VIX, or the FTSE option implied volatility, have been traditionally employed as uncertainty proxies. Other uncertainty substitutes based on conditional volatility estimations are the time-varying volatilities of consumption growth and dividend growth (Bekaert et al., 2009). A more micro-oriented measure used in Bloom (2009) is the cross-sectional spread of firm- and industry-level profit growth. Moreover, Bloom et al. (2014) use data from the Census panel of manufacturing and construct Total Factor Productivity shocks as a residual from a first-order autoregressive equation. They define uncertainty as the cross-sectional dispersion of the calculated residual on a yearly basis.

Survey-based measures of uncertainty attempt to measure directly the uncertainty faced by households or companies. In this strand, Dick, Schmeling and Schrimpf (2013) utilize estimated moments of the density forecasts about real GDP and inflation, taken from the Survey of Professional Forecasters. Bachmann, Elstner, and Sims (2013) also follow this approach exploiting a survey of German firms and they argue that uncertainty appears to be more an outcome of recessions than a cause. A similar approach is taken in Scotti (2013) who studies series for which real-time data are available. She constructs uncertainty indexes, on a given day, as weighted averages of squared surprises from a set of macro releases, where the weights depend on the contribution of the associated real activity indicator to a business condition index.

One innovative approach followed by Baker, Bloom and Davis (2013) relies on the accounting of citations of economic uncertainty related words in the printed press. To the extent that newspapers reflect the public mood, this measure could provide a guide for uncertainty in the economy as a whole. More specifically, in their paper, the authors build an index consisting of three underlying components: newspaper coverage of policy-related economic uncertainty, number and projected revenue effects of federal tax code provisions, and a third component, which uses disagreement among economic forecasters about policy relevant variables.

Although all those uncertainty proxies above have provided key insights to the comprehension of uncertainty, and have been reliable starting points to analyze the economic impacts of uncertainty on both nominal and real variables; most of them have been subject to criticism, for example by Scotty (2013). The main points on it can be summarized as follows. On the one hand, volatility measures blend uncertainty with other notions (such as risk or risk-aversion) because they do not usually take into account the forecastable component of the variation, before calculating proper uncertainty. In this way, expected variations of the variables are frequently misunderstood as uncertainty.

On the other hand, analyst's forecasts have several known drawbacks, documented by JLN and Scotty (2013). First, subjective expectations are only available for a limited number of series. Second, it is not clear whether the responses drawn from these surveys accurately capture the conditional expectations of the economy as a whole[5]. Third, disagreement in survey forecasts could be more an expression of different opinions than of real risk or uncertainty (Diether, Malloy, and Scherbina, 2002). Fourth, even if forecasts are unbiased, disagreement in analyst's point forecasts does not generally equal forecast error uncertainty (Lahiri and Sheng, 2010)[6].

Aiming to overcome these shortcomings, a new branch of the literature has emerged, which proposes to measure uncertainty only after removing the forecastable component of the series. In this line, the work of JLN provides estimates of uncertainty using a data-rich environment, which comprises 132 macro-series and 147 financial series with a monthly frequency, ranging from 1960 to 2011. They approach uncertainty as the average across the conditional stochastic volatilities of the estimated forecasting error in a dynamic factor model. Being the 132 macro series the forecasted objects, they use the first twelve principal components of the 279 series as forecasting variables, together with their squares, their lags (and lags of the forecasted variables) and other external information[7]. They use forecast horizons of 1, 3 and 12 moths in their final estimations.

On the other side, Gilchrist et al. (2014) construct an uncertainty measure using the residuals of a 4-factors model (Fama-French 3 factors plus a momentum factor) of the equity premium, using more than 11,000 stock returns series on a daily basis. Lastly on a methodologically related study, Carriero, Clark and Marcellino (2012) consider common sources of variation in the residuals of a Bayesian VAR model with conditional volatilities driven by a single common unobserved factor. Using a combination of a standard natural conjugate prior for the VAR coefficients and an independent prior on a common stochastic volatility factor, they derive the posterior densities for the parameters of the resulting model.

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5 The same is true for the 'uncertainty-related-key-words' literature.

6 Bachmann, Elstner, and Sims (2013) and Scotti (2013) 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 instead of on uncertainty around objective statistical forecasts.

7 Information selected using an automated algorithm, on top of a conservative t-statistic criterion.

Our model adds to the previous literature because it enables us to provide a *daily* measurement of uncertainty, such as the VIX or the index by Scotty (2013). This is important, because allows monitoring the market in real time, and permits the researcher to develop event-studies with greater precision, including uncertainty as a variable. At the same time, it takes into account the extraction of the contemporaneously forecastable component of the variation, before calculating uncertainty as in Gilchrist et al. (2014). The latter is important to satisfactorily distinguish uncertainty from risk. We procure also to construct estimations of uncertainty as theoretically free as possible.

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 achieve this goal 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, getting a single index of uncertainty for the stock market, and possibly for the economy as a whole, as discussed in Section 4.

The first point is important because given the notion of uncertainty, which is inherently related to unexpected variations of the series, it is very appealing first to discard the pure-forecastable component of the variables before computing any uncertainty measure. In the context of a dynamic factor model, the forecastable variation is understood as the common variation of the series. This first step is closely related to the proposals of JLN and Gilchrist et al. (2014). On the one hand, different from the former, we do not attempt to use the forecasting errors out of sample, because at a daily basis the forecasting errors are very similar to the original series. Indeed they are practically the same, when working with financial returns. Instead, we understood uncertainty as the idiosyncratic variations, which are not common to all the portfolios in our sample, and in this sense 'contemporaneously unexpected' for the Dynamic Factor Model (DFM). Common, and therefore expected variations are more related to the concept of 'risk'. On the other hand, Gilchrist et al. (2014) do use a daily sample and the in-sample residual of a 4-factor model in their implementation, as we do here. But different from us, their explanatory factors are observable in nature, and therefore theoretically supported by a specific model. We want to avoid such theoretically driven strategy. Neither these authors provide an aggregate uncertainty index as we do here.

It should be noticed that using the in-sample residual does not require more information than what is required by JLN. The reason is that their estimation of the unobservable factors in each period uses the full sample. In other words, their principal components are not recursively updated[8], but calculated over the full sample.

We also depart from the previous literature because we introduce a GDFM, instead of a DFM, which is very convenient in the present set up. The GDFM makes use of the information in a more efficient way, exploiting the variation of the idiosyncratic

[8] Jurando, Ludvingson and Ng (2013) performed a real time recursive updating estimation, but they do not use it to construct their uncertainty index in JLN.

components (uncertainty itself) to determine the optimal weigh of the factors in the principal component estimator. Finally we use a considerably simpler modeling strategy than JLN, much less information (only 25 of their 279 series, and we do not use additional regressors such as squares and lags of the variables[9]). Nevertheless, we are able of replicating much of their results, adding some new insights to the comprehension of financial uncertainty. Ours may be understood as a complement to their study, focusing on the financial side of the economy.

