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Much ado about nothing: Sovereign ratings and government bond yields in the OECD

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Much Ado About Nothing: Sovereign Ratings and Government Bond Yields in the OECD

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Much Ado About Nothing: Sovereign Ratings and Government Bond Yields in the OECD*

Abstract

In this paper, we propose a new method to assess the impact of sovereign ratings on sovereign bond yields. We estimate the impulse response of the interest rate, following a change in the rating. Since ratings are ordinal and moreover extremely persistent, it proves difficult to estimate those impulse response functions using a VAR modeling ratings, yields and other macroeconomic indicators.

However, given the highly stochastic nature of the precise timing of ratings, we can treat most rating adjustments as shocks. We thus no longer rely on a VAR for shock identification, making the estimation of the corresponding IRFs well suited for so called local projections – that is estimating impulse response functions through a series of separate direct forecasts over different horizons. Yet, the rare occurrence of ratings makes impulse response functions estimated through that procedure highly sensitive to individual observations, resulting in implausibly volatile impulse responses. We propose an augmentation to restrict jointly estimated local projections in a way that produces economically plausible impulse response functions.

We develop a semiparametric local projections method where smoothness can be imposed as constraint without assuming a specific functional form. The degree of smoothing can be assessed using a standard information criterion.

While rating downgrades can play some role, we find no evidence for an impact of ratings in the most critical case of countries that are unusually well rated compared to their debt situation. Rather, ratings seem to be adjusted when the market evaluation of the risk associated with the high level of debt has already peaked.

Keywords: local projections, semi parametric estimation, impulse response function, sovereign rating, bond yields

JEL Classification: C14, C30, E43, E44

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1 Introduction

Both the drivers and effects of ratings have been intensely debated in the economic literature for more than four decades starting with West (1973). It was primarily the paper by Cantor and Packer (1996), showing that sovereign ratings affect yields even after controlling for a battery of macroeconomic factors, that brought this issue to the attention of macroeconomists. With the Asian crisis occurring mere months after their paper, it fell on fertile ground and paved the way for Ferri et al.'s 1999 seminal hypothesis of pro cyclical ratings that accelerate crises. While Cantor and Packer (1996) still read the empirical finding of ratings affecting yields as evidence that rating agencies provide information to the market, the story of ill founded and lagging ratings accelerating crises by affecting market participants who mistake them for new information was the dominant narrative ever since.

There is little empirical evidence regarding the dynamics of government bond yields caused by a rating change. Plenty of papers have examined the immediate impact of rating announcement and even changes of the rating outlook on the sovereign bond yields. Yet, the dynamic analysis of most papers is limited to fairly simple event studies rather than estimating impulse response functions (IRF) that would truly allow to assess the (causal) effect of a rating announcement. While technically following a vastly different approach, our work is economically most closely related to De Santis (2012), El-Shagi and von Schweinitz (2015a) and El-Shagi and von Schweinitz (2015b), some of the very few previous attempts to estimate IRFs of interest rates following a rating shock. All three of those papers estimate structural vector error correction models (in a wider sense). De Santis (2012) estimates separate VARs for ten Euro area countries including ratings, government deficit to GDP ratio, the domestic term spread and the German term spread. His first difference VAR is augmented using an error correction term that is obtained in a separate level equation in the tradition of Engle and Granger (1987) but estimated through dynamic OLS. Structural identification is achieved through a Cholesky decomposition where the rating is ordered second, following the government deficit. Partly due to the data constraint caused by their fairly small sample (and augmented by the fact that they reduce their sample size by estimating countrywise) this paper neither accounts for the ordinal nature of ratings, nor for the nonlinearities and the asymmetric impact of up- and downgrades that are documented in the literature. While El-Shagi and von Schweinitz (2015a) allows nonlinearities and considers the ordinal nature of ratings and rating changes and El-Shagi and von Schweinitz (2015b) adds potential asymmetries, the increased complexity of doing so restricts the authors to a bivariate system merely including ratings and government yields and excluding government debt, the main driver of risk (and ratings). To our best knowledge, at this time there is no paper estimating impulse response functions that account for both the economic conditions and for the nonlinearities and asymmetries in the impact of ratings. Our paper aims to fill this gap in the literature. Our contribution is twofold. The first contribution is an empirical one. We show how interest rates in countries with different levels of government debt and different (original) ratings respond to changes in the sovereign rating. Thereby, we cannot only assess whether yields in risky countries respond different from yields in less risky countries, but more importantly we can distinguish between countries that are unusually well (or badly) rated compared to their risk exposure (measured through debt). Second, we add to the econometric literature on estimating impulse response functions. We propose a new technique

to estimate impulse response functions through restricted local projections, building on the seminal work of Jordà (2005). By imposing an endogenously determined degree of persistence on the shape of the IRFs, we can overcome identification issues that arise in small samples or (such as in our case) when using data with a limited number of episodes where the shock of interest is experienced.

In general we only find a very limited impact of ratings. While upgrades do not affect the market at all, there is some effect of downgrades. However, in the particularly relevant case of countries that are well rated despite their high level of debt, it seems as if rating agencies only adjust their rating long after the market evaluation of default risk has started increasing.

The remainder of the paper is structured as follows. In section 2 we discuss the previous empirical evidence on the impact of sovereign ratings on yields. In section 3 we develop restricted local projections after briefly introducing the original concept developed by Jordà (2005). Section 4 presents the data and model specification(s) we use. Section 5 summarizes our results and Section 6 concludes.

2 Ratings and Yields

Rating agencies have been subject to extreme scrutiny after every major crisis in the past decades. The criticism they face is twofold: First, ratings seem to be bad predictors of crises. In particular, ratings seem to ignore systemic risk. The agencies have long overlooked the problems of the Asian tigers that culminated in the Asian Flu in the late 1990s, and – to an even larger extent – were oblivious to the risk of the complex financial derivatives based on housing credit that eventually triggered the meltdown of the global financial system in 2007/2008.¹ Anecdotal evidence suggests that rating agencies followed the markets' risk assessment, rather than warning of the emerging risk early on. Yet, many studies find that ratings affect the market, implying that they are seen as new information. Cantor and Packer (1996) have been the first to show that sovereign rating announcements are indeed correlated with unusual movements in the yield. This leads to the second, far more severe, criticism which is that ratings actually propagate and fuel crises. Ferri et al. (1999) have argued that rating agencies become more conservative after missing a crisis to regain trust they lost by missing the problems in first place, thereby deepening the crisis. This finding has been challenged e.g. by Mora (2006) and El-Shagi (2010) who argue that rating agencies do merely follow the market, but are in consequence barely considered as news and thus do not drive the crisis. Yet, in particular in policy circles the hypothesis voiced by Ferri et al. (1999) and similar speculations about vicious cycles of capital flight and deteriorating credit ratings have been immensely popular.²

Correspondingly there has been an abundance of literature trying to assess both the determinants of ratings³ and the consequences of rating changes on financial markets. Reisen and Von Maltzan (1999) perform an event study of sovereign yield spreads in a 30 day window around rating events. Kaminsky and Schmukler (2002) assess the immediate impact on a range of financial indicators in a panel study, and assess

¹In particular when it comes to corporate bonds this seems to be partly driven by a conflict of interest since issuers of debt pay the rating agencies. See e.g. Bolton et al. (2012).

²See e.g. Gärtner et al. (2012) for a more recent discussion of this hypothesis.

³See for example the study by Amstad and Packer (2015) and the references cited therein.

the dynamics of those indicators using an event study. Ismailescu and Kazemi (2010) analyze the effect on credit default swaps in a two day window (finding a significant impact). Arezki et al. (2011) embed rating dummies in a VAR for Euro area countries to model rating shocks.⁴ Afonso et al. (2012) similarly uses European data, performing both an event study and assessing the immediate impact of ratings. Brooks et al. (2004) performs an event study concerning the impact on the domestic stock market. Ferreira and Gama (2007) tests the immediate spillovers on other countries' stock market (accounting for a range of interactions). In short, while there is ample evidence on the impact of ratings over on the day of the rating or the short window from the day before to the day after the rating, most evidence on the dynamics of ratings is based on event studies. Papers modeling the dynamics of the impact of ratings and go beyond event studies, i.e. that control for macroeconomic conditions when assessing the impact of ratings over a longer horizon, are rare. De Santis (2012) and El-Shagi and von Schweinitz (2015a) are two of the exceptions that actually attempt to model the dynamics of yields and ratings.

