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Sovereign credit ratings under fiscal uncertainty

This paper finds that fiscal uncertainty is an important determinant of sovereign credit ratings, and can explain why ratings often appear pro-cyclical during crisis periods.

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European Stability Mechanism

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Abstract

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Keywords: uncertainty, fiscal policy, sovereign credit ratings, ordered outcome estimation

JEL codes: C35, G24, H68

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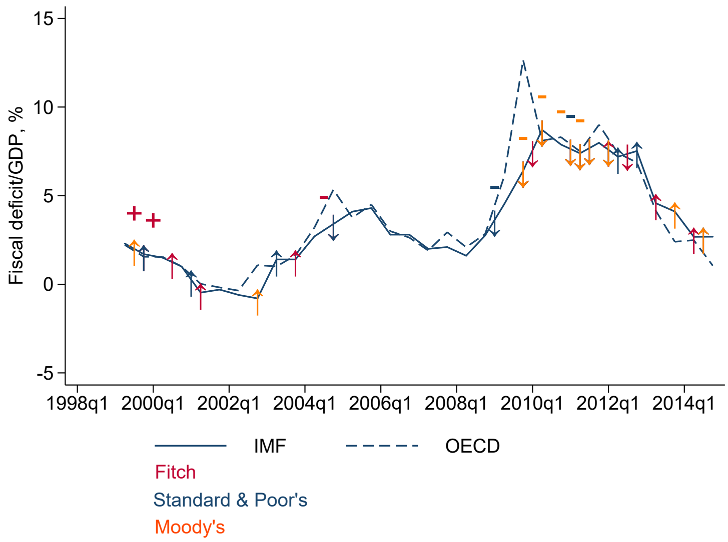
1 Introduction

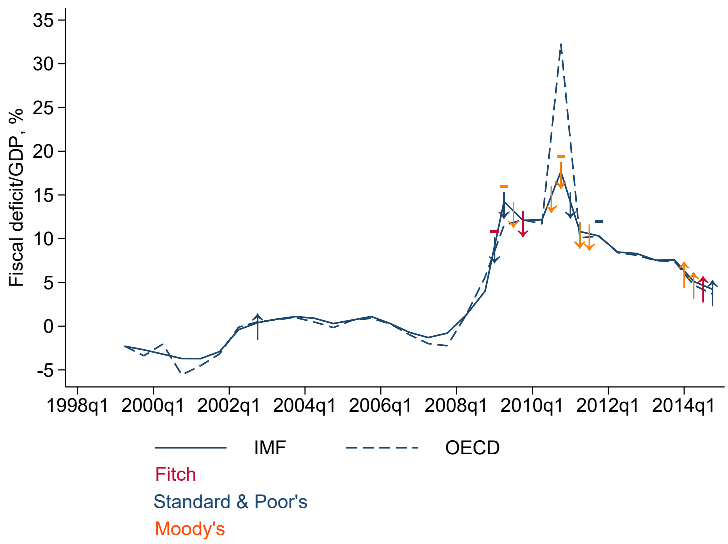
The sudden and largely unexpected standstill in economic activity during the Great Recession highlighted the role of uncertainty in shaping macroeconomic outcomes. It became clear that uncertainty about the future state of the economy has the potential to substantially reduce output growth, investment and hiring (Bloom, 2014). As a consequence of banking sector bailouts and government interventions to stabilise output and labour markets, fiscal positions in a number of advanced economies deteriorated severely, leading to a rise in uncertainty about future fiscal policy and ultimately, concerns about sovereign credit risk. Similar to macroeconomic uncertainty, uncertainty about fiscal policy has been shown to detrimentally affect the economy. Fernández-Villaverde et al. (2015) find that fiscal uncertainty reduces economic activity. Political uncertainty during election years often dampens domestic and foreign direct investment (Julio and Yook, 2012, Julio and Yook, 2016). Whether fiscal consolidation has expansionary effects, or not, depends on the uncertainty about fiscal policy (Croce et al., 2012, Bi et al., 2013). Likewise, Ricco et al. (2016) show that noisy communication of fiscal measures blurs agents' expectations and reduces fiscal multipliers. While Sialm (2006) and Pástor and Veronesi (2013) suggest that investors may require higher risk premia if tax policy becomes uncertain or governments fail to provide an economic protection to financial markets, the effect of fiscal uncertainty on sovereign credit risk has so far not received much attention.

Investors in sovereign debt can rely on a number of experts to provide them with analyses of fiscal policy sustainability, including independent national auditing units, central banks, investment banks and fund managers. In this paper, I focus on credit rating agencies, which have been subject to much debate during the recent global financial and European government debt crisis. Their sovereign debt credit ratings are an expert opinion on the credit risk of a government. Ratings are available for all major advanced economies. Unlike opinions provided by other experts, ratings are revised on a regular basis and are directly comparable across countries. However, rating agencies have frequently been criticised for their failure to anticipate crises and for reacting too late and too excessively with downgrades during crises, compared to what movements in fundamentals, such as the deficit, would imply (e.g. Ferri et al., 1999, Mora, 2006, Dimitrakopoulos and Kolossiatis, 2016). Polito and Wickens (2015) show that a model-based measure of sovereign credit risk that is purely based on fundamentals would have issued a credit warning long before credit rating agencies changed their official ratings for the United States and euro area countries. D'Agostino and Lennkh (2016) decompose sovereign credit ratings into an objective, fundamentals-based component and a subjective component that enters ratings as a form of expert opinion. They conclude that for crisis-hit euro area countries, the subjective component appears to be too optimistic before the crisis, but too pessimistic during and after.

I find that fiscal uncertainty can provide an explanation for why sovereign ratings appear pro-cyclical during crises. While ratings have been shown to react to crises (Monfort and Mulder, 2000), world stock market volatility (Hill et al., 2010) and consumer sentiment (Schumacher, 2014), the direct effects of country-specific fiscal uncertainty have not been



(a) Greece



(b) Ireland

Figure 1: Official fiscal forecasts and sovereign rating migration

analysed. For a sample of advanced economies, I show that fiscal uncertainty indeed increases the probability of rating downgrades. This result holds independent of movements in fiscal and macroeconomic fundamentals and for the three main credit rating agencies Fitch, Standard & Poor's and Moody's. Given its adverse affects on country fundamentals such as growth, investment and risk premia, rating agencies can justify including the degree of fiscal uncertainty in their judgement about sovereign credit risk. I also find evidence that agencies issue rating changes more often during periods of high fiscal uncertainty than implied by the effect of uncertainty on sovereign credit risk alone.

For example, Greece and Ireland were among the countries hit hardest by the sovereign debt crisis that unfolded in the euro area after the economic crash. Figure 1 shows that in both countries the fiscal deficit relative to GDP, as projected in real time by the IMF and

OECD, saw double-digit percentage increases. Concerns about public finances heightened not only because fiscal deficits rose in absolute terms. Equally salient was the fact that uncertainty about fiscal deficits surged significantly. In Figure 1, large deviations of IMF forecasts from OECD forecasts illustrate that the future path of public finances was far from certain in the direct aftermath of the financial crisis in 2009 and at the height of the European government debt crisis in 2011. Figure 1 shows that credit rating agencies adjust their sovereign ratings when projections about the fiscal deficit change substantially (arrows indicate changes to rating categories, plus/minus signs illustrate changes in the rating watch status). This is because the deficit is considered an important sovereign credit risk factor. Figure 1 also suggests that the frequency of rating announcements increases when there is more ambiguity about the future path of the fiscal deficit. More rating changes are observed when IMF and OECD projections deviate from each other more substantially.

Estimating the effect of economic determinants on the probability of a rating change is made difficult by the fact that ratings hardly change over time. Rating stability partly results from the 'through-the-cycle' approach adopted by rating agencies that prevents *en masse* changes when countries are hit by common shocks. In addition, ratings at the upper end of the rating scale are changed less frequently than below-investment grade ratings by construction. Finally, the fact that the commonly adopted rating scale is bounded prohibits rating transition above the top and below the bottom although credit risk may move substantially. This paper proposes a new empirical framework for the analysis of rating determinants. This includes a regression model which consists of two processes. A credit risk process determines the direction of rating changes and depends on the movement in fiscal and macroeconomic fundamentals related to sovereign credit risk. Technical factors of a stability process, like the rating level, determine the probability of whether a rating change is allowed to occur in a given period. Both processes are estimated jointly using a new ordered outcome estimator that builds on Ordered Probit and the Zero-Inflated Ordered Probit estimator by Harris and Zhao (2007). The estimator also accounts for the boundary of the rating scale by imposing a probability of zero on one of the rating change outcomes for boundary observations. It is shown that the new estimator generates less biased estimates than conventional techniques which do not take rating stability into account.

To estimate the reaction of sovereign ratings to fiscal uncertainty, a novel way of measuring such uncertainty is proposed. I construct a fiscal uncertainty index based on the disagreement in official forecasts of the fiscal deficit and common uncertainty shocks faced by forecasters. The deficit is a key variable which is often used to evaluate the sustainability of fiscal policy given that an accumulation of fiscal deficits over time increases the stock of sovereign debt (*cf.* Cimadomo, 2016). Forecasts of the deficit contain information about expected policy changes as well as expectations about governments' attempts to consolidate their budgets. The index builds on the method Lahiri and Sheng (2010) propose for the measurement of macroeconomic uncertainty. Unlike stochastic volatility proxies for fiscal uncertainty (e.g. Fernández-Villaverde et al., 2015), the proposed index can be constructed for relatively short time series, making it comparable across a large range of countries. Compared to recently developed forecast-based macroeconomic uncertainty measures (e.g. Orlik and Veldkamp, 2014, Jurado et al., 2015), the index does not require knowledge about forecasters' individual uncertainty, accommodating the fact that for fiscal variables often only point forecasts are reported. The index also directly captures uncertainty about fiscal policy faced by investors and rating agencies, which distinguishes it from news-based indices, like in Baker et al. (2016), or financial market volatility measures, such as the VIX.

The rest of the paper is organised as follows. The next section explains how fiscal uncertainty is measured. Section 3 develops the empirical framework for the analysis of sovereign rating determinants. Results are presented in section 4. Section 5 concludes.

2 Measuring fiscal uncertainty

The aim of this section is to construct an index that 1) reflects uncertainty about fiscal outcomes, 2) in real time, 3) over time and a large set of countries. While often used to capture uncertainty faced by market participants, it remains unclear to what extent financial volatility indices, like the Chicago Board Options Exchange index of options-implied volatility VIX, indeed reflect uncertainty and not simply mere sentiment or risk aversion (see discussion in Jurado et al., 2015). In particular since 2016, financial market volatility has been subdued despite elevated levels of uncertainty. News-based indices, like the Economic Policy Uncertainty index by Baker et al. (2016), are increasingly used to approximate uncertainty about policy measures but do not necessarily capture uncertainty about the outcome of fiscal data. The fiscal uncertainty index in this paper is therefore based on uncertainty in official forecasts of fiscal data, which are also consistent across a range of advanced economies. While uncertainty measures based on forecast errors (e.g. Rossi and Sekhposyan, 2015) are only available *ex post*, I use information contained in official current-year and year-ahead forecasts of the fiscal deficit to construct a real-time index of uncertainty that prevails about fiscal policy in the near term. The short time dimension and low frequency of fiscal data prevents me from applying computationally demanding methods proposed for the measurement of macroeconomic uncertainty, such as those by Orlik and Veldkamp (2014), Jurado et al. (2015), or stochastic volatility estimates for fiscal instruments as in Fernández-Villaverde et al. (2015). Instead, I follow a strand in the literature that interprets disagreement among forecasters as uncertainty. Disagreement is observable in real time and can be directly inferred from published forecasts. Dispersion in point forecasts is found to understate uncertainty, however. This is explained by risk aversion among forecasters, which prevents them from deviating from the consensus. Bomberger (1996) compares disagreement in point (US inflation) forecasts to a conditional variance measure and finds a significant relationship between both. His work initiated a debate on whether forecaster disagreement truly captures uncertainty (Rich and Butler, 1998, Bomberger, 1999). Disagreement may reflect a mere difference in opinion and not uncertainty (Diether et al., 2002) or forecasters may provide biased answers because they may want to stand out (Laster et al., 1999). Some may provide erroneous answers because they conduct a less thorough analysis than others. Or there may be spurious determinacy if, due to a lack of available information, all forecasters rely on the same information set and provide the same forecast. Bali et al. (2015) clean their dispersion measure from biases – or more generally, predictable components. However, Clements (2008) finds only moderate correlation between forecast dispersion (in GDP growth forecasts) and individual forecast uncertainty, as measured by individual forecast variances. Consequently, Giordani and Söderlind (2003) combine a disagreement measure with individual forecasters' variances. Their approach relies on reported individual variances (density forecasts), but these are not available for fiscal data across a number of advanced economies. Similarly, Boero et al. (2008) decompose their uncertainty measure – the aggregate density across forecasters – into an average of individual variances and the disagreement in point forecasts. This shows that disagreement alone cannot replace a direct measure of uncertainty but can be considered a component of such a measure. Lahiri and Sheng (2010) derive the theoretical 'missing link' between forecaster disagreement and uncertainty from a Bayesian learning model. In their model, each forecaster obtains a public and private signal about the future state of an economic variable. Using Bayes' rule, both sources of information are combined. It is shown that individual forecast uncertainty is a function of the variance of the public signal and the variance of the private signal. The authors then link this theoretical result to an empirical model in which aggregate uncertainty is the sum of the variance of aggregate shocks, accumulated over the forecast horizon, and forecaster disagreement. I use the Lahiri and Sheng (2010) framework because it yields an uncertainty index that is available in real time, meets the constraints set by cross-country fiscal data and addresses the weaknesses of previous disagreement-based uncertainty measures by linking the uncertainty measure to a theoretical forecasting model. To my knowledge, I am the first to use this approach to construct an index of fiscal uncertainty. The closest analysis is Ricco et al. (2016), which focuses on the disagreement in deficit forecasts for the United States to approximate ambiguity in policy communication.

2.1 Forecasting model

Applied to the context of uncertainty about the current and future path of the fiscal deficit, the theoretical forecasting model developed by Lahiri and Sheng (2010) (refined in Ozturk and Sheng, 2018), can be summarised as follows. Let x_{ct} be the realisation of a fiscal variable, say the deficit/GDP ratio, in country c and year t. Forecaster i, which may be the IMF, OECD, or European Commission, provides a prediction of x_{ct}, h periods ahead. I denote this forecast F_{icth}. The individual forecast error made by forecaster i is then

$$e_{icth} = x_{ct} - F_{icth}. \tag{1}$$

The weighted average of individual forecast errors is called the consensus forecast error:

$$e_{cth} = \sum_{i=1}^{N} w_{icth} e_{icth}. \tag{2}$$

It is assumed to be independent over forecast horizons h. The w's denote the weights of individual forecast errors in the consensus forecast error. These may vary for each forecaster i, over time t, countries c or forecast horizon h (for simplicity I will consider equal weights across forecasters in the empirical application).

The individual forecast error can then be decomposed as follows:

$$e_{icth} = \alpha_{ich} e_{cth} + \epsilon_{icth} + \phi_{ich}. \tag{3}$$

The first component is common across all forecasters and approximated by the consensus forecast error e_{cth}. In the context of fiscal forecasting it can be interpreted as an error in the data provided by governments to forecasting institutions. Common errors may result from future policy changes or the misreporting of data. α_{ich} measures the exposure of forecaster i to this common error, i.e. the extent to which forecasters rely on the data they are provided with by fiscal authorities, which may vary across forecasters i, countries c and the forecast horizon h. The second component ϵ_{icth} captures idiosyncratic forecast errors that result from mistakes each forecaster makes in her own expert analysis. ϵ_{icth} is assumed to be orthogonal to e_{cth} and to have a mean of zero. The final component ϕ_{ich} is an additional time-invariant bias forecaster i adds to the forecast every period. The reason for constant biases may be of political nature or caused by other non-economic factors. Since ϕ_{ich} is a predictable component of the forecast error, I ignore it for the rest of this section by setting $\phi_{ich} = 0$ but return to it in section 2.2.

