Fiscal Uncertainty
and
Sovereign Credit Risk

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Abstract

This doctoral thesis studies sovereign credit risk during periods of uncertainty about the state of a government's fiscal position. A new measure of fiscal uncertainty is introduced, based on the disagreement in official forecasts of the public budget deficit, and forecast revisions to approximate common uncertainty shocks. It is shown that in the aftermath of the global financial crisis, fiscal uncertainty increased substantially in advanced economies. The effects of fiscal uncertainty are largely unknown, in particular in the context of sovereign credit risk. To estimate the response of sovereign credit ratings to fiscal uncertainty, a new empirical framework is developed for the analysis of rating determinants. Rating transition is modelled as the joint outcome of two processes, which determine the frequency of rating changes, and their direction. This thesis finds that fiscal uncertainty is perceived a credit risk by rating agencies and increases the probability of a rating downgrade. Fiscal uncertainty also affects the attention paid to sovereign ratings. An event study analysis shows that the attention to rating announcements increases, the more noisy publicly available information about fiscal outcomes is.

JEL Classification: C35, G14, G24, H68

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

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Contents

List of Tables

List of Figures

Chapter 1

Introduction

Until 2007, advanced economies enjoyed a period that came to be known as the 'Great Moderation'. It was characterised by historically low levels of business cycle volatility (Blanchard and Simon, 2001), independent central banks ensured that inflation remained limited and output close to its potential level (Bernanke, 2012), while governments saw their responsibility mainly in supply-side policy measures, in the provision of automatic stabilisers (Taylor, 2000) and in balancing public budgets (Woodford, 2001). The global financial crisis was a turning point in many respects. The shock that emanated from the sub-prime loan market in the United States had repercussions around the globe. As it came largely unexpected, it raised uncertainty levels immensely – uncertainty about the stability of the financial system, uncertainty about consequences for the real economy, and largely also uncertainty about government policy. To counterbalance the abrupt dry-up of credit, fall in output and rise in unemployment, central banks reverted to unconventional monetary policy measures such as sharp reductions in policy rates, emergency provisions of liquidity and large-scale asset purchase programmes. Yet, as monetary policy became constrained by the effective lower bound on interest rates, fiscal policy had to step in (Blanchard et al., 2010). For instance, the President of the European Central Bank stressed on several occasions that "monetary policy cannot be the only game in town" (Draghi, 2016). However, banking sector bailouts and Keynesian instruments to stabilise output and labour markets weighed heavily on public finances. Sovereign credit risk, which previously had been perceived a problem solely of the developing world, rose substantially in the euro area to a point that the future of the currency union would be questioned. Financial assistance was provided to Greece, Ireland, Portugal, Cyprus and Spain by the European Union and the International Monetary Fund. To safeguard the European Monetary Union, the European Financial Stability Facility and the European Stability Mechanism were established in 2010 and 2012. Elevated debt and deficit positions reinforced calls for fiscal consolidation also in other advanced economies, including the United States and the United Kingdom (e.g. OECD, 2012). However, to implement consolidation measures the political climate proved not very conducive as partisan tensions worsened and non-mainstream political movements gained support, which further contributed to uncertainty.

Consequently, three themes that are central to this thesis – economic uncertainty, the active role of fiscal policy, and sovereign credit risk – attracted the attention of policy-makers, as well as the academic literature. Most work addresses these themes separately. For example, a number of studies, some of which are reviewed in Bloom (2014), tries to measure uncertainty about microeconomic and macroeconomic outcomes and study its effect on the behaviour of economic agents. In the area of fiscal policy, the effectiveness of fiscal measures during recessions (Canzoneri et al., 2016), at the lower bound of interest rates (Correia et al., 2013) and when transmitted across countries (Auerbach and Gorodnichenko, 2013), entered the limelight of the analysis. Fairly independent of both these strands, an empirical literature started to focus on the pricing of fiscal and macroeconomic fundamentals into sovereign credit risk premia on financial markets during sovereign debt crises (Bernoth and Erdogan, 2012), as banking sector risk increases (Acharya et al., 2014), or under the expectation of bailouts (Beck et al., 2017). By contrast, this doctoral thesis is an attempt to provide a *combined* account of uncertainty around the conduct of fiscal policy in advanced economies, and the potential effects of fiscal uncertainty on sovereign credit risk.

Understanding the economic effects of uncertainty requires a coherent approximation. This holds for uncertainty about the macroeconomy, about economic policy and about financial market outcomes. It holds importantly also for uncertainty about fiscal outcomes. Chapter 2 is therefore concerned with a systematic way of measuring fiscal uncertainty in advanced economies. From a theoretical perspective, fiscal uncertainty arises from the fact that fiscal instruments follow stochastic processes (e.g. Sialm, 2006, Born and Pfeifer, 2014, and Fernández-Villaverde et al., 2015), because agents are unaware of the costs of different policy options (Pástor and Veronesi, 2013), or because of uncertain expectations about future fiscal consolidations (e.g. Davig et al., 2010, and Bi et al., 2013). How to empirically capture fiscal uncertainty is far less clear. The recent debate about economic implications of uncertainty brought about a range of new measures of macroeconomic uncertainty. For instance, Jurado et al. (2015) exploit the degree of predictability of macroeconomic series while Orlik and Veldkamp (2014) provide a measure associated with the uncertainty about the forecasting model. On one hand, these uncertainty proxies are more closely in line with the theoretical notion of stochastic economic processes than measures based on observed volatility, which are often employed to gauge uncertainty on financial markets, such as the volatility index VIX. On the other hand, these indices are not directly observable and require data about different forecasters' probabilities or utilise complex modelling approaches. This makes them difficult to apply in the context of fiscal policy. By contrast, a popular measure of economic policy uncertainty by Baker et al. (2016) is directly observable but often reflects news about policy rather than uncertainty about fiscal outcomes. Chapter 2 discusses the shortcomings of existing economic uncertainty proxies for an application to fiscal policy in more detail.

The chapter proceeds with the construction of a new fiscal uncertainty index based on the disagreement in official forecasts of the fiscal deficit and common uncertainty shocks faced by forecasters. The index builds on the method Lahiri and Sheng (2010) propose for the measurement of macroeconomic uncertainty. Important adjustments are made to apply this index to fiscal data, forecasts of which are available only at a low frequency from a small number of forecasters and with limited comparability across countries. Given that fiscal forecasters are often overly optimistic about governments' budgets, I clean fiscal forecast data from predictable biases. Another innovation proposed in the chapter, that is applied to the Lahiri and Sheng (2010) approach for fiscal variables, is the measurement of common uncertainty shocks using unexpected forecast revisions. As discussed in Cimadomo (2016), the deficit is a key variable which is often used to evaluate the sustainability of fiscal policy, given that, all else equal, an accumulation of fiscal deficits over time increases the stock of sovereign debt. In addition, forecasts of the deficit contain information about expected policy changes in the near future as well as expectations about governments' attempts to consolidate their budgets. This links the empirical measure of fiscal uncertainty to the theoretical concept of stochastic fiscal instruments and uncertainty about the public budget constraint. The resulting index is straightforward to construct, observable in real time and available for a set of 31 advanced economies. Its evolution over time confirms that the financial crisis brought about a sizeable rise of fiscal uncertainty.

A second part of chapter 2 then links the new index of fiscal uncertainty to a number of potential determinants. The existing literature comes to the conclusion that errors made by fiscal forecasters can be explained by the degree of fiscal policy discretion, and the extent to which the institutional framework constrains policy-makers (e.g. Jonung and Larch, 2006, von Hagen, 2010, Pina and Venes, 2011, de Castro et al., 2013). Yet fiscal forecast errors may also reflect unanticipated changes in the policy environment and politically motivated biases (Artis and Marcellino, 2001 and Merola and Pérez, 2013). The new index provides a more direct measure of the degree of fiscal uncertainty that prevails at the time a fiscal forecast is published. In chapter 2, I analyse the extent to which it can be linked to underlying factors usually associated with uncertainty about fiscal policy in the near term. This serves as a cross-check of how accurately the index captures fiscal uncertainty. Linking the index to possible determinants can also inform policy-makers about ways to potentially reduce fiscal uncertainty. I find that fiscal uncertainty increases during downturns, as risks in the financial sector heighten and before elections, i.e. at times when fiscal policy becomes less predictable. Fiscal uncertainty remains subdued, however, when fiscal policy-makers face budgetary constraints. This distinguishes the index from other measures of uncertainty, like financial market volatility or economic policy uncertainty, which appear to capture investor sentiment or ambiguity about economic policy-making more than uncertainty about fiscal outcomes. The near-term nature of the index also distinguishes it from notions of longer-term uncertainty about the sustainability of public finances.

Chapter 3 turns to the implications of fiscal uncertainty. Given that the newly constructed index points to a sizeable increase during the financial crisis and its aftermath, one could expect non-negligible effects on the economy and the behaviour of economic agents. Bloom (2014) shows that economic uncertainty, generally defined, can have negative effects on output growth, investment and hiring. This is because economic agents delay economic decisions if they are uncertain about economic developments in the near term. In the context of fiscal policy more specifically, Fernández-Villaverde et al. (2015) find that uncertainty reduces economic activity. This is attributed to an endogenous increase in mark-ups. Julio and Yook (2012) and Julio and Yook (2016) conclude that uncertainty during election years can negatively affect domestic as well as foreign direct investment. Furthermore, fiscal uncertainty can compromise the effectiveness of fiscal policy. For instance, uncertainty about the timing and composition of a fiscal consolidation seems to determine whether such a consolidation is expansionary, or not (Bi et al., 2013), while noisy communication of fiscal policy blurs agents' expectations and can reduce fiscal multipliers (Ricco et al., 2016). A reduction in real activity and mitigated government effectiveness would need to be priced in by financial market participants. Theoretical work by Sialm (2006) and Pástor and Veronesi (2013) suggests that investors may require higher risk premia if tax policy becomes uncertain or governments fail to provide a 'put' protection to the market. Taken together, adverse macroeconomic effects, reduced effectiveness of fiscal policy and elevated risk premia on financial markets imply that fiscal uncertainty may also translate into sovereign credit risk.

