
“Expected, Unexpected, Good and Bad Uncertainty”

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Abstract

By distinguishing between four general notions of uncertainty (good-expected, bad-expected, good-unexpected, bad-unexpected) within a common and simple framework, we show that it is bad-unexpected uncertainty shocks that generate a negative reaction of macroeconomic variables (such as investment and consumption), and asset prices. Other notions of uncertainty might produce even positive responses in the macroeconomy. We also show that small uncertainty shocks might have larger impacts on economic activity and financial markets than bigger shocks between one to three years after its realization. We explore the time and magnitude of uncertainty shocks by means of a novel distributed lag nonlinear model. Our results help to elucidate the real and complex nature of uncertainty, which can be both a backward or forward-looking expected or unexpected event, with markedly different consequences for the economy. They have implications for policy making, asset pricing and risk management.

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1. Introduction

Uncertainty is a primary concern in economics and finance and among scientists in general. Bernstein (1998) goes as far as claiming that the interest in measuring and mastering uncertainty marks an important threshold separating modern times from the previous thousands of years of scientific history. Today, it is commonly accepted that uncertainty must be measured, because it is closely related to many economic phenomena. It is related to decisions on current and expected consumption, real and financial investment, to business cycles dynamics, saving decisions, prices of goods and assets, and to the possibility of consumption risk sharing. In short, it is at the core of the study of macroeconomic wellbeing. Empirically, uncertainty has generally been assimilated to a time-varying conditional second moment of the series under study, closely linked to underlying time-varying structural shocks, such as terrorist attacks, political events, economic crises, bubble collapses, systemic risk materialization episodes, wars and credit crunches.

In what follows we conduct a comprehensive empirical examination of the effects of macroeconomic uncertainty on real and financial markets. Our approach is simple and takes distance from the previous literature because in our estimations 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 stands on the fact that the consequences of the decisions of any economic agent cannot be predicted with certainty, but instead agents must form expectations about such consequences in order to be able to set their inter-temporal optimal paths of consumption and saving. Nevertheless, 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 an unexpected component, which is related to the amount of the variation that agents cannot predict.

This approach allows us to empirically assess the effects of uncertainty on the real economy and the financial markets from a more general perspective than the extant literature. In so doing we present our results within a common empirical structure that compares the effects of our four

general notions of uncertainty. We aim to provide a comprehensive yet simple framework helpful to understand the effects of uncertainty on the macroeconomy, and to disentangle the kind of uncertainty that more closely resembles what is expected from the theory. We show that indeed the notion of ‘uncertainty’, that is often empirically assimilated to a conditional second moment of economic activity (or its expectation), indeed is more related to the notion of what we identify here as ‘bad unexpected uncertainty’, which is a construct much more specific than volatility or expected volatility. Other general notions of uncertainty, like expected good and bad volatility or unexpected good uncertainty, impact the 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 strategy of ‘wait and see’. 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.

Our work stands on the theoretical and empirical work developed by Segal et al. (2015) and Berger et al. (2019). The former study claims that good and bad macro-volatility shocks have different impacts on financial prices and on the real economy. It shows that actual investment, expected consumption, prices and other macro-indicators react very asymmetrically to ‘good’ and ‘bad’ volatility shocks (with positive and negative responses respectively). They also show that the market prices such asymmetric risks in economical and statistical significant ways. On the other hand, the latter study shows that it is (backwards) realized-volatility instead of (forwards) realized volatility what significantly depresses the economy and the market. In our approach we blend the insights of both studies, by recognizing that uncertainty can be ‘bad’ or ‘good’ with economically significant different consequences and, at the same time, it can be expected (forward looking) or unexpected (backwards looking). Our approach follows the simple empirical line of Segal et al. (2015), which uses realized semivariances of industrial production to measure good and bad uncertainty shocks, but in addition to them we consider the differences between forward and backward-looking uncertainty. Unlike Berger et al. (2019), we distinguish between expected and unexpected volatility instead of realized and expected volatilities. That is, we specifically measure the unexpected component of the total realized series, which is blended in the notion of realized volatility. In this sense we follow the general idea of Jurado et al. (2015) according to which uncertainty is related to the volatility of the unexpected component of the series under analysis, more than to the total volatility.

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, as those observed during the Great Recession. These spirals make recovery more difficult and costly. Negative spirals and endogenous uncertainty amplification mechanisms have the potential for destabilizing markets. Even small shocks to the economy might end up in a dramatic recession, if certain frictions present in the financial markets amplify the original shocks. To this end we employ a Distributed Lag Nonlinear model proposed by Gasparrini et al. (2010) in the field of medical statistics, which allows us to analyze possible nonlinearities on the effects of uncertainty along the time and scale dimensions. This methodology is based on the definition of a ‘cross-basis’, a bi-dimensional space of functions that describes simultaneously the shape of the relationship across both the *space* of the predictor and the *lag* dimension of the occurrence. We find that the more significant effects after an unexpected-bad uncertainty shock concentrate in magnitudes below the mean of the uncertainty indicator, and not necessarily on 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. Related literature

2.1. Uncertainty and the real economy

The current paradigm for understanding uncertainty was developed within the framework of irreversible investment, in which a firm's future investment opportunities are treated as real options and the importance of waiting until the uncertainty is resolved is emphasized. Hence, aggregate uncertainty shocks¹ are thought to be followed by a reduction in investment, and possibly in labor, and, consequently, by a deterioration in real activity (Bernanke, 1983; Bertola and Caballero, 1994; Abel and Eberly, 1996; Leahy and Whited, 1996; Caballero and Pindyck, 1996; Bloom et al., 2007; Bachmann and Bayer, 2013; Jurado et al., 2015; Chuliá et al., 2017; Meinen and Roche, 2017). Nevertheless, some studies point out that after the original worsening of the variables, a rebound effect related to a 'volatility over-shoot' may be observed (Bloom, 2009; Bloom et al., 2014; Chuliá et al., 2017). It is worth noting that these original impacts on the macroeconomic variables may be amplified as a result of financial market frictions (Arellano et al., 2012; Christiano et al., 2014; Gilchrist et al., 2014).

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 reduces and as the agents realize the true nature of uncertainty (see Gilchrist and Williams (2005), or Pastor and Veronesi (2009) for a discussion of the potential expansionary roles of uncertainty). On the contrary, a negative uncertainty shock should generate a more pronounced negative reaction, associated with smaller or even insignificant rebounds in the economy activity (Segal et al., 2015).

The study of uncertainty is not confined to the firm's investment problem. For example, Romer (1990) suggests that consumers may postpone their acquisition of durable goods in episodes of increasing uncertainty. Ramey and Ramey (1995) and Aghion et al. (2010) have studied the negative relationship between volatility and economic growth.

2.2. Uncertainty and financial markets

¹ Panousi and Papanikolaou (2012) explain possible sources of inefficiency in the investment process arising from idiosyncratic uncertainty, under high-powered incentives and risk-averse managers. Bachmann and Bayer (2013) also study the impact of idiosyncratic uncertainty shocks on business cycles.

The effects of uncertainty on equity prices and other financial variables have also been analyzed. In this stream, a notable example is given by Bansal and Yaron (2004) who provide a model in which markets dislike uncertainty and worse long-run growth prospects reduce equity prices. In the same vein, the study by Bekaert et al. (2009) finds that uncertainty plays an important role in the term structure dynamics and that it is the main force behind the counter-cyclical volatility of asset returns.

More recently, Campbell et al. (2012) have analyzed the role of uncertainty in an extended version of the inter-temporal capital asset-pricing model. These authors report mixed results regarding the sign of the exposure to volatility on the side of asset returns. In a related study, Bansal et al. (2014) investigate the implications of macroeconomic volatility for the time variation in risk premia and for the cross-section of returns. They propose a conditional capital asset-pricing model (CAPM) in which aggregate volatility acts as a risk factor, in addition to cash flow and the discount rate. They 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 et al. (2017) 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).

3. Methodology

3.1. 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., 2014), the cross-sectional dispersion of survey-based forecasts (Dick et al., 2013; Bachmann et al., 2013), credit spreads (Fendoglu, 2014), and the appearance of 'uncertainty-related' key words in the media (Baker et al., 2016). Most 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 et al., 2016; Gilchrist et al., 2014; Jurado et al., 2015; Chuliá et al., 2017).