Taking equations (2) and (3) together and setting $\phi_{ich} = 0$, the restriction $\sum_{i=1}^{N} w_{icth} \alpha_{ich} = 1$ is imposed. The variance of individual forecast errors $Var(e_{icth})$ is then interpreted as a measure of individual uncertainty faced by forecaster i in her forecast h periods ahead of x to be realised at time t in country c. It can be decomposed as follows:

$$Var(e_{icth}) = \alpha_{ich}^2 Var(e_{cth}) + Var(\epsilon_{icth}). \tag{4}$$

The covariance term between e_{cth} and ϵ_{icth} drops out because of the former being the aggregation of the latter, as defined in equations (2) and (3). Individual uncertainty is therefore a function of a common uncertainty shock ($Var(e_{cth})$) and idiosyncratic uncertainty ($Var(\epsilon_{icth})$).

The problem with equation (4) is that individual uncertainty cannot be observed without knowledge of α_{ich} and estimates of ϵ_{icth}. However, Ozturk and Sheng (2018) show that an aggregation of individual uncertainty measures over the sample of forecasters can be written as:

$$u_{cth} \equiv \sum_{i=1}^{N} w_{icth} Var(e_{icth}) = c_{cth} + d_{cth} \tag{5}$$

where w_{icth} again denote aggregation weights. The aggregation yields a measure of the aggregate level of forecast uncertainty that prevails in the economy, or, in other words, the overall uncertainty faced by the average forecaster. Henceforth, u_{cth} will be referred to as overall theoretical uncertainty measure. $c_{cth} \equiv Var(e_{cth})$ is the common uncertainty shock a representative forecaster faces. The aggregation, details of which are provided in Appendix A1, lets individual α_{ich}'s drop out. It also enables me to write the idiosyncratic uncertainty component as disagreement across forecasters d_{cth}, where disagreement is defined as the expected weighted sum of squared individual forecasts (or forecast errors) relative to the consensus forecast (error):

$$d_{cth} \equiv E[\sum_{i=1}^{N} w_{icth}(F_{icth} - F_{cth})^2]. \tag{6}$$

2.2 An empirical uncertainty measure

Equation (5) makes clear that measures directly associating disagreement with uncertainty may underestimate overall uncertainty by ignoring the aggregate shock component. The wedge between uncertainty and disagreement depends on two characteristics of aggregate shocks. First, c_{cth} will be small if the forecast horizon h is small as it captures common shocks that occur between the time the forecast of x is made and the realisation of x at time t. Second, the difference between uncertainty and disagreement will be small if aggregate shocks have a low variability, i.e. during relatively stable periods. Since the focus in this study lies on the recent global financial and European sovereign debt crisis, i.e. periods of substantial volatility, the assumption of stable shocks will be violated and a measure of overall uncertainty will need to take it into account. I therefore construct the empirical measure as follows.

Forecast disagreement estimates The first step consists of obtaining estimates of forecast disagreement d_{cth}, i.e. the variance of point forecasts for a given horizon h, realisation time t and country c. Equation (3) contains the term ϕ_{ic}, which can be interpreted as time-invariant forecast bias: forecasters may consistently underestimate the fiscal deficit. In fact, there exists evidence that IMF forecasts of GDP growth and inflation are biased (Dreher et al., 2008). Artis and Marcellino (2001) found similar evidence for IMF and OECD forecasts of the fiscal deficit, at least for some countries. Biases may stem from over-optimism or pessimism or differences in forecasting technologies. I assume ϕ_{ic} to be known to the public and to be constant over time. To clean forecasts from time-invariant biases, I regress *ex post* observable forecast errors e_{icth} separately for each forecaster i and forecast horizon h on a constant term and a country-fixed effect, allowing for biases to differ across countries. The constant term provides a measure of the average bias in forecaster i's deficit forecast and the country-fixed effect approximates the additional country-specific bias. Assuming that these biases are publicly known and time-invariant, I subtract their estimates from observed forecasts. I then use the observed variance of cleaned forecasts $\hat{F}_{icth}$ as a proxy for disagreement

$$\hat{d}_{cth} = \sum_{i=1}^{N} w_{icth}(\hat{F}_{icth} - \hat{F}_{cth})^2 \tag{7}$$

giving each of the three forecasting institutions equal weight in the consensus forecast $\hat{F}_{cth} = \sum_{i=1}^{N} w_{icth}\hat{F}_{icth}$ and in the observed forecast variance, i.e. $w_{icth} = w_{jcth} = \frac{1}{3}$ for all c, t and h.

Estimates of the variance of aggregate shocks In order to arrive at the aggregate uncertainty index, the second step consists of obtaining a real-time estimate of c_{cth}, the variance of the aggregate shock. The estimate ought to meet the limitations set by cross-country data on forecasts of the fiscal deficit. Lahiri and Sheng (2010) use as a proxy conditional variance estimates from an ARCH model for average forecast errors. However, given that the present sample contains on average only around 24 forecast observations per country, and at most 30, I refrain from such a time series estimation. Instead, I build on Barron et al. (1998) who approximate the time-varying variance of a forecast time series with squared average forecast errors $(x_{ct} - F_{cth})^2$. Given that forecast errors are only observable after the realisation of the forecast variable x_{ct}, I work with forecast revisions. The consensus forecast of the fiscal deficit of year t made $h+1$ periods ahead is calculated as $F_{cth+1} = \sum_{i=1}^{N} w_{icth+1}F_{icth+1}$ as before. I call the revision published in period h F_{cth}. Errors made in $h+1$-period ahead consensus forecasts, $e_{cth+1} = x_{ct} - F_{cth+1}$, will be larger than errors in revisions, $e_{cth} = x_{ct} - F_{cth}$. This is because more information will have become available between $h+1$ and h. e_{cth} will, however, still be different from zero as time h has to pass until x_{ct} is realised at t. I write errors inferred from revisions in consensus forecasts as:

$$F_{cth} - F_{cth+1} = (x_{ct} - e_{cth}) - (x_{ct} - e_{cth+1}) = e_{cth+1} - e_{cth} \tag{8}$$

Forecast revisions may be predictable if forecaster- and country-specific forecast biases are present. I therefore use the bias-cleaned forecasts to compute the measure of the variance of aggregate shocks that were introduced above, i.e. $\hat{F}_{icth}$ and $\hat{F}_{icth+1}$. Forecast revisions may also be predictable by projections of other macroeconomic series published one period before. In order for the estimate of the variance of aggregate shocks to meet the assumption of independence over time, I strip revisions of the consensus forecast off predictable components. To do so, I follow Auerbach and Gorodnichenko (2013) in regressing revisions to fiscal deficit figures on the average revision made one forecasting period before as well as previous projections of the fiscal and macroeconomic variables.[1] The estimate of the residual $(\hat{f}_{cth} - \hat{f}_{cth+1})$ is orthogonal to information ahead of the publication of forecasts. It therefore yields an estimate of unexpected innovations to the consensus forecast.

Under the assumption that common shocks, which occurred between initial forecasts and revisions, are a good indicator for common uncertainty shocks that currently prevail, I use

[1]Estimates are reported in Table A1 in the Appendix for revisions of current-year and one-year-ahead consensus forecasts of the fiscal deficit. Results show that revisions from one period to the next can partly be explained by their lags and previous forecasts of fiscal and macroeconomic fundamentals. In particular year-ahead forecasts are adjusted sluggishly to new information as earlier revisions can explain current revisions at statistically significant levels; the same does not hold for forecasts of current-year values. In addition, the size of the deficit contains some explanatory power, and so does the current account balance as well as previously forecast GDP growth rates (for nowcast revisions only).

the following expression to approximate the variance of aggregate shocks, c_{cth}:

$$\hat{c}_{cth} = [s_1(\hat{f}_{cth+1} - \hat{f}_{cth+2}) + s_2(\hat{f}_{cth} - \hat{f}_{cth+1})]^2 \tag{9}$$

$(\hat{f}_{cth+1} - \hat{f}_{cth+2})$ and $(\hat{f}_{cth} - \hat{f}_{cth+1})$ are the revisions at forecast horizons $h+1$ and h, respectively, cleaned from information that is available before revisions are made public. s_1 and s_2 are smoothing parameters as a raw revision measure might be overestimating the common shock variance by abstracting from inertia. To give more weight to current values compared to past values, I set them to $s_1 = \frac{1}{3}$ and $s_2 = \frac{2}{3}$. The empirical proxy or the variance of aggregate shocks is therefore a weighted average of squared revisions.

Aggregate fiscal uncertainty index The empirical version of the fiscal uncertainty measure across forecasters is then sum of the proxies for the variance of aggregate shocks and the disagreement measure:

$$\hat{u}_{cth} = \hat{c}_{cth} + \hat{d}_{cth} \tag{10}$$

To obtain an index of fiscal uncertainty that is comparable to alternative uncertainty indices, I normalise the empirical uncertainty measures across the entire sample to adopt a mean of zero and a variance of one:

$$U_{cth} = \frac{(\hat{u}_{cth} - \frac{1}{C}\frac{1}{T}\sum_{c=1}^{C}\sum_{t=1}^{T}\hat{u}_{cth})}{\sqrt{(\frac{1}{C}\frac{1}{T}\sum_{c=1}^{C}\sum_{t=1}^{T}(\hat{u}_{cth} - \frac{1}{C}\frac{1}{T}\sum_{c=1}^{C}\sum_{t=1}^{T}\hat{u}_{cth})^2}}. \tag{11}$$

One unit of the index value is therefore equal to the sample standard deviation of the uncertainty measure. I obtain two versions of the uncertainty index for current-year and year-ahead forecasts, denoted U_{ct0} and U_{ct1}, respectively. I also calculate normalised indices for the sub-components of the uncertainty measure separately, replacing $\hat{u}_{cth}$ in equation (11) with $\hat{c}_{cth}$ and $\hat{d}_{cth}$, and using capital letters to label the corresponding common shock index versions C_{ct0} and C_{ct1}, and disagreement index versions D_{ct0} and D_{ct1}.

Table 1: Forecast correlation and errors

	OECD		IMF		EC	
	h=0	*h=1*	*h=0*	*h=1*	*h=0*	*h=1*
Forecast correlation						
OECD	1.000	1.000				
IMF	0.961	0.958	1.000	1.000		
EC	0.983	0.979	0.954	0.959	1.000	1.000
Forecast errors						
Mean	0.37***	0.67***	0.23**	0.59***	0.35***	0.57***
Standard deviation	2.03	2.93	2.13	2.90	2.00	2.85
Australia	-0.45**	0.19	0.12	0.83**		
Austria	0.34*	0.38	0.48**	0.73	0.39*	0.54
Belgium	0.40**	0.54*	0.26*	0.35	0.30*	0.30
Canada	0.06	0.34	0.04	0.64**		
Czechia	-1.08***	-1.22***	-0.50	-1.38***	-0.93***	-1.04**
Denmark	-0.36	-0.41	-0.58*	-0.42	-0.25	-0.33
Estonia	-1.06***	-1.16*	-0.86**	-0.76	-0.64**	-0.98*
Finland	-0.35*	-0.13	-0.40*	-0.12	-0.11	0.01
France	-0.10	0.39	-0.05	0.49**	-0.12	0.25
Germany	-0.33**	-0.42	-0.49**	-0.47	-0.30**	-0.35
Greece	3.75***	4.57***	3.20***	3.85***	3.31***	4.16***
Hungary	0.90*	0.92**	1.53	-0.82**	1.10*	0.56
Iceland	1.00	1.46*	0.93	1.19		
Ireland	0.84	2.25*	0.97	1.70	0.65	1.87*
Israel	-0.48*	0.08	0.69**	1.30***		
Italy	0.14	0.42	0.15	0.48	0.23	0.47*
Japan	-0.52**	-0.45	-0.63***	0.12	-0.53*	-0.37
Korea	0.75*	1.22**	-0.74	-0.54		
Luxembourg	-1.52***	-1.72***	-2.14***	-2.18***	-1.59***	-1.92***
Netherlands	-0.12	0.21	-0.11	0.14	-0.12	0.14
New Zealand	-1.01***	-1.10**	-0.63***	-0.45		
Norway	0.27	-0.27	-0.19	-0.84		
Poland	0.87	0.85	-0.01	0.08	0.76	0.59
Portugal	1.27***	1.98***	1.10***	1.77***	1.22***	1.83***
Slovakia	0.19	0.24	0.40	0.56	-0.20	0.12
Slovenia	1.79*	3.30	0.56	2.26**	0.89	1.20
Spain	0.73**	1.54**	0.62**	1.22	0.64	1.19
Sweden	0.33	0.45	0.03	0.26	0.36	0.49
Switzerland	-0.24	-0.54**	-0.89***	-0.93***		
United Kingdom	-0.20	0.24	0.15	0.63	-0.02	0.41
United States	1.11***	1.72***	0.35	1.70***	1.09***	1.52***
Observations	882	882	858	800	667	623
Countries	31	31	31	31	23	23

Notes: Projections of the fiscal deficit as a percentage of GDP. Errors relative to actual values as reported in 2015 spring publications. *h=0*: nowcast, *h=1*: one year-ahead forecast. Significance level of t-test given by *** p<0.01, ** p<0.05, * p<0.1.

2.3 Official fiscal deficit projections

For the construction of the fiscal uncertainty index, I employ staff projections by the IMF, OECD and European Commission (EC) of the general government deficit, i.e. net borrowing, as a percentage of GDP. The fiscal deficit relative to GDP is a key policy variable that is used to evaluate the stance of fiscal policy across countries. It also plays an important role in the fiscal surveillance framework of the European Union. A deviation of the fiscal deficit above 3 percent triggers corrective actions under the so-called Excessive Deficit Procedure.[2] Being based on forecasts of the fiscal deficit relative to GDP, published for the current year and the year ahead, the index provides a measure of uncertainty about the overall stance of fiscal policy in the near term, rather than a measure of uncertainty related to the long-term sustainability of public finances or uncertainty about particular spending, revenue or interest payment components.

Using fiscal forecasts from the IMF *World Economic Outlook*, the OECD *Economic Outlook* and the European Commission's *European Economic Forecast* instead of forecasts by individual governments or national, non-governmental forecasters ensures that definitions and methodologies applied across countries are sufficiently coherent. My sample covers 31 OECD countries over the period 1999 to 2014.[3] Deficit forecasts are highly correlated with each other (Table 1, top panel). Nevertheless, the standard deviation across all three forecasters is 0.508 for current-year projections and 0.596 for one year-ahead vintages, which is statistically significant at the 0.1 percent level in both cases.

Table 2: Decomposition of forecast errors and forecaster disagreement

	Average forecast error		Forecast standard deviation	
	h=0	*h=1*	*h=0*	*h=1*
Overall forecast	0.16	0.47	0.47	0.55
due to fiscal deficit forecast[a]	0.21	0.50	0.45	0.54
due to GDP forecast[b]	-0.05	0.00	0.25	0.27

Notes: Based on IMF and OECD projections of the fiscal deficit as a percentage of GDP. Average forecast errors and the standard deviation of forecasts across forecasters. *h=0*: nowcast, *h=1*: one year-ahead forecast. (a) Hypothetical forecast errors and the standard deviation of forecasts are calculated using forecasts of the fiscal deficit and realisations of GDP. (b) *Vice versa*, forecasts of GDP and realisations of the fiscal deficit are used.