The effect of fiscal uncertainty on market measures of government credit risk is an area that has so far not received the attention it deserves. While uncertainty about debt sustainability in euro area member states accompanied the substantial increase in bond premia during the European sovereign debt crisis of 2010 to 2012 and political divisions in the United States regarding the government's fiscal consolidation triggered the first-ever sovereign rating downgrade in 2011 (Standard and Poor's, 2011a), the empirical evidence for a link between country-specific fiscal uncertainty and sovereign credit risk is lacking. Chapter 3 tries to fill this gap. To do so, the chapter focuses on sovereign credit ratings. Ratings summarise the expert opinion of rating agencies about the capacity and willingness of governments to repay their debt. Rating scores are reported along an ordinal scale and revised on a regular basis. They are available for all major advanced economies and directly comparable across countries. This distinguishes them from opinions expressed by other experts or market prices of credit risk, such as risk premia on government bonds. Sovereign ratings appear to react to crises (Monfort and Mulder, 2000), world stock market volatility (Hill et al., 2010) and consumer sentiment (Schumacher, 2014). The direct effect of country-specific fiscal uncertainty, however, has not been analysed. Chapter 3 shows that fiscal uncertainty is perceived a credit risk by rating agencies. I find that the probability of a rating downgrade increases not only with a deterioration in the level of fiscal fundamentals but also due to second moment effects, i.e. uncertainty about these fundamentals. Rating agencies are frequently criticised for their failure to anticipate sovereign debt crises, and for reacting too late and too excessively with downgrades during such crises (Ferri et al., 1999, Mora, 2006, and Dimitrakopoulos and Kolossiatis, 2016). Using a model-based sovereign credit risk measure as an alternative to official credit ratings, Polito and Wickens (2014) and Polito and Wickens (2015) find that sovereign ratings of the United States and several European economies should have been downgraded much earlier during the recent crisis. However, the reasons for these deviations of ratings from fundamentals related to credit risk remain unclear. Chapter 3 comes to the conclusion that fiscal uncertainty can explain some of this puzzle. As fiscal uncertainty increases at the height of crises, considering it as an additional driver of credit risk can make ratings appear to be pro-cyclical.

When estimating the effect of fiscal uncertainty, and other credit risk determinants, on the probability that the sovereign rating changes in a given period of time, one faces a number of challenges. Ratings of advanced economies hardly change over time, which makes it difficult to pin down rating determinants. In addition, a large number of countries receive ratings in investment grade categories. This only changed during the sovereign debt crisis in the euro area when a number of countries saw their ratings being reduced to below-investment grade status. From an empirical point of view this means that some categories of the ordinal rating scale are rarely observed. Finally, because the rating scale is not without boundary, standard estimation approaches can yield misleading results. Chapter 3 shows that common approaches used by the empirical literature on rating determinants, like Ordered Probit estimation (e.g. Afonso et al., 2011, Hill et al., 2010), can yield biased estimates if the peculiar characteristics of sovereign rating data are not taken into account. To address these challenges, the chapter proposes a new empirical framework for the analysis of rating determinants. It builds on Harris and Zhao (2007) in modelling stability in ordered outcome estimations with an unobserved process that reduces the probability of some outcomes. The framework is adjusted to the context of sovereign rating migration where the outcome 'no change' in a given period is much more often observed than rating downgrades or upgrades. The new framework also accounts for the boundary of the rating scale, which affects the likelihood of upgrades and downgrades of ratings at the top and bottom end. Using this new framework allows me to evaluate the role of fiscal uncertainty in determining rating changes, alongside fiscal and macroeconomic fundamentals related to sovereign credit risk. In addition, the new framework enables me to assess whether rating agencies change their ratings more frequently during periods of elevated fiscal uncertainty than suggested by movements in sovereign credit risk, for example to gain attention.

Attention may be higher if fiscal uncertainty renders public information about fiscal fundamentals noisy and thereby increases the reliance on economic experts, such as credit rating agencies. Whether this is the case is the research question addressed in Chapter 4. Indirect evidence suggests that sovereign ratings gain more attention during crisis periods. Reisen and von Maltzan (1999) find that downgrades cause larger price movements on sovereign bond markets compared to upgrades while exchange rates respond more sharply to rating announcements when fiscal fundamentals are weak (Alsakka and ap Gwilym, 2012). Hill and Faff (2010) show that stock market reactions to sovereign rating announcements are more pronounced when global sentiment is high. Focussing on the European government debt crisis, Afonso et al. (2012) come to the conclusion that news about ratings of those countries that were most severely affected by the crisis had the largest impact on markets for sovereign credit default swaps, even in countries that were less affected. Yet the direct effect of country-specific fiscal uncertainty on the attention to rating news has not been explored.

In line with the literature, I employ an event study approach to estimate the impact of announcements made by credit rating agencies. Price movements on financial markets within a short window around the announcement are used as an indication of the attention paid to news, such as rating changes. Estimating the effect of fiscal uncertainty on short-term movements of financial market measures related to sovereign credit risk on announcement days allows me to test the hypothesis that investors pay more attention to ratings the noisier the public information about fiscal outcomes is. A common challenge faced by event studies of the effect of rating news on market prices is the fact that these news are often anticipated (Ismailescu and Kazemi, 2010) and spill over across countries (Gande and Parsley, 2005, Böninghausen and Zabel, 2015). This makes it difficult to pin down their direct response. To address this problem, the methodological innovation proposed in Chapter 4 is the use of online search volume data. It is shown that the number of search requests can identify more directly the country-specific and rating agency-specific attention effect, compared to market price data. It may also capture attention more timely and directly than prices if the efficient market hypothesis fails to hold (Da et al., 2011), for instance as sovereign debt markets deteriorate during crises.

This doctoral thesis therefore addresses three themes that gained importance since the end of the Great Moderation in 2007: a) the coherent measurement of uncertainty about fiscal outcomes, b) the effect of fiscal uncertainty on sovereign credit risk, and c) the attention paid to sovereign ratings as a result of fiscal uncertainty. Chapter 5 concludes the thesis by bringing together individual findings. It discusses policy implications, potential caveats and avenues for future research.

Chapter 2

The Rise of Fiscal Uncertainty

2.1 Introduction

In response to the rising interest of academics and policy-makers alike in the role of uncertainty after the Great Recession, a number of new proxies have been proposed to measure uncertainty in the economy and on financial markets. Despite increasing concerns about the conduct of fiscal policy and sovereign credit risk in advanced economies, however, there is little consensus about how to measure more directly uncertainty about future fiscal policy. This may partly be due to the lack of fiscal data sources which can be used to gauge the uncertainty faced by economic agents. For instance, the enormous number of financial instruments provides an opportunity to construct proxies for uncertainty on financial markets, while various surveys exist that inquire about professional forecasters' subjective expectations of future GDP growth, inflation and interest rates. By contrast, only a small number of forecasters assess fiscal outcomes. For example, for 20 advanced economies the data provider Consensus Economics gathers the opinions of different forecasters on GDP and consumer prices; yet only for a subset of 11 countries, government budget balance projections are reported, often for a much shorter time dimension. In addition, the conduct of fiscal policy depends on a range of different political stakeholders and complex institutional set-ups that vary widely across countries, making it harder to approximate fiscal uncertainty coherently. Given the less detailed news coverage of budgetary processes compared to changes to economic policy, news-based indices like the Economic Policy Uncertainty index by Baker et al. (2016) do not fully capture fiscal uncertainty either.

To fill this gap, I propose a new index based on uncertainty in forecasts of fiscal outcomes, namely the fiscal deficit. Expectations about the future level of the fiscal deficit incorporate considerations of different spending and revenue options as well as the likelihood of their implementation. These expectations therefore distill the complexities of fiscal policy in a meaningful way. Fiscal deficit data is also more widely available and better comparable across countries compared to other fiscal measures such as debt, spending or revenue figures. Building on the approach developed by Lahiri and Sheng (2010) for the measurement of macroeconomic uncertainty, I employ the disagreement in and revisions to current-year and year-ahead fiscal forecasts published by the OECD, IMF and European Commission. Disagreement across forecasters is used to measure idiosyncratic uncertainty about fiscal policy while revisions to the average (consensus) forecast serve as a proxy for common uncertainty shocks faced by forecasters. The resulting index measures uncertainty in near-term projections of future fiscal outcomes more directly than the Baker et al. (2016) EPU, or macroeconomic uncertainty indices (Orlik and Veldkamp, 2014, Jurado et al., 2015). The index is comparable across a set of advanced economies and computationally less demanding than proxies of fiscal policy volatility (e.g. Fernández-Villaverde et al., 2015). The fiscal uncertainty index covers the global financial and European sovereign debt crisis and captures uncertainty in real time. This gives it an advantage over *ex post* available forecast errors, or forecast error-based uncertainty proxies (e.g. Rossi and Sekhposyan, 2015). Its evolution over time suggests that fiscal uncertainty rose to striking levels during the financial crisis of 2008, after a decade in which fiscal policy had been relatively predictable. In the aftermath of the crisis, average fiscal uncertainty abated but the cross-sectional dispersion of the index measure remained high for a longer period.

The second part of the chapter proceeds with an analysis of possible drivers of fiscal uncertainty. Understanding the determinants of fiscal uncertainty can inform policy-makers about potential means to reduce this uncertainty given its negative effects on economic outcomes and sovereign credit risk – such as those explored in the following chapter. A better knowledge of the factors linked to the uncertainty faced by fiscal forecasters may also provide new insights for theoretical work on fiscal uncertainty.

The public finance literature often models uncertainty about fiscal policy as uncertainty about discretionary spending or revenue decisions. A commonly adopted approach is to let fiscal instruments follow stochastic processes, in simple models of economic growth (e.g. Dotsey, 1990), or a New Keynesian context (e.g. Sialm, 2006, Davig and Leeper, 2011, Born and Pfeifer, 2014, Fernández-Villaverde et al., 2015). In Pástor and Veronesi (2013), political uncertainty arises from the fact that agents do not know the costs attached to various policy options. This literature strand has in common an emphasis on fiscal uncertainty as the uncertainty about short-run discretionary fiscal policy. A second strand in the literature emphasises the role of uncertainty about fiscal policy in the longer run, which may arise out of concerns about the sustainability of public finances. Davig et al. (2010) analyse the effects of uncertainty about future adjustments of fiscal policy to accommodate unfunded liabilities under rational expectations when permanent debt rollover is not feasible and government revenue is limited. Uncertainty about future fiscal policy may also arise when fiscal consolidations become necessary as fiscal positions turn unsustainable (Bi et al., 2013). Given that fiscal uncertainty in this thesis is measured using uncertainty in forecasts of the current-year and year-ahead fiscal deficit, the focus lies on short-run rather than long-run fiscal uncertainty. However, uncertainty about fiscal policy discretion in the short-run and uncertainty about future fiscal adjustments to address debt sustainability concerns are closely intertwined. Fiscal policy measures in the short run may help stabilise the economy in response to exogenous shocks but increase uncertainty about future financing needs (Croce et al., 2012). *Vice versa*, if fiscal policy has already reached its limits in terms of sustainability, this constrains the scope for discretionary policy and may thereby alleviate uncertainty.

To shed light on the potential drivers of fiscal uncertainty, I regress the fiscal uncertainty index on a number of variables potentially related to uncertainty about fiscal policy in the near term as well as factors that tend to constrain fiscal policy. I find evidence for a strong link between elections and fiscal uncertainty and show that economic and financial crises are also associated with elevated levels of fiscal uncertainty. By contrast, (near-term) fiscal uncertainty is reduced, the more constrained fiscal policy is. This appears to be the case if fiscal fundamentals are severely deteriorated, leaving little room for additional fiscal manoeuvre. In other words: if uncertainty about the long-term sustainability of public finances is high. Likewise, if a country participates in an Economic Adjustment Programme, under which fiscal policy is monitored closely by international institutions, the uncertainty in fiscal forecasts is relatively low.

