Expected, Unexpected, Good and Bad Aggregate Uncertainty

Jorge M. Uribe[*] Helena Chuliá[†]

Abstract

We study aggregate uncertainty and its linear and nonlinear impact on real and financial markets. By distinguishing between four general notions of aggregate uncertainty (good-expected, bad-expected, good-unexpected, bad-unexpected) within a simple, common framework, we show that it is bad-unexpected uncertainty shocks that generate a negative reaction of economic variables (such as investment and consumption) and asset prices. Our results help to elucidate the real, complex nature of uncertainty, which can be both a backward- or forward-looking expected or unexpected event, with markedly different consequences for the economy. We also document nonlinearities in the propagation of uncertainty to both real and financial markets, which calls for the close monitoring of the evolution of uncertainty so as to help mitigate the adverse effects of its occurrence.

Keywords: Aggregate Uncertainty; Nonlinear effects; Economic activity; Asset prices

JEL Codes: C58; E20; E44; G10

Acknowledgement

This study was supported by the Fundación Ramón Areces [2017 Social Sciences grant] and the Spanish Ministry of Economy [grant numbers ECO2016-76203-C2-2-P, ECO2015-66314-R].

[*] Faculty of Economics and Business, Open University of Catalonia. (Barcelona, Spain). Email: juribeg@uoc.edu. ORCID: 0000-0002-5844-2771

[†] Department of Econometrics & Riskcenter-IREA, Universidad de Barcelona, (Barcelona, Spain). Email: hchulia@edu. ORCID: 0000-0001-5020-0519

1. Introduction

Uncertainty is a primary concern in economics and in general among scientists. Today, it is widely accepted that uncertainty must be measured, because it is closely related to so many social phenomena, ranging from decisions about current and expected consumption, real and financial investment and business cycle dynamics to saving decisions, prices of goods and assets, and the possibility of consumption risk sharing. In short, uncertainty is at the core of the study of human economic wellbeing. Here we are interested in measuring how aggregate uncertainty impacts on financial markets and economic activity, and by this mean, on our societies. We will emphasize on the different asymmetries that characterize uncertainty in the aggregate and on the nonlinearities in its propagation.

The current paradigm for understanding the effects of uncertainty on the real economy 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 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, Bond, and Van Reenen 2007; Bachmann and Bayer 2013; Jurado, Ludvigson, and Ng 2015; Chuliá, Guillen, and Uribe 2017; Meinen and Roehe, 2017). Nevertheless, if the uncertainty shock is positive and related to good news in the economy, the negative effects of uncertainty should disappear (or even become positive), as the probability of losses related to investment falls and as the agents realize the true nature of uncertainty (see Gilchrist and Williams 2005, or Pastor and Veronesi 2009). In contrast, a negative uncertainty shock should generate a more pronounced negative reaction, associated with smaller or even insignificant rebounds in the economy's activity (Segal, Shaliastovich, and Yaron 2015).

The effects of uncertainty on equity prices and other financial variables have also been analyzed. In this stream of the literature, a notable example is provided by Bansal and Yaron (2004) who develop a model in which markets dislike uncertainty and where poorer long-run growth prospects reduce equity prices. In the same vein, Bekaert, Engstrom, and Xing (2009) find that uncertainty plays an important role in the term structure and is the main driver of the counter-cyclical volatility of asset returns. More recently, Campbell et al. (2012) have analyzed the role of uncertainty in an extended version of the inter-temporal capital asset-pricing model (CAPM). The authors report mixed results regarding the sign of exposure to volatility on the side of asset returns. In a related study, Bansal and Yaron (2004) investigate the implications of macroeconomic volatility for the time variation in risk premia and for the cross-section of returns. They propose a conditional CAPM in which aggregate volatility acts as a risk factor, in addition to cash flow and the discount rate and find that both the betas and the market price of uncertainty are negative and, therefore, that uncertainty positively contributes to explain equity risk premium. Moreover, a recent study by Ludvigson, Ma, and Ng (2021) finds that higher uncertainty about real economic activity in recessions is most often an endogenous response of the system to other shocks that cause business cycle fluctuations, while uncertainty about financial markets is a likely source of the fluctuations (an exogenous impulse).

In economics, aggregate uncertainty has generally been assimilated, empirically, to a time-varying conditional second moment of the series under study, (e.g. observed volatility of Gross Domestic Product- GDP) closely linked to underlying time-varying structural shocks, such as terrorist attacks, political events, economic crises, bubble collapses, systemic risk materialization episodes, wars and credit crunches. Here we claim that measuring aggregate uncertainty as volatility has led to contradictory statements about uncertainty in the literature, which in turn has obscured our understanding of the phenomenon. Our main idea is simple: uncertainty impacts financial and real markets in unexpected and asymmetric ways, and neither of these two characteristics can be ignored when measuring it.