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 Static Factor Model (SFM) is defined as:

$$x_{it} = \lambda_i F_t + e_{it} \qquad [1]$$

where e_{it} is an idiosyncratic error and λ_i are the factor loadings. This is a vector of weights that unit i puts on the corresponding r static common factors F_t. $C_{it} = \lambda_i F_t$ is the common component of the model. If we define $X_t = (x_{1t}, x_{2t}, \dots, x_{Nt})'$ and $\Lambda = (\lambda_1, \dots, \lambda_N)'$, in vector form, for each period, we have:

$$\underset{(N \times 1)}{X_t} = \underset{(N \times r)}{\Lambda} \underset{(r \times 1)}{F_t} + \underset{(N \times 1)}{e_t} \qquad [2]$$

where $e_t = (e_{1t}, e_{2t}, \dots, e_{Nt})'$. Notice that although the model specifies a static relationship between x_{it} and F_t, F_t itself can be a dynamic vector process. In the case that F_t and X_t are jointly stationary, F_t can be thought to evolve according to a VAR process:

$$A(L)F_t = u_t \qquad [3]$$

where $A(L)$ is a polynomial of the lag operator. The static model can be compared with the Dynamic Factor Model (DFM), defined as:

$$x_{it} = \lambda_i(L) f_t + e_{it} \qquad [4]$$

where $\lambda_i(L) = (1 - \lambda_{i1}L -, \dots, -\lambda_{is}L^S)$ is a vector of dynamic factor loadings of order s. In the case when s is finite, we refer to it as a DFM. On the contrary, a GDFM allows s to be infinite. Stock and Watson (2002, 2010) provide examples of the former and Forni, Hallin, Lippi and Reichlin (2000) introduce the latter. In either case, the (dynamic) factors f_t evolve according to:

$$f_t = C(L)\varepsilon_t \qquad [5]$$

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

[9] We also avoid the use of automated search of regressors, as one employed in JLN, because it could easily derive in model-snooping as explained by White (2000).

One additional classification of the models stated in [2]-[3] and [4]-[5] regards to whether the idiosyncratic disturbances in [2] or [4] are allowed to be weekly correlated or not. When they are not, it becomes an exact factor model. On the contrary, when they are allowed (as in our case), it is an approximate factor model.

The model stated in [4] 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. Both, SFM and DFM can be presented in matrix form as:

$$\underset{(N \times T)}{X} = \underset{(N \times r)(r \times T)}{\Lambda\, F} + \underset{(N \times T)}{e} \qquad [6]$$

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 $\mathrm{F}^{*} = FA$ and $\Lambda^{*} = \Lambda\mathrm{H}^{-1}$, 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).

Notice that the estimation of the factors using Principal Components (PC) or Singular Value Decomposition (SVD), by construction, impose the normalization that $\frac{\Lambda'\Lambda}{N} = I_r$ and $F'F$ being diagonal, which are enough to guarantee identification (up to a column sign rotation).

GDFM were originally proposed by Forni and Reichlin (1998) and Forni et al. (2000). It is a generalization of the DFM because it allows a richer dynamic structure for the factors. It places smaller weights on variables having 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.

There are different alternatives to estimate models in [6]. One of them consists in using a PC, or equivalently SVD, to estimate the factors and their loads. On its side, the GDFM makes use of a two-step estimation strategy discussed in Forni et al. (2000). First, the variance-convariance matrices of the common and the idiosyncratic components in [1] are estimated, by exploiting the first q dynamic principal components operating on the spectral density of x_{it}. Then the information resulting from the first step is used to determine linear combinations of the x's, which are more efficient than standard principal components. Particularly:

$$\hat{C}_t = \left[\Gamma_0^C \hat{Z}'\left(\hat{Z}\hat{\Gamma}_0\hat{Z}'\right)^{-1}\right]\left(\hat{Z}X_t\right) \qquad [7]$$

where $\hat{C}_t$ is the estimation of the common component, Γ_0^C and $\hat{\Gamma}_0$ are contemporaneous-covariance matrices of the common components and the x's, respectively. The first matrix is estimated based on spectral density methods. $\hat{Z}$ are generalized eigenvectors and therefore $\hat{Z}X_t$ are the generalized principal components.

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

3.2. Conditional Volatility Estimation

We use a stochastic volatility (SV) model to estimate the conditional volatility of the idiosyncratic-uncertainty component at a daily frequency. This approach is more convenient than a GARCH-type alternative, as highlighted by Jurando, Ludvigson and Ng (2013), on the basis that GARCH type models (unlike stochastic volatility) are affected by shocks to the second moments that are not independent of their first moment. This in turn is inconsistent with the assumptions of an independent uncertainty shock presumed in the theoretical uncertainty literature. Therefore, using a GARCH-based uncertainty index creates additional identification problems.

Once we recover the series of filtered returns, e_{it}^{u}, a SV model is specified at an individual level, for each $i = 1, \dots N$[10], as:

$$e_t^u = e^{h_t/2}\epsilon_t, \tag{8}$$

$$h_t = \mu + \emptyset(h_{t-1} - \mu) + \sigma\eta_t \tag{9}$$

where ϵ_t and η_t are standard Normal innovations independent 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 8 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 has to be contrasted with the uncentered reparameterization provided by Kastner and Frühwirth-Schnatter (2014):

$$e_t^u \sim N\left(0, e^{\mu + \sigma\tilde{h}_t}\right), \tag{10}$$

$$\tilde{h}_t = \emptyset\tilde{h}_{t-1} + \eta_t,\ \eta_t \sim N(0,1) \tag{11}$$

Whether the first or the second parameterization is preferred for estimation proposes, generally depends on the value of the 'true' parameters. Kastner and Frühwirth-Schnatter (2014) and the references therein, illustrate extensively the cases in which one representation should be favored over another, conducing to efficiency gains. Nevertheless both of them have likelihoods with intractable forms and therefore MCMC sampling techniques are required for Bayesian estimation.

Those authors also provide a strategy to overcome the problem of efficiency loss due to an incorrect selection among the representations in applied problems. They propose to interweave [8]-[9] and [10]-[11] utilizing an ancillarity-sufficiency interweaving strategy (ASIS) introduced by Yu and Meng (2011). Their results indicate that this strategy conduces to 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.

Lastly, once the idiosyncratic stochastic volatility measures are constructed, we are able of estimating the uncertainty index in the stock market as a simple average among the

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

individual volatilities:

$$U_t = \frac{\sum_{i=1}^{N} h_{it}}{N} \quad [12]$$

This scheme corresponds to the equally weighted average, with $\sum_{i=1}^{N} w_i h_{it} \xrightarrow{p} E(U_t)$, where $w = 1/N$.

4. Financial Uncertainty versus Macroeconomic Uncertainty

Although the methodology described in Section 3 directly delivers a simple way to estimate uncertainty in the stock market, which is important by itself, we are frequently interested in quantifying uncertainty in the economy as a whole (i.e. macroeconomic uncertainty). Thus, a natural question that arises in the present context is: when can such an index being interpreted as a macro-uncertainty measure, instead of merely a financial one? Or conversely, when is it possible to take macro-uncertainty indexes currently available in the literature as good proxies for financial uncertainty?

We outline a brief answer to these questions in what follows. However a more elaborated response will be left to future research. Our main points in the outlined-answer can be resumed as follows. First, under the Efficient Market Hypothesis (EMH)[11], our index suffices both, as a financial and a macroeconomic indicator. Under departures of the EMH (for example during bubble episodes) the two measures become complements instead of substitutes, and both of them should be calculated.