This chapter links to a literature on errors made in fiscal projections.[1] Fiscal forecast errors are attributed to economic downturns (Strauch et al., 2004; Jonung and Larch, 2006) and when fiscal rules become binding (von Hagen and Wolff, 2006). Institutions like the IMF, OECD or European Commission seem to be able to reduce forecast errors (Artis and Marcellino, 2001) but cannot eliminate them fully (Merola and Pérez, 2013). Strict fiscal rules and contract-based fiscal governance, on the other hand, lead to smaller fiscal forecast errors (von Hagen, 2010, Pina and Venes, 2011, de Castro et al., 2013). Because fiscal forecast errors are often predictable, they may not always capture uncertainty about future fiscal policies. I deviate from the literature on forecast errors by testing more directly whether economic and political economy factors can explain

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[1] Cimadomo (2016) surveys this literature in more detail.

fiscal policy uncertainty.

By looking at uncertainty about fiscal outcomes more directly, I also link to a literature on the reaction of fiscal policy to the business cycle and on the volatility of discretionary policy. The key question this literature addresses is whether fiscal policy is pro-cyclical, counter-cyclical or does not react to the cycle at all.[2] Results are mixed but overall suggest that fiscal policy has become more counter-cyclical in advanced economies (Galí and Perotti, 2003), in particular if looked at from a real-time perspective (Cimadomo, 2012, Bernoth et al., 2008). Apart from its reaction to the business cycle, this literature confirms that political economy factors affect fiscal policy discretion, such as the dispersion of political power (Lane, 2003), the political orientation of a government (Sørensen et al., 2001), or the election cycle (Hallerberg and Strauch, 2002). Henisz (2004) and Agnello and Sousa (2014) show that political institutions, such as checks and balances and the level of democracy, can explain differences in the volatility of discretionary fiscal policy. In addition, an economic environment with low inflation, low levels of the fiscal deficit and high GDP per capita is found to reduce fiscal volatility (Agnello and Sousa, 2013), while lower foreign foreign reserve holdings seem to be associated with higher fiscal policy volatility (Zhou, 2009). I find that the factors that tend to increase fiscal policy discretion are also related to fiscal uncertainty. Unexpected volatility of discretionary fiscal policy itself is sometimes interpreted as fiscal uncertainty, e.g. by Fernández-Villaverde et al. (2015), but, similar to forecast errors, may not fully reflect uncertainty in agents' expectations. The fiscal policy uncertainty index based on forecast disagreement and revisions proposed in this chapter can fill this gap. I further add to the literature by taking into account factors that became relevant during the Great Recession, namely fiscal-financial sector linkages.

The chapter proceeds as follows. Section 2.2 reviews different measures of economic and policy uncertainty. It continues with the construction of an index of fiscal uncer-

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[2] Golinelli and Momigliano (2009) provide a detailed survey of papers estimating fiscal reaction functions.

tainty. Potential sources of fiscal uncertainty are analysed in section 2.3. Section 2.4 concludes this chapter.

2.2 Measuring fiscal uncertainty

2.2.1 Existing measures of fiscal uncertainty

A classification of existing measures of uncertainty can be made according to their field of application.[3] Uncertainty on financial markets is often approximated by volatility indices, like the Chicago Board Options Exchange index of options-implied volatility VIX. In the context of sovereign credit risk, Beber et al. (2009), Gerlach et al. (2010) and De Santis (2014) find that the VIX can explain much of the common component in euro area sovereign yield spreads, and Remolona et al. (2008) show the same for euro area sovereign CDS spreads. The VIX index has been considered a determinant of sovereign credit ratings by Haque et al. (1996) and Hill et al. (2010) who find that it is a significant driver of Standard & Poor's ratings. To measure uncertainty about the future path of macroeconomic variables, like GDP growth and inflation, macroeconomic uncertainty indices have been developed by Lahiri and Sheng (2010), Orlik and Veldkamp (2014), Jurado et al. (2015), and Rossi and Sekhposyan (2015) amongst others. A third field of application is policy-making. For instance, uncertainty about future economic policies is reflected in an Economic Policy Uncertainty (EPU) index by Baker et al. (2016). The fiscal volatility measure derived for the United States by Fernández-Villaverde et al. (2015) tries to approximate unexpected innovations to the volatility of fiscal policy.

A second classification can be made according to the methodology of measurement. Table 2.1 provides an overview. While volatility measures, such as the VIX, are easily available, it remains unclear, to what extent market volatility does indeed reflect uncertainty and not simply mere sentiment or risk aversion (see discussion in Jurado et al.,

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[3] This classification follows Marakova (2014).

Table 2.1: Measures of fiscal policy uncertainty and macroeconomic uncertainty

Type of measure	Areas of application	Examples
News-based indices	economic policy, finance, consumption forecasting	newspaper-based (Economic Policy Uncertainty by Baker et al., 2016); Lumsdaine, 2010; Beetsma et al., 2013), Google search intensity (Vosen and Schmidt, 2011; Carrière-Swallow and Labbé, 2013), social media (Dergiades et al., 2014)
Variance of fiscal shocks	fiscal policy	Fernández-Villaverde et al. (2015), Agnello and Sousa (2014), Fatás and Mihov (2003)
Volatility measures	finance, macroeconomics, fiscal policy	CBOE VIX, regional stock market volatility measures, macroeconomic volatility indices (Huizinga, 1993; Aizenman and Marion, 1999; Baum et al., 2006; Baum and Wan, 2010; Bali et al., 2014; Segal et al., 2015), fiscal volatility (Henisz, 2004)
Forecast errors	macroeconomics	Rossi and Sekhposyan (2015), Jurado et al. (2015), Orlik and Veldkamp (2014)
Forecast dispersion	macroeconomics	Zarnowitz and Lambros (1987), Bomberger (1996), Bali et al. (2015), Giordani and Söderlind (2003), Boero et al. (2008), Siklos (2013), Lahiri and Sheng (2010)

2015). In particular since 2016, financial market volatility has been subdued despite elevated levels of uncertainty.

Likewise, news-based indices like the EPU may not necessarily capture uncertainty about current and future paths of fundamental variables but predominantly attention by the media. In the context of news as an uncertainty measure, the so-called 'narrative approach' of Romer and Romer (1989) needs to be mentioned. It is a qualitative method to identify policy shocks and has been used to approximate unexpected innovations to government spending (e.g. Romer et al., 2010, Favero and Giavazzi, 2007, Ramey, 2011). Brutti and Sauré (2015) adopt it to identify news about Greek sovereign risk. It is, however, not directly related to the theoretical concept of uncertainty either.

Furthermore, if the interest lies in determinants and effects of fiscal uncertainty, an uncertainty index measure would ideally be observable in real time. This does not apply to measures based on *ex post* forecast errors. To ensure comparabiltiy across a range of countries, another constraint is set by the data that is available: given that fiscal variables are only observed at low (quarterly or semi-annual) frequency, a method for extracting an uncertainty measure is needed that can be applied to relatively short time series ($T \approx 30$). This does not hold for relatively complex, model-based analyses of expected forecast errors, like those proposed by Jurado et al. (2015) and Orlik and Veldkamp (2014). Measures of the variance of fiscal shocks come with a similar disadvantage. While being more strongly related to genuine uncertainty and grounded in theory, fiscal shocks derived from fiscal reaction functions (Taylor, 2000) are available only at low, at best semi-annual frequency which makes respective variance estimates, like in Fatás and Mihov (2003) and Agnello and Sousa (2014), or stochastic volatility estimates as in Fernández-Villaverde et al. (2015), unsuitable for the present analysis.

Instead, I follow a strand in the literature on forecast-based uncertainty measures that interprets disagreement among forecasters as uncertainty. Disagreement is observable in real time and can be directly inferred from published forecasts, hence demands on data availability are small. Zarnowitz and Lambros (1987) find a strong positive correlation between the dispersion of point forecasts (of GDP and inflation) and the diffuseness of corresponding probability distributions. This is important if only point forecasts are reported. 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 standard conditional variance measure. He finds a significant relationship between both measures. His work initiated a debate on whether forecaster disagreement truly captures uncertainty (Rich and Butler, 1998, Bomberger, 1999, see also Marakova, 2014). Disagreement may reflect a mere difference in opinion and not uncertainty (Diether et al., 2002). 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), which are only available for fiscal data of a small 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 thought of as a component of such a measure. Finally, 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 a 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 can yield 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. In my empirical analyses, results obtained from using this new fiscal uncertainty index will be contrasted with results obtained from using as an alternative the EPU by Baker et al. (2016), realised government bond yield volatility as well as fiscal forecast errors.

2.2.2 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), and 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

$$e_{icth} = x_{ct} - F_{icth}. \tag{2.1}$$

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

$$e_{cth} = \sum_{i=1}^{N} w_{icth} e_{icth}. \tag{2.2}$$

It is assumed to be independent over forecasting horizons h. The w's denote the weights of individual forecast errors in the consensus forecast error. They 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:

$$e_{icth} = \beta_{ich} e_{cth} + \epsilon_{icth} + \phi_{ich}. \tag{2.3}$$

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. β_{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 get back to it in section 2.2.3.

Taking equations (2.2) and (2.3) together and setting $\phi_{ich} = 0$, the restriction $\sum_{i=1}^{N} w_{icth}\beta_{ich} = 1$ 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:

$$Var(e_{icth}) = \beta_{ich}^2 Var(e_{cth}) + Var(\epsilon_{icth}). \tag{2.4}$$

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 (2.2) and (2.3). Individual uncertainty is therefore a function of a common uncertainty shock $(Var(e_{cth}))$ and idiosyncratic uncertainty $(Var(\epsilon_{icth}))$.