Our approach allows us to empirically assess the effects of uncertainty on the economy from a more general perspective than the extant literature and to disentangle the kind of uncertainty that more closely resembles what is expected from theory. We distinguish not only between 'bad' uncertainty, related to bad news in the market (i.e. negative growth, financial losses, wars and destabilizing political events, etc.) and 'good' uncertainty, related to good news in the market (i.e. technological innovation, financial gains, economic growth, etc.), but also between 'expected' and 'unexpected' uncertainty. Expected uncertainty is, of course, still uncertainty, in the sense that it rests on the fact that the consequences of the decisions of any economic agent cannot be predicted with certainty, but rather agents must form their expectations about such consequences in order to be able to set their optimal intertemporal paths of consumption and saving. We decompose total uncertainty into two parts: first, an expected component, which proxies for the amount of variation that agents can anticipate for a given variable of interest and, second, an unexpected component, which is related to the amount of variation that agents cannot predict. In so doing, we present our results within a common empirical structure that compares the effects of our four general notions of uncertainty.

Our work has been developed out of the theoretical and empirical ideas formulated by Segal, Shaliastovich, and Yaron (2015) and Berger, Dew-Becker, and Giglio (2020). The former claims that good and bad macro-volatility shocks have different impacts on financial prices and on the real economy. They show that actual investment, expected consumption, prices and other macro-indicators react in a highly asymmetric fashion to 'good' and 'bad' volatility shocks (with positive and negative responses, respectively). They also show that market prices react to these asymmetric risks in both economically and statistically significant ways. The second study shows that it is (backward) realized-volatility, as opposed to (forward) realized-volatility, that significantly depresses the economy and market. In our approach, we combine the insights of these two studies by recognizing that uncertainty can be 'bad' or 'good' with different economically significant consequences and, at the same time, it can be expected (forward-looking) or unexpected (backward-looking). Our approach follows the simple empirical line developed by Segal, Shaliastovich, and Yaron (2015), which uses realized semivariances of industrial production to measure good and bad uncertainty shocks, but, here, in addition, we consider the differences between forward- and backward-looking uncertainty. Unlike Berger, Dew-Becker, and Giglio (2020), we distinguish between expected and unexpected volatility as opposed to realized and expected volatilities. That is, we specifically measure the unexpected component of the total realized series, which is incorporated within the notion of realized volatility. In this sense, we follow the general idea of Jurado, Ludvigson, and Ng (2015) according to which uncertainty is more closely related to the volatility of the unexpected component of the series under analysis than to the total volatility.

We show that the notion of 'uncertainty' that is often empirically assimilated to a conditional second moment of economic activity (or its expectation) is, indeed, more closely related to the notion of what we identify here as 'bad-unexpected uncertainty', which is a much more specific construct than either volatility or expected volatility. Other general notions of uncertainty, such as good- and bad-expected volatility or good-unexpected uncertainty, impact economic activity in a variety of ways that do not always coincide with theoretical models that treat investment as a real option and, in which, given its irreversibility, the optimal approach to managing uncertainty is the 'wait-and-see' strategy. Indeed our results indicate that, in general, the effects generally claimed to follow an uncertainty shock are clearly linked to a bad-unexpected uncertainty shock.

We go one step further by considering nonlinearities in the propagation of uncertainty shocks, both in time and across the magnitudes of uncertainty. We do so because the macroeconomics literature has recently provided theoretical prescriptions and empirical evidence of nonlinear dynamics and amplification mechanisms following uncertainty shocks to the financial markets (Brunnermeier and Sannikov 2014). This nonlinearity is important because it is related to systemic risk and must be fully understood if we want to avoid negative spirals from the real to the financial markets, like those observed during the Great Recession. These spirals make recovery more difficult and costly. Negative spirals and endogenous uncertainty amplification mechanisms have the potential to destabilize markets. Even small shocks to the economy might result in a dramatic recession, if certain frictions present in the financial markets amplify these original shocks. To this end, we employ the distributed lag nonlinear model proposed by Gasparrini, Armstrong, and Kenward (2010) in the field of medical statistics, which allows us to analyze possible nonlinearities in the effects of uncertainty across both the time and scale dimensions.[1] This methodology is based on the definition of a 'cross-basis', a bi-dimensional space of functions that describes simultaneously the shape of

[1] Our approach is different, and in a sense more general than that followed by Jackson, Kliesen, and Owyang (2020) who employ a time-varying threshold VAR model in which non-linearity activates only when uncertainty reaches a local peak. We introduce non-linear effects depending on the magnitude and sign of the uncertainty shock, and in this way, we are able to analyze the non-linear response of a variety of economic and financial variables to a range of shocks of different magnitude and sign, not only around a specific threshold, but alongside the whole distribution of uncertainty.

the relationship across both the *space* of the predictor and the *lag* dimension of the occurrence. We find that the most significant effects occur after a bad-unexpected uncertainty shock of small magnitude, and not necessarily in the tail of 'big' uncertainty shocks, as one might expect. This result highlights the importance of measuring the unexpected uncertainty, even in small magnitudes for policy making and financial investment decisions.