I find evidence for a significant underestimation of fiscal deficits, implying that forecasters have been too optimistic on average. Similar to de Castro et al. (2013), forecast biases, i.e. mean forecast errors, significantly vary across countries. While deficit forecasts for some countries, like Czechia, Estonia, Luxembourg and New Zealand exhibit a negative bias, i.e. have on average been overestimated, the deficit forecasts for countries hit most by the European sovereign debt crisis, Greece, Ireland, Portugal and Spain, as well as the deficit of the United States have on average been underestimated (Table 1, main panel). Table 2 shows

[2]Alternative fiscal indicators such as the cyclically adjusted primary balance, government consumption, spending, revenue and debt/GDP are often not uniquely measured as forecasters employ different methodologies and definitions to compute them. This makes them less readily comparable across countries and time

[3]Forecasts by the European Commission are not available for Australia, Canada, Iceland, Israel, South Korea, New Zealand, Norway, see Table 1. Fiscal uncertainty indices for these countries are based on forecasts published by the IMF and OECD only.

that forecast errors in the deficit-to-GDP ratio are predominantly due to errors made in deficit forecasts, and only to a small extent due to errors made when forecasting nominal GDP. If deficit figures had been fully known *ex ante*, the average error in deficit/GDP one year-ahead forecasts due to imprecise GDP estimates would have been close to zero and nowcast errors would have been small and somewhat negative. Similar to forecast errors, disagreement about the fiscal deficit can explain most of the disagreement about fiscal deficit/GDP ratios (Table 2, panel on the right). Had forecasters got their deficit projections right, the disagreement due to GDP estimates would have been much lower than actual standard deviations. An index of uncertainty about the deficit/GDP ratio therefore captures uncertainty about the future path of the nominal fiscal deficit to the largest extent, and uncertainty about nominal GDP only to a small extent.

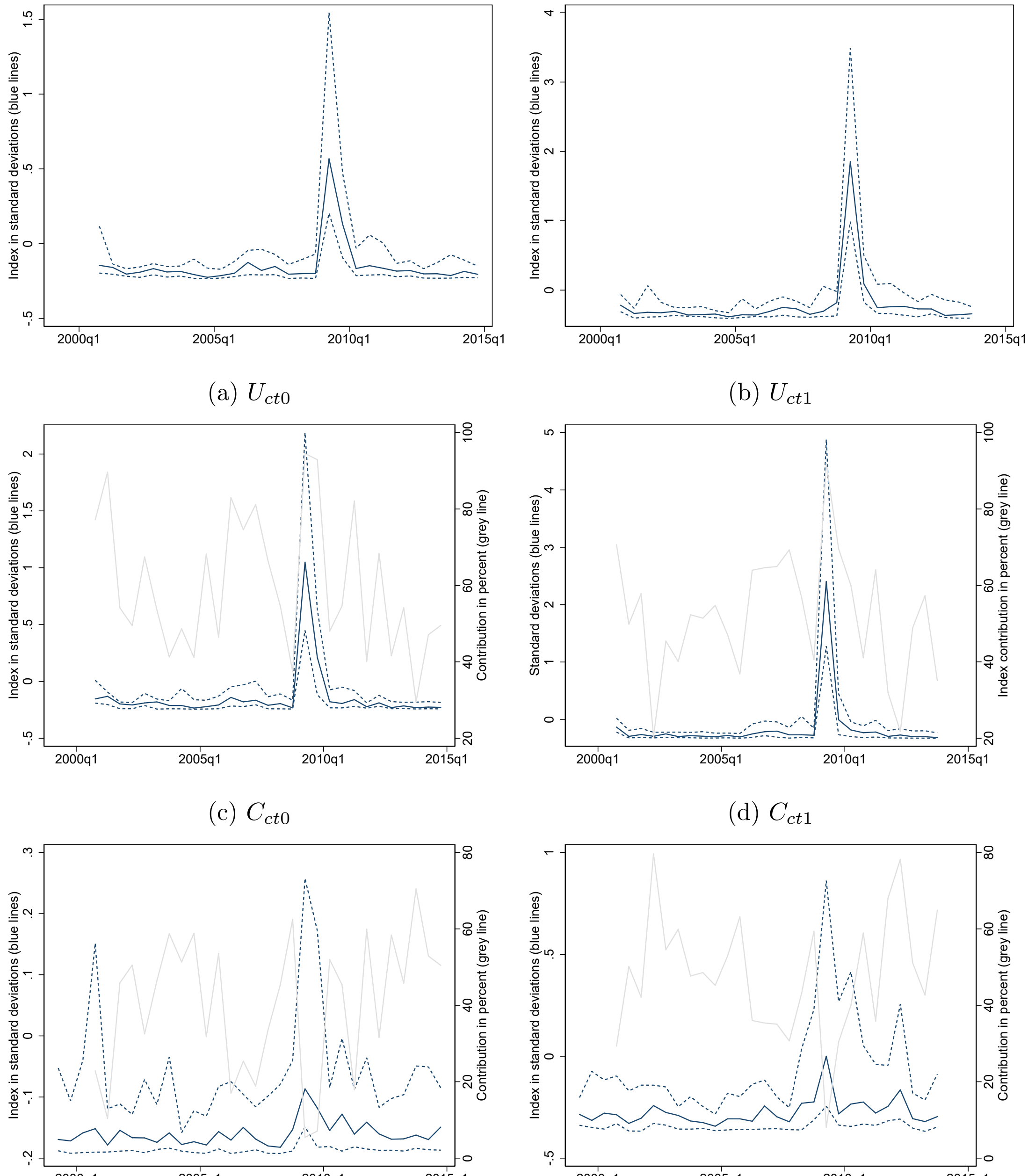
2.4 Index characteristics

Table 3 shows that the current-year measure of fiscal uncertainty $\hat{u}_{ct0}$, i.e. the measure based on deficit nowcasts, has a substantially larger variance than the one year-ahead version $\hat{u}_{ct1}$, which is the measure based on year-ahead deficit forecasts. The disagreement component $\hat{d}_{cth}$ contributes nearly one quarter to the overall variance of the measure. The contribution of the aggregate shock component $\hat{c}_{cth}$ is larger, in particular for the year-ahead measure, as less information is known at the time forecasts are published, which increases the variance of aggregate shocks. This confirms that disagreement alone is not sufficient to capture the overall uncertainty faced by forecasters. Accounting for aggregate uncertainty, which originates in the information provided by governments to forecasting institutions, is important.

Table 3: Decomposition of the fiscal uncertainty measure

	$\hat{u}_{ct0}$			$\hat{u}_{ct1}$		
	Mean	Variance	Contri-bution	Mean	Variance	Contri-bution
Uncertainty $\hat{u}_{cth}$	1.54	41.01	100.0%	1.45	11.41	100.0%
Disagreement $\hat{d}_{cth}$	0.59	9.49	23.1%	0.61	2.58	22.6%
Aggregate shock $\hat{c}_{cth}$	0.95	15.17	37.0%	0.83	6.27	54.9%
Covariance		8.17	19.9%		1.28	11.2%

An overview of the evolution of the fiscal uncertainty index, i.e. the normalised uncertainty measure, and its sub-components is shown in Figure 3. Solid blue lines depict the cross-country median of the index versions for current-year and year-ahead forecasts. Dashed lines mark the interquartile range, illustrating the cross-country dispersion in fiscal uncertainty at each point in time. The effect of the financial crisis of 2008/09 on uncertainty about the fiscal deficit is striking. The degree of uncertainty in forecasts published in spring 2009 supersedes all other episodes of fiscal uncertainty during the 14-year sample period, including small increases during the early and mid-2000s. Figure 3 also suggests that most of the uncertainty in 2009 originated in innovations to fiscal policy during that time rather than disagreement across forecasters: the disagreement component exhibits a substantially smaller increase that year compared to the overall index and common shock sub-index (see solid line in Figures 3e and 3f relative to Figures 3a to 3d).



(a) U_{ct0} (b) U_{ct1}

(c) C_{ct0} (d) C_{ct1}

(e) D_{ct0} (f) D_{ct1}

Figure 3: Time variation in fiscal uncertainty

In fact, the contribution of the disagreement component to the overall index, plotted by the grey lines in Figures 3e and 3f, appears to vary quite substantially over time but drops to nearly zero in 2009. The grey lines in Figures 3c and 3d show, as a mirror image, the contribution of the common shock component to the overall index. After its major contribution to the rise in overall uncertainty during the financial crisis, the importance of common shocks abated and idiosyncratic uncertainty, reflected in the disagreement component of the fiscal uncertainty index, rose. Before the crisis of 2008/09, fiscal uncertainty did not vary much across countries. Even as fiscal uncertainty surged in 2009, it did so in most countries to a similar extent. This is shown by the relatively narrow interquartile range during that period in Figure 3 (dotted lines). By contrast, after the crisis, heterogeneity in uncertainty across countries increases, in particular idiosyncratic uncertainty as measured by forecast disagreement.

To assess how the new fiscal uncertainty index may add to existing measures of economic and fiscal policy uncertainty, it is next compared to a set of conventional indices. The first is the *ex post* observable forecast error in projections of the fiscal deficit/GDP, averaged across the OECD, IMF and EC. The second measure is the Economic Policy Uncertainty index (EPU). It is based on uncertainty-related terms in newspaper articles and was proposed by Baker et al. (2016). It has recently become popular and is now available for 14 countries.[4] Third, as a measure of uncertainty about sovereign credit risk as perceived by financial markets, I use the realised volatility of 10-year government bond yields. I calculate it using the standard deviation of monthly yield observations from the OECD every half year. As a proxy for global uncertainty, I employ the VIX options-implied volatility index published by the Chicago Board Options Exchange. I normalise all measures to take a mean of zero and standard deviation of one.[5]

Table 4: Correlation matrix for uncertainty measures

			$U_{c,t+k,h=1}$			$D_{c,t=k,h=1}$	$U_{c,t+k,h=0}$
k	-2	-1	0	1	2	0	0
Forecast error	0.01	0.13	0.11	0.35	0.43	0.16	0.06
EPU	0.14	0.03	0.05	0.08	0.01	0.11	0.02
Bond yield vol	0.09	0.05	0.05	0.10	0.05	0.21	0.20
VIX	0.14	0.10	0.32	0.44	0.13	0.18	0.09
Deficit/GDP	0.29	0.38	0.38	0.06	-0.05	0.21	0.25

Notes: k is the number of semi-annual periods ahead.

Figure 2 illustrates the time variation of different uncertainty indices, averaged across countries. All measures agree that the period between 2003 and the global financial crisis was a period of subdued uncertainty. The financial crisis of 2008/09 leads to a surge in all indices, yet at different points in time. Financial market volatility, as measured by the VIX, peaked at the height of the financial crisis in 2008, while fiscal uncertainty (year-ahead version) reached its highest level in 2009 when it became clear that the crisis will have real effects on

[4]I use the EPU versions for Australia, Canada, France, Germany, Ireland, Italy, Japan, Korea, Netherlands, Spain, Sweden, United Kingdom, United States, and the European Union version for remaining EU members. The data has been obtained from www.policyuncertainty.com.

[5]Formula (11) is applied to all measures.

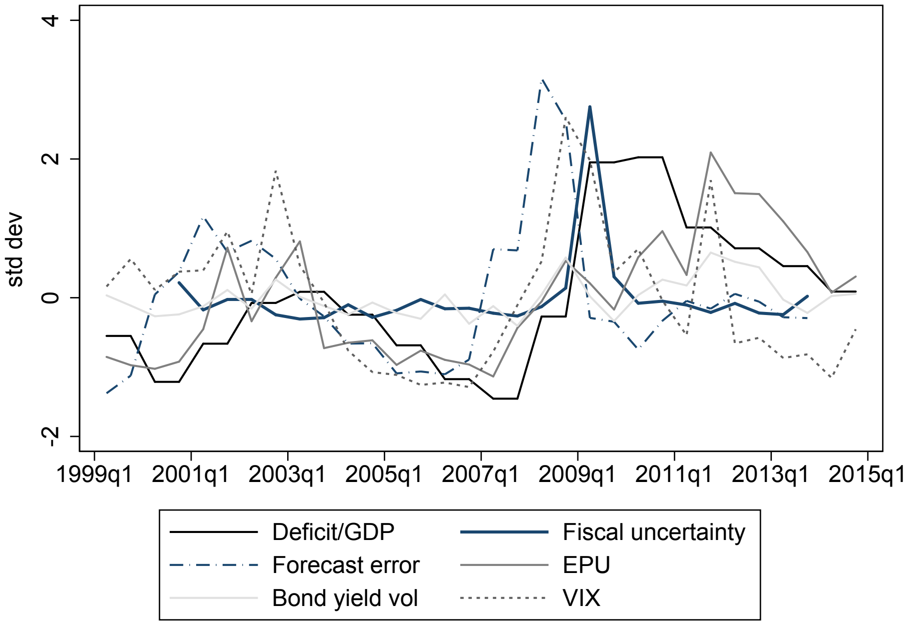


Figure 2: Comparison to other uncertainty measures

governments' budgets. This is confirmed by Table 4. It summarises the correlation between conventional measures of uncertainty and different lags of the fiscal uncertainty index. The correlation between the VIX and fiscal uncertainty is largest for one half-year forward lag of the index. The same holds for government bond yield volatility, which suggests that bond yields reflect global uncertainty more than country-specific uncertainty about fiscal outcomes, although the former may be a good predictor of the latter. By contrast, the co-movement between fiscal uncertainty and the EPU is small. The EPU peaked at the height of the European sovereign debt crisis in 2012, when fiscal uncertainty returned to its mean in most countries (Figure 2). Overall, the fiscal uncertainty index leads the EPU by at least one year (Table 4). Interestingly, average uncertainty about the year-ahead fiscal deficit increases only in 2009, when a large increase in current-year deficits materialises. This suggests that high deficit levels were not anticipated by forecasting institutions. Hence, realised forecast errors can be a misleading proxy for uncertainty experienced in real time.

3 The determinants of sovereign credit ratings

3.1 Sovereign rating data

Data has been collected that covers the long-term debt credit rating of 31 OECD countries over the period 1999 to 2014 provided by the three major credit rating agencies, Moody's, Standard & Poor's and Fitch Ratings. Rating agencies report the results of their assessment of credit risk by assigning a rating from an ordered 21 to 24-notch scale. Notches are sub-categories of a scale with 9 or 10 letter categories AAA, AA, A, BBB, BB, B, CCC, CC, C, Default (labelled Aaa, Aa, A, Baa, Ba, B, Caa, Ca, C, D by Moody's). In addition, credit rating agencies sometimes set a country under 'Watch' or change the 'Outlook' without changing the actual rating. This means that credit risk is scrutinised more carefully and serves as a warning. If certain conditions during the 'Watch' period are not met, such as a credible return to sustainable fiscal policy, rating agencies downgrade the rating. Table 5 shows the number of end-of-quarter observations per rating category.