The problem with equation (2.4) is that individual uncertainty cannot be observed without knowledge of β_{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:

$$u_{cth} \equiv \sum_{i=1}^{N} w_{icth} Var(e_{icth}) = c_{cth} + d_{cth} \tag{2.5}$$

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 (as opposed to empirical) 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 β_{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):

$$d_{cth} \equiv E[\sum_{i=1}^{N} w_{icth}(F_{icth} - F_{cth})^2]. \tag{2.6}$$

2.2.3 An empirical uncertainty measure

Equation (2.5) makes clear that measures that directly associate 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. Remember that equation (2.3) 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 estimate the following equation separately for each forecaster i and forecast horizon h allowing for biases to differ across countries c:

$$e_{icth} = \bar{\phi}_{ih} + \phi_{ich} + (\beta_{ich} e_{cth} + \epsilon_{icth}) \tag{2.7}$$

where $e_{icth} = x_{ct} - F_{icth}$ is the (*ex post* observable) forecast error. It is regressed on the constant term $\bar{\phi}_{ih}$ capturing the average bias in forecaster i's deficit forecast and the country-fixed effect ϕ_{ich} representing the additional country-specific bias. In other words, ϕ_{ich} in equation (2.3) is decomposed into an average forecaster-specific bias and a forecaster- and country-specific bias. $(\beta_{ich} e_{cth} + \epsilon_{icth})$ is the combined residual. Forecasts cleaned from time-invariant, country-specific biases are obtained by subtracting bias estimates from observed point forecasts $\hat{F}_{icth} = F_{icth} - \hat{\bar{\phi}}_{ih} - \hat{\phi}_{ich}$, where hatted variables represent estimated parameters. I use the observed variance of cleaned forecasts $\hat{F}_{icth}$ as a proxy for disagreement

$$\hat{d}_{cth} = \sum_{i=1}^{N} w_{icth} (\hat{F}_{icth} - \hat{F}_{cth})^2 \tag{2.8}$$

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. A number of adjustments to existing work is needed to obtain an estimate that meets 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 autoregressive conditional heteroskedasticity 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:

$$F_{cth} - F_{cth+1} = (x_{ct} - e_{cth}) - (x_{ct} - e_{cth+1}) = e_{cth+1} - e_{cth} \tag{2.9}$$

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 of 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 deficit/GDP ratio, debt/GDP, real GDP growth, unemployment, inflation and the current account balance:

$$(\hat{F}_{cth} - \hat{F}_{cth+1}) = \delta_{ch}(\hat{F}_{cth+1} - \hat{F}_{cth+2}) + X_{cth+1}{}'\Gamma_{ch} + (f_{cth} - f_{cth+1}) \qquad (2.10)$$

where $(\hat{F}_{cth} - \hat{F}_{cth+1})$ is the revision in the consensus forecast, i.e. the average of bias-cleaned individual forecasts, h periods ahead of the realisation at t relative to the consensus forecast published $h+1$ periods ahead. $(\hat{F}_{cth+1} - \hat{F}_{cth+2})$ is the revision undertaken $h+1$ periods ahead relative to forecasts from $h+2$ periods ahead. Matrix X_{cth+1} contains fiscal and macroeconomic data as of forecast horizon $h+1$. δ_{ch} and Γ_{ch} are parameters to be estimated.[4] The estimate of the residual $(\hat{f}_{cth} - \hat{f}_{cth+1})$ is orthogonal to fiscal and macroeconomic information ahead of the publication of forecasts. It therefore yields an estimate of unexpected innovations to the consensus

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[4] Estimates of coefficients δ_{ch} and Γ_{ch} are reported in Table A1 in the Appendix for revisions of current-year and one-year-ahead consensus forecasts of the fiscal deficit. Results are obtained using data introduced in section 2.2.4 and 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).

forecast.

Under the assumption that common shocks, that occurred between initial forecasts and revisions, are a good indicator for common uncertainty shocks that currently prevail, I use the following expression to approximate the variance of aggregate shocks, c_{cth}:

$$\hat{c}_{cth} = [s_1(\hat{f}_{cth+1} - \hat{f}_{cth+2}) + s_2(\hat{f}_{cth} - \hat{f}_{cth+1})]^2 \tag{2.11}$$

$(\hat{f}_{cth+1} - \hat{f}_{cth+2})$ 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 constructed as the simple sum of the proxies for the variance of aggregate shocks and the disagreement measure:

$$\hat{u}_{cth} = \hat{c}_{cth} + \hat{d}_{cth} \tag{2.12}$$

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:

$$U_{cth} = \frac{(\hat{u}_{cth} - \frac{1}{C}\frac{1}{T}\sum_{c=1}^{C}\sum_{t=1}^{T}\hat{u}_{cth})}{\sqrt{(\frac{1}{C}\frac{1}{T}\sum_{c=1}^{C}\sum_{t=1}^{T}(\hat{u}_{cth} - \frac{1}{C}\frac{1}{T}\sum_{c=1}^{C}\sum_{t=1}^{T}\hat{u}_{cth})^2}}. \tag{2.13}$$

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 (2.13) 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}.

2.2.4 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 and targeted by governments. 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.

The fiscal deficit can be derived from the government budget constraint (Cimadomo, 2016):

$$B_t = B_{t-1} + iB_{t-1} - S_t \tag{2.14}$$

where B_t is the level of public debt and i is the nominal interest rate on bonds issued by the government. S_t is the government primary balance that is the amount by which government revenue exceeds primary expenditure, i.e. expenditure less interest payments. Dividing (2.14) by nominal GDP (lower case letters) and defining the growth rate of nominal GDP as $g = \frac{GDP_t - GDP_{t-1}}{GDP_{t-1}}$ yields the dynamic equation of public debt:

$$\Delta b_t = \frac{i-g}{1+g} b_{t-1} - s_t \equiv h_t. \tag{2.15}$$

The change in the debt/GDP ratio, or government budget balance, is the fiscal deficit as a share of GDP h_t. Equation (2.15) implies that the deficit increases as the growth rate of GDP decreases, as the interest rate on outstanding government debt increases, and as the primary balance decreases. The fiscal deficit is therefore considered an important indicator of the sustainability of public finances. It captures interest payments as well as cyclical and automatic components of fiscal policy and thereby differs from estimates of the cyclically adjusted primary balance (CAPB). The latter indicator is often used as a measure of discretionary spending (Galí and Perotti, 2003, Cimadomo, 2016). However, forecast data of the CAPB is only available for a small sample of countries. It is also less comparable across countries and forecasters given that its measurement depends on the definition of cyclical and non-cyclical spending components as well as estimates of the output gap. Likewise, alternative fiscal indicators such as 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. The fiscal uncertainty index is therefore based on forecasts of the fiscal deficit relative to GDP, published for the current year and the year ahead. This renders the index 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.

The IMF, OECD and EC report point forecasts for advanced economies for the current year and one year ahead at a semi-annual frequency in their publications *World Economic Outlook*, *Economic Outlook* and *European Economic Forecast*. My sample covers 31 OECD countries over the period 1999 to 2014.[5] These forecasts are highly correlated with each other (Table 2.2, top panel). OECD and EC projections display

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[5] Forecasts by the European Commission are not available for Australia, Canada, Iceland, Israel, South Korea, New Zealand, Norway, see Table 2.2. Fiscal uncertainty indices for these countries are based on forecasts published by the IMF and OECD only.

the highest correlation coefficients while IMF projections appear to deviate more. 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.

Using fiscal forecasts by the IMF, OECD and European Commission instead of forecasts by individual governments or national, non-governmental research institutes ensures that definitions and methodologies applied across countries are sufficiently coherent.

I find evidence for a significant underestimation of fiscal deficits. Forecast errors are defined as in equation (2.1), i.e. a positive value indicates that actual deficits lie above projections. This implies that forecasters have been too optimistic on average. In fact, Table 2.2 shows that current-year deficit projections significantly deviate from final reported values (2015 spring publications). The IMF forecast error of 0.23 percentage points is lower than OECD and EC errors, and somewhat lower than what Artis and Marcellino (2001) report for an earlier sample that is restricted to G7 countries. The EC forecast error of 0.35 percentage points corresponds to the error de Castro et al. (2013) estimate for their European sample up to the crisis of 2009.

Table 2.2: 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
Noise/signal ratio	55.0%	90.5%	60.6%	92.2%	53.6%	85.5%
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 *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

One year-ahead forecast errors with values between 0.57 and 0.67 percentage points are almost twice as large as nowcast errors. Similar to de Castro et al. (2013), I find that forecast biases, i.e. mean forecast errors, significantly vary across countries. While deficits of Czechia, Estonia, Luxembourg and New Zealand exhibit a negative bias, i.e. have on average been overestimated, the deficits of the 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. The presence of time-invariant and therefore predictable as well as statistically significant average and country-specific forecast biases ($\bar{\phi}_i$ and ϕ_{ci} in equation (2.7)) supports the adopted approach of bias cleaning.

The noise-to-signal ratio reported in the second panel of Table 2.2 is defined as the standard deviation of forecast errors divided by the standard deviation of forecasts. It implies that the relative dispersion of forecast errors compared to the dispersion of forecasts is non-negligible. Ratios above 50 percent for current-year forecasts and around 90 percent for one year-ahead forecasts are higher than those reported by de Castro et al. (2013) for the European Union. They show that final revisions made to forecasts are of substantial size, relative to initial point forecasts.

Table 2.3: 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.

Finally, I decompose average forecast errors into errors made in estimates of the deficit and errors made in estimates of nominal GDP. To do so, I construct hypothetical deficit/GDP forecast errors, holding either the error in deficit forecasts at zero by using final revisions, or, *vice versa* the error in GDP forecasts (Table 2.3, panel on the left). Overall, I confirm the finding for EC forecasts by de Castro et al. (2013) for OECD and IMF forecasts: nominal GDP forecast errors contribute only a small fraction to overall deficit/GDP forecast errors, while deficit forecast errors explain most of the imprecision. 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. This compares to the actual average error of 0.47. Nowcast errors would have been small and somewhat negative (-0.05 relative to the actual average error of 0.16), i.e. deficits would have been over-predicted (indicated by the negative sign). By contrast, had overall year-ahead forecast errors been caused solely by deficit errors, they would have been 6.6 percent larger (0.5 relative to 0.47). Nowcast errors would have been 29.6 percent larger in nowcasts (0.21 relative to 0.16).

A similar exercise is conducted for the standard deviation of forecasts across the IMF and OECD, i.e. the forecasters for which the larger overlap of data is available (Table 2.3, panel on the right). Similar to forecast errors, disagreement about the fiscal deficit can explain most of the disagreement about fiscal deficit/GDP ratios. Had forecasters got their deficit projections right, the disagreement due to GDP estimates would have been 0.25 and 0.27 standard deviations, for nowcasts and year-ahead forecasts respectively, compared to observed standard deviations of 0.47 and 0.55, respectively.

I conclude from the descriptive analysis that the variation in forecast data is sufficiently large in order to construct an index of fiscal uncertainty based both on average revisions in forecasts as well as the disagreement across OECD, IMF and EC forecasts. Such an index captures uncertainty about the future path of the fiscal deficit to the largest extent, and uncertainty about nominal GDP only to a small extent.