In our paper we aim to contribute to filling this gap in the literature. Local projections seem particularly suited to this task because they overcome the technical problems arising when estimating VARs with ordinal variables, and are able to deal with nonlinearities. The previous evidence on ratings – partly drawn from the literature on corporate bonds rather than sovereign ratings – suggests that this is essential.

First, there is strong evidence on asymmetric effects of downgrades and upgrades, where the latter are frequently found to have no impact at all. For abnormal stock returns around corporate bond ratings, this has already been established more than three decades ago by Griffin and Sanvicente (1982) and Holthausen and Leftwich (1986). Similar results have been found for sovereign ratings. Brooks et al. (2004) perform an event study assessing the abnormal returns of the domestic stock market around rating dates and find that only downgrades exhibit significant wealth effects. Ferreira and Gama (2007) find similar asymmetries for spillovers to international stock markets.

Second, with respect to corporate bonds several authors (Hand et al., 1992; Goh and Ederington, 1993) have shown that it matters whether ratings can be expected or not. Goh and Ederington (1993) provides evidence that rating downgrades only matter if they are hard to foresee. Due to the low number of observed events when it comes to sovereign ratings, this approach has not been popular so far when it comes to sovereign risk. Yet, in our paper – albeit technically very different – we follow a similar objective. By modeling nonlinearities of the impact of a rating event depending on the macroeconomic conditions, we are implicitly able to distinguish between situations where rating changes come as a surprise and those where the agencies follow the market, and come to similar conclusions as the afore mentioned papers on corporate bonds.

⁴While the authors only assess the immediate impact, this could technically be used to assess the long run effect, if rating shock fully manifests immediately, and are only propagated through the common interaction of financial variables after that, which seems unlikely.

3 Methodology

3.1 A brief review of local projections

Local projections refer to a recently developed estimation method for impulse responses proposed by Jordà (2005) that rely on a series of direct forecasts, rather than indirect or sequential forecasts as it is done in the VAR literature.

To understand the key idea of local projections it is useful to consider that the impulse response function IRF at horizon h is no more than the difference between two conditional forecasts, one assuming an experimental impulse (the shock) d to equal some vector v and the other assuming said shock to be (a) zero (vector). Denoting the variable of interest at time t y_t , the past of that variable $Y_t = (y_{t-1}, y_{t-2}, y_{t-3}, \dots)$, the past of other explanatory variables by Z_t , and the expectations based on a generic model ϕ by E_ϕ , we can thus write the impulse response function as:

$$IRF(t, h, d) = E_\phi(y_{t+h}|d = v, Y_t, Z_t) - E_\phi(y_{t+h}|d = 0, Y_t, Z_t), \quad (1)$$

where Y_t and Z_t are usually (but not necessarily) set to their unconditional expectation for the one step ahead forecast.

A VAR produces a one step ahead forecast, updates Y_t and Z_t and produces an indirect two steps ahead forecast as one step ahead forecast with this updated information, etc. However, this notation highlights the fact that this is not necessary. Instead, we can produce a series of direct forecasts of y_{t+h} for different h each using a model tailored to predict at this horizon. That is, we estimate a series of equations of the form:

$$y_{t+h} = \sum_{i=1}^p x_{t-i} \beta_{i,h} + \sum_{j=1}^k z_{j,t} \gamma_{j,h} + u_{t,h}, \quad (2)$$

where p is the autoregressive lagorder, k is the number of predetermined regressors (including lags of those), β and γ are coefficients, and u the residuals.

The advantages over a VAR are manifold: (a) The model used to predict h steps ahead is actually optimized for that purpose rather than optimized to produce the best possible one step ahead forecast. This is of course irrelevant if the true data generating process is a VAR, but when the VAR is merely an approximation of a more complex system, this can increase efficiency. (b) Unlike a VAR, local projections do not require to predict all variables that are included in Z and Y , but we can focus on the variable of interest. This in turn makes it (c) much easier to include nonlinearities in the prediction equation, since Z can easily include interaction terms, such as interactions of the variable measuring the shock with other exogenous or predetermined variables.

Of course this comes at a cost. First, the VAR residuals are essential in most common applications to identify the shocks. That is why local projections are particularly well suited for applications as ours, where the identification of the shock is almost trivial, since the shock of interest is (the fluctuation in) an observable variable.

The second problem occurs, when the number of observations is low or – as in our case – the shock is a rare binary event, so inference on the impact of the “shock” is based on few observations. In this case, idiosyncratic shocks of observations following the shock can have an overly large impact, causing highly volatile “zig-zagging” impulse response functions that are economically implausible. In the following section we propose a method to produce smooth, economically more plausible impulse response functions. Rather than estimating the equations individually, we estimate a simultaneous equation system for all horizons that exploits the fact that there should be high autocorrelation, i.e. some degree of persistence, in an impulse response function. Thereby, we can essentially combine benefits of VAR based inference and local projections. This is closely related to recent research by Jordà (2009) who embeds local projections in a simultaneous equation framework to exploit serial correlation to improve the estimation of confidence bounds. Contrary to Jordà (2009), our work focuses on improving inference for the point estimates.

To address our problem it helps to recall that in local projections the impulse response function can be obtained from the coefficient estimates corresponding to the shock variable over different horizons. A smooth impulse response function thus corresponds to smoothly changing coefficients between adjacent forecast horizons. When writing the multiequation system 2 in stacked form (as for example used in seemingly unrelated regression) it becomes obvious that this can be mapped on a problem frequently faced in the distributed lag literature, where lags are often estimated in a structured form both to match theoretical priors and to increase the number of degrees of freedom. In the following sections, we adapt an approach originally used in that area, to be applicable to estimate restricted impulse response functions.

3.2 Semiparametric smoothing

The estimator For our approach how to tackle this issue we borrow from the literature on mixed data sampling (MIDAS), introduced by Ghysels et al. (2002) and popularized by Ghysels et al. (2006). In MIDAS low frequency data is predicted using a large number of lags of high frequency data. When simply estimating this type of model with OLS or comparable, the resulting parameter proliferation gives raise to substantial identification issues not only due to the loss of degrees of freedom but also due to the high multicollinearity typically present in the applications of this literature. To overcome those issues, the original MIDAS approach used different functional forms to structure lags. In this paper, we adapt a more recently developed nonparametric MIDAS approach proposed by Breitung and Roling (2015). Rather than enforcing a specific functional form, Breitung and Roling (2015) penalizes (squared) second differences, i.e. slope changes, between adjacent lags. What makes this method so attractive is that it is both highly flexible, and can at the same time be written in a way that allows simple least square estimation of the smoothed model. Thus, we adopt the same approach, in our case penalizing the squared second difference of corresponding coefficients over different forecast horizons.⁵

Letting T denote the number of observations used for prediction, H the maximum forecast horizon, k the number of further explanatory variables (that are either exogenous or predetermined, i.e. the lags of other

⁵This does, however, implicitly add one further restriction to local projections. While rarely done, it is theoretically possible to use different explanatory variables in equations used to forecast over different horizons. Since we smooth by smoothing corresponding coefficients over different forecast horizons, our approach requires identical explanatory variables for all horizons.

variables), we can define

$$Y = \begin{bmatrix} y_1 & y_2 & \cdots & y_H \\ y_2 & \ddots & & y_{H+1} \\ \vdots & & \ddots & \vdots \\ y_T & y_{T+1} & \cdots & y_{T-1+H} \end{bmatrix} \quad (3)$$

and

$$X = \begin{bmatrix} y_0 & y_{-1} & \cdots & y_{1-p} & z_1^{(1)} & z_1^{(2)} & \cdots & z_1^{(k)} \\ y_1 & \ddots & & y_{2-p} & z_2^{(1)} & \ddots & & z_2^{(k)} \\ \vdots & & \ddots & \vdots & \vdots & & \ddots & \vdots \\ y_{T-1} & y_{T-2} & \cdots & y_{T-p} & z_T^{(1)} & z_T^{(2)} & \cdots & z_T^{(k)} \end{bmatrix}, \quad (4)$$

allowing to rewrite equation 2 in matrix notation:

$$Y = XB + u, \quad (5)$$

where B is a coefficient matrix collecting the γ s and β s from equation 2 and u a vector of errors.