Table 5: Observed sovereign rating changes

	Total		Fitch		S&P		Moody's	
AAA/Aaa (highest quality)	2492	44.6%	826	43.1%	822	42.1%	844	49.1%
AA+/Aa1 (very high)	501	9.0%	158	8.2%	247	12.6%	96	5.6%
AA/Aa2 (very high)	479	8.6%	205	10.7%	128	6.6%	146	8.5%
AA-/Aa3 (very high)	271	4.8%	99	5.2%	107	5.5%	65	3.8%
A+/A1 (high)	385	6.9%	109	5.7%	103	5.3%	173	10.1%
A/A2 (high)	429	7.7%	127	6.6%	154	7.9%	148	8.6%
A-/A3 (high)	363	6.5%	132	6.9%	176	9.0%	55	3.2%
BBB+/Baa1 (good)	268	4.8%	138	7.2%	78	4.0%	52	3.0%
BBB/Baa2 (good)	97	1.7%	40	2.1%	31	1.6%	26	1.5%
BBB-/Baa3 (good)	114	2.0%	20	1.0%	53	2.7%	41	2.4%
BB+/Ba1 (speculative)	110	2.0%	48	2.5%	17	0.9%	45	2.6%
BB/Ba2 (speculative)	24	0.4%	0	0.0%	21	1.1%	3	0.2%
BB-/Ba3 (speculative)	10	0.2%	0	0.0%	1	0.1%	9	0.5%
B+/B1 (highly speculative)	2	0.0%	1	0.1%	0	0.0%	1	0.1%
B/B2 (highly speculative)	5	0.1%	3	0.2%	2	0.1%	0	0.0%
B-/B3 (highly speculative)	13	0.2%	6	0.3%	7	0.4%	0	0.0%
CCC+/Caa1 (substantial risk)	3	0.1%	0	0.0%	0	0.0%	3	0.2%
CCC/Caa2 (substantial risk)	8	0.1%	5	0.3%	3	0.2%	0	0.0%
CCC-/Caa3 (substantial risk)	3	0.1%	0	0.0%	0	0.0%	3	0.2%
CC/Ca/C (very high risk)	4	0.1%	0	0.0%	2	0.1%	2	0.1%
DDD/SD/C to D (Default)	8	0.1%	0	0.0%	1	0.1%	7	0.4%
Total	5,589	100.0%	1,917	100.0%	1,953	100.0%	1,719	100.0%
negative Watch	38	0.7%	11	0.6%	16	0.8%	11	0.6%
downgrades	144	2.6%	45	2.3%	58	3.0%	41	2.4%
no change	5,310	95.0%	1,824	95.1%	1,848	94.6%	1,638	95.3%
upgrades	135	2.4%	48	2.5%	47	2.4%	40	2.3%
positive Watch	17	0.3%	6	0.3%	1	0.1%	10	0.6%

Source: Bloomberg financial database, 31 OECD countries, 1999-2014, end-of-quarter observations.

Three main characteristics strike the eye. First, in contrast, for example, to data on corporate ratings, the sample can only be of moderate size given the cross-country dimension. In particular, the number of observations in speculative, bottom categories is zero or very small, as sovereign default is a relatively rare event. It may be argued that including non-OECD countries in the analysis may increase the number of speculative rating observations but given that rating agency analysts make use of different methodologies and factors when assessing developed countries' credit risk, compared to that of developing countries, a pooled analysis may be misleading as well. As the interest in this paper lies in recent developments in advanced economies, a focus on OECD countries appears to be justified. Furthermore, data on macroeconomic and fiscal fundamentals related to credit risk are more readily available for this class of economies and at a higher frequency (quarterly or semi-annual instead of annual), allowing a more direct analysis of the effect of relatively frequent events on sovereign ratings.

Second, almost half of the observations are found in the top category AAA (or Aaa).

Compared to corporates, this can be explained by the fact that it is much easier for governments to fund themselves, through taxation or reducing the stock of nominal debt through inflation. Therefore, sovereign credit risk is comparatively low.

Third, Table 5 (bottom) shows that sovereign ratings are very stable over time. Overall, only 5 percent of Fitch, S&P and Moody's sovereign ratings are changed every quarter, whereby one-notch as well as multiple-notch downgrades are classified here as a quarterly change. Between 2.4 and 3 percent are rating downgrades, between 2.3 and 2.5 percent are upgrades. Four countries in the sample (Germany, Luxembourg, Norway, Switzerland) do not experience any rating change by either of the three agencies over the entire sample period. Several others, including France, the UK and the US, were downgraded only once or twice following the financial crisis. The stability of sovereign ratings from the perspective of quarterly changes partly results from the fact that credit rating agencies usually revise their ratings only once a year. This approach changed during the European government debt crisis, when sovereign ratings of most affected countries, i.e. Greece, Ireland, Portugal, Spain and Italy, were adjusted several times per year, or even per quarter. Table 5 shows that the Watch or Outlook status was changed with an even lower frequency. In particular, ratings at the upper end of the rating scale barely change. Transition matrices show that upgrades and downgrades happen more often for lower than higher rating categories (Tables A2, A3, and A4 in the Appendix). AAA (Aaa) ratings exhibit the highest persistence.

A theoretical argument for why agencies try to achieve rating stability, alongside accuracy, is provided by Cantor and Mann (2003) and Cantor and Mann (2006): stability, in particular at the upper end of the rating scale, is demanded by investors who incur costs if rating changes trigger portfolio rearrangements. This is because of the sovereign rating ceiling characteristic, according to which ratings of companies based in a certain country usually receive a rating below that of a country's government. Rating agencies achieve stability by adopting a so-called 'through-the-cycle' approach as opposed to point-in-time evaluations. This means that agencies focus on longer-term outlooks and claim to look at deeper structural developments as part of their expert analysis rather than short-term cyclical movements of sovereign credit risk. Further contributing to stability and a means to implement the through-the-cycle approach is the fact that ratings are relative rather than absolute or cardinal measures (e.g. FitchRatings, 2010, Standard and Poor's, 2011b, Moody's, 2013). If a global shock hits all countries to the same extent, this should not translate into a change of ratings holding all else equal. The relative nature of ratings deliberately prevents *en masse* changes. It does not necessarily imply that the distribution of ratings across sovereign issuers remains fixed at all times but in the long run distributions should converge. As a consequence, this definition of credit ratings also impedes direct translations into default probabilities.

3.2 A regression model with two processes

In order to test whether fiscal uncertainty affects the way sovereign ratings are determined by rating agencies, I propose a regression model that consists of two latent processes. This approach accounts for rating stability and the fact that some rating categories are rarely observed in practice. It also allows me to separately estimate the determinants of the frequency of rating changes and the determinants of their direction.

Process 1: sovereign credit risk When assessing whether to adjust a country's credit rating, credit rating agencies are assumed to face a trade-off between two objectives: rating accuracy and stability. Accuracy is achieved through the identification of a set of economic rating determinants and their weight in contributing to sovereign credit risk. Movements in sovereign credit risk determine the direction of rating changes, i.e. upgrades and downgrades. The movement in country c's credit risk from period $t-1$ to t is modelled as a latent process of the form:

$$\Delta R_{ct}^{*} = \beta_0 + (\Delta X_{ct} - \Delta \overline{X}_{ct})'\beta_2 + \beta_3(\Delta U_{ct} - \Delta \overline{U}_{ct}) + \varepsilon_{ct} \tag{12}$$

where R_{ct}^{*} is the latent state of credit risk and the difference operator Δ denotes the movement in credit risk from one period to the next. X_{ct} contains the deficit/GDP ratio, government debt/GDP ratio, real GDP (logs), and the unemployment rate as controls for fiscal and macroeconomic fundamentals, which also enter in differences relative to the preceding period. Adding changes in fiscal uncertainty U_{ct} as a regressor to the credit risk equation allows me to test whether credit rating agencies take it into account as a separate determinant, alongside fiscal and macroeconomic fundamentals. Coefficients β_j reflect the weights assigned by the rating agency in its assessment of sovereign credit risk to macroeconomic and fiscal fundamentals and fiscal uncertainty, respectively. ε_{ct} is the error term reflecting other unobserved factors that are subjectively taken into account by the agency.

Note that I subtract cross-country averages $(\Delta\overline{X}_{ct}, \Delta\overline{U}_{ct})$ from the determinants of the credit risk process (12). This accounts for the fact that credit ratings are relative rather than absolute measures of credit risk. Cross-country averages can be thought of as a common factor, like global business cycle effects. Working with movements in fundamentals cleaned from global business cycles brings the regression model closer into line with approaches by credit rating agencies that look 'through the cycle'. The 'through-the-cycle' approach is one of the sources of rating stability.

Process 2: rating stability Rating stability may also result from a purely technical decision whether to change a rating in a certain period or not. A second process is therefore allowed to determine whether country c's credit rating can be changed at all in period t independent of fiscal and macroeconomic fundamentals. I assume independence between both objectives. The decision about rating stability is modelled as a latent process s_{ct}^{*}. It is unobserved by the public and, thus, the empirical investigator. What enters the observed rating change is a binary outcome. If $s_{ct}^{*} > 0$, a rating change is possible, henceforth marked as $s_{ct} = 1$. Vice versa, $s_{ct}^{*} \leq 0$ results in $s_{ct} = 0$ and c's rating remains unchanged in t. s_{ct}^{*} depends on the following determinants:

$$s_{ct}^{*} = \beta_0^S + C_{ct}'\beta_1^S + \beta_2^S U_{ct} + \epsilon_{it} \tag{13}$$

C_{ct} contains technical measures that contribute to rating stability. I include the previous period's (linearly transformed) rating level as in Lando and Skødeberg (2002) and Mizen and Tsoukas (2012) to control for the fact that ratings at the upper end of the scale are deliberately made more stable. Furthermore, a dummy variable is added, which accounts for whether rating changes have taken place in the previous period (so-called momentum, see Carty and Fons, 1994, Lando and Skødeberg, 2002, Mizen and Tsoukas, 2012). Including the fiscal uncertainty index U_{ct} as an additional regressor allows me to test whether it can explain rating stability. Put differently, it allows me to analyse whether during periods of high uncertainty, ratings are changed more frequently, independent of macroeconomic and fiscal fundamentals and the effect of fiscal uncertainty on credit risk. β^S_j are the coefficients assigned by the rating agency to both stability determinants. ϵ_{it} is the error term of the stability process.

Joint outcome Whether the credit rating of country c in period t will be downgraded, upgraded or left at its previous level is determined jointly by the two latent processes – the index of credit risk (12) and the stability process (13):

$$\Delta R_{ct} = \begin{cases} \text{`downgrade'} & if \quad \Delta R^*_{ct} \leq c_1 \text{ and } s_{ct} = 1 \\ \text{`no change'} & if \quad c_1 < \Delta R^*_{ct} \leq c_2 \text{ and } s_{ct} = 1 \text{ OR} \quad if \quad s_{ct} = 0 \\ \text{`upgrade'} & if \quad c_2 < \Delta R^*_{ct} \text{ and } s_{ct} = 1 \end{cases} \tag{14}$$

Note that only if ratings are allowed to be changed in t *and* if movements in credit risk relative to the cross-country average exceed thresholds c_j, a rating change is observed.

3.3 An adjusted ordered outcome estimator

Sovereign rating stability Section 3.1 implies that an estimator of sovereign rating determinants has to take into account the dominant features of sovereign rating data, including the limited number of ratings in some rating categories and rating stability as a result of limited movements in relative credit risk ('through-the-cycle approach'), technical factors inhibiting the frequency of rating changes (stability process), or because of a high number of observations at the boundary of the rating scale (in particular in the top category AAA).

Previous studies with an interest in the determinants of sovereign credit ratings have regressed linearly transformed rating levels on the levels – not changes – of macroeconomic and fiscal fundamentals related to sovereign credit risk (e.g. Cantor and Packer, 1996, Ferri et al., 1999, Monfort and Mulder, 2000, Mora, 2006). Alternatively, acknowledging the nonlinear nature of ratings, the probability of falling into a specific rating category has been regressed on a latent process of credit risk, itself a function of fundamentals in levels (e.g. Hu et al., 2002, Block and Vaaler, 2004; Depken et al., 2006, Afonso et al., 2011). However, given that data on sovereign ratings are characterised by a low number of, or zero observations in some rating categories, estimating the level of ratings proves difficult. Bruha et al. (2017) and Dimitrakopoulos and Kolossiatis (2016) deal with missing observations using a Bayesian estimation approach, which requires a range of prior assumptions about model parameters. Estimating a model of rating changes rather than levels, like in equation (12), provides an alternative. Purda (2007) and Hill et al. (2010) follow such a procedure.

However, due to rating stability over time, in particular at the upper end of the rating scale, the investigator is confronted with a large number of 'no change' observations relative to very few 'upgrade' and 'downgrade' observations, as discussed in Section 3.1. In the context of categorical outcome estimation, the relative abundance of observations in one outcome category relative to all other outcomes is sometimes referred to as outcome 'inflation'. This inflation of observations for one outcome can yield biased estimates in standard ordered outcome estimation techniques, like Ordered Probit (or Logit). It has been shown that 'pure' inflation in one outcome category leads to an underestimation of relatively rare outcomes in moderate samples. I define 'pure' inflation in this context as inflation due to limited movements in explanatory variables (credit risk). *Vice versa*, a data-generating process with a large distance between cut-off point parameters c_j in equation 14 can lead to the same result. King and Zeng (2001) analyse this problem analytically and by conducting Monte Carlo simulations for a binary Logit model. Their results show that for a sample with properties similar to those of my dataset on sovereign ratings (N of around 2,000, around 5% 'change' events), estimates of the probability of the rare event obtained by the traditional Logit estimator are around one percentage point lower than the true probability.

In addition, if outcome inflation is partly driven by an underlying stability process, like equation (13), biases in Probit or Logit estimates increase. Harris and Zhao (2007) explore the performance of the Ordered Probit estimator when the true data-generating process is category-inflated because of the presence of an unobserved stability process. Monte Carlo simulations show that marginal effects and threshold parameters estimated by Ordered Probit are severely biased and type I errors occur relatively frequently. This provides the econometric rationale for a regression model with two latent processes, as outlined in the previous section, and controlling explicitly for factors that may contribute to stability.

The large number of observations in the top category AAA (Table 5) may further add to rating stability. Given that for these observations, additional upgrades are not feasible even if credit risk improves and technical controls allow for a rating change, the number of 'no change' observations inflates further. To my knowledge, the reduction in the set of feasible outcomes for some observations, which is known *ex ante*, has so far not been explored in the context of categorical outcome estimation.

Outcome probabilities An estimator based on Ordered Probit that estimates a stability process and an ordered outcome process jointly by maximum likelihood has been proposed as Zero-Inflated Ordered Probit estimator by Harris and Zhao (2007). It is designed for set-ups in which the first of a range of ordered outcome categories (category 'zero') is associated with a disproportionally large number of observations. The estimator is comparable in principle to Poisson estimators for count data. In contrast to Heckman-type selection estimators, inflated observations are not truncated. Instead, they are accounted for when estimating the final outcome. More specifically, the standard Ordered Probit likelihood function is manipulated such that estimated final outcome probabilities are conditional on the outcome of the stability process. Bagozzi and Mukherjee (2012) provide a version in which observations in the middle category out of three categories is inflated (the Middle-Category Inflated Ordered Probit estimator MIOP).

In the context of sovereign rating changes, an additional adjustment to the category-inflated estimator is needed to yield unbiased estimates. This is because of the presence of ratings at the boundary of the rating scale: an additional upgrade is infeasible for countries in the top rating category AAA. Conversely, countries in the Default category cannot be downgraded further. Put differently, if a rating lies in the AAA or Default category, it is certain that the probability of an upgrade or downgrade, respectively, is zero and does not need to be estimated. A boundary adjustment can take this into account. Consider two dummy variables D_{ct}^{AAA} and D_{ct}^{D}. D_{ct}^{AAA} (D_{ct}^{D}) takes the value of 1 if the rating in period $t-1$ is AAA (Default), and zero otherwise. If a rating lies in the AAA (Default) category, the agency faces a binary rather than three-outcome decision: 'no change' or 'downgrade' ('upgrade').