Measures based on a prediction error (such as JLN's index) instead of an in-sample residual, degenerate in a standard conditional volatility of the original series, under poor performance of the forecasting model. Therefore, they are not good proxies for uncertainty, but for risk, in the financial markets. Moreover, the degree of unpredictability in the market is directly related to the capability of the financial uncertainty index to measure macroeconomic uncertainty. This happens because under the EMH the prices movements do capture all the information in the economy, included thousands of macroeconomic indicators as in JLN or news as in Scotty (2013). In resume, under high levels of fulfillment of the EMH, the more our measure can be interpreted as a macro-uncertainty indicator, but the less a macro-uncertainty indicator based on prediction of stock prices can be interpreted as a financial uncertainty one.

On the contrary, when departures from the EMH occur, our financial uncertainty index reveals information about financial markets, which is not reflected by macro-uncertainty indexes, for example: information concerning possible over- or under-valuation of equity prices, which indeed is related to investment uncertainty decisions (for instance, nobody knows when a bubble will collapse or an anti-bubble will end). For the same reason, it overestimates the uncertainty of the economy as a whole during such episodes. Therefore, both measures should optimally be computed during such periods.

4.1. Efficient Market Hypothesis and Uncertainty Measurement

[11] Technically, in our context, the EMH is not a sufficient condition for non-predictability of stock returns. Risk neutrally and absent market frictions at a micro level must be added.

The EMH has been extensively studied in the financial and economic literature; therefore we do not attempt to make a review of the works in the area. It suffices to stress some relationships between the EMH and our index, which allow us to interpret it as a macroeconomic uncertainty indicator, instead of merely a financial one. This discussion also provides some theoretical motivation for the exercise performed in Section 5.4 and helps to explain the remarkable similarities of our estimations with previous results in the literature.

Following Fama (1970), a market is said to be efficient if the prices fully reflect all the relevant information in every moment. In practice, it has been assimilated to the prices being described by a martingale process such as:

$$E(P_t|\Omega_{t-1}) = P_{t-1} \qquad [13]$$

where P_t are stock prices at time t and Ω_{t-1} is the information set (a filtration) at time t-1.

The key point is that one implication of the EMH is that the process $\{P_t\}_{t=0}^{T}$ is a martingale with respect to Ω. What Ω contains, has been an area of intensive research. In general lines, if it only contains the past history of the prices, the market is said to be weakly-efficient, if on top of that it contains all public information, it is semi-strongly-efficient; finally it is considered strongly-efficient if all private information also belongs to it.

Of course, on its narrowest form, the EMH rules out phenomena such as bubbles, or even conditional dependence in the second moments of the series, which has been subject to all sorts of criticisms from within academia and outside of it. Nevertheless, some insights of the EHM are still key to understand the behavior of financial returns and have enhanced our comprehension about financial markets in unprecedented ways. Consistently, many of the original implications and assumptions of the EMH have been relaxed in order to transit to more useful interpretations. Nowadays, the empirical tests of efficiency search for non-correlations instead of non-dependences, allowing the second and higher moments of the series to vary freely (see Chap. 2 in Campbell, Lo and MacKinlay (1997)). For the same reason, most of them restrict their attention to the linear world and the modeling of the first moments of the returns. They consider relations as the one described by:

$$p_t = p_{t-1} + x_t \qquad [14]$$

If x_t is a martingale difference sequence (mds) and $p_t = log(P_t)$ is a martingale w.r.t all public information, the market is semi-strong efficient in this new 'soft version' of the EMH. It turns out that under these minimal-requirements the volatility of the 'unpredictable' component equals the volatility of the original series. For example, if we add the subscript i to x_t , we get x_{it} as in Equation 1, then we have that the variance of the forecasted error is given by:

$$E\big[\big(x_{it+1} - E(x_{it+1}|\Omega_t)\big)\big(x_{it+1} - E(x_{it+1}|\Omega_t)\big)\big|\Omega_t\big]$$

$$E[(x_{it+1})(x_{it+1})|\Omega_t]$$

$$E\big[(x_{it+1})(\lambda_i^F F_t + e_{it+1})\big|\Omega_t\big] \qquad [15]$$

where λ_i^F is the projection of x_{it+1} on the static factors space at time t and earlier. This expression trivially simplifies to $E\left[e_{it+1}^2|\Omega_t\right] = var(x_{it+1}|\Omega_t)$ because the EMH imposes λ_i^F to be zero, even if the factors F_t are allowed to include squares or observable variables. Under these circumstances, any attempt to forecast x_{it+1} before calculating the conditional variance is worthless.[12]

Facing it, we propose to define uncertainty in the stock markets as the $var(e_{it}|\Omega_t) \neq var(x_{it}|\Omega_t)$ in [1]. This definition seems more consistent with the natural understanding that one has about uncertainty: it comprises variations in the series that are not subject to any modeling strategy (i.e. idiosyncratic innovations). In this sense, they are contemporaneously unexpected.

4.2. Uncertainty, Bubbles and Prediction

Even efficiency, as described by Equation 14, has been challenged in recent times. At least two different branches of the literature have contradicted it. On the one hand, the econometric detection of bubbles has presented evidence that bubbles episodes can be detected and they have used, precisely, the kind of information that is at odds with [14] to achieve this goal. It is the explosive behavior of the process which allows them to identify the bubbles, as a change in the regime describing x_t, from I(0) to I(1). This in turn implies that x_t is by no means a mds as needed for traditional EMH strategies (Homm and Beritung, 2012; Phillips and Yu, 2011; Phillips, Shi and Yu, 2011; Phillips, Whu and Yu, 2012; Anderson and Brooks, 2014; Yuhn, Kim and Nam, 2015; Zhou and Sornette, 2003; Sornette and Zhou, 2004; Sornette, Woodard and Zhou, 2009). On the other hand, prediction of the equity premium has been demonstrated to be possible and utility gains can be achieved by using forecasting models to allocate portfolio resources (Almadi, Rapach and Suri, 2014; Neely, Rapach, Tu and Zhou, 2014; Rapach and Zhou, 2013).

Some other authors have stressed the fact that the EMH does not necessarily exclude predictability. Because it could arises instead as a consequence of risk-aversion or frictions in the market microstructure (Singleton, 2006). Either as a departure from the EMH, as we interpret it here, or as a consequence of risk aversion or market frictions, predictability of the assets returns can potentially break the relationship in [15] and therefore it could open the door to alternative estimations of uncertainty in the stock markets, using forecasting errors instead of in-sample residuals as we do here. Notice that the latter does not imply that those alternatives would be superior to ours, even when possible. Indeed, they do not seem to provide further information, even when using more information in the estimation, as shown in the next section.