2.2.5 Index characteristics

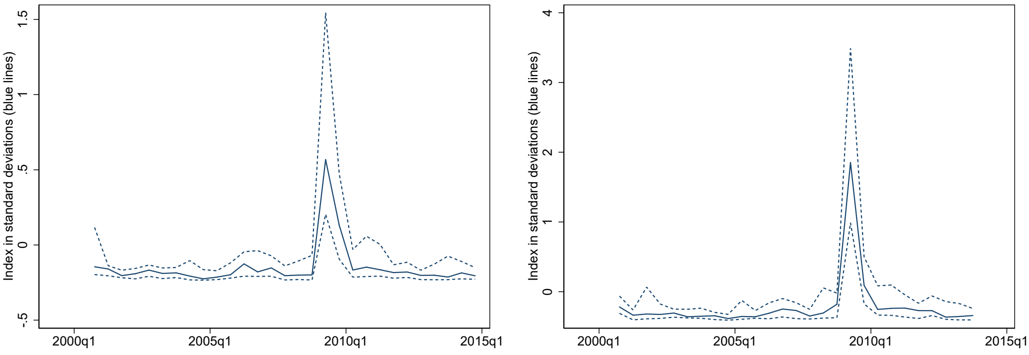
Decomposition Table 2.4 shows that the current-year measure of fiscal uncertainty $\hat{u}_{ct0}$, i.e. the measure based on deficit nowcasts, has a substantially larger variance than the one year-ahead version $\hat{u}_{ct1}$, which is the measure based on year-ahead deficit forecasts. The disagreement 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 2.4: Decomposition of the fiscal uncertainty measure

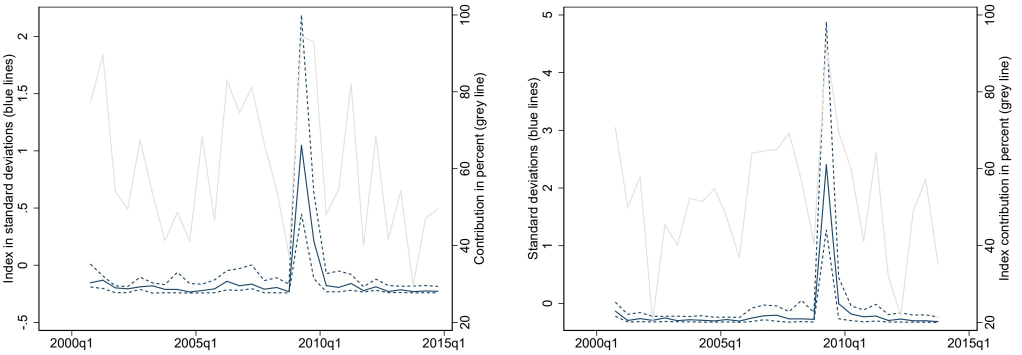
		$\hat{u}_{ct0}$			$\hat{u}_{ct1}$	
	Mean	Variance	Contri-bution	Mean	Variance	Contri-bution
Uncertainty $\hat{u}_{cth}$	1.54	41.01	100.0%	1.45	11.41	100.0%
Disagreement $\hat{d}_{cth}$	0.59	9.49	23.1%	0.61	2.58	22.6%
Aggregate shock $\hat{c}_{cth}$	0.95	15.17	37.0%	0.83	6.27	54.9%
Covariance		8.17	19.9%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

Variation across time and countries An overview over the evolution of the fiscal uncertainty index, i.e. the normalised uncertainty measure, and its sub-components is shown in Figure 2.1. 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 2.1 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 2.1e and 2.1f relative to Figures 2.1a to 2.1d). In fact, the contribution of the disagreement component to the overall index, plotted by the grey lines in Figures 2.1e and 2.1f, appears to vary quite substantially over time but drops to nearly zero in 2009. The grey lines in Figures 2.1c and 2.1d 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.

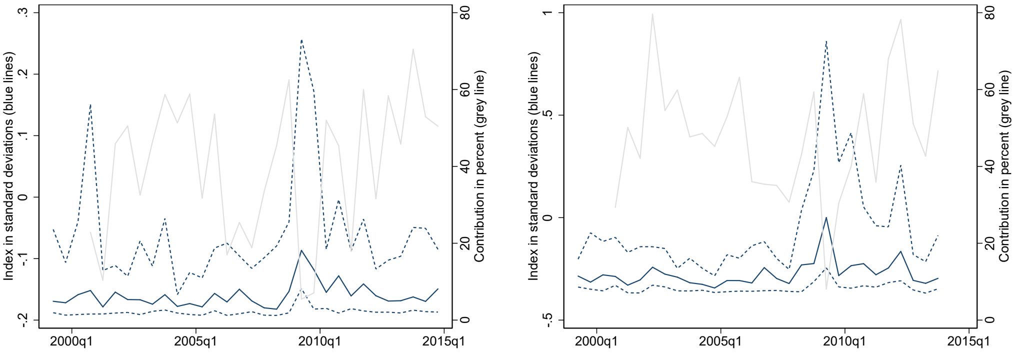
Before the crisis of 2008/09, fiscal uncertainty did not vary much across countries. Even as fiscal uncertainty surged in 2009, it did so in most countries to a similar extent. This is shown by the relatively narrow interquartile range during that period in Figure 2.1 (dotted lines). In fact, Pesaran (2015) tests of weak cross-sectional dependence suggest that the fiscal uncertainty index is substantially correlated across countries (Table A2 in the Appendix). By contrast, after the crisis, heterogeneity in uncertainty across countries increases, in particular idiosyncratic uncertainty as measured by forecast disagreement (while the property of cross-sectional dependence remains statistically significant for all index versions after 2009).



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



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



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

Figure 2.1: Time variation in fiscal uncertainty

Figures A1 to A4 in the Appendix plot the fiscal uncertainty index and its components separately for each country of the sample. The cross-country heterogeneity is large. This is also summarised in Table 2.5, which gives an overview of country-specific characteristics of fiscal uncertainty. With index versions being normalised across the whole sample, a positive country-specific mean suggests that uncertainty has been above the sample average. This applies to the countries hit most by the financial crisis including Greece, Iceland and Ireland, but also Korea. It also applies to Norway, a country that ran substantial surpluses during the mid-2000s, when oil prices were high and volatile, which presumably made fiscal forecasting more difficult. In general, high disagreement contributes to high overall uncertainty. Exceptions include (year-ahead) uncertainty in Ireland, Spain, and the United Kingdom, which is predominantly driven by aggregate uncertainty shocks. Forecaster disagreement has been relatively low in these countries. Likewise, for a majority of the sample, uncertainty about current-year deficits feeds through to uncertainty about the deficit one year ahead. An exception is Poland, for which I measure relatively low levels of current-year uncertainty but substantial levels of year-ahead uncertainty.

Comparison to existing uncertainty measures To assess how my fiscal uncertainty index may add to existing measures of economic and fiscal policy uncertainty, I compare it 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.[6] Third, as a measure of uncertainty about sovereign credit risk as perceived by financial

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[6] 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.

Table 2.5: Variation in fiscal uncertainty across countries

	Years	U_{ct0}		D_{ct0}		U_{ct1}		D_{ct1}	
		mean	sd	mean	sd	mean	sd	mean	sd
Australia	13.5	-0.04	*0.25*	0.00	*0.24*	-0.05	*0.59*	-0.02	*0.47*
Austria	13.5	-0.20	*0.08*	-0.17	*0.03*	-0.28	*0.32*	-0.29	*0.11*
Belgium	13.5	-0.19	*0.14*	-0.19	*0.01*	-0.27	*0.42*	-0.29	*0.12*
Canada	13.5	-0.15	*0.15*	-0.14	*0.11*	-0.22	*0.48*	-0.21	*0.27*
Czechia	8	-0.12	*0.23*	-0.15	*0.06*	-0.18	*0.39*	-0.27	*0.11*
Denmark	13.5	-0.15	*0.16*	-0.13	*0.08*	-0.14	*0.44*	-0.12	*0.37*
Estonia	2	-0.20	*0.01*	-0.11	*0.03*	-0.39	*0.05*	-0.30	*0.10*
Finland	13.5	-0.11	*0.25*	-0.16	*0.05*	-0.09	*0.70*	-0.27	*0.12*
France	13.5	-0.19	*0.11*	-0.18	*0.03*	-0.27	*0.36*	-0.31	*0.09*
Germany	13.5	-0.15	*0.18*	-0.18	*0.03*	-0.21	*0.74*	-0.32	*0.07*
Greece	13.5	0.27	*1.31*	0.57	*2.41*	0.07	*0.85*	0.24	*1.06*
Hungary	8	0.07	*0.58*	-0.07	*0.19*	-0.28	*0.12*	-0.13	*0.24*
Iceland	13.5	0.48	*1.15*	0.26	*0.55*	0.15	*0.55*	0.26	*0.88*
Ireland	13.5	1.03	*4.57*	0.78	*4.58*	0.28	*1.92*	-0.09	*0.47*
Israel	2	-0.13	*0.06*	-0.08	*0.11*	-0.38	*0.03*	-0.32	*0.05*
Italy	13.5	-0.20	*0.06*	-0.17	*0.03*	-0.30	*0.18*	-0.29	*0.09*
Japan	13.5	0.00	*0.36*	0.09	*0.31*	-0.01	*0.70*	0.09	*0.40*
Korea	10.5	0.31	*0.47*	0.60	*0.84*	0.61	*0.98*	1.10	*1.42*
Luxembourg	11.5	-0.14	*0.14*	-0.12	*0.08*	-0.08	*0.45*	-0.01	*0.42*
Netherlands	13.5	-0.13	*0.26*	-0.17	*0.04*	-0.07	*1.13*	-0.24	*0.31*
New Zealand	11.5	0.02	*0.29*	0.06	*0.39*	-0.01	*0.48*	0.03	*0.75*
Norway	13.5	0.40	*0.79*	0.27	*0.44*	1.67	*2.13*	2.29	*3.03*
Poland	3	-0.17	*0.05*	-0.08	*0.05*	0.98	*3.32*	1.41	*4.34*
Portugal	13.5	-0.15	*0.10*	-0.13	*0.14*	-0.15	*0.33*	-0.19	*0.28*
Slovakia	10.5	-0.10	*0.26*	-0.06	*0.43*	-0.21	*0.49*	-0.17	*0.35*
Slovenia	2	0.03	*0.23*	0.19	*0.44*	0.11	*0.57*	0.32	*0.72*
Spain	13.5	-0.03	*0.50*	-0.15	*0.12*	0.05	*1.15*	-0.13	*0.52*
Sweden	13.5	-0.14	*0.17*	-0.14	*0.08*	-0.20	*0.52*	-0.27	*0.09*
Switzerland	7	-0.18	*0.11*	-0.15	*0.05*	-0.24	*0.24*	-0.16	*0.27*
United Kingdom	13.5	-0.01	*0.58*	-0.11	*0.15*	0.05	*1.61*	-0.24	*0.29*
United States	13.5	-0.04	*0.38*	-0.02	*0.29*	0.01	*0.88*	0.05	*0.85*
Total	346	0	*1*	0	*1*	0	*1*	0	*1*

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.[7]

Figure 2.2 illustrates the time variation of different uncertainty indices, averaged across countries. All measures agree that the period between 2003 and the global

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[7] Formula (2.13) is applied to all measures.