The remainder of the paper is structured as follows. Section 2 reviews the related literature. Section 3 describes the methodology. Section 4 presents the data we use. Results are in Section 5. Section 6 presents our concluding remarks.

2. Methodology

2.1. *Empirical measures of uncertainty and estimation of good and bad volatility shocks*

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' profits (Bloom 2009), estimated time-varying productivity (Bloom et al. 2018), the cross-sectional dispersion of survey-based forecasts (Dick, Schmeling, and, Schrimpf 2013; Bachmann and Bayer 2013), credit spreads (Fendoglu 2014), and the appearance of 'uncertainty-related' key words in the media (Baker, Bloom, and Davis 2016). More recently, a new branch of the literature has emerged, which proposes measuring uncertainty only after the forecastable component of the series has been removed (Carriero, Clark, and Marcellino 2016; Gilchrist and Williams 2014; Jurado, Ludvigson, and Ng 2015; Chuliá, Guillen, and Uribe 2017).

In this paper, we aim to go one step further, and propose measuring good and bad uncertainty by distinguishing good from bad volatility shocks to industrial production series.[2] To this end, we rely on recent advances made in relation to realized variance (RV) estimation and, in particular, to realized semivariances (RS), as presented by Barndorff-Nielsen, Kinnebrock, and Shepard (2010). In other words, if we consider the traditional RV estimator, as explained

[2] We use industrial production series due to their higher frequency data availability (monthly) compared to that of real consumption series (annual).

for example in Andersen, Bollerslev, and Diebold (2010), then the RV estimator of the variable Y can be expressed as:

$$RV = \sum_{j=1}^{n} \left(Y_{t_j} - Y_{t_{j-1}} \right)^2, \tag{1}$$

where $0 = t_0 < t_1 < \cdots < t_n = 1$ are the times at which observations are available (monthly in our case) and *n* represents the number of observations of *Y* available during one period (a year in our case). This has been proven to be an extremely useful methodology for estimating and forecasting conditional variances for risk management and asset pricing. Nevertheless, Barndorff-Nielsen, Kinnebrock, and Shepard (2010) stress that this measure is silent about the asymmetric behavior of jumps, which is important, for example, for estimating downside or upside risk. Thus, they propose a new RS estimator as follows:

$$\begin{aligned} RS^{-} &= \sum_{j=1}^{n} \left(Y_{t_j} - Y_{t_{j-1}} \right)^2 1_{Y_{t_j} - Y_{t_{j-1}} \leq 0} \\ RS^{+} &= \sum_{j=1}^{n} \left(Y_{t_j} - Y_{t_{j-1}} \right)^2 1_{Y_{t_j} - Y_{t_{j-1}} \geq 0} \end{aligned}, \tag{2}$$

where 1_y is an indicator function taking the value of 1 if argument *y* is true, and 0 otherwise, $0 = t_0 < t_1 < \cdots < t_n = 1$ are the times at which observations are available (monthly in our case) and *n* represents the number of observations of *Y* available during one period (a year in our case).[3] The first of these equations provides a direct estimate of downside risk while the second does the same for upside risk. Barndorff-Nielsen, Kinnebrock, and Shepard (2010) also provide the asymptotic properties of this estimator, using the arguments and the central limit theorem for bipower variation of uneven functions, developed by Kinnebrock and Podolskij (2008).

We seek to distinguish expected from unexpected uncertainty; thus, following the theoretical insights of the model developed by Segal, Shaliastovich, and Yaron (2015), we define good (bad-)expected uncertainty as the predictable component of RS^{+} (RS^{-}). The predictable

---

[3] We use monthly industrial production series to construct realized semivariances at the annual frequency.

component is estimated as the projection of the (annual) realized semivariances in (2) on a set of (annual) predictors. The set of benchmark predictors includes the RS^{-} and RS^{+} own lags, a lag of real consumption growth (Δc_{t-1}), a lag of the real market return (rr_{t-1}^{MARKET}), a lag of the real price-earnings ratio (P/E_{t-1}), a lag of the real risk-free rate (r_{t-1}^{F}), and a lag of the default spread ($spread_{t-1}$). Accordingly, we propose defining unexpected uncertainty, both good and bad, as the residual series of the out-of-sample regression, as follows:

$$RS_t^- = \underbrace{b_0^- + b_1^- RS_{t-1}^- + b_2^- RS_{t-1}^+ + b_3^- \Delta c_{t-1} + b_4^- \; rr_{t-1}^{MARKET} + b_5^- \; P/E_{t-1} + b_6^- r_{t-1}^F + b_7^- spread_{t-1}}_{\textit{Expected bad uncertainty}} + \underbrace{u_t^-}_{\textit{Un. bad unc.}}$$

$$RS_t^+ = \underbrace{b_0^+ + b_1^+ RS_{t-1}^- + b_2^+ RS_{t-1}^+ + b_3^+ \Delta c_{t-1} + b_4^+ rr_{t-1}^{MARKET} + b_5^+ \; P/E_{t-1} + b_6^+ r_{t-1}^F + b_7^+ spread_{t-1}}_{\textit{Expected good uncertainty}} + \underbrace{u_t^+}_{\textit{Un. good unc.}}$$