Using equations (13) and (12), and accounting for the boundary of the rating scale, which reduces the set of feasible outcomes, the probability function of a Boundary-Adjusted Middle-Category Inflated Ordered Probit estimator (henceforth referred to as BAM) can be written as:

$$\Pr(\Delta R_{ct}) = \begin{cases} \Pr(\Delta R_{ct} = \text{`downgrade'} | C_{ct}, U_{ct}, X_{ct}, D_{ct}^{D}, D_{ct}^{AAA}) & = & (1 - D_{ct}^{D})\Phi(s_{ct}^{*})\Phi(c_1 - (\Delta R_{ct}^{*})) \\ \Pr(\Delta R_{ct} = \text{`no change'} | C_{ct}, U_{ct}, X_{ct}, D_{ct}^{D}, D_{ct}^{AAA}) & = & [1 - \Phi(s_{ct}^{*})] + \Phi(s_{ct}^{*})[\Phi(c_2 - (\Delta R_{ct}^{*})) \\ & & -\Phi(c_1 - (\Delta R_{ct}^{*}))] \\ & & +D_{ct}^{AAA}\Phi(s_{ct}^{*})[1 - \Phi(c_2 - (\Delta R_{ct}^{*}))] \\ & & +D_{ct}^{D}\Phi(s_{ct}^{*})\Phi(c_1 - (\Delta R_{ct}^{*})) \\ \Pr(\Delta R_{ct} = \text{`upgrade'} | C_{ct}, U_{ct}, X_{ct}, D_{ct}^{D}, D_{ct}^{AAA}) & = & (1 - D_{ct}^{AAA})\Phi(s_{ct}^{*})[1 - \Phi(c_2 - (\Delta R_{ct}^{*}))]. \end{cases} \tag{15}$$

where Φ is the cumulative normal distribution function. Note that if the stability process was 'inactive', i.e. $s_{ct} = 1$ for all c and t, then $\Phi(s_{ct}^{*}) = 1$ and equation (15) reduces to the standard Ordered Probit likelihood function for three outcomes. The presence of dummy indicators D_{ct}^{AAA} and D_{ct}^{D} allows me to take directly into account the boundary of the rating scale as an additional source of rating stability. For ratings that would see a change according to equations (13) and (12), this change will not be observed if these ratings lie at the boundary of the scale.

Likelihood function I assume that the error terms of the stability process and credit risk process, ϵ_{it} and ε_{it}, are independent of each other. Let $\theta = (\beta^{S\prime}, \beta', c_j')'$ be a vector containing the parameters from equations (13) and (12) to be estimated by the BAM estimator. Using the probabilities from (15), the log likelihood function becomes:

$$
\log\mathcal{L}(\theta) = \begin{cases} \log[\prod_{i=1}^{N}\prod_{t=1}^{T}[\Pr(\Delta R_{ct} = \text{'downgrade'})]] & if \quad \Delta R_{ct} = \text{'downgrade'} \\ \log[\prod_{i=1}^{N}\prod_{t=1}^{T}[\Pr(\Delta R_{ct} = \text{'no change'})]] & if \quad \Delta R_{ct} = \text{'no change'} \\ \log[\prod_{i=1}^{N}\prod_{t=1}^{T}[\Pr(\Delta R_{ct} = \text{'upgrade'})]] & if \quad \Delta R_{ct} = \text{'upgrade'}. \end{cases} \tag{16}
$$

Marginal effects In what follows, I calculate marginal effects of changes in the determinants of the credit risk process conditional on $s_{ct} = 1$, and $D_{ct}^{AAA} = 0$ and $D_{ct}^{D} = 0$. The effect of a change in a fundamental variable on the probability of a rating change is the most interesting from a policy perspective. In addition, conditional marginal effects estimates obtained by BAM in this way are comparable to respective estimates obtained by Ordered Probit. I focus on marginal effects at the average of explanatory variables on the probability of a downgrade.

Conditionality implies setting $s_{ct} = 1$ as well as $D_{ct}^{AAA} = 0$ and $D_{ct}^{D} = 0$. This allows me to make use of the standard Ordered Probit expression to calculate marginal effects at the average:

$$
\underset{\Pr(\Delta R_{ct}=\text{'downgrade'})}{ME} = \frac{\partial \Pr(\Delta R_{ct} = \text{'downgrade'})}{\partial x} = \phi(-\widehat{\beta}\overline{x})\widehat{\beta} \tag{17}
$$

where ϕ is the probability density function of the standard normal distribution. $\widehat{\beta}$ is the parameter estimate and $\overline{x}$ is the sample average of a variable x.

Goodness of fit The goodness-of-fit of binary outcome regression models is often evaluated using true positive (sensitivity) and true negative (specificity) rates. For that, the estimated (predicted) outcome is classified as positive or negative depending on whether the probability predicted by the regression model exceeds a certain threshold or not. Likewise, expressions for outcome probabilities given in equation (15) can be used to predict the probability of falling into categories 'downgrade, 'no change', or 'upgrade' with estimated model parameters $\hat{\theta} = (\hat{\beta^{S}}, \hat{\beta}, \hat{c_j})$. Using pre-defined thresholds τ_k, predictions can then be classified as 'downgrade, 'no change', or 'upgrade':

$$
\hat{R_{ct}} = \begin{cases} \text{'downgrade'} & \text{if} \quad \hat{\Pr}(\Delta R_{ct} = \text{'downgrade'}) > \tau_{\text{'downgrade'}} \\ \text{'no change'} & \text{if} \quad \hat{\Pr}(\Delta R_{ct} = \text{'no change'}) > \tau_{\text{'no change'}} \\ \text{'upgrade'} & \text{if} \quad \hat{\Pr}(\Delta R_{ct} = \text{'upgrade'}) > \tau_{\text{'upgrade'}}. \end{cases} \tag{18}
$$

To calculate the sensitivity and specificity for all three possible outcomes, I set threshold parameters τ_l to the unconditional probability of each outcome $\tau_k = \frac{1}{N}\sum_{c=1}^{C}\sum_{t=1}^{T} R_{ct}^{k}$, where k is one of {'downgrade', 'no change', 'upgrade'}. In other words, a predicted outcome is classified as a 'downgrade' if the predicted probability of 'downgrade' exceeds the unconditional probability of a 'downgrade'. The same holds for 'no change' and 'upgrade' observations. Sensitivity is then defined as the share of correctly classified outcomes relative to all observed outcomes of that type, $\frac{\sum \hat{R}^k_{ct}}{\sum R^k_{ct}}$. Specificity is the share of correctly classified alternative outcomes, e.g. 'no change' and 'upgrade' for 'downgrade', relative to all alternative outcomes $\frac{\sum \hat{R}^{l\neq k}_{ct}}{\sum R^{l\neq k}_{ct}}$. Furthermore, varying τ_k allows me to depict true positive rates (sensitivity) as a function of false positive rates (1- specificity). This yields receiver operating characteristic (ROC) curves for each outcome, which are used to evaluate the model's goodness-of-fit.

Monte Carlo evidence In order to assess the performance of the BAM estimator relative to the MIOP and Ordered Probit estimator in the context of rating data, I conduct a series of Monte Carlo simulations, using generated data with moments similar to actual data (details are provided in the Technical Appendix A2). Table 6 summarises simulation results for different set-ups in which the inflation of observations in the middle categories of three categories is either driven by limited regressor movements ('pure' inflation), by an independent selection process, by observations for which only two outcomes are feasible (boundary observations) or a combination of all three. Biases that stem from a high degree of 'pure' inflation cannot be sufficiently eliminated within the realm of standard maximum likelihood estimation, as illustrated by bias estimates and root mean squared errors in the top panel of the table across all three estimators. By contrast, inflation that stems from an unobserved stability process, given that 'pure' inflation is moderate, can be dealt with by using the MIOP estimator which produces smaller absolute biases than standard Ordered Probit (second panel). If, on the other hand, inflation is due to a high number of observations for which some outcomes are known to be infeasible (boundary observations in the context of sovereign credit ratings), given moderate levels of 'pure' inflation, the proposed boundary-adjusted estimator BAM can yield sufficiently unbiased estimates (third and fourth panel). This, however, comes at the cost of relatively large standard errors (SE, fifth column), which accurately reflect the uncertainty in estimates (standard deviation SD, sixth column). This is in contrast to Ordered Probit, which may lead to incorrect inference as average standard errors do not reflect the empirical uncertainty of estimates. In addition, small sample biases make the use of data with high frequency, long time series, or pooled datasets indispensable if the cross-sectional dimension is by nature limited (Table A5 in the Appendix). Finally, minimising the number of regressors, and thereby the number of parameters to be estimated, can improve maximum likelihood estimates by Ordered Probit, MIOP and BAM (Table A6 in the Appendix).

3.4 Fundamentals data

I augment the dataset on advanced economies' ratings at quarterly frequency with projections published in the OECD *Economic Outlook* and IMF *World Economic Outlook* to capture macroeconomic and fiscal information available in real time. For the variables deficit/GDP (defined as before), debt/GDP (general government gross financial liabilities per GDP, OECD), real GDP growth (IMF) and the unemployment rate (OECD), I use data on the previous year's estimated realisation ($t-1$), the forecast for the current year (t) and the forecast for the following year ($t+1$) from spring and autumn publications. It has been

Table 6: Simulation results

Middle-category inflation	Estimator	Bias	RMSE	SE	SD
		Baseline			
34.8%	OP	0.011	0.054	0.052	0.052
	MIOP	0.016	0.056	0.053	0.053
	BAM	0.016	0.056	0.053	0.053
82.6%	OP	0.024	0.087	0.078	0.083
	MIOP	0.036	0.093	0.081	0.086
	BAM	0.035	0.094	0.081	0.087
92.9%	OP	0.051	0.129	0.114	0.119
	MIOP	0.081	0.154	0.125	0.131
	BAM	0.081	0.154	0.125	0.131
		+ Selection process			
42.2%	OP	-0.435	0.437	0.035	0.033
	MIOP	0.012	0.059	0.057	0.058
	BAM	0.012	0.059	0.057	0.058
84.6%	OP	-0.256	0.264	0.062	0.065
	MIOP	0.028	0.094	0.086	0.090
	BAM	0.027	0.096	0.086	0.092
93.7%	OP	-0.175	0.203	0.096	0.103
	MIOP	0.066	0.157	0.130	0.143
	BAM	0.064	0.158	0.130	0.145
		+ Boundary observations			
50.8%	OP	-0.504	0.505	0.034	0.026
	MIOP	-0.228	0.236	0.068	0.060
	BAM	0.021	0.066	0.062	0.062
86.7%	OP	-0.326	0.330	0.062	0.053
	MIOP	-0.035	0.109	0.108	0.103
	BAM	0.046	0.108	0.094	0.097
94.5%	OP	-0.230	0.248	0.096	0.093
	MIOP	0.027	0.204	0.171	0.203
	BAM	0.113	0.195	0.148	0.159
		+ Selection process & boundary observations			
56.4%	OP	-0.587	0.588	0.033	0.026
	MIOP	-0.280	0.294	0.071	0.090
	BAM	0.016	0.071	0.067	0.069
88.2%	OP	-0.408	0.412	0.059	0.056
	MIOP	-0.111	0.182	0.106	0.145
	BAM	0.040	0.114	0.100	0.107
95.1%	OP	-0.305	0.320	0.093	0.098
	MIOP	-0.042	0.234	0.160	0.230
	BAM	0.102	0.204	0.152	0.176

Note: 10 regressors, sample size of 1,800.

shown that a relatively parsimonious set of macroeconomic and fiscal variables related to sovereign credit risk can explain a significant part of the variation in sovereign ratings across countries and time (Cantor and Packer, 1996, Afonso et al., 2011, Hill et al., 2010). Keeping in mind that a relatively large number of regressors may bias estimates of the regression model of rating changes, I restrict the set of controls to these fundamentals. I use current-year annual changes and expected one-year ahead annual changes in those four variables as potential regressors to account for the forward-looking nature of ratings. Changes are computed using the data published in respective projections and not relative to past projections, in order to account for information updates potentially known to rating agency staff in real time.[6] The timing is the following: data from spring projections are assigned to Q2 and serve as determinants of changes in ratings between the end of Q1 and the end of Q2. Autumn projections are assigned to Q4 and used as regressors for rating changes between the end of Q3 and the end of Q4. For Q1 and Q3, projections are linearly interpolated.

The same approach is applied to the semi-annual index of fiscal uncertainty developed in Section 2. I use the forward-looking full index version U_{ct1} as the main regressor and also report results for the current-year version and disagreement component alone. Not only is the index of fiscal uncertainty reflecting uncertainty about the fiscal deficit directly in real time and comparably across countries. It is also plausibly exogenous to decisions taken by rating agencies during the period after official forecasts have been published. It reflects uncertainty at a lower frequency than market-based volatility measures or the news-based EPU, which may endogenously respond to rating activity.[7]

4 Results

4.1 Baseline results

Table 7 reports baseline results. These are obtained for data that is pooled across the three credit rating agencies Fitch, S&P and Moody's to increase the sample size and reduce potential small-sample biases. BAM estimates for the set of fiscal and macroeconomic controls are compared to Ordered Probit results, whereby Ordered Probit estimates are obtained from separate, unconditional estimations of the stability and credit risk process. Results in columns I and II (lower panel) show that debt/GDP and unemployment have the expected positive effect on credit risk and thus the downgrade probability. The effect of GDP growth is negative, independent of the estimator, which confirms comparable findings in Hill et al. (2010), who estimate their regression model of rating changes by Ordered Probit. The effect of deficit/GDP on credit risk is positive but not statistically significant. Marginal effects on the probability of a downgrade are reported in percent. For instance, an increase in debt/GDP increases the probability of a downgrade by up to 8.2 percent; a 1 percent higher growth rate reduces the downgrade probability by up to 23.7 percent (using BAM estimates from column II).

As expected from Monte Carlo simulations, OP estimates are substantially smaller in absolute terms compared to BAM estimates, which take into account the effects of the boundary of the rating scale and the stability of sovereign ratings. Comparing estimates reported in columns I and II, I find that BAM estimates are all substantially larger in absolute terms. This confirms that standard Ordered Probit estimates are likely to be biased. In fact,

[6] For the deficit/GDP, I work with differences between $t-1$ and t estimates and for debt/GDP and the unemployment rate I consider projected changes between t and $t+1$. Real GDP growth rates are used directly as reported.

[7] I also estimated the model using the VIX, bond market volatility and EPU as measures of uncertainty yielding similar results which are not reported but available upon request.