In this proposal, we aim to go one step forward, and distinguish bad from good volatility shocks to industrial production series. To this end we rely on recently advances about realized variance estimation and in particular on realized semivariances as presented by Barndorff-Nielsen et al. (2010). In other words, consider the traditional RV estimator, as explained for example in Andersen et al. (2010). The RV estimator of the variable Y can be expressed as:

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

where $0 = t_0 < t_1 < \dots < t_n = 1$ are the times at which observations are available. This has been proven to be an extremely useful methodology to estimate and forecast conditional variances for risk management and asset pricing. Nevertheless, Barndorff-Nielsen et al. (2010) stress out that this measure is silent about the asymmetric behavior of jumps, which is important for example to estimate downside or upside risk. Thus, they propose a new RS estimator as follows:

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

where $\mathbf{1}_y$ is an indicator function taking the value of 1 if the argument y is true, and 0 otherwise. The former equation provides a direct estimate of downside risk and the latter of upside risk. Barndorff-Nielsen et al. (2010) also provide the asymptotic properties of this estimator, using the arguments and the central limit theorem for bipower variations 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 et al. (2015), we define good (bad) expected uncertainty as the predictable component of RS^+ (RS^-). The predictable component is estimated as the projection of the realized semivariances in (2) on a set of 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-earning 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

to define unexpected uncertainty, both good and bad, as the residual series of the out of sample regression, as follows:

$$\begin{aligned}
 RS_t^- &= \underbrace{b_0^- + b_1^- RS_{t-1}^- + b_2^- RS_{t-1}^+ + b_3^- \Delta c_{t-1} + b_4^- rr_{t-1}^{MARKET} + b_5^- P/E_{t-1} + b_6^- r_{t-1}^F + b_7^- spread_{t-1}}_{\text{Expected bad uncertainty}} + \underbrace{u_t^-}_{\text{Un. bad unc.}} \\
 RS_t^+ &= \underbrace{b_0^+ + b_1^+ RS_{t-1}^- + b_2^+ RS_{t-1}^+ + b_3^+ \Delta c_{t-1} + b_4^+ rr_{t-1}^{MARKET} + b_5^+ P/E_{t-1} + b_6^+ r_{t-1}^F + b_7^+ spread_{t-1}}_{\text{Expected good uncertainty}} + \underbrace{u_t^+}_{\text{Un. good unc.}}
 \end{aligned} \quad (3)$$

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

Next, we carry our two set of regressions. First, we regress macroeconomic indicators and asset prices (x) for horizon h years on the expected variation of real consumption (c)² and our empirical proxies for expected bad uncertainty (V_b) and expected good uncertainty (V_g). In the second set of regressions, we use instead our proxies for unexpected bad uncertainty (U_b) and unexpected good uncertainty (U_g):

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

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

where $h=1$ and 5 years. In our explanatory regressions we used standardized variables on both sides of equations (4) and (5) in order to make regression coefficient among the variables and among the regressions comparable (this is called 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 allow us to read their magnitude on top of their sign.

Finally, to measure the nonlinear effects in time and magnitude of uncertainty we introduce to the economics literature the model proposed by Gasparrini et al. (2010). This is a distributed lag non-linear model (DLNM), which corresponds to a modeling framework that is able to simultaneously represent non-linear exposure–response dependencies and delayed effects.

² We include the expected variation of real consumption growth following Segal et al. (2015). To construct a proxy for the expected consumption growth rate, we use a similar approach to Equation (3).

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:

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

where $\mu_t \equiv E(Y)$, g is a monotonic link function that belongs to the set of distributions of the exponential family. The functions s_j denote 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 include other predictors with linear effects specified by the associated coefficients γ_k . Gasparrini et al. (2010) define a DLNM as follows:

$$s(x_t; \boldsymbol{\eta}) = \sum_{j=1}^{\vartheta_x} \sum_{k=1}^{\vartheta_l} \mathbf{r}_{tj}^T \mathbf{c}_{.k} \eta_{jk} = \mathbf{w}_t^T \boldsymbol{\eta}, \quad (7)$$

where \mathbf{r}_{tj} is a vector of lagged series for the time t transformed through the *basis function* j . In turn, a basis function is defined as a set of transformations of the original variable x_t that generate a new set of variables termed *basis variables*. The main choices typically rely on functions describing smooth curves, such as polynomials or spline functions (as in our case). The vector \mathbf{w}_t is obtained by applying the $\vartheta_x \cdot \vartheta_l$ cross-basis functions to x_t . Extending the idea of basis, a cross-basis is a bi-dimensional space of functions describing simultaneously the shape of the relationship along x and its distributed lag effects. The matrix \mathbf{C} that consists of vector elements $\mathbf{c}_{.k}$ is a $(L + 1) \times \vartheta_l$ matrix of basis variables derived from the application of the specific basis functions to the lag vector $\boldsymbol{\ell}$, and $\boldsymbol{\eta}$ is a vector of unknown parameters.

4. Data

We use annual data from 1929 to 2016 for real gross domestic product, gross private domestic investment, non-residential gross domestic investment, 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 Keneth French's web page.

We use monthly data on real industrial production from the FRED to estimate annual good (bad) expected (unexpected) uncertainty in the aggregated macroeconomy.

5. 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 et al. (2015) motivates each of the two sets of regressions for the macroeconomic series and for asset price series. In each set of regressions we included expected consumption, on top of good and bad uncertainty as explanatory variables. Nevertheless, we changed the definition of good and bad uncertainty in both cases. In the first columns we present the case when uncertainty is defined as the expected volatility of real monthly GDP growth, while for the latter columns we defined uncertainty as the unexpected component of such volatility. As explained before, the volatility of industrial production was modeled like 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 earning ratio 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 uncertainty forecast was made 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 two, forecasting was conducted using five years ahead forecasts.

Table 1. Effects of macroeconomic uncertainty (1 year ahead forecasts)

The table shows the beta-coefficients of the effects of the expected variation of real consumption (c), good-expected (Vg), bad-expected (Vb), good-unexpected (Ug) and bad-unexpected (Ub) uncertainty on macroeconomic indicators and asset prices (Equations (4) and (5)). It also shows the adjusted R²s of these regressions. The four uncertainty indicators were estimated by out sample one-year ahead recursive

regressions, with annual data from 1929 to 2016. The first regression consisted of 20 observations, while the subsequent estimations were recursive, and incorporated one additional observation at a time. Bold numbers indicate the significance of the coefficients. T-statistics in parenthesis.

| | Expected | | | | Unexpected | | | |
|-----------------------------------|-------------------------|-------------------------|-------------------------|--------|-------------------------|-------------------------|-------------------------|--------|
| | c | Vg | Vb | Adj-R2 | c | Ug | Ub | Adj-R2 |
| <i>Macroeconomic Aggregates</i> | | | | | | | | |
| Consumption growth | 0,58 (4,95) | -0,21 (-1,33) | 0,18 (2,17) | 37,37 | 0,54 (4,52) | 0,28 (1,94) | -0,26 (-2,28) | 44,24 |
| GDP Growth | 0,46 (4,53) | -0,01 (-0,04) | 0,20 (2,13) | 27,74 | 0,42 (4,19) | 0,05 (0,34) | -0,30 (-3,93) | 32,93 |
| Market dividend growth | 0,27 (1,61) | -0,12 (-0,90) | 0,10 (0,75) | 6,67 | 0,25 (1,45) | 0,15 (1,16) | -0,16 (-1,24) | 9,33 |
| Earnings Growth | -0,11 (-0,69) | 0,24 (1,99) | 0,21 (1,78) | 8,98 | -0,16 (-0,89) | -0,19 (-1,55) | -0,40 (-1,79) | 17,32 |
| Gross capital investment growth | 0,43 (4,47) | 0,01 (0,10) | 0,23 (1,64) | 28,25 | 0,39 (4,23) | 0,05 (0,37) | -0,34 (-2,93) | 34,42 |
| Non-residential investment growth | 0,62 (6,50) | -0,23 (-2,30) | 0,02 (0,21) | 40,74 | 0,60 (6,19) | 0,21 (1,94) | -0,04 (-0,48) | 39,83 |
| <i>Asset Prices</i> | | | | | | | | |
| Price/earning ratio | 0,53 (3,51) | 0,32 (2,53) | -0,54 (-4,05) | 44,85 | 0,55 (3,27) | -0,30 (-2,90) | 0,43 (3,21) | 38,73 |
| Risk free rate | 0,04 (0,22) | -0,04 (-0,22) | -0,23 (-1,61) | 1,15 | 0,05 (0,28) | 0,00 (-0,02) | 0,23 (1,59) | 0,11 |
| Default spread | -0,41 (-3,36) | 0,24 (2,63) | -0,23 (-2,33) | 22,36 | -0,35 (-2,51) | -0,32 (-3,21) | 0,36 (2,14) | 32,95 |
| Market return | -0,27 (-2,24) | 0,05 (0,44) | 0,24 (2,00) | 6,62 | -0,32 (-2,32) | 0,05 (0,50) | -0,39 (-2,96) | 14,12 |

Macroeconomic reaction: First, we focus on the macroeconomic reactions to uncertainty. From the theory we know that consumption, real income, market dividend, earnings and both residential and nonresidential investment are expected to plunge after an uncertainty shock is observed. Nevertheless, positive uncertainty is expected to stimulate economic activity and therefore to positively impact macroeconomic variables. In general lines, we observe that these theoretical insights seem to hold for the case when uncertainty is defined as *unexpected volatility*, but not very

much for the expected component of uncertainty. It is also evident that, in terms of statistical significance and magnitude, bad unexpected uncertainty is far more relevant than its expected or good counterparts. Agents care more about bad news and especially when this news is beyond their original expectations. This is also confirmed by the fact that in most of the regressions the adjusted R squared is larger for the models that work with unexpected uncertainty.

Indeed, when we define uncertainty as the expected component of volatility we get 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 agree 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 nonresidential investment, even when bad unexpected uncertainty preserves the right theoretical sign, it remains statistically not significant. Noticeable the expected component of good uncertainty decreases nonresidential investment while it increases earnings.

When we examine the R2 of the regressions we confirm that the unexpected component of uncertainty explain better the variations of the macroeconomic series than the models with their expected counterparts (the only exception being the model for non-residential investments that shows similar R2 statistics in both cases, slightly above for the former model with expected variables than for the model that includes the unexpected ones (40.74 against 39.83 respectively)).

Asset price reaction: Now we turn our attention to the effects of uncertainty on asset prices. This time, for the case of the stock market premium and the default spread the story comes across the same lines than for the case of the macroeconomic variables analyzed above. That is, the unexpected component of uncertainty has a greater impact than the expected component, which is particularly larger for 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 for the case of the market price/earning ratio, expected uncertainty aligns more with the theoretical expected signs, 0.32 for good expected uncertainty and -0.54 for bad expected uncertainty. Note that this situation reverts for the model with unexpected variations of

uncertainty (-0.30 and 0.43 for good unexpected and bad unexpected uncertainty respectively). Our proxy for the real risk free rate does not seem to be explained by neither of the two models (with R² statistics close to zero in both cases).