(3)

2.2. *Effects of macroeconomic uncertainty on real and financial markets*

Next, we carry our two sets of predictive regressions. First, we regress annual macroeconomic indicators and asset prices (x_t) for horizon h years ahead on the expected variation of real consumption (c_t)[4] in year t and our empirical proxies for expected bad uncertainty (V_{bt}) and expected good uncertainty (V_{gt}) in year t. In the second set of regressions, we use instead our proxies for bad-unexpected uncertainty (U_{bt}) and good-unexpected uncertainty (U_{gt}) in year t:

$$\frac{1}{h}\sum_{j=1}^{h} \Delta x_{t+j} = \alpha + \gamma c_t + \beta_{V_g} V_{gt} + \beta_{V_b} V_{bt} + \varepsilon_t \tag{4}$$

$$\frac{1}{h}\sum_{j=1}^{h} \Delta x_{t+j} = \alpha + \gamma c_t + \beta_{U_g} U_{gt} + \beta_{U_b} U_{bt} + \varepsilon_t \tag{5}$$

[4] We include the expected variation of real consumption growth following Segal, Shaliastovich, and Yaron (2015).To construct a proxy for the expected consumption growth rate, we project future consumption growth on the same set of predictors used in Equation (3).

where h=1 and 5 years. In our explanatory regressions, all the variables are at the annual frequency and we used standardized variables on both sides of equations (4) and (5) so as to make the regression coefficients among the variables and among the regressions comparable (what is referred to in the statistical literature as a "beta-coefficient regression"). In this case, the intercepts are by construction set equal to zero and the slopes are directly measured in relative terms, which allows us to read their magnitude in addition to their sign.

Finally, to measure the nonlinear effects in time and the magnitude of uncertainty, we introduce the model proposed by Gasparrini, Armstrong, and Kenward (2010) to the economics literature. This is a distributed lag non-linear model (DLNM), that is, a modeling framework that can simultaneously represent both non-linear exposure-response dependencies and delayed effects. Following the original proposal, consider a general model representation to describe the time series of outcomes Y_t with $t = 1, \dots, T$ given by:

$$g(\mu_t) = \alpha + \sum_{j=1}^{J} s_j\left(x_{tj}; \boldsymbol{\beta}_j\right) + \sum_{k=1}^{K} \gamma_k u_{tk}, \tag{6}$$

where $\mu_t \equiv E(Y)$, g is a monotonic function where Y belongs to the set of distributions of the exponential family. The functions s_j stand for smoothed relations between the variables x_j and the linear predictor, defined by the parameters contained in vectors $\boldsymbol{\beta}_j$. The variables u_k might include other predictors with linear effects specified by the associated coefficients γ_k. Functions s_j could be in principle parametric or non-parametric. However, the approach introduced by Gasparrini, Armstrong, and Kenward (2010) is parametric and fully relies on what is known as basis functions.

A basis is a space of functions of which $s(x)$ is an element. Hence, related basis functions consist of a set of fully known transformations of the original variable x that produce a new set of variables denominated basis variables. In this way, the complexity and richness of the relationship will depend on the kind of basis and its dimension. The main choices in the literature typically rely on functions describing smooth curves, such as polynomials or spline functions, or on threshold parameterizations. A general representation is given by:

$$s(x_t;\boldsymbol{\beta}) = z_{t\cdot}^T\boldsymbol{\beta}\ , \tag{7}$$

where $z_{t\cdot}$ is the t-th row of the $n \times v_x$ basis matrix $\boldsymbol{Z}$ resulting from the application of the basis functions to the original vector of covariates x. Notice that, in this way, $\boldsymbol{Z}$ can be included in the design matrix of the model (6) joint with the unknown parameters $\boldsymbol{\beta}$ before estimation**.**

In the presence of effects that occur whit a lag, as it is often the case in macroeconomics we may be interested as well in adding a temporal dimension to the analysis, in terms of the past values of the covariates x_{t-l}. Where l is a lag, denoting the period occurred between the impulse-effect on the Right-Hand-Side variable and the response of the Left-Hand-Side variable. Such delayed relationship can be assumed to be linear, in which case we are in presence of a distributed lag model (DLM). These models allow the effect of a single event to be distributed over a given time interval, using different parameters to explain the contributions of the different lags to the overall effect. A DLM model can be described by the following equation:

$$\mathrm{s}(\mathrm{x}_\mathrm{t};\boldsymbol{\eta}) = \mathbf{q}_{\mathrm{t}\cdot}^{\mathrm{T}}\mathbf{C}\boldsymbol{\eta}, \tag{8}$$

where $\boldsymbol{C}$ is a $(L+1)$ matrix of basis variables that results from applying the previously defined basis functions to the lag vector l , and $\boldsymbol{\eta}$ is a vector of unknown parameters.