In practical terms, those alternative measures can be informative just under some degree of predictability of stock returns. As stated above, some studies have reported good performance (at least better than random) when forecasting monthly, quarterly or annual stock returns. Predictors often incorporate lags of the variables, macroeconomic series, observable or unobservable factors, or even 'technical indicators' (mainly moving averages and momentum factors). Nevertheless, on a daily basis, not all of these predictors are

[12] If the expected value were equal to a constant different from zero, it would imply the same result up to a scale, which makes no difference in the argument.

available, and it seems to be difficult to forecast even the sign of the next day returns (Christoffersen and Diebold, 2006; White, 2000). Indeed, no model has achieved a satisfactory out sample performance at this frequency. In this case, we are once again in a situation in which uncertainty *must* be measure as proposed in Section 3.

In conclusion, we argue that financial uncertainty in no case should be measure by means of a macro-uncertainty indicator that uses forecasting errors and macro-series (under the EMH it can be misleading, leading us to take risk as uncertainty, and under departures of the EMH it does not reflect uncertainty, due to over- or under- valuation episodes). On the contrary, financial-uncertainty indicators as ours can provide a good account of uncertainty under regular times (low-predictability of asset returns) and they have the additional advantage of being available at a greater frequency. Macro-uncertainty indicators can be an important complement during crises and bubble episodes, when predictability increases (Almadi, Rapach and Suri, 2014).

5. Data and Results

5.1. Data

In our empirical exercise we use twenty-five portfolios of stocks belonging to NYSE, AMEX, and NASDAQ, sorted according to size and Book to Market considerations, as provided by Kenneth French on his website[13]. Those portfolios are the intersections of 5 portfolios formed on size (market equity, ME) and 5 portfolios formed on the ratio of book equity to market equity (BE/ME). The BE/ME breakpoints are NYSE quintiles. Those portfolios have been widely used in the factor asset-pricing models literature (see Cochrane (2005) whom makes it clear the reason), and they can bee seen as a good summary of the whole market dynamics. It would be possible to estimate the index, using instead the returns of all listed firms, but it would imply much more computational troubles, while with little expected gains following the Mutual-Fund theorem statement. Moreover Sentana (2004) motives the use of portfolios to extract the subjacent factors by proving that many portfolios converge to the factors as the number of assets increases.

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

In Section 5.4 we estimate a VAR model. The Data for this exercise was 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 non-farm sector; Real Personal Consumption Expenditures in 2009 prices; the Personal Consumption Expenditures Price Index; the New Orders index named NAPMNOI; Average Weekly Hours of Production and Nonsupervisory Employees for the Manufacturing sector (the all-sectors 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. Every series were seasonally adjusted when necessary, and the

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

sample spans from February 1959 to September 2014, which is the longest period possible using these series.

5.2. 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 individual 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 marked by the NBER on its web site. Picks of the index coincide with well-documented uncertainty episodes in the financial markets and the real economy, such as the Great Depression, the Great Recession, The terrorist attacks of 09/11 and the Black Monday of October 1987.

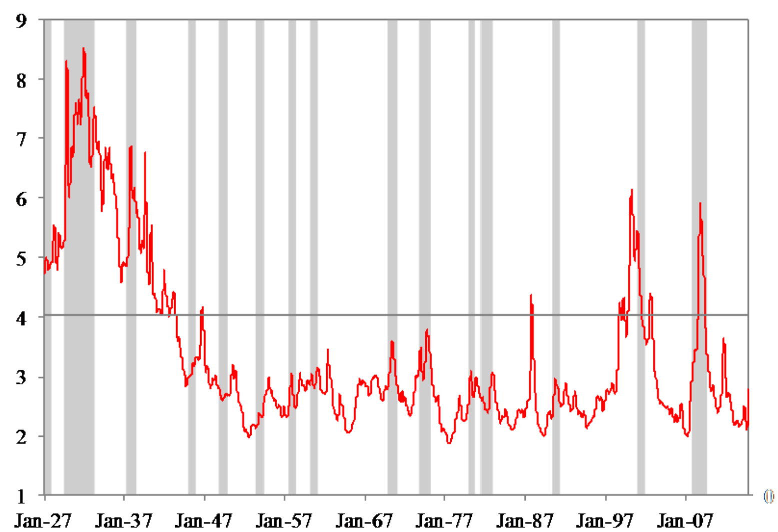


Figure 1: Uncertainty Index: Jan-06-27 to Sep-30-14: First 153 observations have been discarded and last 153 have been replaced by calculations using a (scaled) one-side filter version of the GDFM (Forni, Hallin, Lippi and Reichlin, 2005). The reason for doing so is that original GDFM are biased at the beginning and 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 (pick-to-trough), including the picks and troughs. 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, for convenience of the reader.

Recession's dates such as August 1929-March 1933, May 1937-June 1938 and December 2007-June 2009 are clearly correlated with the amount of uncertainty in the market, although interestingly, not all recessionary episodes are preceded or followed by a big uncertainty shock. For example, the uncertainty pick of the index in March 2000 takes place one year before the economic contraction in March 2001. Several other recessions during the decades of 40's, 50's and 60's do not seem to be associated with episodes of high or even increasing uncertainty.

More important, uncertainty in the stock markets appears to be correlated 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, Kim and Nam (2015), namely, 1987 (Black Monday), 2000 (information technology (IT) boom) and 2007 (housing market boom). Indeed, such episodes, understood as periods in which the asset returns and its volatility take distance from the growth or volatility of their fundamentals, could be the main driver of uncertainty episodes, (even more than recessions) at least for the last part of our sample. Many of such episodes have been identified in the recent literature and they constitute a very active area of current research within the financial econometrics field (see references in Section 3.2) and even from outside the economic profession, particularly as an application of statistical mechanics tools to financial problems (see Budinski-Petkovića, LončArevi, Jakšić and Vrhovac (2014) and references therein). The latter, given the now well-documented fact that bubbles and, in general, financial prices growths seem to behave according to a log periodic power law (Zhou and Sornette, 2003, ;Sornette and Zhou, 2004; Sornette, Woodard and Zhou, 2009).

In Table 1 we report some descriptive statistics of a monthly (end-of-the month) version of the uncertainty index. We construct a monthly index to make comparisons with other uncertainty indexes easier. The skewness, kurtosis, persistence and half-life of the shocks, for the full sample and for two sub-samples (January 1927 to March 1940 and April 1940 to September 2014) are presented. This partition was done after testing for multiple breaks in the autoregressive model of the shocks persistence (AR(1) with drift). The multiple-breaks statistic is due to Bai and Perron (1998, 2003) and intuitively it is a set of Chow statistics, calculated using recursive regressions over subsamples of increasing lengths. Several candidates to breaks are selected using the biggest F-statistics for which the null hypothesis in the Chow tests (i.e. parameters stability) is rejected. Then asymptotic (corrected) critical values are used to contrast the null of no-breaks[14].

Table 1. Summary Statistics

Statistic	Sample period Jan 1927- Sep 2014	 Jan 1927- Mar 1940	 Apr 1940- Sep 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: moths (years)	101 (8.42)	18.3 (1.53)	31.9 (2.65)

Source: Own elaboration.