Table 7: Baseline results for rating determinants

	I	II	III	IV	V
	OP	BAM	BAM	BAM	BAM
Stability:					
Fiscal uncertainty				0.015*	1.16
				[0.01]	[5.66]
Rating level	-0.03***	-0.02***	-0.01	-0.005	-0.24***
	[0.00]	[0.00]	[0.01]	[0.00]	[0.05]
Momentum	2.38	1.64	-0.18	-0.24	217***
	[1.49]	[1.19]	[0.21]	[0.17]	[11.5]
Credit risk:					
Fiscal uncertainty			0.87***	0.70**	1.64***
			[0.29]	[0.33]	[0.51]
Deficit/GDP	0.11	1.05	0.19	0.19	0.08
	[0.11]	[0.90]	[0.16]	[0.16]	[0.28]
Debt/GDP	0.12**	8.16*	0.29*	0.29**	0.37
	[0.05]	[4.22]	[0.15]	[0.15]	[0.26]
GDP growth	-0.87***	-23.7***	-1.41***	-1.43***	-3.68***
	[0.30]	[9.04]	[0.48]	[0.48]	[0.85]
Unemployment	1.97***	40.7**	3.60***	3.61***	4.85***
	[0.48]	[16.2]	[1.00]	[1.02]	[1.48]
Observations	4,859	4,859	4,128	4,128	4,128
Sensitivity ↓	73.8%	66.7%	81.3%	81.3%	75.2%
Specificity ↓	72.3%	87.4%	72.8%	71.9%	81.0%
Sensitivity =	82.7%	62.2%	55.4%	54.8%	71.2%
Specificity =	44.6%	82.1%	92.0%	93.0%	73.2%
Sensitivity ↑	64.6%	100.0%	91.5%	93.0%	76.9%
Specificity ↑	67.2%	50.9%	65.1%	64.6%	73.5%

Notes: BAM estimation: marginal effects on the probability of 'change' (stability process) and 'downgrade' (credit risk process) are computed at the sample average of all variables. OP estimation: separate estimation of the stability and credit risk process. Standard errors (in brackets) are computed using the delta method, significance level given by *** p<0.01, ** p<0.05, * p<0.1. ↓: downgrade, ↑: upgrade, =: no change. Watch observations not considered in columns I to IV but are treated as rating changes in column V. Fiscal uncertainty measure: U_{ct1}.

the rating level is found a significant determinant of rating changes independent of movements in fundamentals related to credit risk (see top panel of Table 7 which reports parameter estimates for the stability process). Ratings at the upper end of the rating scale (high rating level), are changed significantly less frequently than ratings at the lower end, as the negative coefficient estimate for this variable in the stability process indicates. Differences between OP and BAM are also reflected in goodness-of-fit measures (bottom of Table 7). BAM identifies all rating upgrades (upwards pointing arrow) correctly (sensitivity of 100 percent) but under-predicts downgrades (downwards pointing arrow) and the outcome 'no change' (indicated by equal sign). By contrast, OP over-predicts rating changes substantially. Only 44.6 percent of 'no change' observations are classified by OP as such (specificity), compared to 82.1 percent for BAM.

Columns III and IV include fiscal uncertainty as a determinant of the credit risk process and both the credit risk and stability process, respectively, improving the overall goodness-of-fit of the model. In particular, the predictive power of downgrades increases (higher sensitivity in columns III and IV of Table 7). This result comes at the expense of poorer 'no change' predictions. Fiscal uncertainty is considered a credit risk factor by rating agencies. The coefficient for fiscal uncertainty in the credit risk process is positive and statistically significant in all specifications. A one-standard deviation increase in fiscal uncertainty increases the probability of a downgrade by between 0.7 and 0.9 percent. An increase in fiscal uncertainty of that size corresponds to the average change during the financial crisis. However, a number of countries experienced much larger surges in fiscal uncertainty during the global crisis, for instance Iceland with 4.4 standard deviations, Ireland with 3.5 and Norway with 2.7. This shows that credit rating agencies take fiscal uncertainty into account as a second-moment effect when assessing a country's credit risk.

Interestingly, the estimated effect is larger, when changes in the Watch status are included in the rating data (column V). This suggests that rating agencies are more likely to issue a warning first when uncertainty rises, while major and minor rating changes are announced more often as fundamentals change.

Fiscal uncertainty also has a positive effect on the frequency of rating changes, independent of movements in credit risk (top panel of Table 7). A possible interpretation is that credit rating agencies change ratings more frequently during periods of higher uncertainty compared to what would be justified by movements in credit risk. When watch changes are considered amongst rating change observations, fiscal uncertainty loses its explanatory power in the stability process. This could suggest that incentives faced by credit rating agencies to issue rating changes more frequently than justified by credit risk are larger for actual movements along the rating scale.

Table A7 in the Appendix reports results for alternative versions of the fiscal uncertainty index. While largely confirming results for the forward-looking uncertainty measure U_{ct1}, the statistical significance for the disagreement component D_{ct1} and the current-year index version U_{ct0} is lower. D_{ct1} and U_{ct0} are significant determinants of the credit risk process once Watch observations are included. U_{ct0} has a significant effect on rating stability, independent of movements in credit risk if Watch observations remain excluded.

4.2 Agency-specific results

To gauge differences in rating agency behaviour, I estimate the model for each agency separately. Results are reported in Table 8 for the forward-looking and current-year version of the fiscal uncertainty index. Overall, I find that the two-process regression model fits the data equally well for all three agencies, in terms of sensitivity and specificity. However, rating agencies seem to apply a different weighting system to fiscal and macroeconomic fundamentals. While all four fundamentals have sizeable effects on the probability of a change in Fitch ratings, S&P appears to respond mainly to changes in debt/GDP and growth, while growth and changes in unemployment are significant drivers of Moody's ratings. Depending on the uncertainty index version employed, I find significant effects of fiscal uncertainty on credit risk for all three rating agencies. Results for fiscal uncertainty as a determinant of the stability process appear to be mostly driven by Moody's rating transition, for which fiscal uncertainty is statistically significant in the upper panel of Table 8. While coefficients for the other two rating agencies are not statistically significant, the size of the coefficient varies widely, also across the two index versions. This may suggest that the incentives to change ratings more frequently during periods of higher ambiguity about fiscal deficits, independent of credit risk movements, vary across agencies and the perceived level of uncertainty. Given that agency-specific estimates are based on a smaller sample relative to pooled specifications, a note of caution is warranted that reported standard errors may be somewhat too large.

Table 8: Agency-specific results for rating determinants

	I	II	III	IV	V	VI
	Fitch		Standard & Poor's		Moody's	
Uncertainty measure:	U_{ct1}	U_{ct0}	U_{ct1}	U_{ct0}	U_{ct1}	U_{ct0}
Stability:						
Fiscal uncertainty	1.82	7.17	1.07	27.3	71.2	7.54**
	[1.21]	[4.38]	[1.26]	[28.66]	[319]	[3.51]
Rating level	-2.53***	-0.10***	-0.13	-0.45	-0.200	-0.07***
	[0.08]	[0.03]	[0.10]	[0.66]	[0.59]	[0.02]
Momentum	-2.36***	3.30	-8.13	-21.6	16.0	4.02
	[0.85]	[9.00]	[11.1]	[43.0]	[74.1]	[5.71]
Credit risk:						
Fiscal uncertainty	0.63	0.50*	0.55*	0.61***	0.61**	-0.63
	[0.60]	[0.27]	[0.30]	[0.20]	[0.29]	[0.64]
Deficit/GDP	0.41***	0.49	0.28*	0.07	-0.23	0.00
	[0.14]	[0.39]	[0.16]	[0.30]	[0.25]	[0.92]
Debt/GDP	0.27**	0.98	0.26*	0.28*	0.17	2.45**
	[0.13]	[0.74]	[0.15]	[0.16]	[0.14]	[1.25]
GDP growth	-1.25***	-3.21**	-1.87***	-2.30***	-1.44**	-4.43*
	[0.42]	[1.36]	[0.57]	[0.77]	[0.61]	[2.58]
Unemployment	3.28***	8.33***	2.62	2.90	3.53**	20.8***
	[0.97]	[3.09]	[1.66]	[2.90]	[1.40]	[6.15]
Observations	1,418	1,416	1,429	1,427	1,281	1,279
Sensitivity ↓	89.7%	76.9%	76.9%	73.1%	78.4%	75.7%
Specificity ↓	74.3%	84.8%	70.2%	75.4%	75.2%	85.3%
Sensitivity =	52.4%	71.3%	51.9%	65.1%	66.9%	73.6%
Specificity =	95.5%	68.2%	90.8%	78.9%	84.2%	77.2%
Sensitivity ↑	88.9%	85.2%	87.5%	75.0%	85.0%	90.0%
Specificity ↑	66.7%	70.6%	63.7%	70.9%	74.5%	76.3%

Notes: BAM estimation: marginal effects on the probability of 'change' (stability process) and 'downgrade' (credit risk process) are computed at the sample average of all variables. Standard errors (in brackets) are computed using the delta method, significance level given by *** p<0.01, ** p<0.05, * p<0.1. ↓: downgrade, ↑: upgrade, =: no change. Watch observations are not treated as rating changes.

4.3 Time variation in agency methodology

To deepen the understanding of rating agency behaviour, I augment the analysis by considering two changes to the baseline specification. The criticism rating agencies faced during the recent crisis may have led them to change their methodology after 2009 in order to restore their reputation. De Vries and de Haan (2016), for instance, find that after the crisis in the euro area, rating agencies have become more cautious and changed ratings less frequently than movements in bond yield spreads would have suggested, compared to crisis years. On the other hand, agencies might also change the weight they assign to the determinants of credit risk in order to make ratings more accurate. Bernoth and Erdogan (2012) find that over time, financial markets change their pricing behaviour of sovereign bonds in a sense that weights received by fundamental variables in determining sovereign bond yields are time-varying. I therefore split the sample at the crisis year 2009 and estimate the model separately for each sub-sample (Table 9). Results suggest that rating agencies somewhat changed their focus away from debt/GDP to growth, unemployment and the deficit after 2009. With respect to fiscal uncertainty, results depend on the uncertainty index version employed but overall suggest that fiscal uncertainty has gained importance as a credit risk determinant. Second moment effects have become somewhat more important after the global financial crisis and during the European sovereign debt crisis.

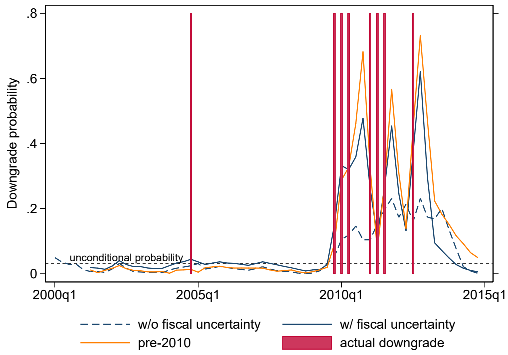
Table 9: Split-sample results for rating determinants

	Pre-2009		Post-2009	
Uncertainty measure:	U_{ct1}	U_{ct0}	U_{ct1}	U_{ct0}
Stability:				
Fiscal uncertainty	9.58	30.4***	-7.65	8.96*
	[11.3]	[11.5]	[7.86]	[5.06]
Rating level	-0.42	-0.41	-0.24	-0.11
	[0.26]	[0.29]	[0.17]	[0.07]
Momentum	-70.5	-76.1	73.6	10.6
	[66.1]	[55.1]	[56.4]	[18.5]
Credit risk:				
Fiscal uncertainty	0.38	1.51	1.11***	0.02
	[0.53]	[0.97]	[0.44]	[0.54]
Deficit/GDP	-0.56	-0.45	0.45**	0.79
	[0.49]	[0.51]	[0.22]	[0.53]
Debt/GDP	0.47***	0.44**	0.12	0.06
	[0.14]	[0.22]	[0.24]	[1.44]
GDP growth	-0.74*	-0.69*	-2.71***	-6.26***
	[0.40]	[0.39]	[0.94]	[2.29]
Unemployment	2.09	1.84	4.26***	8.89
	[1.47]	[1.46]	[1.65]	[8.26]
Observations	2,451	2,451	1,989	1,989
Sensitivity ↓	72.2%	75.0%	78.3%	69.8%
Specificity ↓	81.1%	83.9%	72.3%	80.9%
Sensitivity =	67.8%	70.0%	49.1%	71.8%
Specificity =	91.4%	87.7%	89.4%	71.2%
Sensitivity ↑	100.0%	100.0%	80.8%	88.5%
Specificity ↑	71.2%	71.7%	67.2%	67.7%

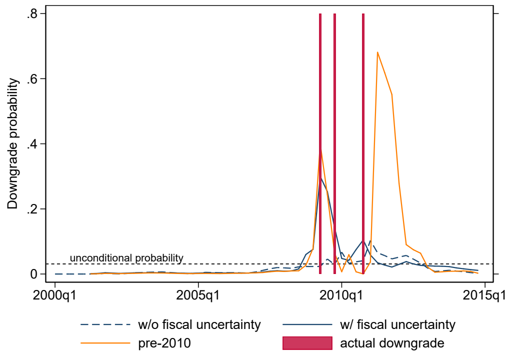
Notes: BAM estimation: marginal effects on the probability of 'change' (stability process) and 'downgrade' (credit risk process) are computed at the sample average of all variables. Standard errors (in brackets) are computed using the delta method, significance level given by *** p<0.01, ** p<0.05, * p<0.1. ↓: downgrade, ↑: upgrade, =: no change. Watch observations are not treated as rating changes.

4.4 Model predictions

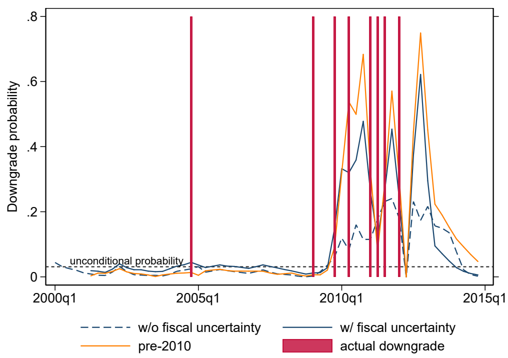
From the point of view of policy, an interesting question is whether sovereign credit ratings were changed more often during the financial and European government debt crisis than rating changes implied by judgement-free models (e.g. Polito and Wickens, 2014, Polito and Wickens, 2015, D'Agostino and Lennkh, 2016). The empirical framework developed in this paper can be used to predict rating changes.



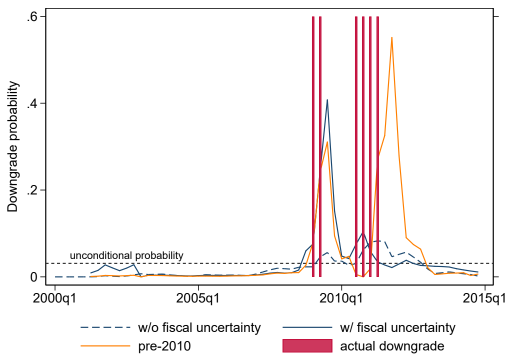
(a) Greece, Fitch



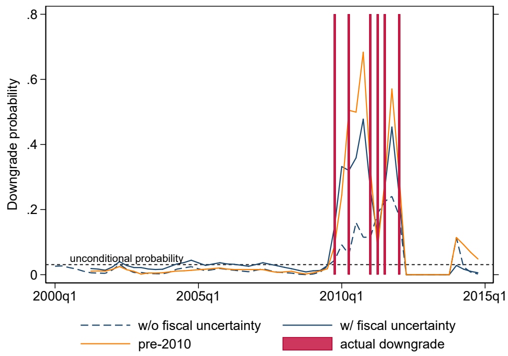
(b) Ireland, Fitch



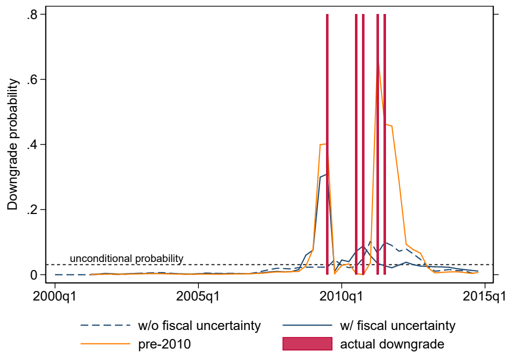
(c) Greece, S&P



(d) Ireland, S&P



(e) Greece, Moody's



(f) Ireland, Moody's

Figure 4: Estimated downgrade probabilities, Greece and Ireland

I compute model-implied downgrade probabilities using equation (15) and BAM estimates of model parameters. Parameters are taken from three model specifications: one that excludes fiscal uncertainty (corresponding to column II of Table 7), one that includes fiscal uncertainty (corresponding to column IV of Table 7), and one that includes fiscal uncertainty but is estimated only up to 2009 (corresponding to column I of Table 9). This also provides an additional check of the predictive power that fiscal uncertainty adds to a model of sovereign rating changes. Estimates from the post-2009 specification can be thought of as out-of-sample predictions.