Gasparrini et al. (2010) generalized DLM models by allowing a non-linear relationship both in the space of the predictor and along different lags, which they label as a distributed lag non-linear model (DLNM). This model is defined as follows:

$$s(x_t;\boldsymbol{\eta}) = \sum_{j=1}^{\vartheta_x}\sum_{k=1}^{\vartheta_l}\boldsymbol{r}_{tj.}^T\boldsymbol{c}_{.k}\eta_{jk} = \boldsymbol{w}_{t\cdot}^T\,\boldsymbol{\eta}, \tag{9}$$

where $\boldsymbol{r}_{tj.}$ is a vector of lagged effects for time t converted through the basis function j. The vector $\boldsymbol{w}_{t.}$ is obtained by applying the $\vartheta_x \cdot \vartheta_l$ cross-basis functions to x_t. Extending the idea of a basis, a cross-basis is a bi-dimensional space of functions describing simultaneously the shape of the relationship along x and its distributed effects at different lags. The matrix $\boldsymbol{C}$ that consists of vector elements $\boldsymbol{c}_{.k}$ is a $(L+1) \times \vartheta_l$ matrix of basis variables derived from the application of the specific basis functions to the lag vector ℓ. Finally, $\boldsymbol{\eta}$ is a vector of unknown parameters to be estimated. In other words, first we choose a basis for x as in equation 7. This basis defines the dependency in the space of the predictor variables (i.e. uncertainty and other covariates) and allows us to specify $\boldsymbol{Z}$. Then we create the additional time dimension that consists of lagged effects of the predictors, as in equation (8). We do so for each one of the basis variables of x contained in $\boldsymbol{Z}$. This generates an array R, representing the lagged occurrences of each of the basis variables of x. As emphasized by Gasparrini, Armstrong, and Kenward (2010) such a construction is symmetric, hence the order of the two transformations can be reversed. For more details on the construction and practical implementation we recommend the reader to revise the original paper.

3. Data

We use annual data from 1929 to 2016 for real gross domestic product, gross private domestic investment, non-residential gross domestic investment, and real personal consumption expenditures in durable goods and services (chained 2009 dollars) from the Bureau of Economic Analysis. Moody's seasoned Aaa and Baa Corporate Bond yields (annual end of the period) and effective federal funds rate data are from the Federal Reserve Economic Data (FRED of St. Louis). Consumer price index, earnings, real dividend and S&P were retrieved from Robert Shiller's web page. Additionally, we use market return and risk-free rate data from Kenneth French's web page. We use monthly data on real industrial production from FRED to estimate annual good (bad) expected (unexpected) uncertainty.

4. Results

In Tables 1 and 2 we show the results of our regressions in Equations (4) and (5), which employ standardized versions of the series to make the magnitude of the associated coefficients alongside the variables comparable. The theoretical model proposed by Segal, Shaliastovich, and Yaron (2015) motivates each of the two sets of regressions for the macroeconomic series and for the asset price series. In each set of regressions, we included expected consumption in addition to good and bad uncertainty as explanatory variables. Nevertheless, we changed the definition of good and bad uncertainty in both cases. In the first four columns, we present the results when uncertainty is defined as the expected volatility of real monthly GDP growth, while in the second four columns we defined uncertainty as the unexpected component of this volatility. As explained above, the volatility of industrial production was modeled as realized semivariances that build upon positive and negative growth rates in order to distinguish between good and bad uncertainty. Then, the expected component was modeled using a linear regression that includes lags of the semivariances (good and bad), consumption growth, the real market return, the price to earnings ratio, the risk-free rate and the default spread, within the explanatory variables set. The unexpected component corresponds to the residual of the regression in each period. In Table 1, the uncertainty forecast was made by projecting the semivariance one year ahead, which means that we used up to year *t* observations to predict *t+1* industrial production growth volatility, while in Table 2, forecasting was conducted using five-year ahead forecasts.

Macroeconomic reaction: First, we focus on the macroeconomic reactions to uncertainty. In line with theory, we know that consumption, real income, market dividend, earnings and both residential and non-residential investment can be expected to plunge after an uncertainty shock. Nevertheless, positive uncertainty is expected to stimulate economic activity and, therefore, to impact macroeconomic variables positively. In general, these theoretical insights seem to hold for the case when uncertainty is defined as *unexpected volatility*, but this is not the case here for the expected component of uncertainty. It is also evident that, in terms of statistical significance and magnitude, bad-unexpected uncertainty is considerably more relevant than its expected or good counterparts. Agents care more about bad news, especially when this news is beyond their original expectations. This conclusion is also confirmed by the fact that in most of the regressions, the adjusted R^2 is larger for the models that work with unexpected uncertainty.

Indeed, when we define uncertainty as the expected component of volatility we obtain counterintuitive signs in some cases. For instance, the impact of bad-expected uncertainty on consumption and income is positive and statistically significant (0.18 and 0.20, respectively), while the impact of good uncertainty is not insignificant. However, positive and negative unexpected uncertainties render comparable effects on consumption (0.28 and -0.26, respectively) that are in line with theoretical expectations. In the case of GDP, earnings growth and gross capital investment, the impact of unexpected uncertainty is negative and statistically significant. Only for market dividend and non-residential investment – even when bad- unexpected uncertainty retains the right theoretical sign – does it remain statistically non-significant. Of note here is the fact that the expected component of good uncertainty decreases non-residential investment while it increases earnings.