From Table 1 it is apparent that using the full sample to calculate persistence can lead to spurious estimation of the summary statistics. : Indeed, the sample distribution of the uncertainty index in the two subsamples looks very different. In the first part of the period, persistence is smaller, and therefore the 'shocks' disappear in a shorter period of time (1.53 years) than in the second sub-sample (2.65 years). There is also lesser number of observations distant from the mean and the distribution presents a slightly asymmetric

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

behavior (skewness equal to 0.32). On the contrary, even when the second part of the estimation presents smaller shocks in magnitude (Figure 1), the distribution that characterizes them tend to generate more 'outliers', as documented by a kurtosis of 6.92, being more likely for these shocks to be above the mean than below it (1.7 is the asymmetric coefficient). These shocks also have a higher persistence and a half-life of 2.65 years, almost duplicating the half-life of the first sub-sample.

Compared to other estimations of persistence of macro-uncertainty, as the ones provided by JLN, ours are smaller. For instance they report a persistence of 53.58 months in their estimations, while in the second part of our sample the persistence is 31.9 moths. This could be interpreted as evidence of financial-uncertainty shocks being less persistent than macro-uncertainty shocks. Nevertheless it has to be noticed that JLN also report the persistence and half-lives of frequently used proxies for uncertainty, as the VXO and the cross-sectional standard deviation of the returns. They show that these uncertainty-related measures are far less persistent that 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 to those of the macro-uncertainty shocks than to the ones due to volatility measures.

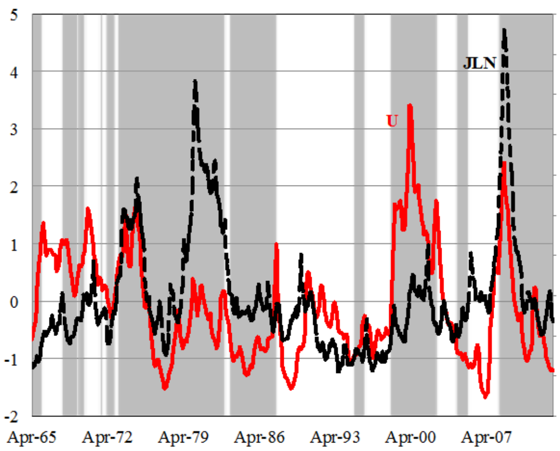
5.3. Comparisons with Macro-uncertainty Indexes

The methodologically closest measure of uncertainty to ours is the uncertainty index of JLN. Whereas their proposal can be interpreted directly as a 'macro-uncertainty' indicator, given their emphasis on the economic variables, instead of the purely financial ones. Given these facts, it seems to be a good candidate to compare our index in order to look for convergent and divergent paths. In order to compare the indexes, we first reduce our sample to fit theirs. Our resampled data starts in January 1960 and ends in May 2013[15]. After doing so we recalculate our uncertainty index aiming to use the same dates than they employ. 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 shadowed areas in the plot correspond to 'high' and 'low' correlation periods. The Pearson's correlation for the full sample between the indexes is barely above 22%, which could be interpreted, at a first glance, as different forces behind the macro-uncertainty and the financial-uncertainty. However this correlation seems itself very volatile. We also calculate moving-windows correlations of five years during the sample and what we found is more informative than the static correlation. The correlation remains above 50% the 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%, showing practically not difference in the indexes' dynamics. It reached even higher values during the 70's and we observe correlations between 40% and 80% in the period lasting from May 1994 to February 2003 (right-panel). There are also two periods in which this correlation turned 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 stronger impetus than before.

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

Lastly, when we analyze the levels of the uncertainty indexes, those are particularly different during the periods from March 1979 to May 1983 and July 1998 to January 2003. Our intuition for the divergent paths that we found during these periods is basically in line with our theoretical predispositions. While uncertainty in the financial markets is driven significantly by bubble episodes, bubble episodes are not always the drivers of the recessions in the real economy, and therefore are not related one-to-one with macro-uncertainty. Thus, the financial-uncertainty index highlights uncertainty associated to bubble episodes (for instance during the dot.com) that did not materialize as strong recessionary phases in the real economy, and therefore, are not captured by the JLN-uncertainty index. In the same vein, recessionary episodes such as those from 1979 to 1983, not particularly related to the financial market, are not especially pronounced in our financial-uncertainty indicator.



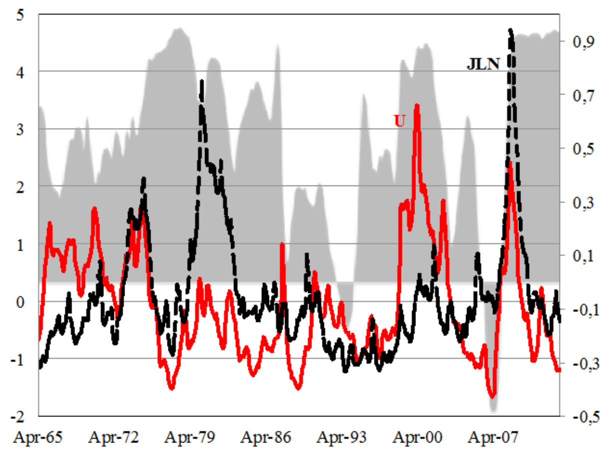


Figure 2: Uncertainty Comparisons I: The solid line represents the uncertainty Index (U), while the dotted line represents the Jurado-Ludvigson-Ng's Index (JLN) with forecast horizon $h = 1$, both from Apr-65 to May-13. In the left-hand shadowed areas corresponds to correlation periods above 0.5. In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

We also compare our index with the VIX, another frequently proxy for macro and financial uncertainty (Figure 3). The VIX is available only after January 1990. We found a correlation of 65.2% using the full sample. The dynamics of the VIX and the uncertainty index look pretty similar with a correlation above 70% for the last ten years within the sample. Nevertheless such dynamics are considerable different (looking at levels of correlations) for the first ten years in the sample. Once 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 seems positively related to uncertainty.

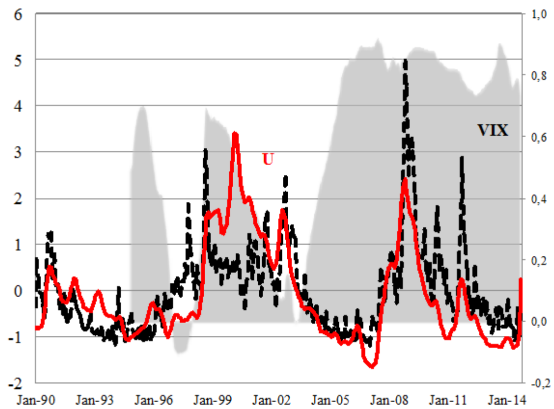


Figure 3: Uncertainty Comparisons II: The solid line represents the uncertainty Index (U), while the dotted line represents the VIX, both from Jan-90 to Sep-14. Shadowed areas are the 5 years rolling correlations and therefore they start only after Jan-95.