Table 2 presents the results when we construct our uncertainty proxies using five-years ahead forecasts instead of one-year ahead out of sample forecasts. Most noticeable, all the theoretical signs of unexpected uncertainty are fulfilled by the regressions. Moreover the models that include the unexpected component of volatility present, in general, a better adjustment than the models that include the expected component of volatility in the set of regressors, as measured by the associated R²s 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 R²s reported in table 2 with those recorded in table 1. This reduction most likely follows from a reduction of the explanatory power of expected consumption on the macroeconomic series and asset prices than from 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 those recorded in table 1. In all these cases the effect increases to the point to becoming larger than the opposite effect of bad uncertainty, which anyway still remains significant in all the 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 the model with expected uncertainties renders a larger R²s than the model with unexpected uncertainties. Interestingly, while bad expected uncertainty reduces the risk free rate in 0.24 points, bad unexpected uncertainty increases it by 0.26 points.

All in all, we show that, in general, the effects generally claimed to follow an uncertainty shock are clearly linked to a bad-unexpected uncertainty shock. The effects of other general notions of uncertainty, like expected good and bad volatility or unexpected good uncertainty, do not always coincide with theoretical expected effects.

Table 2. Effects of macroeconomic uncertainty (5 year ahead forecasts)

The table shows the beta-coefficients of the effects of the expected variation of real consumption (c), good-expected (Vg), bad-expected (Vb), good-unexpected (Ug) and bad-unexpected (Ub) uncertainty on macroeconomic indicators and asset prices (Equations (4) and (5)). It also shows the adjusted R²s of these regressions. The four uncertainty indicators were estimated by out sample five-year ahead recursive regressions,

with annual data from 1929 to 2016. The first regression consisted of 20 observations, while the subsequent estimations were recursive, and incorporated one additional observation at a time. Bold numbers indicate the significance of the coefficients. T-statistics in parenthesis.

| | Expected | | | | Unexpected | | | |
|-----------------------------------|-----------------------|-------------------------|-------------------------|--------|-----------------------|-------------------------|-------------------------|--------|
| | c | Vg | Vb | Adj-R2 | c | Ug | Ub | Adj-R2 |
| <i>Macroeconomic Aggregates</i> | | | | | | | | |
| Consumption growth | -0,03 (-0,34) | 0,01 (0,07) | -0,19 (-1,50) | -1,54 | 0,10 (0,85) | 0,54 (2,78) | -0,30 (-1,84) | 14,79 |
| GDP Growth | -0,09 (-0,90) | 0,00 (-0,03) | -0,05 (-0,46) | -3,38 | 0,00 (0,04) | 0,40 (3,44) | -0,31 (-4,27) | 12,39 |
| Market dividend growth | -0,08 (-0,57) | -0,04 (-0,27) | 0,22 (1,47) | 0,56 | -0,08 (-0,55) | 0,06 (0,58) | -0,32 (-2,86) | 6,77 |
| Earnings Growth | -0,01 (-0,05) | -0,06 (-0,67) | 0,02 (0,25) | -4,79 | 0,04 (0,38) | 0,28 (1,52) | -0,31 (-1,87) | 2,93 |
| Gross capital investment growth | -0,05 (-0,66) | -0,10 (-0,98) | 0,03 (0,29) | -3,48 | 0,03 (0,44) | 0,42 (3,72) | -0,34 (-4,99) | 13,90 |
| Non-residential investment growth | -0,07 (-0,81) | -0,07 (-0,49) | 0,11 (1,03) | -3,78 | -0,04 (-0,41) | 0,21 (1,67) | -0,30 (-3,93) | 3,14 |
| <i>Asset Prices</i> | | | | | | | | |
| Price/earning ratio | 0,37 (2,45) | -0,31 (-1,95) | 0,35 (2,79) | 15,31 | 0,38 (2,35) | 0,26 (2,03) | -0,40 (-4,16) | 19,96 |
| Risk free rate | -0,23 (-1,12) | -0,15 (-0,88) | -0,24 (-1,70) | 18,51 | -0,27 (-1,15) | 0,04 (0,25) | 0,26 (1,95) | 14,05 |
| Default spread | -0,11 (-0,83) | -0,16 (-1,02) | 0,10 (0,87) | -1,51 | -0,23 (-1,52) | -0,40 (-1,70) | 0,43 (2,23) | 14,02 |
| Market Returns | -0,18 (-1,63) | 0,15 (1,33) | 0,19 (1,86) | 5,26 | -0,11 (-0,99) | 0,16 (1,43) | -0,46 (-3,93) | 12,77 |

In what follows we expand our analysis as to consider possible nonlinearities on the effect of uncertainty over the macroeconomic indicators and asset prices considered before, both in time (across different lags) and alongside the uncertainty indicator itself. We use a distributed lags nonlinear model to decompose the effect of uncertainty in time and magnitudes, which allows us to explore possible non-linear effects of uncertainty on the economy stressed out by the theoretical literature. Figure 1 shows the effect of good and bad, expected and unexpected, uncertainties on the annual variation of real consumption growth rate. The reported results were drawn from estimations that use annual data from 1950 to 2016. The color scale captures the magnitude of the effect in each subplot that reflects the four possible combinations of expected

and unexpected, good and bad, uncertainty. The horizontal axis measures the effect conditional on the uncertainty level, while the vertical axis shows the effect at different lags. The four uncertainty indicators were estimated by out of sample one-year ahead recursive regressions, with annual data from 1929 to 2016. The first regression consisted of 20 observations, while the subsequent estimations were recursive, and incorporated one additional observation at a time. By analyzing the figure one can see that, indeed, the effect of uncertainty on consumption is nonlinear. According to the results reported in table 1, we also see in this case that bad unexpected uncertainty is associated to the more significant negative effects on real consumption, while the effect of bad expected uncertainty seems to be the opposite, it increases the consumption growth rate. Moreover, bad unexpected uncertainty asserts its larger effects on consumption when it is below zero, which corresponds to the variable mean in the standardized model. Expected bad uncertainty also has a larger effect when it lies below its own mean. In terms of time, bad unexpected uncertainty impacts consumption especially during the first two years after the shock and in the fifth year following it. The impacts of bad expected uncertainty reach a peak the first year after the shock and lasts up to the fourth year.

Good uncertainty is also associated with a negative impact on consumption, with the only exception of very high-unexpected good uncertainty levels, which foster consumption the first year after uncertainty is realized. This effect seems to revert from year two to four, as can be observed in the upper-right panel of the figure. The impacts of good expected uncertainty on consumption are mainly negative and focus on very high and low levels of the uncertainty indicator.

Figure 1. Impacts of expected and unexpected, good and bad, uncertainty, on real consumption growth: The figure shows the effect of good and bad, expected and unexpected uncertainty on the annual variations of real consumption. The effects were estimated by a distributed lag nonlinear model that allows us to analyze nonlinearities originating from the level of uncertainty and time dynamics, according to the number of periods elapsed after the uncertainty shock is observed. Data sample spans 1950-2016. The color scale depicts the magnitude of the effect. The horizontal axis measures the effect conditional on the uncertainty level, while the vertical axis shows the effect at different lags. The four uncertainty indicators were estimated by out sample one-year ahead recursive regressions, with annual data from 1929 to 2016. The first regression consisted of 20 observations, while the subsequent estimations were recursive, and incorporated one additional observation at a time.