Our objective is jointly minimizing the weighted squared residuals obtained from the model and (weighted) squared second differences between parameters in the same row of B . That is rather than minimizing:

$$SSR = \sum_{h=0}^{H-1} \sum_{t=1}^T (y_{t+h} - x_t B_h)^2 \quad (6)$$

we would like to minimize:

$$SSR' = \sum_{h=0}^{H-1} \omega_h \sum_{t=1}^T (y_{t+h} - x_t B_h)^2 + \sum_{i=1}^{p+k} \lambda_i^2 \sum_{h=3}^H (b_{i,h-2} - 2b_{i,h-1} + b_{i,h})^2, \quad (7)$$

where λ_i is a scaling factor determining the degree of smoothing⁶ for coefficient i , B_h is the h^{th} column of B , $b_{i,h}$ is the h^{th} entry of the i^{th} row of B ,⁷ and ω_h is the (GLS) weight for equation h , as outlined below. This notation makes it obvious that we would essentially like to treat (weighted) second differences much like residuals. Since the second difference can be obtained by a simple matrix multiplication, we can easily extend a standard least square estimator to account for changes between coefficients by estimating:

$$\begin{bmatrix} \text{vec}(Y) \\ \mathbf{0} \end{bmatrix} = \begin{bmatrix} I_H \otimes X \\ D \otimes \text{diag}(\lambda) \end{bmatrix} B^* + \begin{bmatrix} \text{vec}(u) \\ \xi \end{bmatrix}, \quad (8)$$

⁶Note that our notation deviates from Breitung and Roling (2015) since – for our application – redefining Breitung’s λ as λ^2 allows for a considerably easier notation in the latter part of our technical exposition.

⁷For the remainder of this paper, we will mostly stick to this structure, where capital letters denote matrices, the same capital letters with a single index represent an individual column from this matrix, and the corresponding lower case letter with two indexes an individual scalar from this matrix.

where $\lambda = (\lambda_1, \lambda_2, \dots, \lambda_{(p+k)})$, B^* is the vectorized coefficient matrix, ξ the pseudo residuals generated by deviations of the second differences of corresponding coefficients over forecast horizons from zero, and D is an $((H-2) \times H)$ matrix given by

$$D = \begin{bmatrix} 1 & -2 & 1 & 0 & \cdot & 0 \\ 0 & 1 & -2 & 1 & \cdot & 0 \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ 0 & \cdot & \cdot & 1 & -2 & 1 \end{bmatrix}. \quad (9)$$

and I_H is an identity matrix of order H . For ease of notation we define $\tilde{X} = I_H \otimes X$, $\tilde{Y} = \text{vec}(Y)$ and $\tilde{D} = D \otimes \text{diag}(\lambda)$.

Since DB'_h yields a vector with the second differences of B_h , $\tilde{D} = (D \otimes \text{diag}(\lambda))B^*$ yields a vector with the second differences of coefficients with adjacent horizons, each premultiplied with the respective entry of λ . Since the vectorized left hand side is augmented by a zero vector of corresponding length, those weighted second differences are treated like residuals when applying a simple least square estimator to equation 8.

Breitung and Roling (2015) could use a simple OLS estimator, since they applied smoothing to coefficients within one equation. Contrarily, our stacked equation requires borrowing a generalized least squares (GLS) estimator from the estimation of seemingly unrelated regressions (SUR). Forecast errors (a) have a different variance across equations since forecasts deteriorate in the forecast horizon, and (b) forecast errors accumulate over forecast horizons.

While we use the assumptions of a standard SUR model, where there is no autocorrelation of residuals, this error structure assumed in most SUR models is technically still a too strong simplification in our case. By construction the residuals of h step ahead forecasts follow an $h-1$ moving average process, since they cover overlapping unpredictable shocks that thus enter the forecast error. When considering forecasts made at time t and $t+s$, the same problem of overlapping periods of unpredictable shocks applies to all forecasts at time $t+s$ where $1 \leq h \leq H-s$ and the forecasts made at t where $s+1 \leq h \leq H$. While this can easily be considered by computing the respective cross correlations in an actual small sample application of our approach, our data is so large that we have to rely on the simplified SUR covariance matrix to keep it computationally feasible. The weighting of the changes in the coefficient vector(s) over different forecast horizons is achieved through setting λ . Thus, for the purpose of constructing the covariance matrix V that determines the weights ω , we can simply normalize the weight to 1.

Defining $v = [u' \xi']'$ we thus can write $V = E(v'v)$ as:

$$V = \begin{bmatrix} \tilde{V} & \mathbf{0} \\ \mathbf{0} & I_{(H-2)(p+k)}, \end{bmatrix} \quad (10)$$

where $\Sigma = u'u$ and $\tilde{V} = \Sigma \otimes I_H$.

This yields the smoothed least square estimator:

$$\hat{B}^* = (\tilde{X}'\tilde{V}^{-1}\tilde{X} + \tilde{D}'\tilde{D})^{-1}\tilde{X}'\tilde{V}^{-1}\tilde{Y} \quad (11)$$

Of course, as common to SUR estimation Σ – and thus V is unknown and hence has to be replaced by an estimate. We opt for an approach that is a compromise between 2 step least squares (where V is obtained from an initial OLS estimate) and iterative least squares (where the system is iteratively reestimated, using V based on the last iterations residuals until convergence is achieved). While most of the information is contained in the OLS residuals, we would like to have an estimate of V that already is provided by a smoothed estimator. Thus we estimate a first smoothed model using V based on the OLS estimate, and then estimate one final time using the estimate of V generated by the first smoothed model.

Choosing the degree of smoothing Breitung and Roling (2015) show that the smoothing parameter can be mapped on the corresponding effective loss of degrees of freedom. This intuitively becomes clear when considering $\lambda = \mathbf{0}$ on the one hand and allowing the elements of λ to go to infinity on the other hand. In the first case, the penalty is essentially omitted, yielding the unrestricted estimate, where H coefficients are estimated for each variables, that is $H(k + p)$ coefficients in total. When the penalization increases, we approach a situation where eventually any change in the second differences is omitted, resulting in constant slope IRFs, that is, for each of the $(k + p)$ variables we effectively merely estimate the two coefficients necessary to identify a straight line. More generally, the effective loss of degrees of freedom or pseudo dimension of the model κ_λ is given by $tr(P)$ where $P\tilde{Y} = \tilde{Y}$, that is

$$\kappa_\lambda = tr(\tilde{X}(\tilde{X}'\tilde{V}^{-1}\tilde{X} + \tilde{D}\tilde{D})\tilde{X}') \quad (12)$$

This allows to apply an information criterion to choose the degree of smoothing. In the application of Breitung and Roling (2015) it is possible to perform a simple grid search to minimize the information criterion, since their λ is a scalar and they estimate a single equation model. Yet, in our application – and possibly many applications of smoothed OLS for local projections – this is unfeasible. Since \tilde{X} is a $(T \cdot H) \times ((p + k) \cdot H)$ matrix, the computation of κ_λ quickly becomes a considerable computational burden. In our specific example with almost 100,000 observations and 60 daily forecasts, \tilde{X} has close to 6 million rows, implying that κ_λ is the trace of a $6,000,000 \times 6,000,000$ matrix. While it is possible to compute the trace without ever computing the entire matrix (which would be impossible to store) by block wise computation and summation of the diagonal elements, this simplified approach still takes quite some time to compute even for a single estimation. Reevaluating κ_λ in a grid search over all entries of λ (8 to 15 in our example), is essentially impossible due to computational constraints.