5.4. VAR Dynamics

In this section we explore the dynamic relationship of our uncertainty index with some macroeconomic and financial variables. We use the model by Christiano, Eichenbaum and Evans (2005). This model has been widely studied in the literature and therefore is a well-known reference useful to match our uncertainty estimates. The model is given in reduced form by:

$$Y_t = A(L)Y_{t-1} + e_t \qquad [16]$$

where, Y_t is a matrix $(T \times N)$ containing the N column-vectors of the model. Specifically $Y_t = [Y_{1t}, R, Y_{2t}, U]'$. 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 placed last (as also is done in JLN and Bloom (2009)) our Uncertainty Index[16], U. We estimate a VAR with 12 lags (instead of four quarters as in Christiano et al. (2005) to cover the same time-span). All the variables enter in log-levels, but R and Uncertainty that enter in original units and M2, which enters in growth rates. We recover the structural innovations by means of a Cholesky decomposition of the variance-covariance matrix. As it 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 in their neighborhood, 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 reaction of Production and Employment to uncertainty shocks has been studied before, for example in JLN or Bloom (2009). The former authors find very similar results to ours, even when using their uncertainty index, which requires by far more information, processing time and modeling design, than required by our index. Production reacts

16 See Section 4.1 for a more detailed description of the data used in this section.

negatively to uncertainty increments and the persistence of the shock goes beyond the two years horizon. The forecast error of the production series is explained by the uncertainty shock in 10.5% for the sixth month after the innovation, and up to 23.8% 12 months ahead[17].

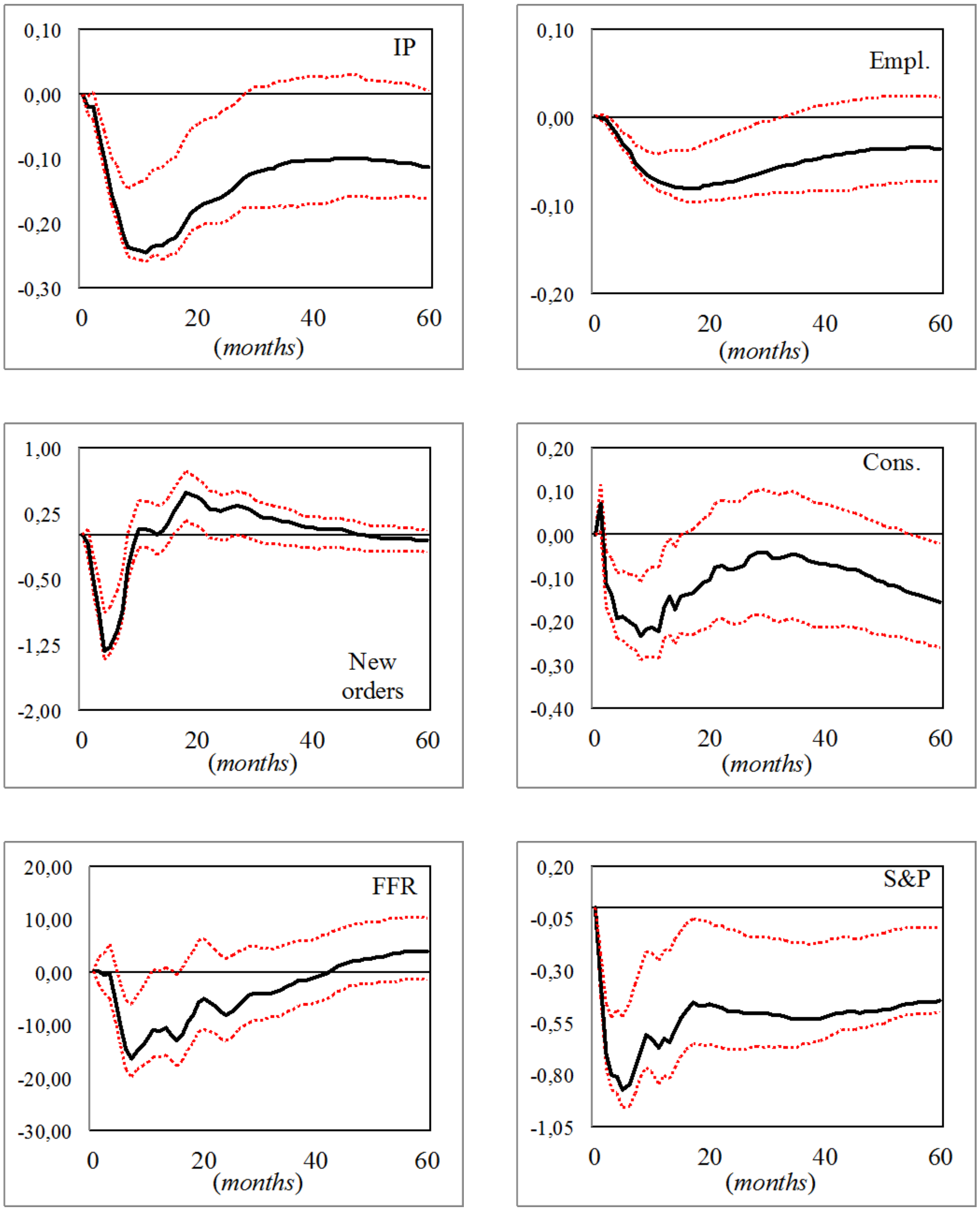


Figure 4: Economic Dynamics under Uncertainty: We use a VAR (12) comprising 11 variables. The edges are in percentages but the FFR, which is in basic points. The figure displays the reaction of the variables to an unexpected increment of uncertainty. The estimation period runs from February 1959 to September 2014. Confidence bands (86%) are calculated using bootstrapping techniques as explained in Efron and Tibshirani (1993).

17 See Table 2 in the Appendix.

Analogously, although in smaller magnitude, employment decreases following a positive uncertainty shock and the impact persists two and a half years after (six months more than in the production case)[18]. We do not find evidence supporting the 'rebound' effect proposed by Bloom (2009) when we look at production, as neither do JLN. However, the rebound effect is evident when analyzing the New Orders variable, which is a better proxy for actual investment. First, the new orders decrease facing uncertainty, and the negative impact last approximately 8 months, but there is a 'rebound' statistically significant effect in moths 16 to 19. The reason for this effect not to be present in the production dynamics could be that, after the original uncertainty shocks, negative feedback from consumption and expected demand, follows.

Although there exists theory that links explicitly uncertainty shocks to consumption, for instance Romer (1990), little empirical evidence has been presented to document this relationship. We find that after an increment in uncertainty, consumption is severely affected, more or less in the same proportion than production, and more than employment. The shock tends to disappear faster (1.3 years before the upper confidence band touches zero), but it is also apparent that it leads the series to stabilize in a lower level than production series.

Financial prices such as the stock market index are significantly affected by uncertainty in the financial markets, as predicted by the theory. Indeed, the strong decreasing of the market index facing uncertainty, and the stabilization of the sequence in a lower level, is completely consistent with the theory provided by Bansal and Yaron (2004). Basically, the intuition lays on the fact that markets don't like uncertainty and after an uncertainty increment, they discount of the expected cash flows is stronger, causing the market to reduce the prize of the stock. Notice that we refer here to a 'systemic uncertainty shock' and not to idiosyncratic uncertainty. To what extend idiosyncratic-uncertainty shocks can affect the individual stock prizes in the same fashion, remains as an unanswered question.

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 the 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 these cases it is the second or third most important source of variation. It affects at a lesser extent other series such as consumption (7.6%) or the Fed Funds (4.7%), but still in these cases it is the fourth or fifth cause of the variation among the eleven considered variables.