Expected

Unexpected

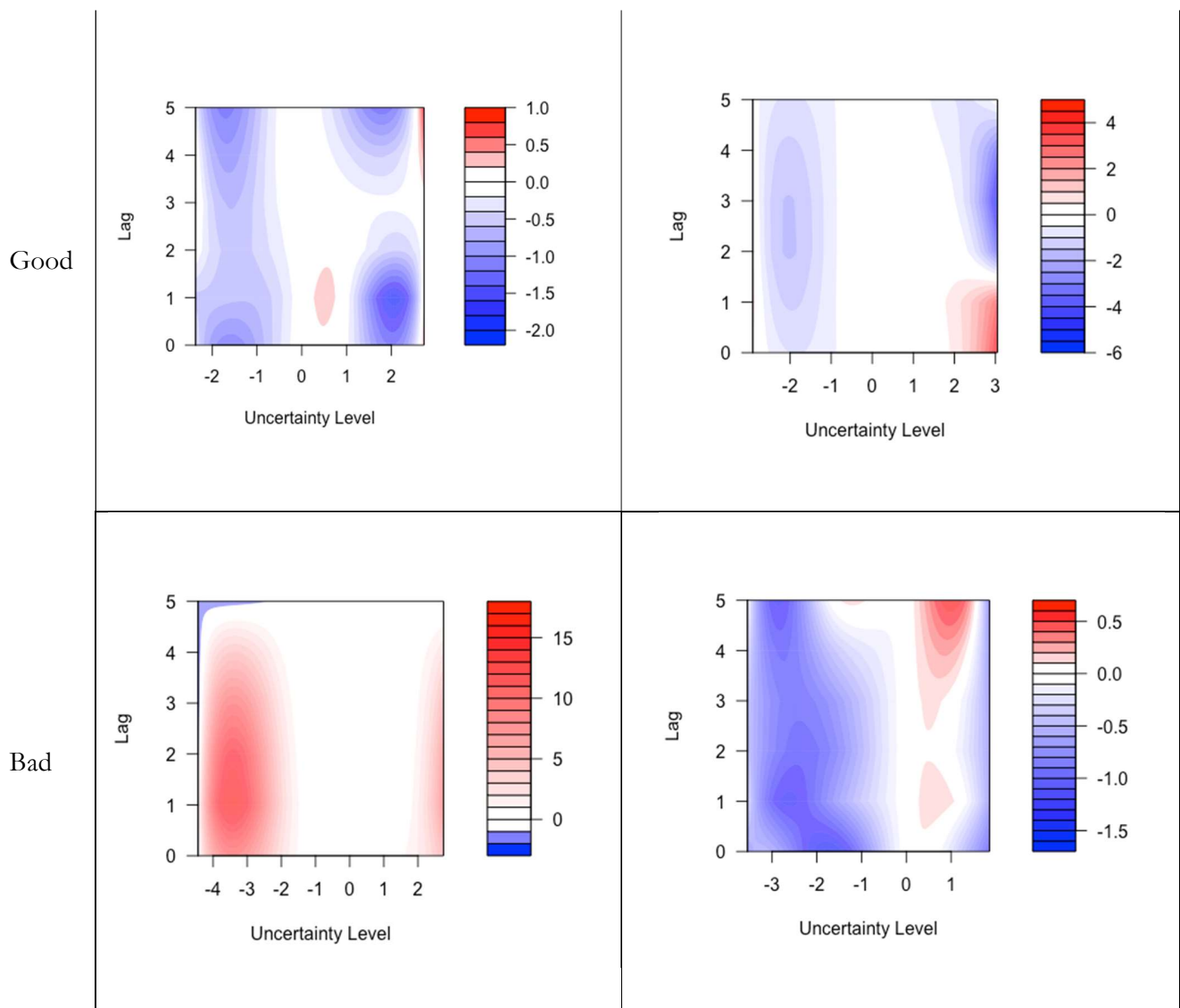


Figure 2. Impacts of expected and unexpected, good and bad, uncertainty, on real GDP growth: The figure shows the effect of good and bad, expected and unexpected uncertainty on the annual variations of GDP. The effects were estimated by a distributed lag nonlinear model that allows us to analyze nonlinearities originating from the level of uncertainty and time dynamics, according to the number of periods elapsed after the uncertainty shock is observed. Data sample spans 1950-2016. The color scale depicts the magnitude of the effect. The horizontal axis measures the effect conditional on the uncertainty level, while the vertical axis shows the effect at different lags. The four uncertainty indicators were estimated by out sample one-year ahead recursive regressions, with annual data from 1929 to 2016. The first regression consisted of 20 observations, while the subsequent estimations were recursive, and incorporated one additional observation at a time.

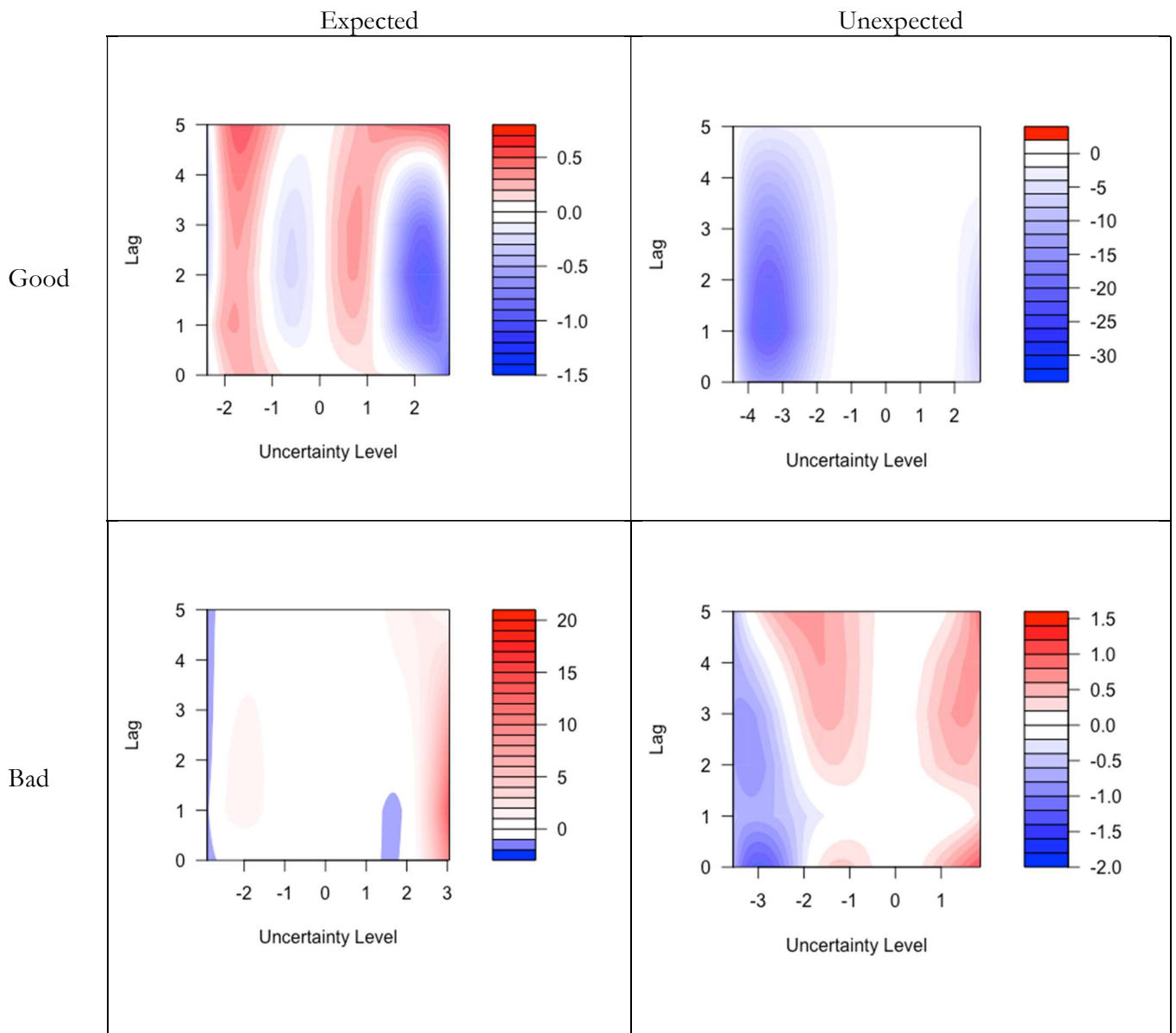


Figure 2 conveys the same information than Figure 1, but in relation to real GDP growth. As can be observed, the effects of uncertainty are again nonlinear, as represented by different colors on the surface of each plot. For instance, unexpected bad uncertainty, which is known to have a negative impact on economic activity, from tables 1 and 2, does imply a reduction of economic activity from lags 1 to 4 after a shock is observed, but only for *relatively small* uncertainty shocks (below the mean of the indicator). In contrast, extremely high-unexpected negative shocks can indeed be associated to increments in economic activity, especially from 2 to 5 years after the shock. Nevertheless for values of the indicator close to its mean, the effects remain close to zero in most of the cases (see the lower-right subplot of figure 2). The effects of expected bad uncertainty are also very sizable, particularly for extremely bad-high-expected uncertainty shocks (see panel bad-expected). Too much expected good uncertainty also seems to reduce economic activity, and only low expected good uncertainty fosters economic activity, as measured by income growth.

The impacts of uncertainty on investment activity (Figure 3) are perhaps the more widely documented from both 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. Indeed, this behavior is confirmed for unexpected bad uncertainty shocks (lower-right panel of figure 3) and for very high levels of unexpected bad uncertainty in Figure 4 (non-residential investment). Nevertheless, the panorama is again mixed for good unexpected uncertainty shocks, which seem to decrease gross investment for relatively small shocks, and to foster it for shocks above the mean of the good unexpected uncertainty indicator. On its side, bad expected uncertainty seems to present a counterintuitive sign for gross investment, and for nonresidential investment (when it is high).

Figure 3. Impacts of expected and unexpected, good and bad, uncertainty, on real gross investment growth: The figure shows the effect of good and bad, expected and unexpected uncertainty on the annual variations of gross investment. The effects were estimated by a distributed lag nonlinear model that allows us to analyze nonlinearities originating from the level of uncertainty and time dynamics, according to the number of periods elapsed after the uncertainty shock is observed. Data sample spans 1950-2016. The color scale depicts the magnitude of the effect. The horizontal axis measures the effect conditional on the uncertainty level, while the vertical axis shows the effect at different lags. The four uncertainty indicators were estimated by out sample one-year ahead recursive regressions, with annual data from 1929 to 2016. The first regression consisted of 20 observations, while the subsequent estimations were recursive, and incorporated one additional observation at a time.