We therefore use a simplified choice of λ where we restrict the different elements to produce a roughly similar degree of smoothing as measured by the implied loss of degrees of freedom. We generally set $\lambda_i = 0$ for all right hand side variables that do not include the variable measuring the shock, i.e. where smoothness is without consequence for the smoothness of the IRF. Then we compute the loss of freedom for a range of λ s, where $\lambda_i = 10 \wedge \lambda_{j \neq i} = 0$ for all i corresponding to the variables where the coefficients are to be smoothed across forecast horizons.

Writing $\nu_i = (p + i) - \kappa_i$ where κ_i is the pseudo dimension of the model, generated by the λ vector described above, where merely the i^{th} element is set to 10 and all others to zero, we then define:

$$\lambda^* = \left(\lambda_1^*, \lambda_2^*, \dots, \lambda_{(p+k)}^* \right), \text{ where } \begin{cases} \lambda_j^* = 0, & \text{if the corresponding variable does not con-} \\ & \text{tain the measure of the shock} \\ \lambda_j^* = \frac{\max_i \nu_i}{\nu_j}, & \text{otherwise.} \end{cases} \quad (13)$$

Rather than looking over the entire space spanned by possible values of λ we then do a simple grid search over multiples of λ^* .

When assessing the AIC, we use a simplified estimate of Σ where Σ is restricted to be a diagonal matrix, i.e. we do not consider cross correlations. The reason is twofold. First, our benchmark is the basic local projection method where the coefficients are independently estimated, thus implicitly only considering the variances rather than the full covariance structure. Second, the smoothing does induce strongly distorting the covariance structure, due to the high autocorrelation of interest rates. We believe that this is the reason why the increase in $\log(\det(\Sigma))$ as a response to smoothing is far more pronounced if non diagonal elements are considered. Since we do not want to penalize the declining fit twice due to that side effect, we concentrate on the fit equation by equation when determining the degree of smoothing. Yet, the actual estimation considers the full covariance matrix.

4 Data & Model

4.1 Model

The baseline model With interest rates responding extremely fast to any shock - not only rating shocks that are considered in this paper - most of the macroeconomic information that does affect the interest rate, is fairly well covered by the interest rate itself when using a daily frequency. Thus, the dynamics of the interest rate without changes in the rating are fairly well modeled using a simple autoregressive model. Since local projections do not require to track the shock throughout the economy as a VAR does, there is essentially no need to explicitly model the entire macroeconomy if we are primarily interested in the response of the interest rate. We can thus go for a fairly parsimonious specification. The main reason why we are interested in more control variables is to explore how they interact with ratings.

While there is some evidence that the immediate response to changes in the rating depends on the original level of the rating, it is unclear whether this comes from a difference in underlying risk factors or is actually driven by diverging ratings. Thus we do not only condition the response to rating shocks on the rating level but also on debt over GDP which – following the literature – seems to be the major risk factor.

Annual data such as debt in an analysis using daily data is only possible that easily due to the local projections approach. Since we do not have to model the dynamics of all the important driving factors, we can easily use simple interpolations of variables that are only available at a lower frequency, providing they are persistent enough that an interpolation still contains most of the relevant information, as outlined in the data subsection.

We are specifically interested in assessing whether specific combinations of debt and rating, have an impact on how the impulse responses look like, so our model includes the interaction of debt over GDP

and the rating (and the interactions of said interactions with the rating change dummies). We also include squared ratings (again including the interaction with rating dummies) in the model. This accounts for the nonlinearities in the rating level found in the previous literature, and is particularly important since it guarantees that the impact of the debt-rating interaction is not merely picking up a nonlinearity in the rating level itself, which would be possible due to the unsurprising correlation of debt and ratings. Including those interactions our model takes the form:

$$\begin{aligned}
i_{n,t+h} = & A(L)i_{n,t-1} + \beta_1 d_{n,t} + \beta_2 r_{n,t} + \beta_3 r_{n,t} d_{n,t} + \beta_4 r_{n,t}^2 \\
& + \beta_5 up_{n,t} + \beta_6 up_{n,t} d_{n,t} + \beta_7 up_{n,t} r_{n,t} + \beta_8 up_{n,t} d_{n,t} r_{n,t} \\
& + \beta_9 up_{n,t} r_{n,t}^2 + \beta_{10} down_{n,t} + \beta_{11} down_{n,t} d_{n,t} \\
& + \beta_{12} down_{n,t} r_{n,t} + \beta_{13} down_{n,t} d_{n,t} r_{n,t} + \beta_{14} down_{n,t} r_{n,t}^2 \\
& + \eta_t + u_n + \varepsilon_{n,t},
\end{aligned} \tag{14}$$

where $i_{n,t}$ is the government bond yield in country n at time t , r_t is the corresponding rating, d_t the ratio of government debt to GDP and up and $down$ are dummies indicating rating up- and downgrades respectively, i.e. $up_t = \mathbb{1}_{\Delta r_t > 0}$, $down_t = \mathbb{1}_{\Delta r_t < 0}$. η_t , u_n , and $\varepsilon_{n,t}$ are time specific, country specific and idiosyncratic components of the error term respectively.

Since the model is computationally fairly intensive, we simplify estimation by using a 4th order Almon polynomial over 30 days of lagged interest rates to capture the past dynamics of the interest rate rather than using the raw daily observations.

The extended event study Evidence from event studies suggests, that there are unusual movements in the risk premium long before a rating action takes place. To allow for an easy comparison with the previous literature, we therefore augment our model in a way to capture those movements. Contrary to traditional event studies that merely compare the interest rate movement around a rating event with “usual” interest rate movements, our approach allows to control for other factors, such as the further past of the interest rate, debt, the rating level etc. Yet, one caveat of event studies remains: We can not assess causality. That is, it is unclear whether an interest rate movement before a rating adjustment is due to the anticipation of the rating adjustment or cause of the rating adjustment. Since we merely describe a correlation structure over time, rather than actually assessing the causal reaction to an impulse, we dub this version of the model extended event study, rather than impulse response analysis.

To obtain those extended event studies (referred to as EES for the remainder of the paper), we estimate the set of equations given by:

$$\begin{aligned}
i_{n,t+h} = & A(L)i_{n,t-1-B} + \beta_1 d_{n,t-B} + \beta_2 r_{n,t-B} + \beta_3 r_{n,t-B} d_{n,t-B} + \beta_4 r_{n,t-B}^2 \\
& + \beta_5 u p_{n,t} + \beta_6 u p_{n,t} d_{n,t-B} + \beta_7 u p_{n,t} r_{n,t-B} \\
& + \beta_8 u p_{n,t} d_{n,t-B} r_{n,t-B} + \beta_9 u p_{n,t} r_{n,t-B}^2 \\
& + \beta_{10} \text{down}_{n,t-B} + \beta_{11} \text{down}_{n,t} d_{n,t-B} \\
& + \beta_{12} \text{down}_{n,t} r_{n,t-B} + \beta_{13} \text{down}_{n,t} d_{n,t-B} r_{n,t-B} + \beta_{14} \text{down}_{n,t} r_{n,t-B}^2 \\
& + \eta_t + u_n + \varepsilon_{n,t},
\end{aligned} \tag{15}$$

where B denotes the backward looking horizon.

We estimate separately for $h \in \{-B \dots -1\}$ and $h \in \{1 \dots H\}$ thereby allowing for a break in both levels and gradients when the rating event happens. Since the rating might occur any time during the day t , we exclude t completely from the analysis.

Forecast horizon and spacing We run models with forecast horizons of 1 to 60 days, to assess the short run impact, and 1 to 26 weeks to assess the medium term impact of ratings. To keep the model computationally feasible we only compute forecasts with a weekly spacing for the latter model, although the model is still estimated using daily data. To capture the immediate impact as precisely as possible given our data, the first weekly forecast is made for the day immediately after the rating. That is, the 60 day model is based on $h \in \{1, \dots 60\}$ while the 26 week model is based on $h \in \{1, 8, 15, \dots 176\}$.