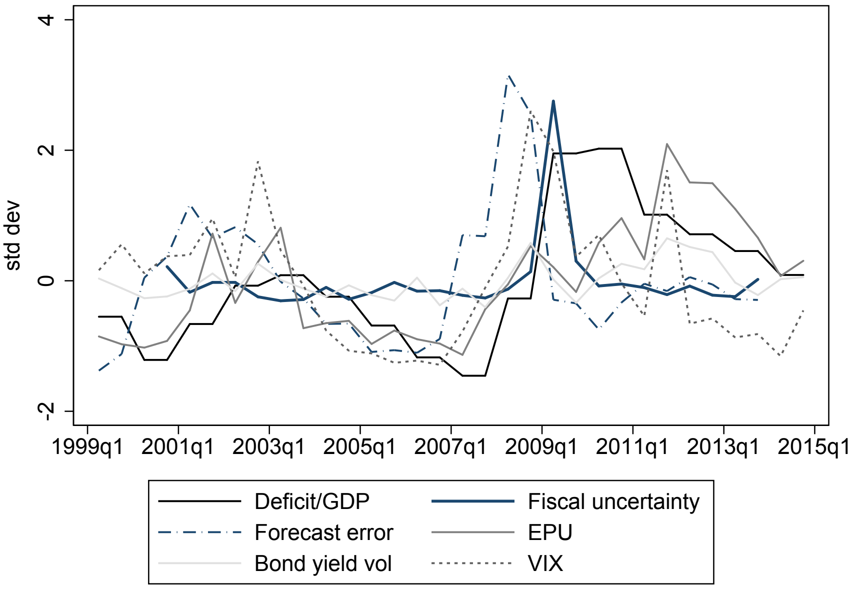

Figure 2.2: Comparison to other uncertainty measures

Table 2.6: 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.

financial crisis has been 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 governments' budgets. This is confirmed in Table 2.6. 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 my 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 2.2). Overall, the fiscal uncertainty index leads the EPU by at least one year (Table 2.6). 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 very misleading proxy for uncertainty experienced in real time. While the variation across countries is large, patterns in the evolution of the new fiscal uncertainty index in comparison to other measures of uncertainty are confirmed for a number of countries in Figure A5 in the Appendix.

2.3 The determinants of fiscal uncertainty

The aim of this section is to analyse in more detail potential factors associated with fiscal uncertainty. Both from a policy perspective as well as to inform theoretical work on fiscal uncertainty, understanding the drivers of this uncertainty is important.

2.3.1 Related literature and hypotheses

The surge in fiscal uncertainty during the Great Recession suggests that uncertainty about future fiscal policy correlates with the business cycle. A reason may be that announced discretionary fiscal policy not only tends to be counter-cyclical in advanced economies, as suggested by Bernoth et al. (2008) and Cimadomo (2012). Announced policy may also be more volatile during downturns, leading to heightened uncertainty.

I therefore assess the relationship between the fiscal uncertainty index and measures of the business cycle. Another cause for the extreme rise in fiscal uncertainty after 2008 may have been the substantial deterioration of the international banking system during the financial crisis, in response to which governments provided substantial support to ailing banks. Panageas (2010) shows theoretically that such transfers alter optimal taxation policy. A negative feedback loop between risks in the banking sector and sovereign risk was initiated. This has been studied extensively by Corsetti et al. (2013), Philippon and Schnabl (2013), Acharya and Rajan (2013) and Acharya et al. (2014). To test the hypothesis that such a feedback loop contributed to uncertainty about fiscal policy, I consider a measure of banking sector risk as a potential uncertainty determinant.

On the other hand, a number of fiscal and macroeconomic factors may reduce fiscal uncertainty. If governments aim at stabilising their debt levels in the long run, net spending is expected to decline, or the primary balance to increase, as debt levels rise (Bohn, 1998). This is also illustrated by the dynamic equation of public debt (equation 2.15): higher levels of debt may limit the scope for fiscal policy and therefore be negatively related to fiscal uncertainty. *Vice versa*, concerns about the sustainability of fiscal policy and a lack of clarity about fiscal consolidation could lead to the opposite outcome, as argued in Bi et al. (2013) and Croce et al. (2012). However, I would expect debt sustainability concerns to be reflected in longer-term measures of uncertainty rather than the index constructed above, which focuses on uncertainty about fiscal policy in the short run. Equation (2.15) also implies that low GDP growth or higher interest rates paid on government debt may counteract the objective of stabilising the real stock of debt and constrain fiscal policy in the near term, which may reduce fiscal uncertainty. Likewise, fiscal uncertainty may increase with higher inflation, which helps stabilise the stock of nominal debt held in domestic currency, and thereby provide room for unanticipated fiscal policy measures. In the analysis, I include a number of fiscal and macroeconomic variables to test whether fiscal uncertainty is correlated with them. If the debt stabilisation motive would indeed lead governments to reduce fiscal uncertainty in the short term, I would expect the level of debt and government bond yields to be negatively correlated with uncertainty, while growth and inflation should be associated with an increase.

According to the political business (or budget) cycle literature (Nordhaus, 1975), fiscal policy discretion increases during periods when elections take place. This may be because politicians have incentives to buy votes by lowering taxes or increasing spending. The credibility of such measures may make fiscal policy more uncertain prior to elections. In addition, elections may lead to uncertainty about the future composition of government and thereby increase the uncertainty about fiscal policy. While the degree of economic development in advanced economies, the quality of their institutions, stable electoral rules and fiscal policy constraints should limit the degree of fiscal uncertainty in these countries (Persson, 2002), the post-crisis change in the political climate may be able to explain some of the rise of fiscal uncertainty.[8]

On the contrary, strict fiscal rules and contract-based fiscal governance have been found to reduce fiscal forecast errors (von Hagen, 2010, Pina and Venes, 2011, de Castro et al., 2013), unless governments misreport more frequently as fiscal rules become binding (von Hagen and Wolff, 2006). Henisz (2004) and Agnello and Sousa (2014), for instance, show that political institutions, such as checks and balances and the level of democracy, can explain differences in the volatility of discretionary fiscal policy. In fact, most advanced economies have implemented fiscal rules over the course of the last decade. In the European Union, the Stability and Growth Pact set the limit on

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[8] See Klomp and De Haan (2013) and Dubois (2016) for a survey of the political economy literature on the conditions under which political budget cycles can arise. Sørensen et al. (2001), Hallerberg and Strauch (2002) and Bernoth et al. (2008) find that elections increase fiscal policy discretion. This may explain why errors in fiscal forecasts are larger prior to elections (de Castro et al., 2013, Pina and Venes, 2011). Brück and Stephan (2006) argue that governments cheat in their fiscal forecasts when elections are coming up. Dreher et al. (2008) show that a political alignment with the US can explain IMF forecast errors before elections. This evidence implies that an upcoming election may also increase fiscal uncertainty.

the fiscal deficit at 3 percent of GDP, above which an Excessive Deficit Procedure is triggered. Countries with a debt/GDP ratio above 60 percent are required to bring debt levels down in the medium term, which is meant to enforce debt stabilisation. A reduction in the scope for fiscal policy imposed by fiscal rules is therefore expected to lower fiscal uncertainty. Over the course of the sovereign debt crisis in the euro area, a number of peripheral countries entered into an Economic Adjustment Programme. Such a programme further tightens the constraints placed on fiscal policy and is enforced by the IMF and European institutions. As part of the programme, countries pre-commit to fiscal targets over a longer time horizon. In what follows, I test whether fiscal rules and the participation in an Economic Adjustment Programme can be linked to differences in fiscal uncertainty across countries and time.

2.3.2 Empirical strategy

My empirical analysis of potential determinants of fiscal uncertainty builds on the Mincer and Zarnowitz (1969) test of forecast rationality:

$$e_{icth} = \alpha_{ich} + [F^{d}_{icth}]'\beta + v_{icth} \tag{2.16}$$

A forecast F, for instance of the fiscal deficit d of country c, to be realised at time t, made h periods ahead, is considered rational if its forecast error e is pure noise, i.e. is unbiased and uncorrelated with the forecast. For the constant term this would imply $\alpha_{ich} = 0$, and for the coefficient for the level of the forecast $\beta = 0$. Analyses of forecast errors made by official forecasters show that this is very often not the case (von Hagen, 2010, Pina and Venes, 2011, de Castro et al., 2013). In fact, by including other fiscal and macroeconomic variables and political economy factors to the regression equation, forecast error analyses show that errors are predictable along a number of dimensions (see previous section).

Given the interest on fiscal uncertainty determinants, I instead regress the new uncertainty measure on the squared average forecast of the fiscal deficit at forecast horizon h, ${F_{cth}^{d}}^{2}$, other forecasts F_{cth}^{M} and potential fiscal uncertainty determinants C_{ct} and P_{ct+h}:

$$U_{cth} = [{F_{cth}^{d}}^{2}]'\beta_1 + {F_{cth}^{M}}'\beta_2 + {C_{ct}}'\beta_3 + {P_{ct+h}}'\beta_4 + v_{cth} \tag{2.17}$$

Given that my measure of uncertainty is observable at the time the forecast is published, and average uncertainty about fiscal forecasts is defined as the aggregate variance of forecast errors $u_{cth} \equiv \sum_{i=1}^{N} w_{icth} Var(e_{icth})$ (equation (2.5) above), equation (2.17) can be interpreted as a real-time equivalent to a Mincer and Zarnowitz (1969) test of forecast rationality, applied to the variance of forecast errors. ${F_{cth}^{d}}^{2}$ in this equation is the squared forecast of the fiscal deficit. If forecast errors are indeed linked to the level of the deficit, then fiscal uncertainty should increase in the squared deficit figure, not the level. Furthermore, the fiscal index uncertainty index constructed above has not been scaled relative to the level of the deficit.[9] One could divide U_{cth} by ${F_{cth}^{d}}^{2}$ to obtain unbiased estimates of parameters $\beta_{j\neq 1}$. Controlling for it on the right-hand side of the equation is the alternative.

In line with the literature on forecast errors, I augment the regression model with three additional regressor sets. Matrix F_{cth}^{M} contains h-period ahead consensus projections of other fiscal and macroeconomic variables. In particular, I account for the business cycle, the level of debt/GDP, the government bond yield as well as inflation. Matrix C_{ct} collects as measures of financial sector risk the CDS spread of domestic banks, and stock market volatility. Political economy variables, including an election indicator, and fiscal rule proxies enter matrix P_{ct+h}.

The error term v_{cth} is assumed to consist of a country-fixed effect u_{ch} and an id-

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[9] This is because of data properties, such as the fact that for a number of data points the fiscal deficit is exactly zero.

iosyncratic error ε_{cth}. Country-fixed effects capture persistent differences in fiscal uncertainty across countries, potentially as a result of different institutional frameworks. Idiosyncratic errors reflect the index component that cannot be attributed to uncertainty about future fiscal policies as approximated by economic or political economy factors. These errors may instead be interpreted as the uncertainty that arises from technical mistakes made by forecasters, or pure differences in opinion. Given that fiscal uncertainty is highly dependent across countries (see tests for cross-sectional dependence in Table A2 in the Appendix), I further allow for a common error component f_t to affect country-specific uncertainty with factor loadings γ_{ch}:

$$v_{cth} = u_{ch} + \gamma'_{ch} f_{th} + \varepsilon_{cth} \tag{2.18}$$

Cross-sectional dependence of fiscal uncertainty may be caused by fiscal policy spillovers across countries. Giuliodori and Beetsma (2008) account for spillovers explicitly using a spatial lag specification. Applied to fiscal uncertainty, factor f_{th} is approximated with equally weighted fiscal uncertainty indices of all other countries in the sample. In addition, I estimate equation (2.17) using the Common Correlated Effects estimator (CCE, Pesaran, 2006).[10] This approach accounts for the common error component by including cross-sectional averages of the dependent variable as well as other variables potentially responsible for co-movement in the set of regressors. Alongside averages of the dependent variable, I include averages of the squared forecast of the fiscal deficit and of real GDP growth. In addition, a dummy variable for the first half of 2009 is added given that the financial crisis itself constituted a large common shock. Depending on the specification, I also include averages of other regressors to reduce the cross-sectional dependence of the error term and potential biases in model parameters. The CCE approach allows for a high flexibility about the sources of common shocks but remains ignorant about potential channels through which shocks spill over, compared

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[10] The Stata routine `xtdcce2` provided by Ditzen (2016) implements the CCE estimator.

to a spatial lag specification. As for some countries the T dimension lies below 10, I apply the recursive mean adjustment method to correct for small sample time series biases (see Ditzen, 2016).