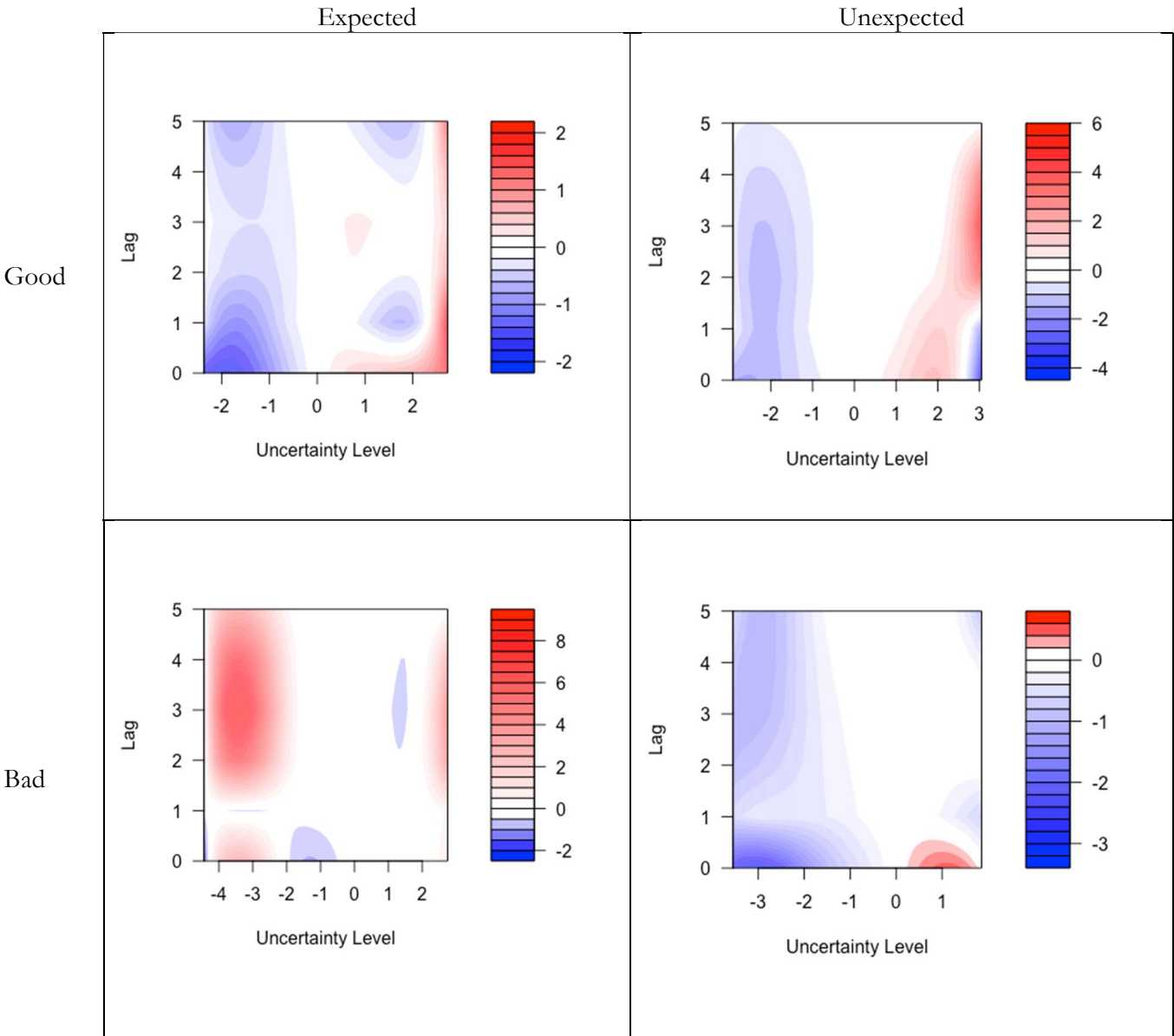
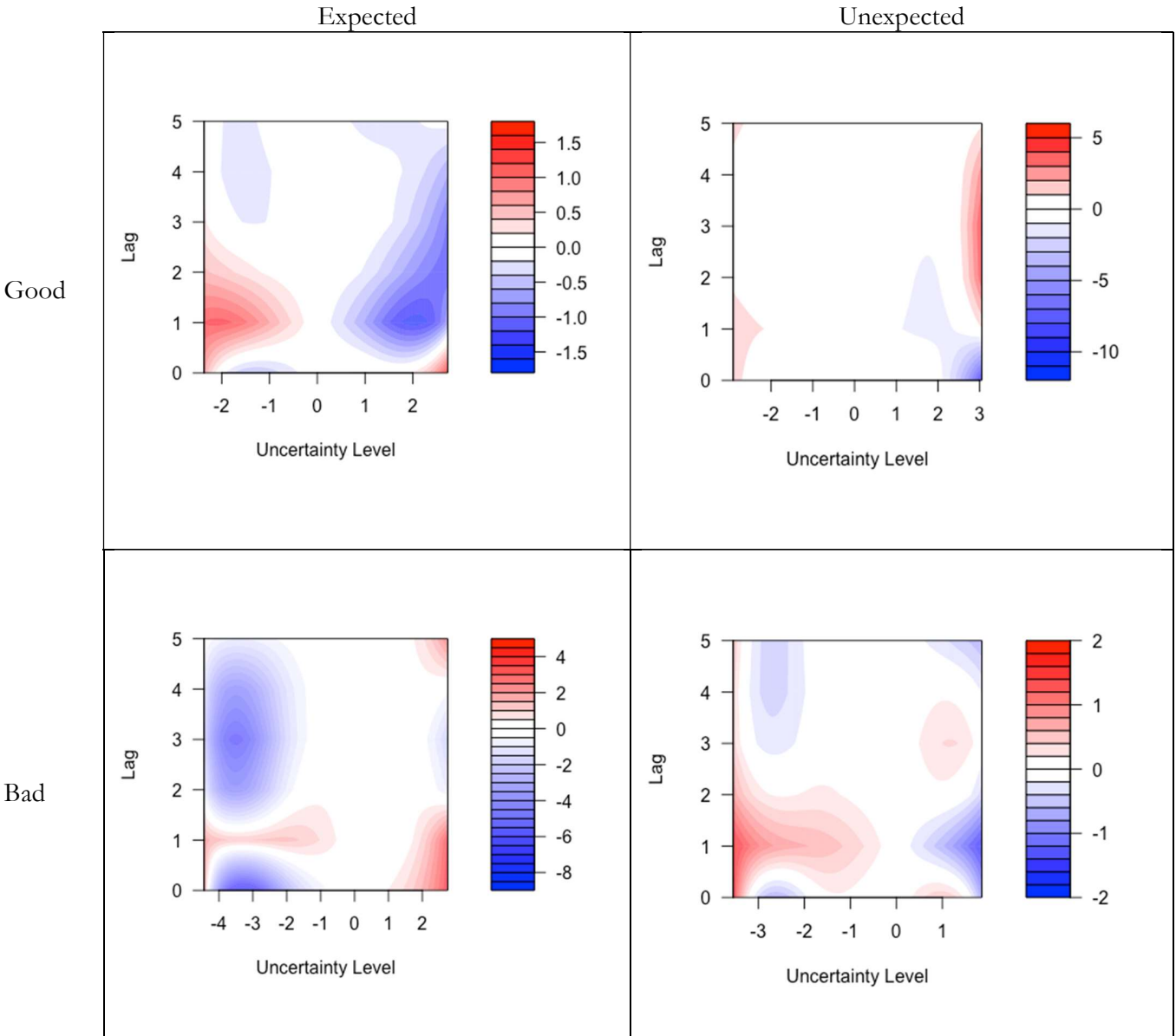


Figure 4. Impacts of expected and unexpected, good and bad, uncertainty, on real gross private nonresidential investment growth: The figure shows the effect of good and bad, expected and unexpected uncertainty on the annual variations of gross private nonresidential investment. The effects were estimated by a distributed lag nonlinear model that allows us to analyze nonlinearities originating from the level of uncertainty and time dynamics, according to the number of periods elapsed after the uncertainty shock is observed. Data sample spans 1950-2016. The color scale depicts the magnitude of the effect. The horizontal axis measures the effect conditional on the uncertainty level, while the vertical axis shows the effect at different lags. The four uncertainty indicators were estimated by out sample one-year ahead recursive regressions, with annual data from 1929 to 2016. The first regression consisted of 20 observations, while the subsequent estimations were recursive, and incorporated one additional observation at a time.



We also estimate the effects of our four different definitions of uncertainty on market dividends growth, earnings growth, on the price/earnings ratio, on the default spread and the market equity premium in Figures 5 to 9. In general, we document nonlinear responses of the financial markets to uncertainty shocks, which depend on the level of the uncertainty indicator and the nature of the uncertainty shock. For instance, both good expected and bad unexpected shocks seem to have the largest effects on the financial markets, while bad expected shocks have the smallest effects. Big good expected uncertainty shocks reduce dividend growth and earnings and increase the default spread, while the same expected good uncertainty shocks when small show the opposite sign.

On its side, when the effects of bad expected uncertainty shocks are present they display the opposite sign compared to the shocks of the same magnitude bad which are good. Bad unexpected uncertainty shocks generate opposite effects dependent on whether they are small or big. Big shocks decrease dividend growth (unlike medium size shocks), decrease the price earnings ratio and increases the default spread. Once again small bad unexpected uncertainty shocks present a larger impact on the financial markets than medium size or large shocks.

In terms of the real risk free rate we observe that small unexpected uncertainty shocks (both good and bad) and good expected uncertainty shocks tend to decrease it, while big good and unexpected shocks increase it. The equity premium is also significantly affected by the different uncertainty shocks considered here (see Figure 10). Particular noticeable are the negatives effects of big good expected uncertainty shocks and small bad unexpected uncertainty shocks.

All in all, our results show that, in general, the more significant effects after an unexpected-bad uncertainty shock concentrate in magnitudes bellow the mean of the uncertainty indicator, and not necessarily on the tail of 'big' uncertainty shocks, as one might expect.