For the EES we use a pre event window that exactly mirrors the forecast window.

4.2 Data

Our sample covers the OECD countries from January 1980 to December 2010, where the OECD stopped reporting data on government debt for its members. Since some of our data – in particular the aforementioned data on government debt that is collected by the OECD – is only available after a country joined the OECD, the panel is unbalanced.

Yields The interest rate we use is the yield on government bonds with a 5 year maturity denominated in domestic currency as reported in DataStream.

This is in stark contrast to the previous literature, that usually used some kind of interest rate spread. One reason of course is to avoid importing global movements of the interest rate into the model. More importantly, the choice of the interest rate was more restricted due to the event study technique commonly used for the dynamic analysis of sovereign ratings. To have a meaningful economic interpretation, event studies require a benchmark. This is why the bulk of the literature attempted to measure the risk premium directly, thereby having a zero risk premium as the natural benchmark case.

The early literature (e.g. Cantor and Packer (1996)) therefore used the spread over US treasuries, which restricts them to US dollar denominated debt. Since advanced economies issue the vast majority of their

debt in domestic currency, and have done so throughout our entire sample (see Abbas et al. (2014)), this approach is unfeasible for a sample of OECD countries.

An obvious alternative that became more popular recently are CDS spreads. Yet, being invented in the early 1990s and becoming popular roughly a decade later, this would greatly reduce our sample size.

Since the benchmark is provided by the model forecast with no shock, our approach allows more flexibility with the choice of the indicator used to determine interest rate effects. By including time fixed effects, we still account for global interest rate fluctuations. Therefore, as long as we assume that ratings have no major impact on inflation within the horizon of the impulse response (which would cause a deviation between the real and nominal response), we can use the nominal interest rate for domestic currency rather than restricting our sample or using the less relevant segment of foreign denominated debt.

Ratings Matching our interest rate data, we use rating data that is based on the creditor ratings for long term debt denominated in domestic currency issued by the major three rating agencies, Moody's, Standard and Poors (S&P) and Fitch.

To measure ratings we use the arithmetic mean of the standard numerical conversion of ratings to a scale from 1 to 24 that assumes equidistant rating classes (see Table 1).

Since our sample is focused on advanced economies and does not cover the bulk of the European debt crisis, the worst ranking we observe is 12.33, i.e. rating agencies disagreeing between BB- and BB, in Greece in the late 1990s and Turkey for parts of the year 2005. The median rating is 23.67 with ratings of AAA accounting for 49.5% of our sample.

We merely observe 96 rating actions, 43 of them being upgrades, 53 being downgrades. In 33 of the upgrades and 39 of the downgrades, i.e. the vast majority of events, only a single rating agency adjusted the rating. 7 out of 26 countries in our sample do not experience any rating adjustment in our sample period.

If we take the idea of downward spirals of downgrades and capital flights triggered by an initial rating action serious, only the first rating action in such a sequence would be a shock, whereas the later rating actions (despite being uncertain in their precise timing) and their effect should be considered part of the impulse response. We account for distortions created by sequential rating actions in one country in two ways.

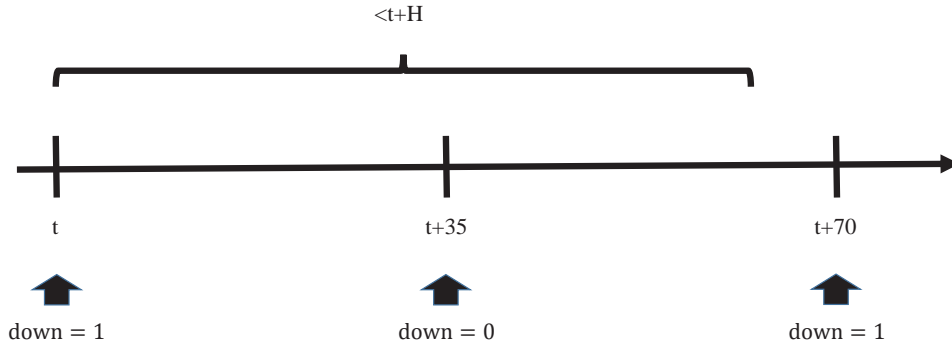
Our first approach to account for sequential ratings is to remove rating events that happen within a quarantine window in the same country after an initial rating upgrade or downgrade. After this window expires, rating actions are considered as shocks again, whether or not further rating actions (that are not considered as shocks) occurred during the quarantine window. If we set the window to 60 days we are left with both 38 upgrades and 38 downgrades that are considered shocks. If we account for sequential downgrades more strictly, and only count the first rating action in a sequence of rating actions with a distance of 60 days or less between ratings we lose two more upgrades and two more downgrades. Figure 1 visualizes both of those approaches using the example of three sequential downgrades with a spacing of 35 days.

The results for both methods are qualitatively identical. The estimates reported in the main body of the paper use the stricter version depicted in Figure 1b.

Table 1: Rating grades and transformation

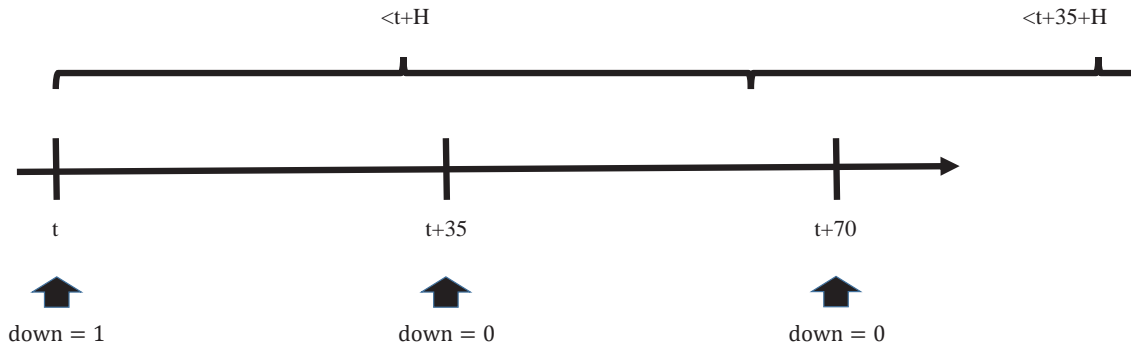
Grade	Moody's	S&P	Fitch	Assigned Value
Prime	Aaa	AAA	AAA	24
High grade	Aa1	AA+	AA+	23
	Aa2	AA	AA	22
	Aa3	AA-	AA-	21
Upper medium grade	A1	A+	A+	20
	A2	A	A	19
	A3	A-	A-	18
Lower medium grade	Baa1	BBB+	BBB+	17
	Baa2	BBB	BBB	16
	Baa3	BBB-	BBB-	15
Non-investment grade speculative	Ba1	BB+	BB+	14
	Ba2	BB	BB	13
	Ba3	BB-	BB-	12
Highly speculative	B1	B+	B+	11
	B2	B	B	10
	B3	B-	B-	9
Substantial risks	Caa1	CCC+	CCC+	8
Extremely speculative	Caa2	CCC	CCC	7
	Caa3	CCC-	CCC-	6
In default with little prospect for recovery	Ca	CC	CC	5
		C	C	4
In default	C	D	DDD	3
			DD	2
			D	1

Source: This conversion table is reproduced from El-Shagi and von Schweinitz (2015b) but can be found in similar form in a large number of other papers.



Note: In this version of the estimation, we remove all ratings within a certain window after the initial rating (usually the maximum horizon H). Any occurrence of further ratings after this quarantine window is considered a rating and starts a new quarantine window.

(a) Basic sequence removal



Note: In this version of the estimation, we remove all ratings within a certain window after the initial rating and the length of the quarantine window (where ratings are not considered as shocks) is reset to its original length after a new rating. That is, only the first rating action in an arbitrarily long sequence of ratings would be considered a shock, if the pairwise distance between adjacent actions does not exceed the quarantine window. Since this is fairly restrictive, we only apply the window length used in our short term impulse response analysis which is 60 days.