Results for Greece and Ireland are plotted in Figure 4 as examples for countries most severely affected by the European government debt crisis. Actual rating changes are marked as red bars in all figures. In-sample predictions of the probability of a downgrade from a model that excludes fiscal uncertainty as a rating determinant are plotted as dashed blue lines. Solid blue lines illustrate the movement of downgrade probabilities implied by a model that includes fiscal uncertainty as a measure. Yellow lines capture predicted downgrade probabilities from a full specification estimated until 2009. A downgrade can be considered predicted once the estimated downgrade probability exceeds the unconditional downgrade probability of 3.1 percent, which corresponds to the overall sample average of downgrades per quarter. Dashed horizontal lines mark that threshold.

I find that a model that accounts for fiscal uncertainty fares surprisingly well in predicting rating downgrades of Greece and Ireland. In a number of cases, the probability estimate exceeds the unconditional threshold shortly before a series of actual rating downgrades. This confirms that the model is able to predict sovereign rating changes. This is in particular true for Ireland in 2008, prior to downgrades of the country's ratings by all three agencies. Figure A1 in the Appendix provides similar results for Spain and Portugal. For Spain, initial downgrades in 2010 may not be picked up but the estimated downgrade probability rises substantially during the country's debt crisis of 2011-2012. Interestingly, the estimated probability of a Portuguese downgrade lies consistently above the unconditional threshold prior to the financial crisis, but rises significantly as the country enters the crisis period.

Comparing the estimates from a model specification that includes the fiscal uncertainty index to one that does not, Figure 4 illustrates that the latter specification provides a substantially poorer prediction of rating downgrades. For most of the examples, the estimated probability from such a specification remains below the threshold for a longer time into the crisis, than predictions from the fiscal uncertainty specification, and only surges in 2010-11. Once fiscal uncertainty is taken into account as a rating determinant, actual ratings no longer appear to be lagging movements in model-implied rating changes. This confirms that fiscal uncertainty, both as a determinant of sovereign credit risk as well as a factor contributing to a higher frequency of rating announcements, can explain the pro-cyclical movement of ratings during crisis episodes. Only for the safe haven countries Germany and the United States, the specification without fiscal uncertainty yields superior estimates: Figure A2 in the Appendix shows that the model-implied downgrade probability remains below the threshold as no downgrades are observed. By contrast, probability estimates based on the fiscal uncertainty specification rise briefly for Germany at the height of the Great Recession of 2009, or in 2002 for the United States, despite the fact that no actual downgrade was observed.

Out-of-sample results are mixed. While probability predictions from a model, that is estimated for the sample up to 2009, generally move in parallel with full-sample estimates (yellow lines), they react somewhat more sluggishly to increases in credit risk after 2010 compared to full-sample results. This may be because estimates assign too small a weight to fiscal uncertainty as a determinant of sovereign credit risk, and too large a weight to fiscal uncertainty as a determinant of rating stability.

5 Conclusion

This paper addresses two policy-relevant questions that have arisen during the recent global financial and European government debt crisis: First, what is the effect of heightened fiscal uncertainty on sovereign credit risk? And second, what can explain the sometimes pro-cyclical behaviour of rating agencies during crises? To answer these questions I construct a new index that reflects uncertainty about fiscal policy in real time and is comparable across a range of advanced economies. I then consider the fiscal uncertainty index as a potential determinant of sovereign credit rating changes in a new empirical framework which accounts for the strong stability of ratings over time. I find that fiscal uncertainty exhibits a large variation across countries but reached unprecedented levels in the direct aftermath of the global financial crisis. I show that credit rating agencies take fiscal uncertainty as an important determinant of sovereign credit ratings into account. Fiscal uncertainty helps predict rating changes, in particular during crisis periods, and can explain why ratings often appear pro-cyclical during such periods. To an extent that fiscal uncertainty has detrimental effects on the fundamentals of an economy, accounting for it as a risk factor appears to be justified. However, I also find evidence for a larger frequency of rating changes during periods of high fiscal uncertainty that cannot be explained by uncertainty effects on credit risk alone, which may imply that rating agencies sometimes also respond to other incentives, in addition to an accurate assessment of fiscal policy sustainability.

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A1 An aggregate measure of uncertainty

To derive an aggregate measure of uncertainty from the variance decomposition $Var(e_{icth}) = \alpha_{ich}^2 Var(e_{cth}) + Var(\epsilon_{icth})$, Ozturk and Sheng (2018) follow Campbell et al. (2001) and find an expression of individual forecast errors that does not require estimates of α_{ich}:

$$e_{icth} = e_{cth} + v_{icth} \tag{A1}$$

where v_{icth} is the difference between individual and consensus forecast errors.

Plugging equation (A1) into the expression $e_{icth} = \alpha_{ich} e_{cth} + \epsilon_{icth} + \phi_{ich}$, setting $\phi_{ich} = 0$ and re-arranging yields:

$$v_{icth} = (\alpha_{ich} - 1)e_{cth} + \epsilon_{icth} \tag{A2}$$

The variance of e_{icth} can then be written as:

$$\begin{aligned} Var(e_{icth}) &= Var(e_{cth}) + Var(v_{icth}) + 2Cov(e_{cth}, v_{icth}) \\ &= Var(e_{cth}) + Var(v_{icth}) + 2(\alpha_{ich} - 1)Var(e_{cth}) \end{aligned} \tag{A3}$$

The covariance term $Cov(e_{cth}, v_{icth})$ in this expression does not drop out because e_{cth} and v_{icth} are not orthogonal, unlike e_{cth} and ϵ_{icth}. The second line follows from equation (A2).

Aggregating across forecasters eliminates the covariance term however, as well as individual α_{ich}'s:

$$\sum_{i=1}^{N} w_{icth} Var(e_{icth}) = Var(e_{cth}) + \sum_{i=1}^{N} w_{icth} Var(v_{icth}) \tag{A4}$$

Ozturk and Sheng (2018) write the observed disagreement among forecasts, and hence among forecast errors, as:

$$\begin{aligned} \sum_{i=1}^{N} w_{icth}(e_{icth} - e_{cth})^2 &= \sum_{i=1}^{N} w_{icth}[(\alpha_{ich} - 1)e_{cth} + \epsilon_{icth}]^2 \\ &= \sum_{i=1}^{N} w_{icth}[(\alpha_{ich} - 1)^2 e_{cth}^2 + \epsilon_{icth}^2 + 2(\alpha_{ich} - 1)e_{cth}\epsilon_{icth}]. \end{aligned} \tag{A5}$$

The problem with expression (A5) is that it represents a random variable prior to observing the forecast. To obtain a real-time expression, expectations are taken to yield a measure of non-random disagreement d_{cth}, given the assumptions $E(e_{cth}\epsilon_{icth}) = 0$ and $E(e_{cth}) = 0$:

$$\begin{aligned} d_{cth} &\equiv E[\sum_{i=1}^{N} w_{icth}(e_{icth} - e_{cth})^2] \\ &= \sum_{i=1}^{N} w_{icth}[(\alpha_{ich} - 1)^2 E(e_{cth}^2) + E(\epsilon_{icth}^2) + 2(\alpha_{ich} - 1)E(e_{cth}\epsilon_{icth})] \\ &= \sum_{i=1}^{N} w_{icth}[(\alpha_{ich} - 1)^2 Var(e_{cth}) + Var(\epsilon_{icth})]. \end{aligned} \tag{A6}$$

The variance of expression (A2) is $Var(v_{icth}) = (\alpha_{ich} - 1)^2 Var(e_{cth}) + Var(\epsilon_{icth})$. It can be used to replace the right hand side of equation (A6) to obtain the following expression for

d_{cth}:

$$d_{cth} = \sum_{i=1}^{N} w_{icth} Var(v_{icth}) \tag{A7}$$

Equation (A7) together with equation (A4) yields the final expression of forecast uncertainty derived in Lahiri and Sheng (2010) and Ozturk and Sheng (2018):

$$\sum_{i=1}^{N} w_{icth} Var(e_{icth}) = Var(e_{cth}) + d_{cth}. \tag{A8}$$

Ozturk and Sheng (2018) further note that the difference between the proxy of idiosyncratic uncertainty $\sum_{i=1}^{N} w_{icth} Var(v_{icth})$ and its true expression $\sum_{i=1}^{N} w_{icth} Var(\epsilon_{icth})$ is determined by the variance of α_{ich}, $\sum_{i=1}^{N} (\alpha_{ich} - 1)^2$, and the common shock. This can be shown by taking the weighted average of $Var(v_{icth})$:

$$\sum_{i=1}^{N} w_{icth} Var(v_{icth}) = \sum_{i=1}^{N} w_{icth} (\alpha_{ich} - 1)^2 Var(e_{cth}) + \sum_{i=1}^{N} w_{icth} Var(e_{icth}). \tag{A9}$$

If the variance of α_{ich} across forecasters is small, the proxy coincides with the true measure of idiosyncratic uncertainty.

A2 Monte Carlo experiment

The data for simulations is generated using the stability process (13) and the credit risk process (12). In particular, I construct ten regressors x_{jct}^{gen}:

$$x_{jct}^{gen} = \rho_j x_{jct-1}^{gen} + e_{jct}, \tag{A10}$$

where ρ_j is the autoregressive parameter of the jth regressor series which I set to 0.95 in line with typical properties of actual macroeconomic time series. Initial values x_{jc0}^{gen} are normally distributed as $\sim iid\ N(0,5)$, and the errors e_{jct} follow a standard normal distribution. I set all elements of vector β in the credit risk process (12) to 1. Doing so makes coefficient estimates easily comparable. I also consider a linear index of (first-differenced) fundamentals of the form $\Delta x_{index,ct}^{gen} = \Delta x_{1ct}^{gen} + \Delta x_{2ct}^{gen} + ... + \Delta x_{10ct}^{gen}$ to evaluate the estimator performance with respect to the number of regressors. As a result, the single coefficient for the index is also 1.

The regressor C_{ct}^{gen} of the stability process (13) is generated as $\sim iid\ 10 * [\text{uniform}(0,1) - 0.5]$ for every cross-section c and time period t. β^C is set to 1; the intercept in equation (13) is 4. The error terms of the credit risk and stability processes, ε_{ct} and ϵ_{ct} in equations (12) and (13), are both set to follow a standard normal distribution independent of each other. This meets the assumptions of Probit-based estimators. Parameters c_1, c_2 are used to determine the level of 'pure' inflation. Given the symmetric set-up and remaining parameter choices, I set $c_1 = -c_2$. $c_1 = -1.5$ generates a near balance of outcomes across the three categories 'downgrade', 'no change', 'upgrade'; around 33 percent of outcome observations fall into either category. $c_1 = -4$ inflates the middle-category outcome 'no change' to 76 percent, and $c_1 = -6$ creates around 93 percent 'pure' inflation. The specification of the stability process increases the overall inflation in the 'no change' outcome. Replacing $s_{ct} = 1$ for all c and t 'turns' the selection process 'off'. By the means of a dummy variable D_{ct}^{AAA} that is set to 1 if $uniform(0,1) > 0.5$ independent of t, and zero otherwise, I assign whether a panel observation lies at the upper end of the rating scale. Given its relatively small importance in practice, the lower end of the rating scale is left without bound, i.e. $D_{ct}^{D} = 0$ for all observations. D_{ct}^{AAA} adds a third source of middle-category inflation. It is turned 'off' if D_{ct}^{AAA} is set to zero for all c and t. The value of the final outcome ΔR_{ct} is assigned according to equation (14) above.

I set the cross-sectional dimension N of my generated dataset to 30 in line with my actual dataset for advanced economies. Concerning the time dimension, I allow the generated autoregressive processes Δx_{jct}^{gen} to 'burn in' and discard the first 100 time-observations. I use the next 60 time periods for a dataset of moderate size with 1,800 observations. In practice, this corresponds to an estimation of the regression model for each rating agency individually. To create a large-sample benchmark, I instead consider 600 additional time periods which yields a total of 18,000 observations. This would correspond to using more frequent data and longer series in practical applications.

48 different Monte Carlo set-ups are considered, for each of which $I = 2,000$ iterations

Monte Carlo set-ups

1)	‘pure’ middle-category inflation:	33% vs 76% vs 93%
2)	inflation due to stability process:	off vs on
3)	inflation due to boundary observations:	off vs on
4)	sample size:	1,800 vs 18,000
5)	number of regressors:	10 vs 1 index

are simulated. The set-up with 33% ‘pure’ inflation, no inflation due to the stability process or boundary observations, $N = 1,800$ observations and 10 regressors will be referred to as the baseline set-up. In every iteration, new errors ε_{ct} and ϵ_{ct} are generated, while remaining variables X_{ct} and C_{ct} are held fixed across iterations. For every set-up, the first coefficient in the coefficient for the credit risk process β (or the coefficient for the index), is estimated by Ordered Probit, MIOP and BAM. Estimator performance is evaluated using the mean bias per set-up, i.e. the average deviation of the estimated parameter from the true parameter over iterations v, $\frac{1}{I}\sum_{v=1}^{I}(\hat{\beta}_{1v} - \beta_1)$, the root mean squared error of the estimated coefficient over iterations v, $RMSE(\hat{\beta}_1) = \sqrt{\frac{1}{I}\sum_{v=1}^{I}(\hat{\beta}_{1v} - \beta_1)^2}$, the average standard error (SE) over iterations per set-up as well as the standard deviation of estimates $\hat{\beta}_1$ (SD).

Table A1: The determinants of average deficit revisions

	Revisions to nowcasts	Revisions to year-ahead forecasts
Lag	0.054	0.177***
	[0.07]	[0.04]
Lagged deficit/GDP forecast	0.062***	0.051***
	[0.01]	[0.01]
Lagged debt/GDP forecast	0.001	-0.001
	[0.00]	[0.00]
Lagged GDP growth forecast	0.062**	-0.019
	[0.03]	[0.01]
Lagged inflation forecast	0.073	0.015
	[0.05]	[0.02]
Lagged unemployment forecast	-0.001	0.019
	[0.01]	[0.01]
Lagged current account forecast	0.035***	0.039***
	[0.01]	[0.01]
Observations	791	728
R-squared	0.042	0.068

Notes: Pooled OLS regression, significance level given by *** p<0.01, ** p<0.05, * p<0.1. Deficit nowcasts and forecasts averaged across the OECD, IMF and European Commission.

Table A2: Transition matrix Fitch

Rating (t-1) \ Rating (t)	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB-	B+	B	B-	CCC
AAA	99.52	0.48	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AA+	2.53	93.67	2.53	1.27	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AA	0.00	2.88	95.19	1.44	0.48	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AA-	0.00	0.00	2.97	91.09	2.97	1.98	0.00	0.99	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
A+	0.00	0.00	0.00	1.89	94.34	0.94	2.83	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
A	0.00	0.00	0.00	0.00	3.97	92.86	2.38	0.00	0.79	0.00	0.00	0.00	0.00	0.00	0.00	0.00
A-	0.00	0.00	0.00	0.00	0.00	4.55	90.15	3.79	0.00	1.52	0.00	0.00	0.00	0.00	0.00	0.00
BBB+	0.00	0.00	0.00	0.00	0.00	0.74	5.15	92.65	0.74	0.74	0.00	0.00	0.00	0.00	0.00	0.00
BBB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	15.79	81.58	2.63	0.00	0.00	0.00	0.00	0.00	0.00
BBB-	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	10.34	75.86	13.79	0.00	0.00	0.00	0.00	0.00
BB+	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.08	93.22	0.00	1.69	0.00	0.00	0.00
BB-	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.35	91.30	4.35	0.00	0.00	0.00
B+	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	16.67	66.67	8.33	0.00	8.33
B	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	11.11	77.78	11.11	0.00
B-	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	25.00	62.50	12.50
CCC	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	40.00	60.00

Note: Fitch sovereign credit ratings, quarterly transitions, percentages.
Data source: Bloomberg.