Inspection of the R^2 of the regressions confirms that the unexpected component of uncertainty provides a better explanation of the variations in the macroeconomic series than do the models with their expected counterparts [the one exception being the model for non-residential investments which presents similar R^2 statistics in both cases, albeit slightly higher for the former model with expected variables than for the model that includes unexpected variables (40.74 vs. 39.83 respectively)].

Asset price reaction: We now turn our attention to the effects of uncertainty on asset prices. In line with theory, we expect uncertainty to negatively impact asset prices and returns and to increase the default spread. Here, for the case of the stock market premium and the default spread, the outcomes are in line with those for the macroeconomic variables analyzed above. That is, the unexpected component of uncertainty has a greater impact than that of the expected component, being especially marked in the case of bad-unexpected uncertainty. This impact is statistically significant in the model with unexpected uncertainty, and also agrees with the theoretical signs. Only in the case of the market price/earnings ratio is expected uncertainty more closely in line with the theoretical expected signs, that is, 0.32 for good-expected uncertainty and -0.54 for bad- expected uncertainty. This might be because the price-earnings ratio is known to reflect expectations about the firms' future growth rates and, as such, it is a forward-looking variable in which expected uncertainty plays a more significant role than its unexpected counterpart. Note that this situation is reversed for the model with unexpected variations of uncertainty (-0.30 and 0.43 for good-unexpected and bad-unexpected uncertainties, respectively). Our proxy for the real risk-free rate does not seem to be explained by either of the two models (with R^2 statistics close to zero in both cases).

[Insert Table 1 here]

Table 2 presents the results when we construct our uncertainty proxies using five-year ahead forecasts instead of one-year ahead out-of-sample forecasts. Most strikingly, all the theoretical signs of unexpected uncertainty are fulfilled by the regressions. Moreover, in general, the models including the unexpected component of volatility present a better adjustment than those that include the expected component of volatility in the set of regressors, as measured by the associated R^2s of each regression. The latter holds for both macroeconomic series and asset prices. We also observe a reduction in the model adjustment when we compare the R^2s reported in Table 2 with those recorded in Table 1. This reduction is most likely attributable to a reduction in the explanatory power of expected consumption in the macroeconomic series and asset prices than to the overall effect of uncertainty. Indeed, in the case of good-unexpected uncertainty, we observe an increase in the magnitude of the effect on consumption, GDP growth and gross capital investment compared to the effects recorded in Table 1. In all these cases, the effect increases to the point at which it becomes greater than the opposite effect of bad uncertainty, though this continues to be significant in all three cases. For other variables, such as market dividend or earnings growth, the effect of positive unexpected uncertainty remains statistically insignificant even when bad uncertainty is significant. Only for the risk-free rate does the model with expected uncertainties present a larger R^2 than that recorded by the model with unexpected uncertainties. Interestingly, while bad expected uncertainty reduces the risk-free rate by 0.24 points, bad-unexpected uncertainty increases it by 0.26 points.

Overall, we show that, in general, the effects generally claimed to follow from an uncertainty shock are clearly linked to those following a bad-unexpected uncertainty shock. The effects of other general notions of uncertainty, such as good- and bad-expected volatility or good-unexpected uncertainty, do not, however, always coincide with the theoretically expected effects.[5,6]

[Insert Table 2 here]

In what follows we expand our analysis to take into account possible nonlinearities on the effect of uncertainty, both in time (across different lags) and in conjunction with the magnitude of the uncertainty shocks. We consider the most popular macroeconomic and financial indicators in the literature, namely real consumption growth, real gross investment growth, the price/earnings ratio and the market return.

We use a distributed lag nonlinear model to decompose the effect of uncertainty in time and in magnitudes, which allows us to explore possible non-linear effects of uncertainty on the economy as stressed in the theoretical literature. Figure 1 shows the effect of good and bad, expected and unexpected, uncertainties on the annual variation in the real consumption growth rate. The reported results were drawn from estimations using annual data from 1950 to 2016. The color scale captures the magnitude of the effect in each subplot, reflecting the four possible combinations of good and bad, expected and unexpected, uncertainty. The horizontal axis measures the effect conditional on the magnitude of uncertainty shocks, while the vertical axis shows the effect at different lags. Zero on the horizontal axis corresponds to the mean of the standardized variable so that shocks lower (higher) than zero represent shocks of small (big) magnitude. We use the same uncertainty proxies that we used when assessing the effects of macroeconomic uncertainty on real and financial markets (i.e. expected bad uncertainty (*Vb*), expected good uncertainty (*Vg*), bad-unexpected uncertainty (*Ub*) and good-unexpected uncertainty (*Ug*)) at an annual frequency.