2.3.3 Data

Semi-annual data on macroeconomic and fiscal fundamentals for 31 advanced economies over the period 1999 to 2014 are taken from the OECD and IMF projections published in the *Economic Outlook* and *World Economic Outlook*. Table 2.7 reports summary statistics and the number N of country-semi-annual observations for which data is available. I employ fiscal forecasts of the fiscal deficit/GDP (general government net borrowing as a percentage of GDP, OECD and IMF average), and debt/GDP (general government gross financial liabilities as a percentage of GDP, OECD). To account for the business cycle, I use annual real GDP growth (IMF), the output gap calculated as the share of cyclical real GDP over an HP-filtered real GDP series (OECD), or, alternatively, the unemployment rate (OECD). One-year ahead forecasts are used when the year-ahead uncertainty measure U_{ct1} is employed as the dependent variable; current-year projections of fiscal and macroeconomic measures serve as regressors of current-year deficit uncertainty U_{ct0}. In addition, I use the 10-year government bond yield (annual change every half-year, OECD), and the annual change in the consumer price index (OECD) as measures of interest rates on government debt and inflation.

To test whether banking sector risk contributes to fiscal uncertainty, I employ data on banking sector CDS spreads. I use the half-year difference of the logged average of 5-year US-Dollar CDS prices for bonds issued by major banks per country (Bloomberg).[11]

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[11] The following banks are included: AU: National Australia Bank, Westpac, Australia and New Zealand Banking Group, Commonwealth Bank; AT: Hypo Group Alpe Adria, Erste Group; BE: Dexia, KBC; CA: Royal Bank of Canada; FR: BNP Paribas, Crédit Agricole, Natixis, Société Générale; DE: Commerzbank, Deutsche Bank, Landesbank Baden-Württemberg; EL: National Bank, Alpha; IS: Landsbanki Íslandi, Glitnir, Kaupthing; IE: Bank of Ireland, Allied Irish Banks; IT: Unicredit, Intesa Sanpaolo, Mediobanka; JP: Nomura, Mizuho, Mitsubishi UFJ, Sumitomo Mitsui; KR: Hana, Kookmin Bank, Shinhan, Woori; NL: ABN Amro, ING, Rabobank, Fortis; NZ: Australia and New Zealand

Table 2.7: Determinants of fiscal uncertainty – descriptive statistics

Variable	N	Mean	Std Dev	Min	Max
Deficit/GDP (nowcast), %	693	1.70	4.72	-20.2	27.4
Deficit/GDP (forecast), %	693	1.52	4.31	-19.2	15.5
Debt/GDP (nowcast), %	693	68.5	38.3	3.5	228.4
Debt/GDP (forecast), %	693	69.5	39.5	1.5	233.1
Real GDP growth (nowcast), %	693	1.57	2.41	-10.6	8.8
Real GDP growth (forecast), %	693	2.22	1.42	-4.0	7.5
Output gap (nowcast), %	652	-0.30	4.99	-19.0	31.8
Output gap (forecast), %	652	-0.33	5.24	-18.3	33.5
Unemployment rate (nowcast), %	693	7.21	3.71	1.3	27.8
Unemployment rate (forecast), %	693	7.30	3.79	1.8	28.4
10-year bond yield, % pa	684	4.42	2.10	0.6	25.1
Inflation (nowcast), %	693	2.07	2.46	-10.0	16.1
Inflation (forecast), %	693	1.95	2.03	-4.8	15.2
Bank CDS spread, log of %	410	4.35	1.41	1.8	8.0
Stock market volatility, index	693	0.05	1.18	-0.5	23.3
Election, dummy	693	0.14	0.35	0	1
Snap election, dummy	693	0.04	0.19	0	1
Fixed election regime, dummy	693	0.26	0.44	0	1
Expenditure rule, dummy	672	0.39	0.49	0	1
Revenue rule, dummy	672	0.14	0.34	0	1
Balanced budget rule, dummy	672	0.89	0.31	0	1
Debt rule, dummy	672	0.79	0.41	0	1
Ecoonomic Adjustment Programme, dummy	693	0.03	0.18	0	1

Table 2.7 shows that the bank CDS data are available only for a sub-sample of $N = 410$ country-semi-annual observations. In addition, I control for realised volatility on domestic stock markets using the bi-annual standard deviation of monthly index values of each country's main stock price index (OECD).

In line with the literature on political budget cycles, I collect data on national elections at which voters decide over the composition of the central government. These are taken from various country-specific sources. For countries with parliamentary systems, I use the date of elections for the main legislative assembly, usually the lower house of parliament. For presidential systems, the date of the first round of presidential elections is chosen. I define a dummy variable that takes the value of 1 if an election is scheduled

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Banking Group; NO: DnB NOR; PT: Caixa Geral de Dépositos, Banco Comercial Português, Banco Espírito Santo; ES: Banco Santander, Banco Bilbao Vizcaya Argentaria, La Caixa, Bankia; SE: SEB, Swedbank, Nordea, Handelsbanken; CH: UBS, Crédit Suisse; UK: Barclays, HSBC, Lloyds, Royal Bank of Scotland; US: Bank of America, Citigroup, JP Morgan Chase, Wells Fargo.

for the current year, or alternatively, the following year. On average, elections take place every four years (once in around 7 half-annual periods, see Table 2.7). Elections may be called as a result of uncertainty about fiscal policy and therefore be endogenous. I follow Julio and Yook (2012) and allow for different election effects for those countries that follow a fixed election cycle, as classified in their study, using a dummy indicator. In around a quarter of the countries, that are part of the sample, this is the case. In addition, I control for whether an election has been called as a snap election, i.e. earlier than the usual election cycle suggests.

To approximate the prevailing fiscal framework, I make use of fiscal rule indicators, which are provided by the IMF. They indicate whether a country has implemented expenditure rules, revenue rules, budget balance rules, or debt rules. Given that time-invariant country-specific effects are picked up by fixed effects u_{ch}, IMF indicators account for the effect an implementation of fiscal rules has on fiscal uncertainty, i.e. the time variation in fiscal rule indicators is exploited. Mean values for these dummy indicators in Table 2.7 show that expenditure and revenue rules are less common while balanced budget and debt rules are in place for the majority of semi-annual country observations (a mean of the dummy variable greater than 0.5). Finally, I define a dummy variable that takes the value of 1 for the period during which a country is part of a European Economic Adjustment Programme.[12]

2.3.4 Results

Baseline results Results from a baseline specification are reported in Table 2.8, with year-ahead fiscal uncertainty as the dependent variable (U_{ct1}) and fiscal fundamentals as well as a business cycle measures as regressors. I find that fiscal uncertainty is higher, the larger the squared value of the fiscal deficit. This confirms that forecast errors are not rational and indicates that year-ahead deficits become harder to predict, the more

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[12] Greece: from 2010-1, Portugal: 2011-1 to 2014-1, Ireland: 2011-1 to 2013-2, Spain: 2012-2 to 2013-2.

they are different from zero. The squared forecast term is kept as a control in all subsequent specifications to control for the proportionality of the fiscal uncertainty index relative to the level of the forecast deficit. The business cycle has a negative effect on fiscal uncertainty. Results suggests that when economic downturns are anticipated, the reaction of fiscal policy becomes less certain. However, the statistical significance varies across different business cycle approximations. An increase in expected unemployment increases fiscal uncertainty as uncertainty about a policy response rises. More frequently changing measures of the state of the macroeconomy, like projected real GDP growth (column IV) and the year-ahead output gap (column V), have a negative effect but are not found to be significant uncertainty determinants. It may be because both measures are more volatile and movements of GDP over the cycle are not necessarily associated with large unanticipated fiscal policy responses, unlike less frequent swings in unemployment.

Furthermore, the coefficient for the debt/GDP ratio is negative and statistically significant throughout. While this may contradict common perceptions of fiscal uncertainty as a concept that applies to long-term concerns about fiscal policy sustainability, I interpret the finding as support for the hypothesis that debt stabilisation may decrease the degree of fiscal uncertainty. High levels of debt seem to constrain fiscal policy, which, in turn, renders it more predictable. Similarly, the long-term interest rate has a negative effect on fiscal uncertainty. I also interpret this as an outcome of constraints to fiscal policy, which are set by borrowing conditions. These findings are consistent with uncertainty about fiscal policy in the short term, which is reflected in the fiscal uncertainty index. As government bond yields may themselves be driven by fiscal and macroeconomic fundamentals, I will report subsequent results based on a specification that excludes yields. Findings about the effect of fiscal and macroeconomic fundamentals are robust to including inflation expectations, a variable that is itself not statistically significant.

Columns I, II and III of Table 2.8 compare different estimation approaches to account for cross-sectional dependence. Relative to a standard Fixed Effects regression that does not explicitly take common shocks to fiscal uncertainty into account (column I), a spatial lag approach controls for cross-sectional dependence by adding the average level of the dependent variable in all other countries as an explanatory variable to the specification. Column II shows that this leads to a twofold increase in the goodness-of-fit. The explanatory power of the regression model is enhanced because other countries' fiscal uncertainty (spatial lag term) appears to play an important part in explaining a given country's fiscal uncertainty. This is in line with findings on fiscal policy spillovers in Giuliodori and Beetsma (2008). On average, a one-standard deviation increase in foreign countries' fiscal uncertainty indices increases uncertainty about the domestic fiscal deficit by more than 0.8 standard deviations. However, the spatial lag approach does not fully account for fiscal uncertainty spillovers: a Pesaran (2015) test for weak cross-sectional dependence cannot reject the hypothesis that residuals are only weakly dependent (reported at the bottom of Table 2.8). By contrast, the CCEP approach of adding cross-sectional averages of fiscal uncertainty as well as of the deficit, growth and a crisis dummy variable eliminates cross-sectional dependencies in the error structure (column III, bottom). More flexibly accounting for international spillovers also raises the goodness-of-fit considerably, as illustrated by an R-squared above 0.8.