Table A3: Transition matrix S&P

Rating (t-1) \ Rating (t)	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC	CC	SD/D
AAA	99.03	0.97	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AA+	2.80	94.80	2.40	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AA	0.00	1.55	93.02	5.43	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AA-	0.00	0.00	1.92	92.31	3.85	1.92	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
A+	0.00	0.00	0.00	1.96	92.16	4.90	0.98	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
A	0.00	0.00	0.00	1.31	3.27	90.85	3.27	1.31	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
A-	0.00	0.00	0.00	0.00	0.00	4.55	92.61	1.70	0.00	1.14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BBB+	0.00	0.00	0.00	0.00	0.00	0.00	7.59	87.34	2.53	1.27	1.27	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BBB	0.00	0.00	0.00	0.00	0.00	0.00	3.13	12.50	78.13	6.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BBB-	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	8.16	87.76	2.04	2.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BB+	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.00	88.00	4.00	4.00	0.00	0.00	0.00	0.00	0.00	0.00
BB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.23	96.77	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BB-	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.35	91.30	0.00	0.00	0.00	4.35	0.00	0.00
B+	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	16.67	66.67	16.67	0.00	0.00	0.00	0.00
B	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	25.00	62.50	12.50	0.00	0.00	0.00
B-	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	12.50	87.50	0.00	0.00	0.00
CCC	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	33.33	33.33	33.33	0.00
CC	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	50.00	50.00
SD/D	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00	0.00

Note: S&P sovereign credit ratings, quarterly transitions, percentages.
Data source: Bloomberg.

Table A4: Transition matrix Moody's

		Rating (t)																	
		Aaa	Aa1	Aa2	Aa3	A1	A2	A3	Baa1	Baa2	Baa3	Ba1	Ba2	Ba3	B3	Caa1	Caa3	Ca	C
Rating (t-1)	Aaa	99.41	0.59	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Aa1	3.13	92.71	2.08	1.04	0.00	0.00	0.00	1.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Aa2	1.97	1.32	93.42	0.66	1.32	0.66	0.00	0.66	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Aa3	1.54	0.00	3.08	93.85	1.54	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	A1	0.00	0.00	0.00	0.59	95.88	2.35	1.18	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	A2	0.00	0.00	0.00	0.68	2.74	93.84	1.37	0.00	0.68	0.00	0.68	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	A3	0.00	0.00	0.00	0.00	1.75	7.02	84.21	3.51	1.75	1.75	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Baa1	0.00	0.00	0.00	0.00	3.70	3.70	1.85	83.33	0.00	5.56	0.00	1.85	0.00	0.00	0.00	0.00	0.00	0.00
	Baa2	0.00	0.00	0.00	0.00	0.00	0.00	4.00	4.00	88.00	0.00	4.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Baa3	0.00	0.00	0.00	0.00	0.00	0.00	2.27	4.55	4.55	84.09	4.55	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Ba1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	6.38	91.49	0.00	0.00	2.13	0.00	0.00	0.00	0.00
	Ba2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	16.67	75.00	8.33	0.00	0.00	0.00	0.00	0.00
	Ba3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	7.69	92.31	0.00	0.00	0.00	0.00	0.00
	B3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.57	92.86	3.57	0.00	0.00	0.00
	Caa1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	50.00	0.00	50.00	0.00
	Caa3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	33.33	66.67	0.00	0.00
	Ca	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	50.00	50.00
	C	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	14.29	0.00	85.71

Note: Moody's sovereign credit ratings, quarterly transitions, percentages.
Data source: Bloomberg.

Table A5: Simulation results: large sample

Middle-category inflation	Estimator	Bias	RMSE	SE	SD
		Baseline			
34.5%	OP	0.001	0.016	0.016	0.016
	MIOP	0.003	0.017	0.016	0.016
	BAM	0.003	0.017	0.016	0.016
82.0%	OP	0.001	0.023	0.024	0.023
	MIOP	0.004	0.024	0.024	0.024
	BAM	0.004	0.024	0.024	0.023
92.6%	OP	0.004	0.036	0.034	0.036
	MIOP	0.008	0.038	0.035	0.037
	BAM	0.008	0.038	0.035	0.037
		+ Selection process			
41.8%	OP	-0.428	0.428	0.011	0.012
	MIOP	0.001	0.018	0.018	0.018
	BAM	0.001	0.018	0.018	0.018
84.1%	OP	-0.267	0.268	0.019	0.020
	MIOP	0.002	0.027	0.026	0.027
	BAM	0.002	0.028	0.026	0.028
93.4%	OP	-0.213	0.215	0.029	0.030
	MIOP	0.002	0.048	0.037	0.048
	BAM	0.003	0.047	0.037	0.047
		+ Boundary observations			
50.9%	OP	-0.511	0.511	0.011	0.008
	MIOP	-0.179	0.181	0.022	0.029
	BAM	0.002	0.018	0.019	0.018
86.5%	OP	-0.354	0.354	0.019	0.017
	MIOP	-0.108	0.114	0.033	0.034
	BAM	0.006	0.029	0.028	0.029
94.4%	OP	-0.295	0.296	0.029	0.028
	MIOP	-0.090	0.103	0.045	0.051
	BAM	0.011	0.042	0.040	0.040
		+ Selection process & boundary observations			
56.3%	OP	-0.584	0.585	0.010	0.009
	MIOP	-0.208	0.213	0.024	0.043
	BAM	0.002	0.021	0.021	0.021
88.0%	OP	-0.431	0.432	0.018	0.018
	MIOP	-0.154	0.163	0.036	0.056
	BAM	0.003	0.031	0.030	0.031
95.1%	OP	-0.372	0.373	0.028	0.028
	MIOP	-0.141	0.157	0.047	0.068
	BAM	0.004	0.046	0.043	0.046

Note: 10 regressors, sample size of 18,000.

Table A6: Simulation results: one regressor

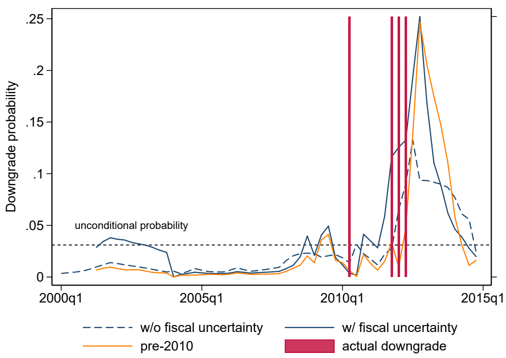
Middle-category inflation	Estimator	Bias	RMSE	SE	SD
		Baseline			
34.8%	OP	0.005	0.037	0.036	0.037
	MIOP	0.009	0.039	0.037	0.038
	BAM	0.009	0.039	0.037	0.038
82.6%	OP	0.010	0.060	0.056	0.059
	MIOP	0.020	0.065	0.059	0.062
	BAM	0.020	0.065	0.059	0.062
92.9%	OP	0.017	0.082	0.079	0.080
	MIOP	0.042	0.098	0.089	0.089
	BAM	0.042	0.098	0.089	0.089
		+ Selection process			
42.2%	OP	-0.425	0.425	0.018	0.021
	MIOP	0.006	0.041	0.041	0.040
	BAM	0.006	0.041	0.041	0.040
84.6%	OP	-0.258	0.262	0.038	0.042
	MIOP	0.009	0.065	0.062	0.065
	BAM	0.007	0.068	0.062	0.067
93.7%	OP	-0.191	0.201	0.060	0.062
	MIOP	0.024	0.103	0.091	0.101
	BAM	0.024	0.102	0.091	0.100
		+ Boundary observations			
50.8%	OP	-0.495	0.495	0.017	0.017
	MIOP	-0.210	0.216	0.054	0.051
	BAM	0.011	0.046	0.044	0.045
86.7%	OP	-0.338	0.339	0.034	0.026
	MIOP	-0.058	0.099	0.082	0.080
	BAM	0.025	0.073	0.068	0.069
94.5%	OP	-0.262	0.266	0.056	0.045
	MIOP	-0.027	0.148	0.130	0.146
	BAM	0.057	0.120	0.105	0.106
		+ Selection process & boundary observations			
56.4%	OP	-0.577	0.577	0.015	0.014
	MIOP	-0.269	0.282	0.058	0.084
	BAM	0.006	0.049	0.047	0.048
88.2%	OP	-0.415	0.416	0.031	0.027
	MIOP	-0.146	0.193	0.076	0.126
	BAM	0.012	0.079	0.072	0.078
95.1%	OP	-0.332	0.335	0.052	0.048
	MIOP	-0.103	0.186	0.110	0.155
	BAM	0.043	0.127	0.107	0.119

Note: 1 regressor, sample size of 1,800.

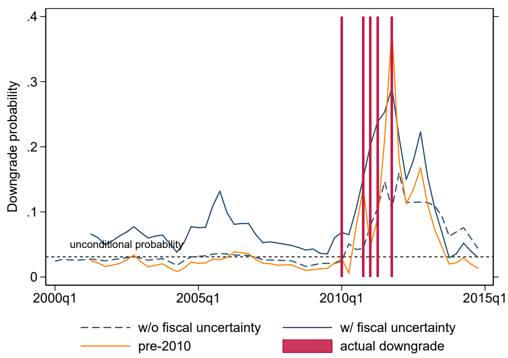
Table A7: Rating determinants and uncertainty index versions

	I	II	III	IV
Uncertainty measure:	D_{ct1}	D_{ct1}	U_{ct0}	U_{ct0}
Stability:				
Fiscal uncertainty	0.39	-1.92	10.6**	14.1
	[1.71]	[2.60]	[5.28]	[9.75]
Rating level	-0.28**	-0.24***	-0.13**	-0.23***
	[0.13]	[0.04]	[0.06]	[0.04]
Momentum	-9.07	219***	0.41	224***
	[8.07]	[5.94]	[7.96]	[9.05]
Credit risk:				
Fiscal uncertainty	0.63	1.79***	0.27	0.48***
	[0.56]	[0.68]	[0.27]	[0.12]
Deficit/GDP	0.19	0.13	0.13	-0.12
	[0.15]	[0.29]	[0.39]	[0.38]
Debt/GDP	0.31**	0.46	0.87	0.34
	[0.15]	[0.29]	[1.09]	[0.24]
GDP growth	-1.41***	-3.72***	-3.45**	-3.70***
	[0.52]	[1.01]	[1.20]	[0.82]
Unemployment	3.70***	5.01***	7.33*	5.02***
	[1.06]	[1.79]	[3.74]	[1.50]
Observations	4,635	4,635	4,122	4,122
Sensitivity ↓	81.6%	74.6%	75.8%	73.3%
Specificity ↓	71.3%	80.0%	82.6%	81.4%
Sensitivity =	53.7%	70.7%	71.1%	71.8%
Specificity =	92.0%	74.0%	74.4%	73.6%
Sensitivity ↑	91.7%	76.1%	84.5%	76.9%
Specificity ↑	64.2%	73.0%	72.3%	73.5%

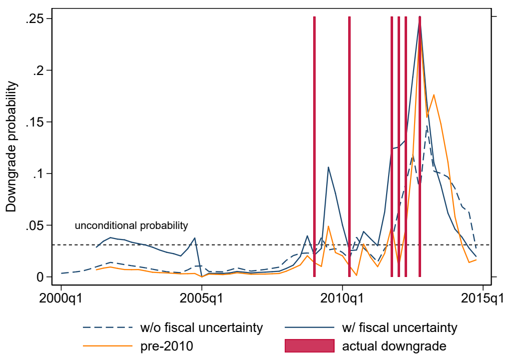
Notes: BAM estimation: marginal effects on the probability of 'change' (stability process) and 'downgrade' (credit risk process) are computed at the sample average of all variables. Standard errors (in brackets) are computed using the delta method, significance level given by *** $p<0.01$, ** $p<0.05$, * $p<0.1$. ↓: downgrade, ↑: upgrade, =: no change. Watch observations are treated as rating changes in columns II, IV.



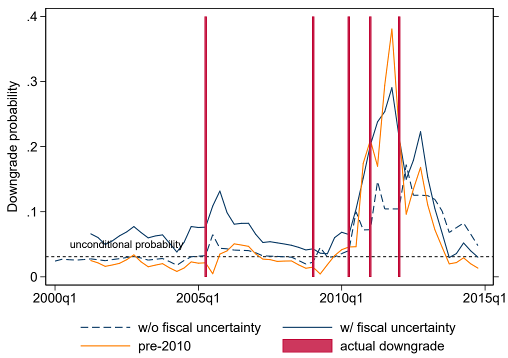
(a) Spain, Fitch



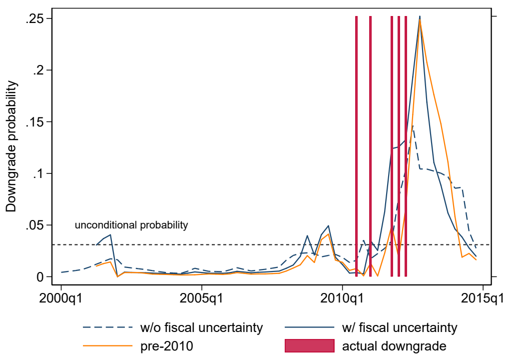
(b) Portugal, Fitch



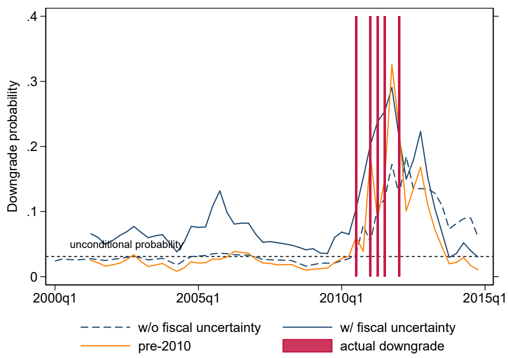
(c) Spain, S&P



(d) Portugal, S&P

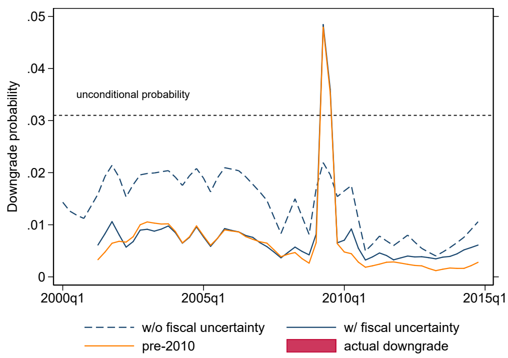


(e) Spain, Moody's

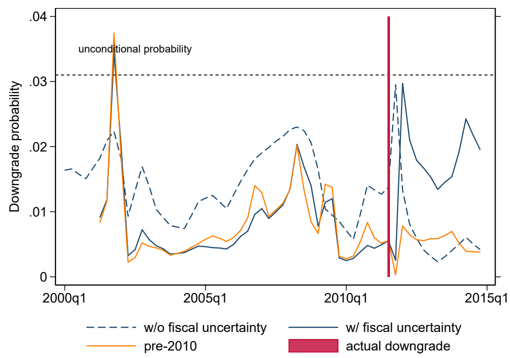


(f) Portugal, Moody's

Figure A1: Estimated downgrade probabilities, Spain and Portugal



(a) Germany, S&P



(b) United States, S&P

Figure A2: Estimated downgrade probabilities, Germany and United States

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