[5] We have estimated Table 1 and 2 including a lag of the forecasted variable on the Right-Hand-Side of the forecasting equations. These estimates can be consulted in the Appendix in Table A1 and A2. As can be observed our main conclusions remain unchanged.

[6] We have estimated a model with all four uncertainty shocks included simultaneously on the Right-Hand-Side of the forecasting equation. These estimates highlight the importance of bad uncertainty and the greater magnitude of the effects of the unexpected component of uncertainty.

Simple inspection of the figure shows that, indeed, the effect of uncertainty on consumption is nonlinear. In accordance with the results reported in Table 1, we also see in this case that bad-unexpected uncertainty is associated with the most significant negative effects on real consumption, while the impact of bad-expected uncertainty seems to run in the opposite direction, increasing the consumption growth rate. Moreover, bad- unexpected uncertainty seems to have its greatest effects on consumption when shocks are small. Bad-expected uncertainty also has a greater effect when it lies below its own mean. In terms of time, the uncertainty shocks in general seem to be persistent. The impact of bad-expected uncertainty reaches a peak the first year after the shock and persists until the fourth year.

Good uncertainty is also associated with a negative impact on consumption, with the one exception of very high good-unexpected uncertainty shocks, which foster consumption the first year after uncertainty occurs. This effect seems to be reversed from year two to four, as can be observed in the upper-right panel of the figure. The impact of good-expected uncertainty on consumption is mainly negative and concentrates on very high and low uncertainty shocks.

[Insert Figure 1 here]

[Insert Figure 2 here]

The impact of uncertainty on investment activity (Figure 2) is perhaps the most widely documented from both the theoretical and empirical perspectives. Uncertainty reduces investment while the "wait-and-see" strategy becomes optimal for firms (and households) and even for financial investors, until uncertainty is finally realized. Nevertheless, the panorama is again mixed for good-unexpected uncertainty shocks, which seem to reduce gross investment for relatively small shocks, and to promote it for shocks above the mean of the good-unexpected uncertainty indicator. In the case of bad-expected uncertainty, this seems to present a counterintuitive sign.

We also estimate the effects of our four different definitions of uncertainty on two popular measures of financial market dynamics: the aggregate market return (Figure 3) and the price/earnings ratio (Figure 4). In both cases, we document nonlinear responses of the financial markets to uncertainty, dependent on the level and nature (i.e. good, bad, expected, unexpected) of the uncertainty shocks. In the case of aggregate market return, we observe that it is mainly affected by relatively small bad-unexpected uncertainty shocks, one to three years after the shock occurs. In the case of the price/earnings ratio, big good-expected and small bad-unexpected shocks have the most noticeable effects. These results are consistent with those documented in Tables 1 and 2, but unlike those results, these highlight the nonlinear response of financial prices to uncertainty shocks.

All in all, our results show that, in general, the most significant effects of a bad-unexpected uncertainty shock concentrate in magnitudes below the mean of the uncertainty indicator, but not necessarily in the tail of 'big' uncertainty shocks, as might be expected.

[Insert Figure 3 here]

[Insert Figure 4 here]

5. Conclusion

We estimate the impact of different notions of uncertainty on key economic variables and asset prices. Specifically, we distinguish between good-expected, good-unexpected, bad-expected and bad-unexpected uncertainty shocks. We found that the general understanding of aggregate uncertainty, which involves treating investment as a real option and which predicts the negative reaction of prices, investment and real consumption to uncertainty shocks, is more closely related to the notion of bad-unexpected uncertainty, which is at odds with the understanding of uncertainty as a forward-looking event. We also show that it is only the unexpected component of realized volatility that generates the negative dynamics predicted by most of the theoretical literature.

In the second part of this study, we have used a novel distributed lag nonlinear model that allows us to simultaneously represent non-linear exposure-response dependencies and the delayed effects of macroeconomic variables to different notions of uncertainty. Here, we show that small uncertainty shocks might in fact have the greatest impact on economic variables and asset prices, in the latter case especially one to three years after the shock occurs. Overall, we document nonlinearities in the propagation of uncertainty to both real and financial markets, which calls for the close monitoring of the evolution of uncertainty so as to help mitigate the adverse effects of its occurrence.

References

Abel, A. B., and J. C. Eberly. 1996. "Optimal investment with costly reversibility." *The Review of Economic Studies* 63: 581–593.

Andersen, T. G., T. Bollerslev, and F. X. Diebold. 2010. "Parametric and Nonparametric Volatility Measurement." In *Handbook of Financial Econometrics,* Volume 1: Tools and Techniques, edited by Y. Aït-Sahalia, and L.P. Hansen, 67–137. Amsterdam and Boston: Elsevier.

Bachmann, R., and C. Bayer. 2013. "'Wait-and-See' business cycles?" *Journal of Monetary Economics* 60 (6): 704–719.

Baker, S., N. Bloom, and S. Davis. 2016. "Measuring Economic Policy Uncertainty." *Quarterly Journal of Economics* 131 (4): 1593–1636.