(b) Strict sequence removal

Figure 1: Accounting for sequential ratings

Debt We use debt data as reported by the OECD. The OECD stopped reporting data on government debt during the first heated period of the European debt crisis. Thus, the data is only available until the end of 2010, which restricts our sample to this period. Debt is measured as share of central government debt over GDP. The data is only available in annual frequency. However, due its high persistence and the fact that we

are mostly interested in the interaction with rating changes (since level effects are mostly captured by the fixed effects) this is of little consequence. We use a cubic interpolation to smooth over time, mostly to avoid the artificial introduction of sharp breaks into the series, that would distort the covariance structure.

4.3 Scenarios

We assess the IRFs separately for upgrades and downgrades for a range of different starting conditions in terms of the previous level of rating and debt.

In addition to evaluating the IRFS for upgrades and downgrades at the median, we also consider a *good* scenario depicting a well rated, little indebted country, and a *bad* scenario where a badly rated and highly indebted country faces a rating shock. To account for the potential endogeneity of ratings (even if they are the first in a sequence), we also assess downgrades for the median rating and debt of those observations where we actually observe downgrades in our sample. Finally we consider a scenario that we dub *overrated* where a well rated but highly indebted country faces a rating downgrade. Although the data we have does not cover situations as critical as those faced during the European debt crisis, this is essentially simulating a similar type of problem.

Since upgrades are not possible starting from an AAA rating, the good scenario for upgrades starts at the median rating of 23.67 rather than above. Table 2 summarizes the levels of rating and debt used in our scenarios. The scenario labeling follows the convention of <direction of rating change> @ <conditions>.

Label	Δ Rating	Debt	Rating
Up@Median	+	47%	23.67
Up@Good	+	21%	23.67
Up@Bad	+	98%	17.33
Down@Median	-	47%	23.67
Down@Good	-	21%	24.00
Down@Bad	-	98%	17.33
Down@Overrated	-	98%	24.00
Down@Typical	-	62%	20.00

Note: The scenario labeling follows the convention of <direction of rating change> @ <conditions>. Since the observations differ marginally between estimations using different maximum horizons, the actual level of debt differs slightly between the estimations using a maximum horizon of 26 weeks and the estimations using a maximum horizon of 60 days. This is why we report representative rounded values for all scenarios in the table. *Good* refers to low debt good rating, *Bad* correspondingly refers to high debt, low rating. *Median* refers to the full sample median values for both debt and rating. *Typical* refers to the median for the subsample where downgrades are observed, and *Overrated* refers to high debt good rating situations.

Table 2: Summary of the scenario parameters

5 Results

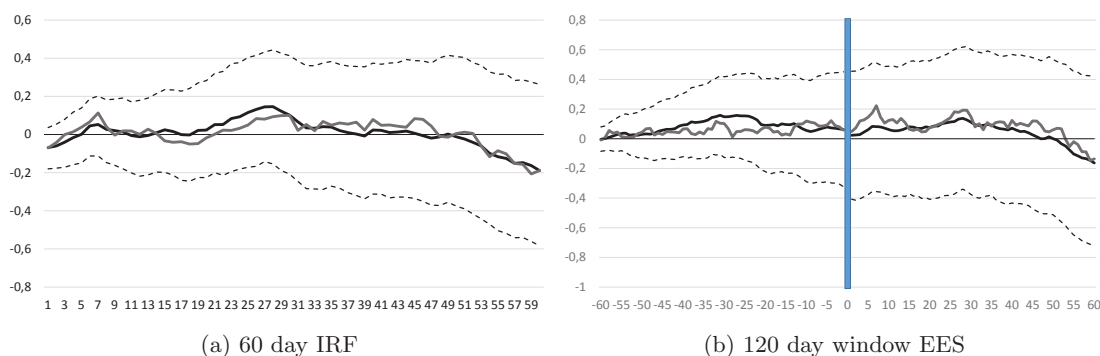
For ease of exposition our results section will focus on the scenarios Up@Median, Down@Median, Down@Overrated and Down@Typical. We find that the nonlinearities are of little consequence with respect to the upgrades.

Concerning downgrades the results for the *Good* and *Median* scenarios are qualitatively similar, as are the *Bad* and *Typical* scenarios.

All figures report the unrestricted estimate of the IRF or EES for comparison. Recall that the system is estimated as a whole, so the smoothness restriction can (and will) slightly change other coefficients. Thus, in particular if the effect of a rating shock is small and insignificant, it can happen that the “smooth” IRF or EES seems to be markedly different rather than a smooth version of the unrestricted function. Yet, the key interpretation in this case usually is, that there is no or merely a small effect at this particular horizon. In every case where there is a significant and economically meaningful effect, the key dynamics of the restricted IRF follow the direction of the unrestricted estimate, but omit the high volatility that is driven by the lack of observations and the correspondingly high influence of individual observations.

5.1 Impulse response functions

Rating upgrades Our results strongly support the importance of modeling asymmetric responses to rating up- and downgrades. We find very little statistically significant impact of rating upgrades on yields, neither when evaluating the impulse response at the median, nor in any other scenario.



Note: The smoothed estimate of the IRF or EES is shown as a bold black line with the dashed line representing the corresponding confidence bounds. For comparison the unrestricted estimate is given as a gray line. The blue shaded area is the day of the rating.

Figure 2: The short run effect of rating upgrades evaluated at the median

Figure 2 shows both the 60 day impulse response functions (2a) and the extended event study (2b) following a rating upgrade evaluated at the median (for debt and rating levels). Generally the event study shows results similar to the forecast. We neither observe significant interest rate movements before a rating announcement nor after. This might reflect that upgrades usually happen when the market has acknowledged the higher creditworthiness of a country for quite a while. A potential reduction in the interest rate would thus have happened in the further past, rather than occur in the vicinity of a rating upgrade. This is in line with the frequently voiced concern that rating agencies might be particularly conservative when it comes to upgrades.

Rating downgrades Things look markedly different for rating downgrades. Figure 3 compares the IRFs for downgrades for the short run (using daily forecasts up to a maximum forecast horizon H of 60 days) and the medium term (using weekly forecasts up to a maximum horizon of 176 days). Apart from giving more details due to its daily frequency of forecasts, the short term IRFs differ due to the implicit difference in the definition of a rating shock. As outlined in more detail in the data section, we only consider downgrades that are not preceded by another rating event in the past H days, causing a slightly different selection of events to be included. This causes minor differences in the results of the unrestricted estimate for identical horizons. However, qualitatively and in terms of the order of magnitude the results are robust.