Figure 5. Impacts of expected and unexpected, good and bad, uncertainty, on real market dividends growth: The figure shows the effect of good and bad, expected and unexpected uncertainty on the annual growth of the real market dividend. The effects were estimated by a distributed

lag nonlinear model that allows us to analyze nonlinearities originating from the level of uncertainty and time dynamics, according to the number of periods elapsed after the uncertainty shock is observed. Data sample spans 1950-2016. The color scale depicts the magnitude of the effect. The horizontal axis measures the effect conditional on the uncertainty level, while the vertical axis shows the effect at different lags. The four uncertainty indicators were estimated by out sample one-year ahead recursive regressions, with annual data from 1929 to 2016. The first regression consisted of 20 observations, while the subsequent estimations were recursive, and incorporated one additional observation at a time.

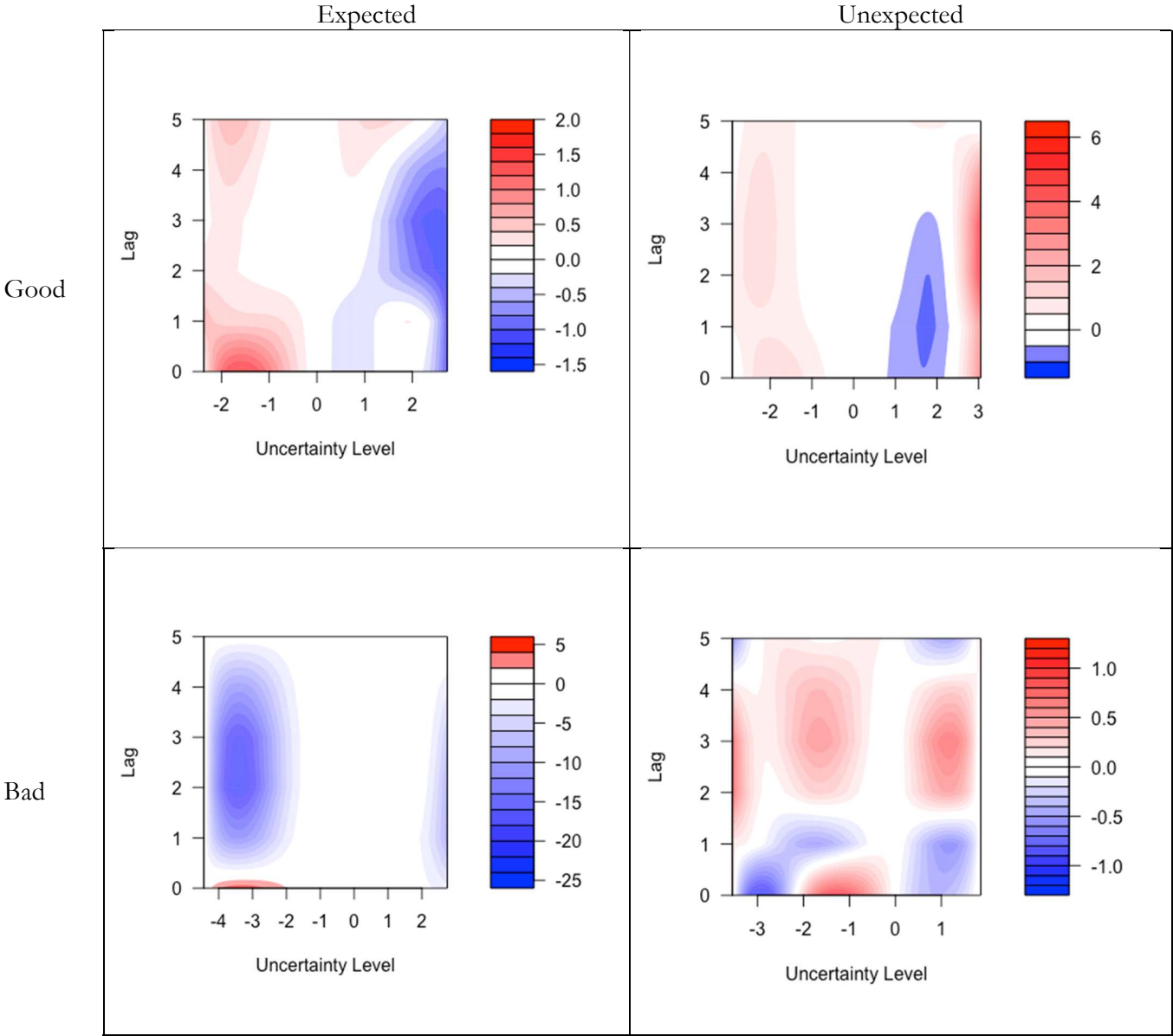


Figure 6. Impacts of expected and unexpected, good and bad, uncertainty, on real earnings growth: The figure shows the effect of good and bad, expected and unexpected uncertainty on the annual earning growth. The effects were estimated by a distributed lag nonlinear model that allows us to analyze nonlinearities originating from the level of uncertainty and time dynamics, according to the number of periods elapsed after the uncertainty shock is observed. Data sample spans 1950-2016. The color scale depicts the magnitude of the effect. The horizontal axis measures the effect conditional on the uncertainty level, while the vertical axis shows the effect at different lags. The four uncertainty indicators were estimated by out sample one-year ahead recursive regressions, with annual data from 1929 to 2016. The first regression consisted of 20 observations, while the subsequent estimations were recursive, and incorporated one additional observation at a time.

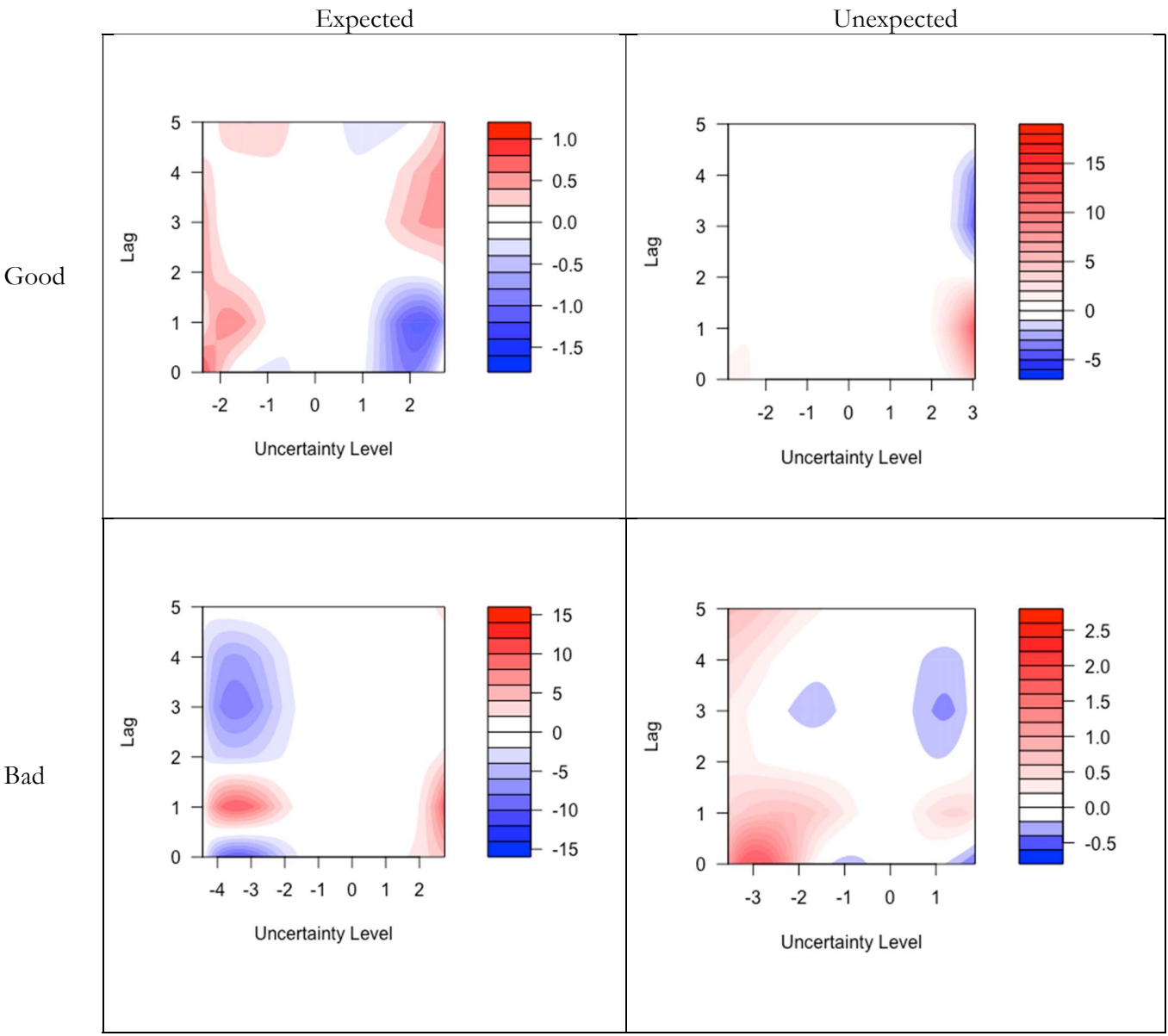


Figure 7. Impacts of expected and unexpected, good and bad, uncertainty, on the price/earnings ratio: The figure shows the effect of good and bad, expected and unexpected uncertainty on the price-earning ratio. The effects were estimated by a distributed lag nonlinear model that allows us to analyze nonlinearities originating from the level of uncertainty and time dynamics, according to the number of periods elapsed after the uncertainty shock is observed. Data sample spans 1950-2016. The color scale depicts the magnitude of the effect. The horizontal axis measures the effect conditional on the uncertainty level, while the vertical axis shows the effect at different lags. The four uncertainty indicators were estimated by out sample one-year ahead recursive regressions, with annual data from 1929 to 2016. The first regression consisted of 20 observations, while the subsequent estimations were recursive, and incorporated one additional observation at a time.