Lastly, the Federal Funds Rates also seems an uncertainty-sensitive variable. Facing an uncertainty shock the Central bank tends to reduce the interest rate (which confirms that the reduction in equity prizes is due to uncertainty and not to possible confounding interest movements). This reduction is particularly persistent during the first year and then it starts to disappear. Nevertheless, the variance decomposition of the Fed rates only owns to the

[18] JLN report an impact of the uncertainty shock on production, which persists more than 60 moths. We also find that indeed the IRF tends to stabilize in a lower level after facing the shock, as can bee seen in Figure 4. But this is only true for the average-level. Note that the boost-trapped confidence intervals of our exercise prevent us to set the effects beyond three years as statistically different from zero.

uncertainty shock between 4% and 5% of its total variation.

The Cholesky identification strategy allows us to discern which is the effect in the other direction. In other words, to answer the question: does the monetary policy reduction decreases uncertainty? Indeed as can be seen in Figure 5, a loosening monetary policy does affect uncertainty. The effects are to be expected to occur with a lag of one year, continue for one year more, and disappear after this period. This finding is in line with similar effects documented by Bekaert et al. (2013), although they use non-corrected uncertainty measures and a different strategy to differentiate it from risk. Our results in this direction add to the research agenda that aims to explore the relationship between policy intervention and uncertainty. It is in line with the calls for an active monetary policy facing uncertainty as advocated by Fendoğlu (2014). However these effects are small in magnitude (see Table 2), only between 2% and 6% in uncertainty is due to the monetary policy innovations.

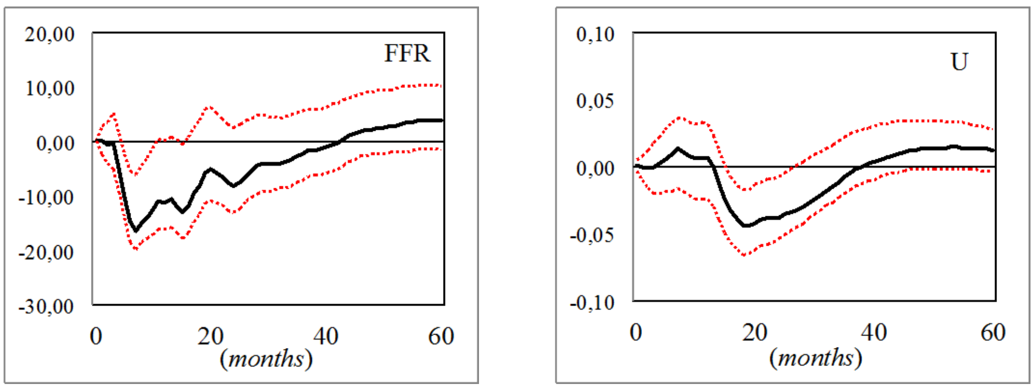


Figure 5: Policy intervention and uncertainty: We use a VAR (12) comprising 11 variables. The edges are in basic points and units, respectively. We replicate the left-panel from Figure 5 and we multiply times minus one the response to an increase in the federal fund rates, to be consistent with the text. 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, we compare the responses of the variables facing uncertainty using our proposal and the JLN's index in Figure 6. The qualitatively and quantitative results reported above do not change significantly depending on the uncertainty measure.

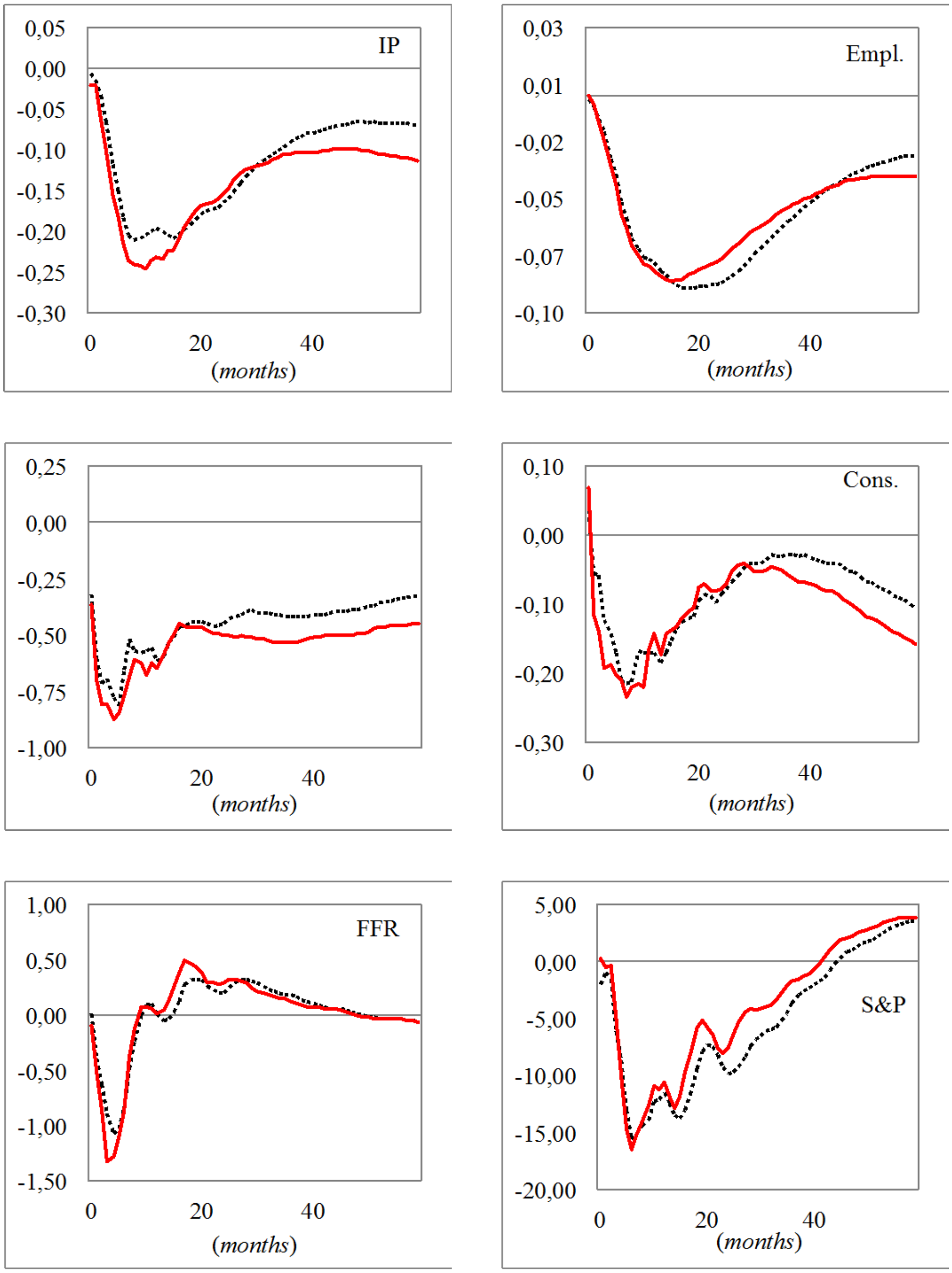


Figure 6: Economic Dynamics under Uncertainty: Comparisons from two indexes JLN and U. We use a VAR (12) comprising 11 variables. The figure displays the reaction of the variables to an unexpected increment of a standardized uncertainty measure as the U-index (solid line) or the JLN-index (dotted line). The estimation period for the U-index runs from February 1959 to September 2014. The JLN-index is only publicly available form July 1960 to May 2013 on one of its author's web page; therefore we use this period to estimate the IRFs in this case.