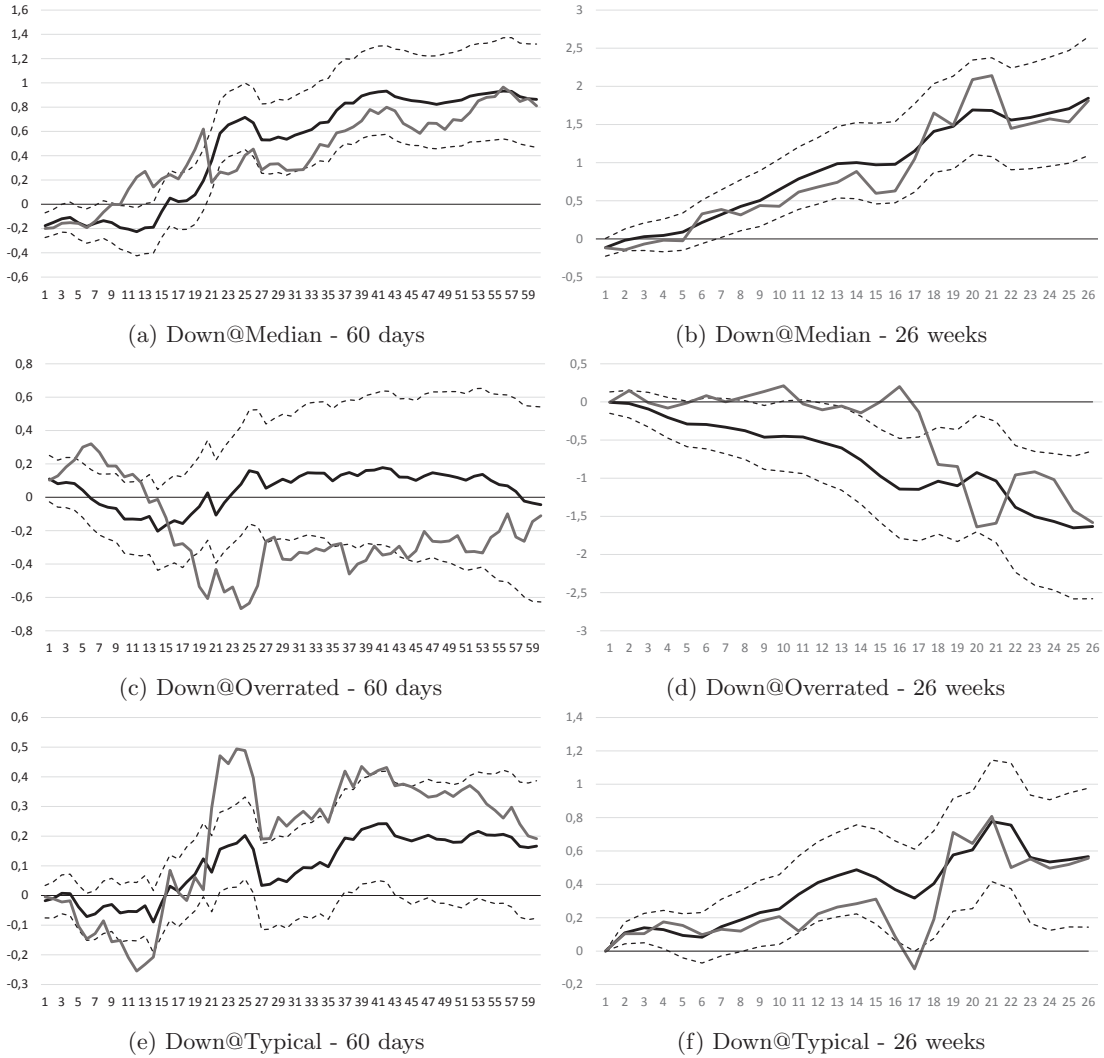
There is no substantial immediate impact of rating changes on the interest rate, indicating that the rating is not considered to be major news by the financial market. However, at the median the difference between a country facing a downgrade and a similar economy with a stable rating is clearly visible at a longer horizon. In the unrestricted estimation, we observe some sharp up and downturns. However, those seem to overinterpret the sparse evidence due to the overparameterization of the unrestricted model, and disappear almost completely in the preferred restricted specification. What remains is a fairly stable increase that has not come to a halt at our maximum forecast horizon. Over time the interest rate increases quite considerable and significantly, reaching a premium of more than 200 basis points after half a year. Compared to the standard deviation of 1.2 percentage points of the interest rate after being adjusted for country and time specific effects, this is a fairly sizable increase. Yet, it is far below the order of magnitude that is troubling in the sense of driving a country into a crisis or even default as hypothesized by some critics of rating agencies. This is in line with the previous findings of El-Shagi and von Schweinitz (2015a) who find a moderately sized impact of ratings while ratings are B or better, as they are in our complete sample of industrialized economies.

Most interestingly, the effect becomes markedly smaller for countries that typically have to face a rating downgrade, and it completely disappears and even reverses for countries that – when looking at government debt – seem to be rated overly optimistic.

One possible interpretation of the *Typical* scenario is a situation where rating changes are quite common and thus easily foreseen. Thus, it is barely surprising that the actual event – the rating adjustment – is less consequential than rating actions in situations where they are more surprising.

The negative impact of ratings on yields in the *Overrated* scenario is more troubling, with respect to the quality of ratings. If we believe that the market is not completely oblivious of risk (which is of course one possible, albeit unlikely, interpretation of this finding) it seems as if unjustified ratings are particularly persistent to an extent where the rating changes after the problems already started. In other words, unless we believe that high debt countries do not pay a risk premium at all, the decline of the interest rate after the rating indicates that the rating changes after the risk premium has peaked.

While this is in stark contrast to the idea that downgrades in troubled countries create a downward spiral of worsening ratings, capital flight and rising risk premia, it reflects extremely badly on the validity of sovereign ratings.

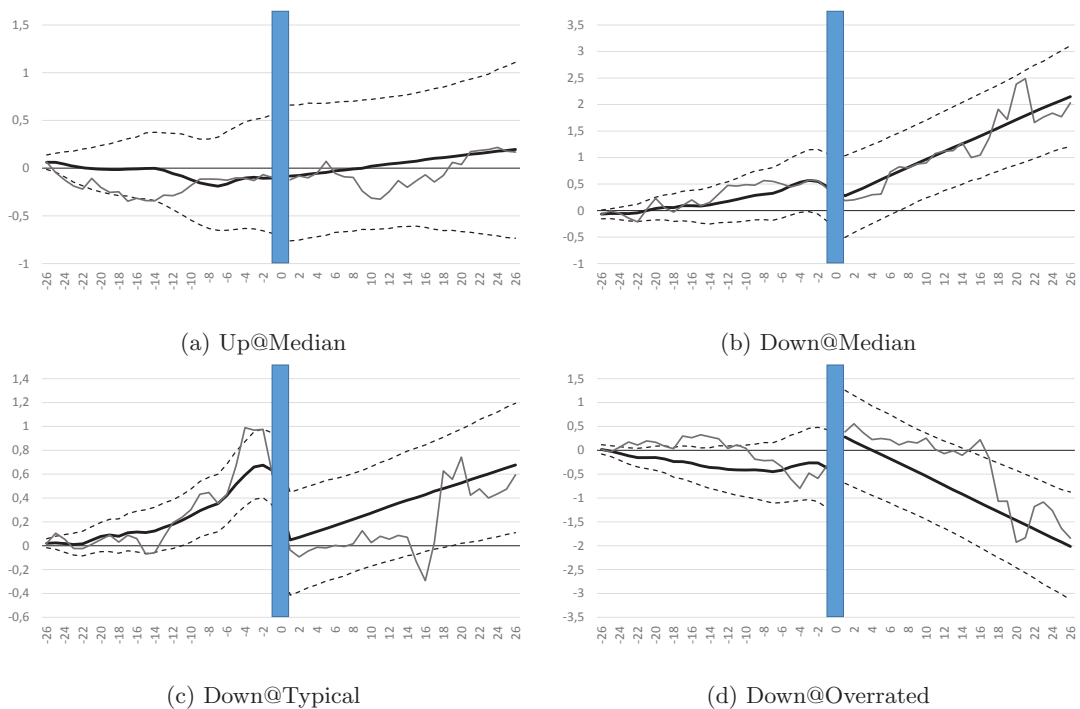


Note: The smoothed estimate of the IRS is shown as a bold black line with the dashed line representing the corresponding confidence bounds. For comparison the unrestricted estimate is given as a gray line. The blue shaded area is the day of the rating.

Figure 3: Impulse response functions for downgrades

5.2 Extended event studies

Our event studies confirm the general picture derived from the forecasts. Figure 4 summarizes the EES with a 26 week window before and after the rating action. Even when considering half a year we find no unusual interest rate movements prior to or after an upgrade, reinforcing our finding of extremely conservative behavior with respect to rating upgrades.



Note: The smoothed estimate of the EES is shown as a bold black line with the dashed line representing the corresponding confidence bounds. For comparison the unrestricted estimate is given as a gray line. The blue shaded area is the day of the rating.

Figure 4: 26 week EES

Rating downgrades seem to occur during a general upward movement of the interest rate, i.e. most likely the risk premium, that is briefly interrupted right before the rating. A causality going from an expected downgrade to an interest rate decrease (as seen right before the rating hits) seems unlikely, in particular since we find that the economy returns to its path of increasing interest rates right after the rating. Potentially, this – very moderate – decline in the interest rate is rather due to strategic timing on the side of the rating agencies. Since there has been fairly harsh criticism stating that rating agencies reinforce downward trends, the rating agencies might pick calm periods to reevaluate OECD countries.