Bansal, R., and A. Yaron. 2004. "Risks for the long run: a potential resolution of asset pricing puzzles." *Journal of Finance* 59 (4): 1481–1509.

Barndorff-Nielsen, O. E., S. Kinnebrock, and N. Shephard. 2010. "Measuring downside risk - realised semivariance." In *Volatility and Time Series Econometrics: Essays in Honor of Robert F. Engle*, edited by T. Bollerslev, J. Russell, and M. Watson, 117–136. Oxford: Oxford University Press.

Bekaert, G., E. Engstrom, and Y. Xing. 2009. "Risk, uncertainty, and asset prices." *Journal of Financial Economics* 91 (1): 59–82.

Berger D., I. Dew-Becker, and S. Giglio. 2020. "Uncertainty shocks as Second-Moment News Shocks." *Review of Economic Studies* 87 (1): 40–76

Bernanke, B. (1983). "Irreversibility, uncertainty and cyclical investment." *Quarterly Journal of Economics* 98 (1): 85–106.

Bertola, G., and R. Caballero. 1994. "Irreversibility and aggregate investment." *The Review of Economic Studies* 61: 223–246.

Bloom, N. 2009. "The impact of uncertainty shocks." *Econometrica* 77 (3): 623-685.

Bloom, N., S. Bond, and J. Van Reenen. 2007. "Uncertainty and investment dynamics." *The Review of Economic Studies* 74 (2): 391–415.

Bloom, N., M. Floetotto, N. Jaimovich, I. Saporta-Eksen, and S.J. Terry. 2018. "Really Uncertain Business Cycles." *Econometrica* 86 (3): 1031–1065.

Brunnermeier, M., and Y. Sannikov. 2014. "A macroeconomic model with a financial sector." *American Economic Review* 104 (2): 379–421.

Caballero, R. J., and R. S. Pindyck. 1996. "Uncertainty, investment, and industry evolution." *International Economic Review* 37 (3): 641–662.

Campbell, J., S. Giglio, C. Polk, and R. Turley. 2012. "An intertemporal CAPM with stochastic volatility." *NBER Working Papers* 18411.

Carriero, A., T. E. Clark, and M. Marcellino. 2016. "Common drifting volatility in large Bayesian VARs." *Journal of Business and Economic Statistics* 34 (3): 375–390.

Chuliá, H., M. Guillén, and J. M. Uribe. 2017. "Spillovers from the US to Latin American and G7 stock markets: A VAR-Quantile analysis." *Emerging Markets Review* 31 (C): 32–46.

Dick, C. D., M. Schmeling, and A. Schrimpf. 2013. "Macro Expectations, aggregate uncertainty, and expected term premia." *European Economic Review* 58: 58–80.

Fendoğlu, S. (2014). "Optimal Monetary policy rules, financial amplification, and uncertain business cycles." *Journal of Economics Dynamics and Control* 46: 271–305.

Gasparrini, A., B. Armstrong, and M. G. Kenward. 2010. "Distributed lag non-linear models." *Statistics in Medicine* 29 (21): 2224–2234.

Gilchrist, S., and J. Williams. 2005. "Investment, Capacity, and Uncertainty: A Putty-Clay Approach." *Review of Economic Dynamics* 8 (1): 1–27.

Gilchrist, S., J. W. Sim, and E. Zakrajsek. 2014. "Uncertainty, Financial Frictions, and Investment Dynamics." *NBER working papers* 20038.

Jackson, L. E., K. L. Kliesen, and M. T. Owyang. 2020. "The nonlinear effects of uncertainty shocks." *Studies in Nonlinear Dynamics and Econometrics* 24 (4): 20190024.

Jurado, K., S. C. Ludvigson, and S. Ng. 2015. "Measuring uncertainty." *American Economic Review* 105 (3):1177–1216.

Kinnebrock, S., and M. Podolskij. 2008. "A note on the central limit theorem for bipower variation of general functions." *Stochastic Processes and their Applications* 118 (6): 1056–1070.

Leahy, J., and T. M. Whited. 1996. "The effect of uncertainty on investment: some stylized facts." *Journal of Money, Credit and Banking* 28 (1), 64–83.

Ludvigson, S., S. Ma, and S. Ng. 2021. "Uncertainty and business cycles: exogenous impulse or endogenous response?" *American Economic Journal: Macroeconomics* 13 (4): 369–410.

Meinen, O., and O. Roehe. 2017. "On measuring uncertainty and its impact on investment: Cross-country evidence from the euro area." *European Economic Review* 92 (C): 161–179.

Pastor, L., and P. Veronesi. 2009. "Technological Revolutions and Stock Prices." *American Economic Review* 99 (4): 1451–1483

Segal G., I. Shaliastovich, and A.Yaron. 2015. "Good and bad uncertainty: Macroeconomic and financial market implications." *Journal of Financial Economics* 117 (2): 369–397.

Appendix

[Insert Table A1 here]

[Insert Table A2 here]

[Insert Table A3 here]

[Insert Table A4 here]