5.5. 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 a ‘one-side-filer’ version of the GDFM proposed by Forni et al. (2005) instead of the two-side original GDFM. 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 an iterative fashion, recalculating each model with rolling windows of 80 days (aprox. one quarter). The latter approach speaks directly above parameter stability. The main results are summarized in Figure 7.

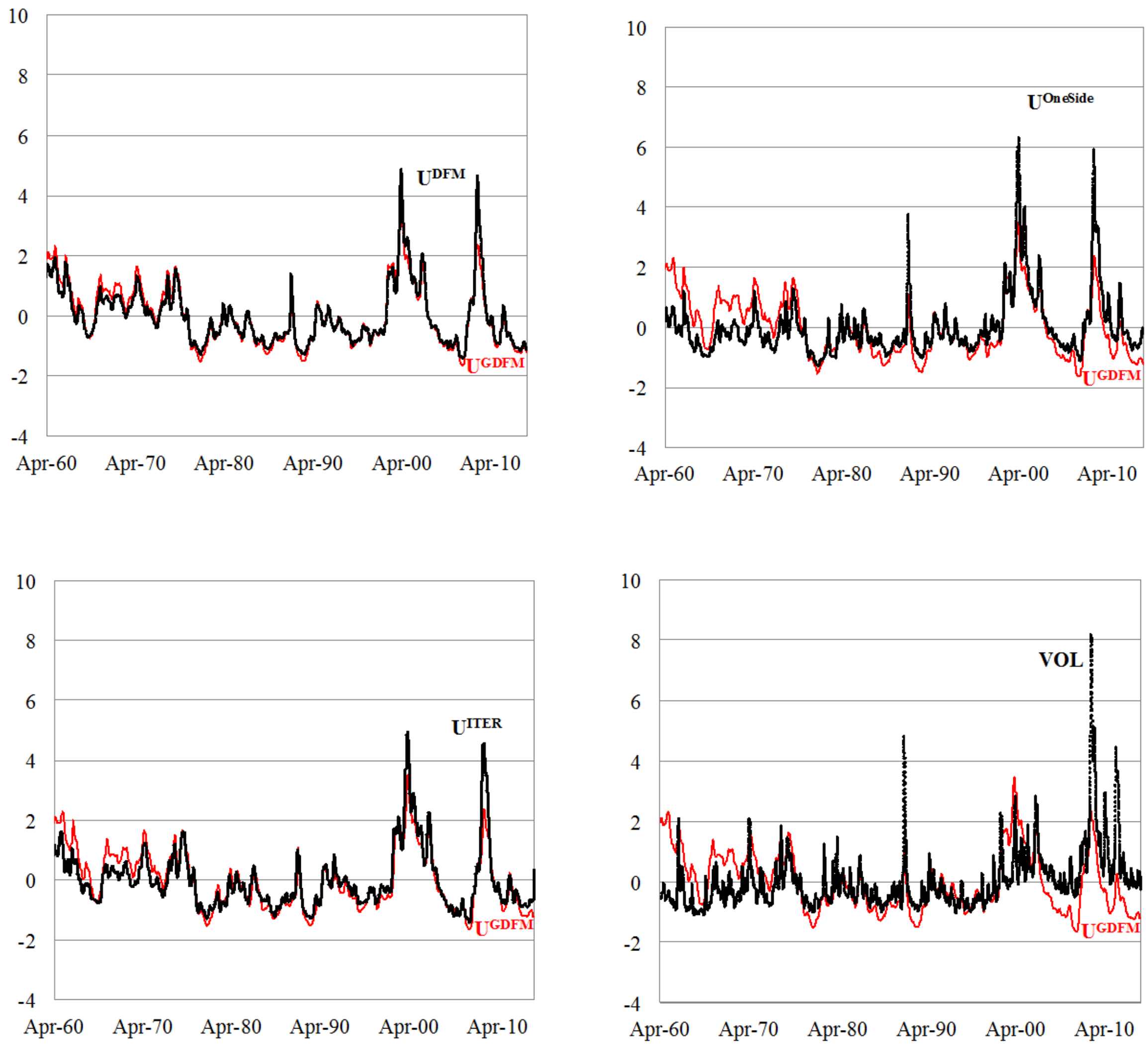


Figure 7: Robustness exercises: The uncertainty index using GDFM (solid line) is compared with different alternatives: a DFM (top-left), a one-side filter version of the GDFM (top-right), an iterative algorithm (bottom-left) and a conditional volatility measure of the original series (bottom-right).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

In general lines the uncertainty index behaves very similar regardless the factor methodology used to extract the idiosyncratic components of the series. Neither it changes when using recursive estimations. Although it behaves considerably different to the stochastic volatility of the original series, which is not surprising and indeed, in-line with previous findings in the literature, which highlight that volatility measures tend to overestimate the uncertainty of the economy because they blend uncertainty with risk, or risk aversion.

6. Conclusion

We propose an index of time-varying financial uncertainty. The construction of the index is relative simple and it does not relay on excessive data mining devices or exigent information requirements. We construct the index on a daily basis, for the United States' economy from 1927 to 2014.

Our estimations allow us to identify different periods of uncertainty. Some of them coincide with well-documented uncertainty episodes, such as big recessions, wars, terrorist attacks or political events. Other are more associated, especially for recent decades, to bubble episodes in the stock market. We also document a change in the uncertainty persistence, and other characteristics from 1940 to 2014, compared to the period between 1927 and 1940. Current uncertainty is more persistent and is plagued with greater extreme-observations, although it is smaller in magnitude than earlier uncertainty.

We discuss under which circumstances ours is a better measure of financial uncertainty and when does it agree with other measures previously available. We conclude that significant departures between macro uncertainty and financial uncertainty can be expected during 'bubble times' and we present evidence of this fact.

Nevertheless, 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 uncertainty tend to disappear slowly. We also present novel empirical evidence about the negative effect of uncertainty in consumption, inventory investment (which presents an overshooting effect facing uncertainty) and stock market prices, which supports previously highlighted theoretical and empirical advances in the discipline.

Lastly we explore the relationship between uncertainty and policy variables. We found that there is a close relation between the reference rate in the economy and uncertainty. The interest rate tends to decrease facing an uncertainty shock and the uncertainty shock decreases after a reduction in the monetary policy position, with a lag of one-year. However, the latter effect is very small when explaining the total variation of the forecasted errors of the uncertainty variable. This raises questions about the capability of the central banks combating uncertainty by means of traditional monetary policy.

7. References

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Appendix

In the estimations we make use of some routines from the web page of Prof. 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 Prof. Mario Forni. (http://morgana.unimore.it/forni_mario/matlab.htm). To estimate stochastic volatilities we use the r-package 'stochvol', 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%

Source: Own elaboration.
We use a VAR (12) comprising 11 variables, in the following Cholesky-order from contemporaneously exogenous to: 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.