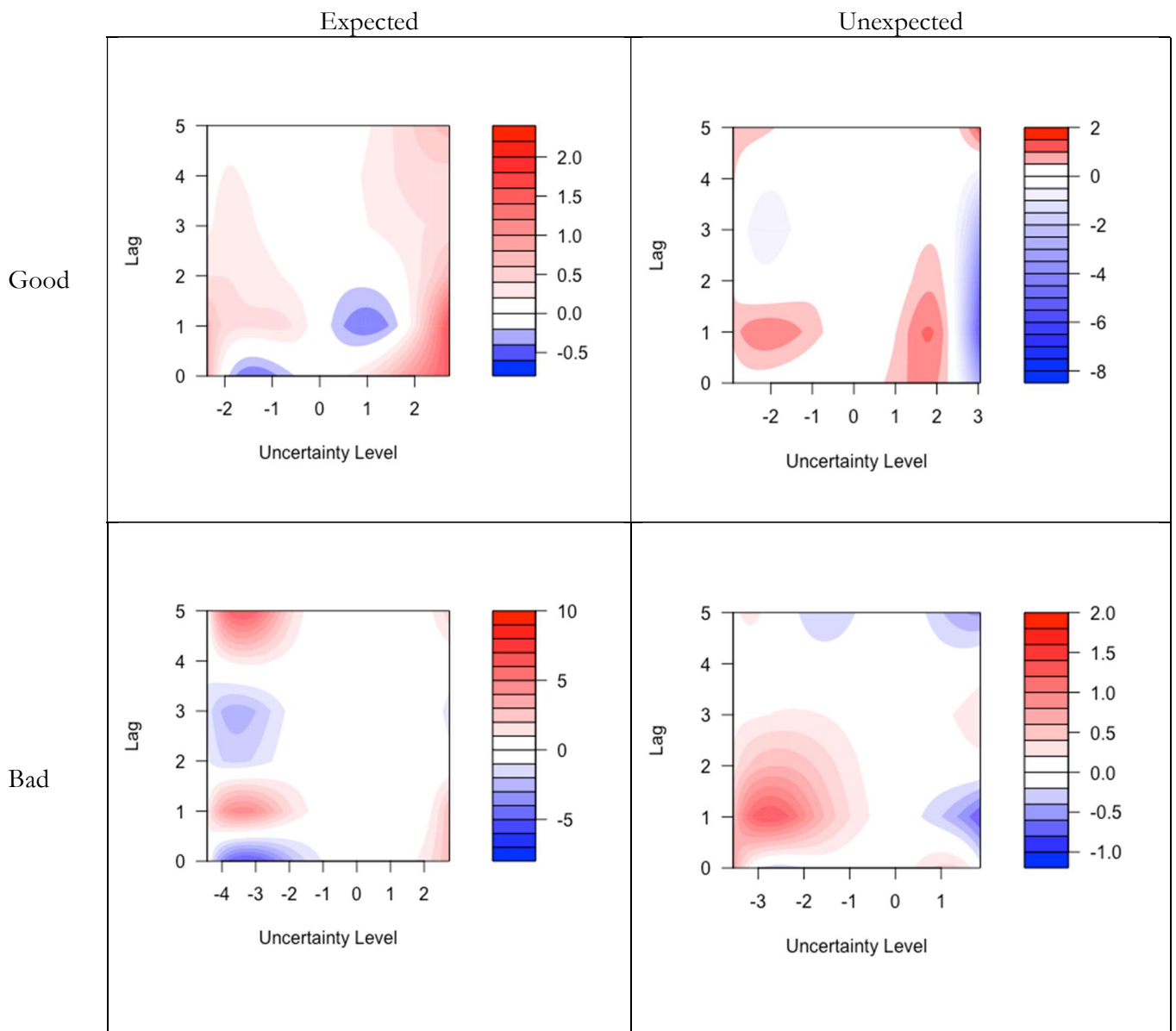


Figure 8. Impacts of expected and unexpected, good and bad, uncertainty, on the real risk free rate: The figure shows the effect of good and bad, expected and unexpected uncertainty on risk free rate. The effects were estimated by a distributed lag nonlinear model that allows us to analyze nonlinearities originating from the level of uncertainty and time dynamics, according to the number of periods elapsed after the uncertainty shock is observed. Data sample spans 1950-2016. The color scale depicts the magnitude of the effect. The horizontal axis measures the effect conditional on the uncertainty level, while the vertical axis shows the effect at different lags. The four uncertainty indicators were estimated by out sample one-year ahead recursive regressions, with annual data from 1929 to 2016. The first regression consisted of 20 observations, while the subsequent estimations were recursive, and incorporated one additional observation at a time.

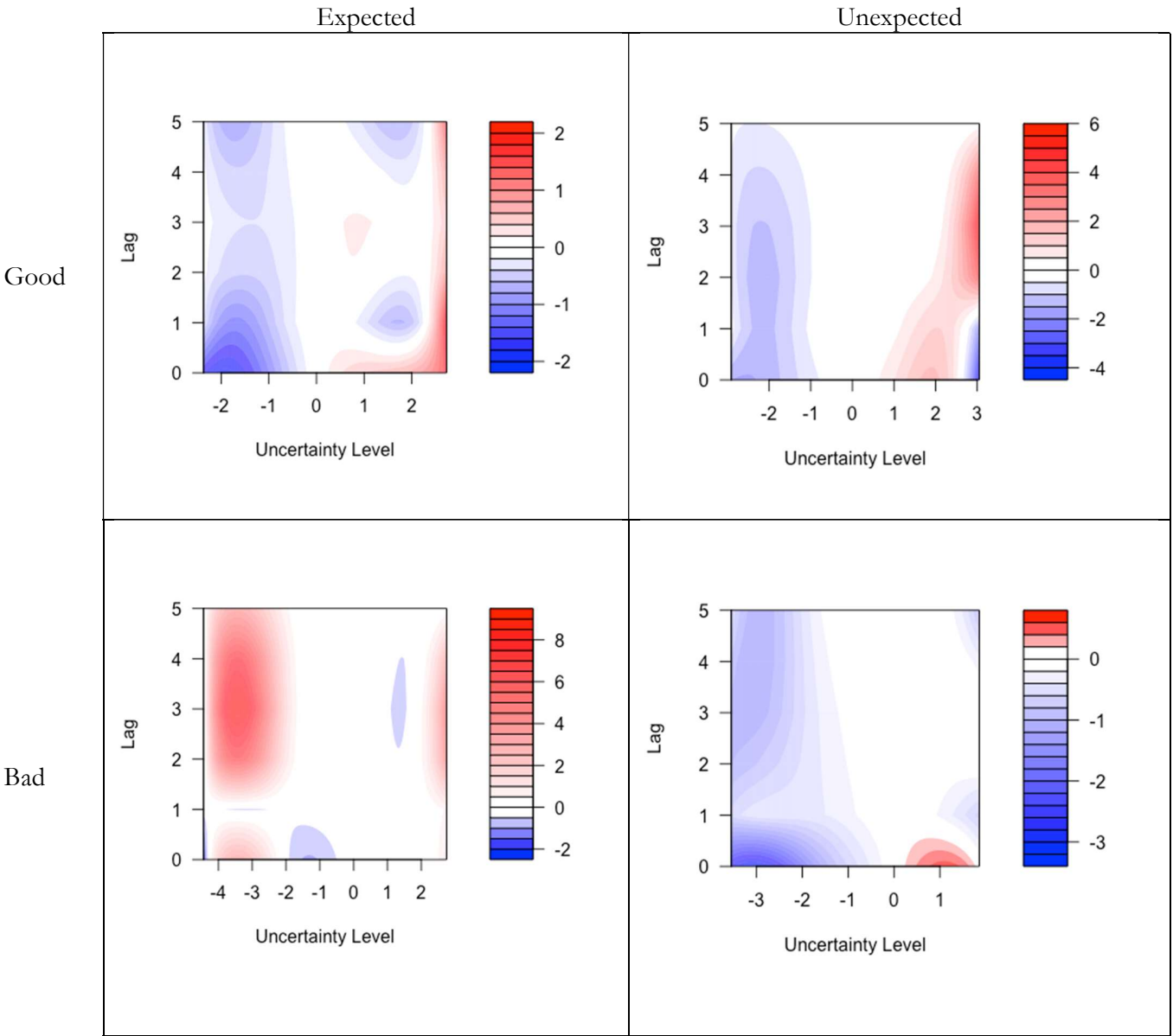


Figure 9. Impacts of expected and unexpected, good and bad, uncertainty, on the default spread: The figure shows the effect of good and bad, expected and unexpected uncertainty on the default spread between yields Moody's AAA and Moody's BAA corporate bonds. The effects were estimated by a distributed lag nonlinear model that allows us to analyze nonlinearities originating from the level of uncertainty and time dynamics, according to the number of periods elapsed after the uncertainty shock is observed. Data sample spans 1950-2016. The color scale depicts the magnitude of the effect. The horizontal axis measures the effect conditional on the uncertainty level, while the vertical axis shows the effect at different lags. The four uncertainty indicators were estimated by out sample one-year ahead recursive regressions, with annual data from 1929 to 2016. The first regression consisted of 20 observations, while the subsequent estimations were recursive, and incorporated one additional observation at a time.