While the decline seems harsher when looking at the *Down@Typical* scenario, this impression is basically an illusion created by scale. The decline in the interest rate prior to a rating action is very minor. What does differ, is the increase in the interest rate after the rating, which is much smaller in this scenario. This again points into the direction that downgrades that can easily be foreseen are of little consequence to the market.

With respect to downgrades in *Overrated* countries, we confirm our previous suspicion that the agencies essentially adjust grossly wrong ratings not before the problems peak. We find literally no indication of meaningful interest rate movements before the rating takes place, but the interest rate slowly declines after.

Again, unless we believe that there is no risk premium in the first place, this indicates that rating agencies respond when the risk premium has stabilized at its peak. There is a minor interest rate jump upwards between the day before and the day after the rating. While this movement is insignificant, it leaves some room to the interpretation that the markets consider the possibility that ratings are indeed news and initially react correspondingly. However, besides its insignificance, the estimated increase in the interest rate is fairly small and very short lived.

5.3 Robustness

Considering every rating action By considering sequential rating actions as a single event by only considering the first up- or downgrade, we implicitly assume that rating actions happening in quick succession after an initial shock are part of the original impulse response rather than new shocks. As a robustness check, we consider every single rating action instead, without respect to their relative timing. The results are similar in terms of both shape of the IRF and magnitude of the effects.

Considering only countries that experienced rating actions Some countries did not experience a single rating event during our entire sample. It is possible that those highly stable countries are structurally different from countries that have been subject to rating changes, to an extent where the dynamic properties of the interest rate can no longer be considered comparable to the dynamics of the interest rate in other countries, even at times when those other countries are not subject to a rating event. We therefore reestimate the model only including countries that experienced at least one rating event during our sample. Again, the results are similar in terms of the shape of the IRF and the magnitude of the observed effects.

6 Conclusions

At least for OECD countries, our results strongly indicate that the importance of rating agencies is hugely overestimated by some of their staunchest critics. While interest rates do move around a rating, we find that the impact is limited in magnitude and a causality can not clearly be established, given that interest movements start clearly before the rating. Even in those cases where we find rising interest rates following rating downgrades, the magnitudes we find are far from the ones that we would expect to see, if there truly were downward spirals triggered by those downgrades. Most importantly, in the critical case of countries, that are unusually well rated compared to their debt situation, we find no evidence for a role of rating agencies, but ratings being adjusted when the problems have already peaked. While this does merit a substantial criticism of rating agencies concerning the lack of information they actually provide to the market, it does not support claims of vicious cycles driven by rating agencies.

References

- Abbas, S. A., Laura, B., Mark, d. B., Asmaa, E.-G., Malin, H., 2014. Sovereign Debt Composition in Advanced Economies: A Historical Perspective. IMF Working Papers.
- Afonso, A., Furceri, D., Gomes, P., 2012. Sovereign Credit Ratings and Financial Markets Linkages: Application to European Data. *Journal of International Money and Finance* 31 (3), 606–638.
- Amstad, M., Packer, F., 2015. Sovereign ratings of advanced and emerging economies after the crisis. *BIS Quarterly Review* December.
- Arezki, R., Candelon, B., Sy, A. N. R., 2011. Sovereign Rating News and Financial Markets Spillovers: Evidence from the European Debt Crisis. IMF working papers, 1–27.
- Bolton, P., Freixas, X., Shapiro, J., 2012. The Credit Ratings Game. *The Journal of Finance* 67 (1), 85–111.
- Breitung, J., Roling, C., 2015. Forecasting Inflation Rates Using Daily Data: A Nonparametric MIDAS Approach. *Journal of Forecasting*.
- Brooks, R., Faff, R. W., Hillier, D., Hillier, J., 2004. The National Market Impact of Sovereign Rating Changes. *Journal of Banking & Finance* 28 (1), 233–250.
- Cantor, R., Packer, F., 1996. Determinants and Impact of Sovereign Credit Ratings. *The Journal of Fixed Income* 6 (3), 76–91.
- De Santis, R. A., 2012. The Euro Area Sovereign Debt Crisis: Safe Haven, Credit Rating Agencies and the Spread of the Fever from Greece, Ireland and Portugal.
- El-Shagi, M., 2010. The Role of Rating Agencies in Financial Crises: Event Studies from the Asian Flu. *Cambridge Journal of Economics* 34 (4), 671–685.
- El-Shagi, M., von Schweinitz, G., 2015a. Risk and Return: Is there an Unholy Cycle of Ratings and Yields? *Economics Letters* 129, 49–51.
- El-Shagi, M., von Schweinitz, G., 2015b. The Joint Dynamics of Sovereign Ratings and Government Bond Yields. Tech. rep., IWH-Diskussionspapiere.
- Engle, R. F., Granger, C. W., 1987. Co-Integration and Error Correction: Representation, Estimation, and Testing. *Econometrica*, 251–276.
- Ferreira, M. A., Gama, P. M., 2007. Does Sovereign Debt Ratings News Spill over to International Stock Markets? *Journal of Banking & Finance* 31 (10), 3162–3182.
- Ferri, G., Liu, L.-G., Stiglitz, J. E., 1999. The Procyclical Role of Rating Agencies: Evidence from the East Asian Crisis. *Economic Notes* 28 (3), 335–355.

- Gärtner, M., Griesbach, B., et al., 2012. Rating Agencies, Self-Fulfilling Prophecy and Multiple Equilibria?: An Empirical Model of the European Sovereign Debt Crisis 2009-2011. School of Economics and Political Science, Department of Economics, University of St. Gallen.
- Ghysels, E., Santa-Clara, P., Valkanov, R., 2002. The MIDAS Touch: Mixed Data Sampling Regression Models. Tech. rep., Anderson Graduate School of Management, UCLA.
- Ghysels, E., Santa-Clara, P., Valkanov, R., 2006. Predicting Volatility: Getting the Most out of Return Data Sampled at Different Frequencies. *Journal of Econometrics* 131 (1), 59–95.
- Goh, J. C., Ederington, L. H., 1993. Is a Bond Rating Downgrade Bad News, Good News, or No News for Stockholders? *The Journal of Finance* 48 (5), 2001–2008.
- Griffin, P. A., Sanvicente, A. Z., 1982. Common Stock Returns and Rating Changes: A Methodological Comparison. *The Journal of Finance* 37 (1), 103–119.
- Hand, J. R., Holthausen, R. W., Leftwich, R. W., 1992. The Effect of Bond Rating Agency Announcements on Bond and Stock Prices. *The Journal of Finance* 47 (2), 733–752.
- Holthausen, R. W., Leftwich, R. W., 1986. The Effect of Bond Rating Changes on Common Stock Prices. *Journal of Financial Economics* 17 (1), 57–89.
- Ismailescu, I., Kazemi, H., 2010. The Reaction of Emerging Market Credit Default Swap Spreads to Sovereign Credit Rating Changes. *Journal of Banking & Finance* 34 (12), 2861–2873.
- Jordà, Ò., 2005. Estimation and Inference of Impulse Responses by Local Projections. *American Economic Review*, 161–182.
- Jordà, Ò., 2009. Simultaneous Confidence Regions for Impulse Responses. *The Review of Economics and Statistics* 91 (3), 629–647.
- Kaminsky, G., Schmukler, S. L., 2002. Emerging Market Instability: Do Sovereign Ratings Affect Country Risk and Stock Returns? *The World Bank Economic Review* 16 (2), 171–195.
- Mora, N., 2006. Sovereign Credit Ratings: Guilty beyond Reasonable Doubt? *Journal of Banking & Finance* 30 (7), 2041–2062.
- Reisen, H., Von Maltzan, J., 1999. Boom and Bust and Sovereign Ratings. *International Finance* 2 (2), 273–293.
- West, R. R., 1973. Bond Ratings, Bond Yields and Financial Regulation: Some Findings. *Journal of Law and Economics* 16 (1), 159–168.

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