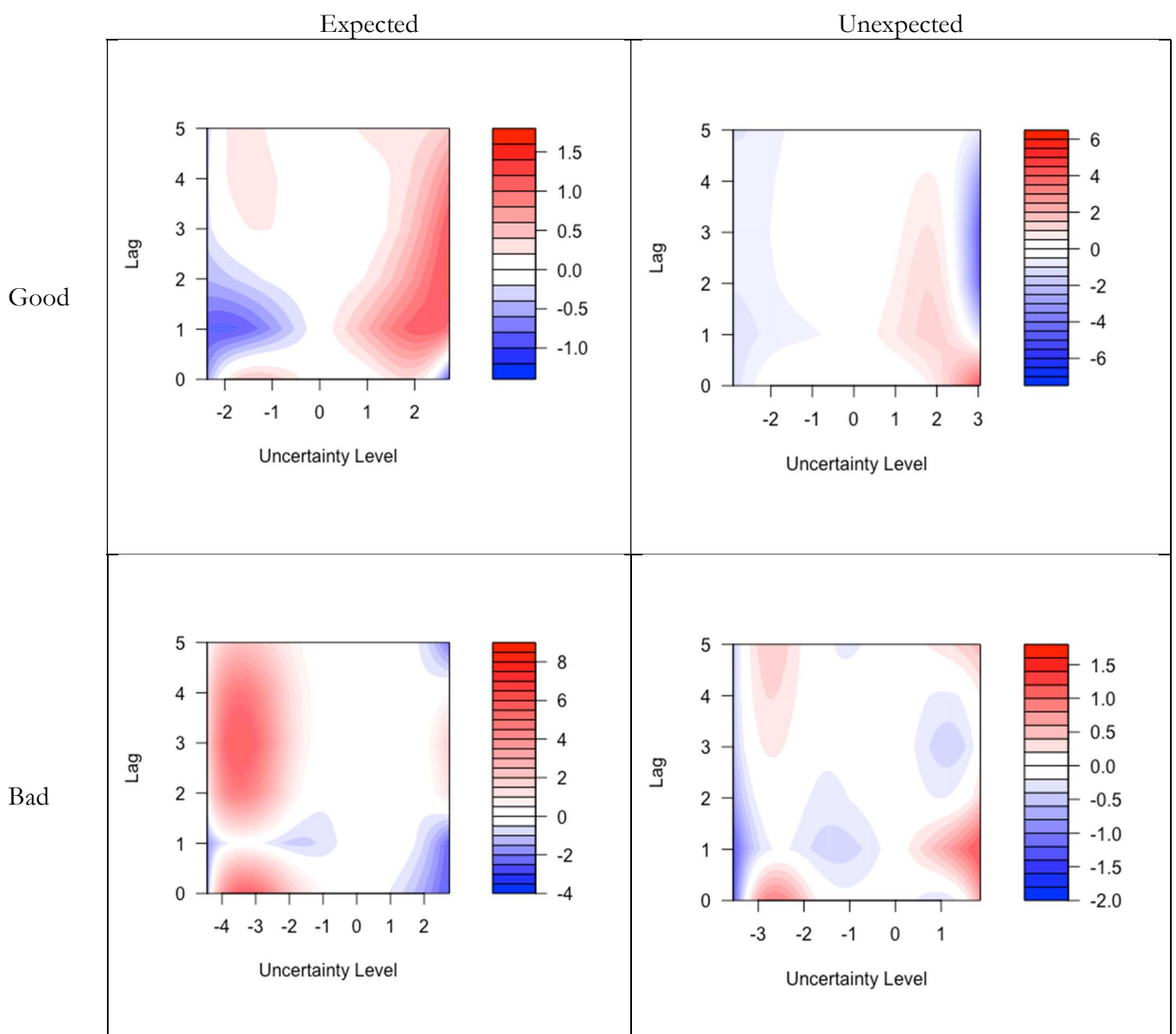
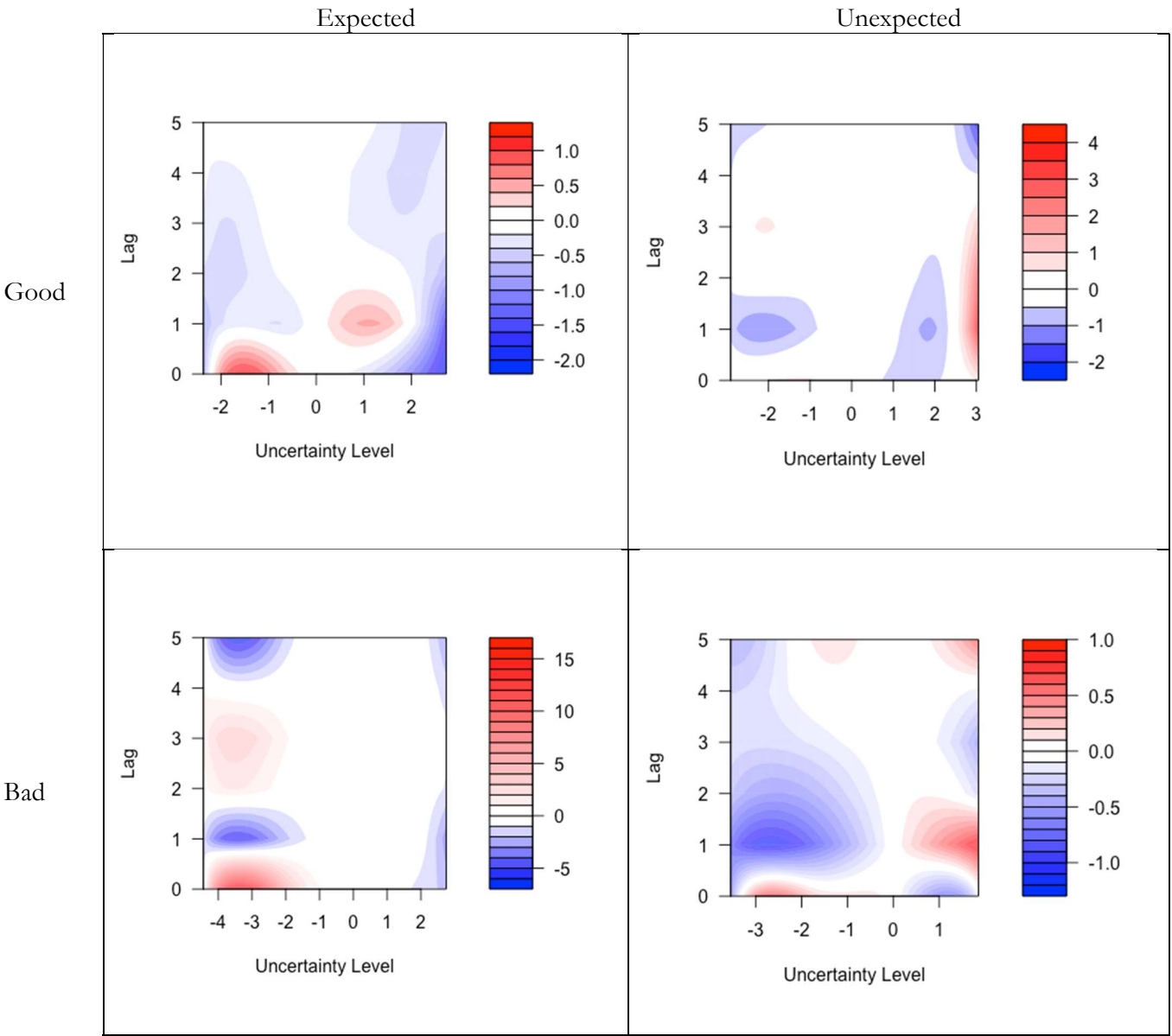


Figure 10. Impacts of expected and unexpected, good and bad, uncertainty, on the equity premium: The figure shows the effect of good and bad, expected and unexpected uncertainty on the annual excess return of the market index above the risk free rate. The effects were estimated by a distributed lag nonlinear model that allows us to analyze nonlinearities originating from the level of uncertainty and time dynamics, according to the number of periods elapsed after the uncertainty shock is observed. Data sample spans 1950-2016. The color scale depicts the magnitude of the effect. The horizontal axis measures the effect conditional on the uncertainty level, while the vertical axis shows the effect at different lags. The four uncertainty indicators were estimated by out sample one-year ahead recursive regressions, with annual data from 1929 to 2016. The first regression consisted of 20 observations, while the subsequent estimations were recursive, and incorporated one additional observation at a time.



6. Conclusion

We estimate the impacts 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 uncertainty, which involves treating investment as a real option and which predicts negative reaction of prices, investments and economic activity to uncertainty shocks, is more related to the notion of unexpected bad uncertainty shocks, which is at odds with the understanding of uncertainty as a forward looking effect. We also show that it is only the unexpected component of realized volatility which generates the negative dynamics expected from uncertainty.

In the second part of our results we show that small uncertainty shocks might produce the largest impacts on economic variables and asset prices, especially between one and three years after the shock is realized. To this end we use a novel distributed lags nonlinear model that allow us to simultaneously represent non-linear exposure–response dependencies and delayed effects of macroeconomic variables to different notions of uncertainty. Overall we document important nonlinearities in the propagation of uncertainty to the real and financial markets, which motivates a close monitoring of uncertainty evolution that help to mitigate the adverse consequences of uncertainty.

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A large, semi-circular graphic composed of many thin, parallel lines in a light blue color, set against a darker blue background. The lines are arranged in a way that creates a sense of depth and movement, resembling a stylized fingerprint or a modern architectural element. It occupies the lower two-thirds of the page.