Results for financial sector risk Table 2.9 shows that risks in a country's banking sector increase fiscal uncertainty, albeit only with a lag. Contemporaneous effects are not statistically significant. Up to four lags of financial sector variables are added to the specification as fiscal effects of banking sector risk may become effective only gradually. In fact, 1 percent increase in banking sector CDS spreads leads to a more than 0.1 standard deviation increase in fiscal uncertainty half a year later (first lag). The effect increases over time as bank bailouts may be provided and consequences for the public

Table 2.8: Baseline results for fiscal uncertainty determinants

	I	II	III	IV	V	VI	VII
	FE	Spatial FE	CCEP	CCEP	CCEP	CCEP	CCEP
Deficit squared	0.014***	0.010***	0.003***	0.003***	0.004***	0.004***	0.003***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Debt/GDP	-0.013***	-0.008***	-0.005***	-0.003***	-0.004***	-0.006***	-0.005***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Unemployment	0.083***	0.031*	0.017*			0.018	0.017
	[0.02]	[0.02]	[0.01]			[0.01]	[0.01]
GDP growth				-0.011			
				[0.02]			
Output gap					-0.000		
					[0.00]		
Bond yield						-0.024*	
						[0.01]	
Spatial lag		0.828***					
		[0.05]					
Inflation							0.010
							[0.01]
Observations	693	693	693	693	652	680	693
Countries	31	31	31	31	31	30	31
R-squared	0.255	0.471	0.882	0.881	0.884	0.854	0.882
p-value CD statistic	0.000	0.006	0.560	0.794	0.220	0.191	0.656

Notes: Dependent variable: U_{ct1}. Common Correlated Effects estimates: cross-sectional averages of fiscal policy uncertainty, deficit/GDP and GDP growth included as well as the crisis dummy. Standard errors in brackets, significance level given by *** p<0.01, ** p<0.05, * p<0.1. Specification VII also controls for the current account balance which is not statistically significant.

purse materialise. Accounting for up to four semi-annual lags (column II) shows that fiscal uncertainty effects are largest 1.5 years (3 semi-annual lags) after the increase in banking sector risk. This result also holds when stock market volatility is controlled for (column IV). The fact that financial sector measures, similar to long-term interest rates, are somewhat correlated with macroeconomic and fiscal outcomes explains why debt/GDP and unemployment are less statistically significant in these specifications.

Political economy determinants Table 2.10 reports a series of results for political economy factors that may be related to fiscal uncertainty. In general, upcoming elections render forecasts of the fiscal deficit uncertain (columns I to IV). This is in line with findings in the literature on forecast errors and political budget cycles (e.g.

Table 2.9: Financial sector determinants of fiscal uncertainty

	I	II	III	IV
Deficit/GDP squared	0.008***	0.006***	-0.002*	0.006**
	[0.00]	[0.00]	[0.00]	[0.00]
Debt/GDP	-0.008**	-0.005	0.001	-0.002
	[0.00]	[0.00]	[0.00]	[0.01]
Unemployment	0.038	0.003	-0.007	0.007
	[0.03]	[0.03]	[0.02]	[0.04]
Bank CDS spread	-0.005	-0.007		-0.070
	[0.14]	[0.16]		[0.27]
Lag 1	0.128	0.340**		0.150
	[0.14]	[0.17]		[0.28]
Lag 2	0.515***	0.386**		0.125
	[0.14]	[0.17]		[0.31]
Lag 3		0.998***		0.637**
		[0.17]		[0.31]
Lag 4		0.073		0.136
		[0.17]		[0.33]
Stock volatility			-0.040	0.372
			[0.04]	[0.50]
Lag 1			0.056	2.031***
			[0.06]	[0.48]
Lag 2			0.011	-0.759
			[0.04]	[0.50]
Lag 3			0.031	-0.420
			[0.03]	[0.46]
Lag 4			0.042*	-0.010
			[0.02]	[0.45]
Observations	353	316	541	316
Countries	20	19	31	19
R squared	0.602	0.632	0.946	0.783
p-value CD statistic	0.038	0.398	0.517	0.874

Notes: Dependent variable: U_{ct1}. Common Correlated Effects estimates, cross-sectional averages of fiscal policy uncertainty, deficit/GDP and GDP growth included as well as the crisis dummy. Standard errors in brackets, significance level given by *** p<0.01, ** p<0.05, * p<0.1.

Sørensen et al., 2001, Hallerberg and Strauch, 2002, de Castro et al., 2013). On average, if an election is scheduled for the upcoming year, the uncertainty about that year's fiscal deficit increases by 0.06 standard deviations (column I). This result is robust to controlling for snap elections, which are often not anticipated during the year prior to the election and should not affect fiscal uncertainty (column II). The statistically not significant coefficient for the snap election dummy suggests further that calling unanticipated elections is unlikely to be a reaction to heightened uncertainty, address-ing potential endogeneity concerns. In addition, an interaction between the election dummy and an indicator for the fixed election regime in column III is statistically significant and larger than the average effect reported in column I. For countries, where elections follow a set schedule, official forecasters face substantial uncertainty about fiscal forecasts during the year before the election. To explore the channel through which elections affect fiscal uncertainty in more detail, I interact the election dummy with the level of the fiscal deficit in column IV. If increases in the deficit ahead of an election were anticipated, as suggested by the political budget cycle literature, one would expect that such an increase raises uncertainty. The empirical evidence points in the opposite direction. Fiscal uncertainty about future deficits is higher during the year preceding an election, the lower the level of the projected fiscal deficit. This may be because fiscal authorities deliberately report lower deficit projections to offical forecasters prior to elections, supporting the argument made in Brück and Stephan (2006).

Fiscal space is constrained if a country's fiscal policy is subject to an Economic Adjustment Programme. Consequently, fiscal uncertainty is reduced considerably when fiscal policy is scrutinised by the IMF and institutions of the European Union as part of such a programme. On average, participating in a programme is associated with a reduction in fiscal uncertainty of more than 0.2 standard deviations (column V of Table 2.10). As a note of caution it should be mentioned that this result does not necessarily imply causality as countries with higher initial levels of fiscal uncertainty may have been more likely to enter a programme. Yet within those countries, the programme period is marked by substantially lower levels of fiscal uncertainty. Unlike the literature on forecast errors and determinants of fiscal policy discretion, I do not find statistically significant effects of fiscal rules on fiscal uncertainty (column VI). This may have to do with the fact that there is not sufficient time variation in the adoption of fiscal rules across advanced economies, especially in the European Union, or because rules have been adopted largely simultaneously.

Table 2.10: Political economy determinants of fiscal uncertainty

	I	II	III	IV	V	VI
Deficit/GDP squared	0.003***	0.003***	0.003***	0.002***	0.003***	0.004***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Debt/GDP	-0.005***	-0.005***	-0.005***	-0.004***	-0.004***	-0.005***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Unemployment	0.017*	0.017*	0.016	0.017*	0.024**	0.025**
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
Election	0.061*	0.085**	-0.015	0.116***		
	[0.03]	[0.04]	[0.04]	[0.04]		
Snap election		-0.088				
		[0.07]				
Election * Fixed			0.321***			
			[0.08]			
Election * Deficit/DGP				-0.046***		
				[0.01]		
Programme					-0.263*	
					[0.14]	
Expenditure rule						-0.046
						[0.07]
Revenue rule						-0.009
						[0.15]
Balanced budget rule						-0.095
						[0.35]
Debt rule						0.016
						[0.38]
Observations	693	693	693	693	693	672
Countries	31	31	31	31	31	30
R squared	0.883	0.883	0.886	0.889	0.883	0.861
p-value CD statistic	0.542	0.587	0.587	0.246	0.253	0.954

Notes: Dependent variable: U_{ct1}. Common Correlated Effects estimates, cross-sectional averages of fiscal policy uncertainty, deficit/GDP and GDP growth included as well as the crisis dummy. Standard errors in brackets, significance level given by *** p<0.01, ** p<0.05, * p<0.1.

Fiscal uncertainty index versions Results presented so far have given insights about potential drivers of uncertainty about the fiscal deficit of the upcoming year. The composite index of fiscal uncertainty has been used, based on forecast revisions to approximate common uncertainty shocks and forecast disagreement. Table A3 in the Appendix presents results from other index versions. It shows that results for the deficit/GDP, banking sector and political economy determinants apply also to forecast disagreement alone (D_{ct1}, columns I, II, III). Unlike for the full index version, debt/GDP and unemployment are not statistically significant. This confirms descriptive findings of section 2.2.5: forecast revisions capture predominantly business cycle-related common forecast uncertainty while forecast disagreement is a good proxy for sources of idiosyncratic fiscal uncertainty. Somewhat weaker results are obtained for the current-year version of the fiscal uncertainty index, U_{ct0} (columns IV, V, VI). While results for fiscal and macroeconomic fundamentals as well as for banking sector CDS spreads are similar, the election dummy is not found statistically significant. This can be explained by the fact that, as elections take place, their fiscal effects for the ongoing year are better known than effects of elections in the following year. Similarly, the nowcast disagreement component D_{ct0} appears to mainly reflect the type of uncertainty that stems from fiscal and macroeconomic fundamentals (columns VII, VIII, IX).

Determinants of alternative uncertainty measures Table A4 in the Appendix shows that other measures of fiscal uncertainty, or policy uncertainty, show somewhat different responses to the uncertainty determinants considered here. In particular, I compare results to those obtained using as the dependent variable the Baker et al. (2016) Economic Policy Uncertainty index, realised government bond yield volatility and forecast errors. Differences relative to the fiscal uncertainty index proposed in this chapter suggest that these measures may either reflect other types of uncertainty, or do not capture uncertainty at all.

Turning to more detailed results, I find that the EPU is not significantly correlated with my financial sector risk proxy and the election dummy (columns II, III). In addition, debt/GDP is found to have a positive effect on EPU at statistically significant levels, contrary to the debt stabilisation hypothesis and findings for my fiscal uncertainty index. The business cycle, as approximated by unemployment, appears to have the opposite effect: high unemployment is associated with lower uncertainty about economic policy. This appears implausible and suggests that the EPU at best reflects other types of uncertainty.

Findings for government bond yield volatility are more similar to results for fiscal uncertainty (columns IV, V, VI). Squared deficit/GDP and unemployment have a significantly positive effect on bond yield volatility while debt/GDP has a negative effect. An increase in banking sector CDS spreads affects sovereign bond yield volatility with a one-year lag, which is comparable to findings for forecast uncertainty (column V). Only election effects are found to be insignificant (column VI).

I also obtain mixed findings for *ex post* observable forecast errors. For a comparison with the forecast uncertainty index, I regress the absolute value of one year-ahead and current-year forecast errors of the fiscal deficit on uncertainty determinants (columns VIII to XII). This is to account for the fact that errors may be large in a positive or negative direction but reflect uncertainty in both instances. Overall, debt/GDP has a negative effect on forecast errors, while the effect of unemployment is positive, in line with findings for the index. Absolute forecast errors, however, appear to be larger, the closer the deficit/GDP is to zero (as indicated by the negative coefficient on the squared deficit term). While banking sector risk is positively correlated with absolute year-ahead forecast errors, the effect of elections is negative, contrary to findings for the fiscal uncertainty index.

I conclude that the widely used EPU index captures other aspects of policy uncertainty compared to the fiscal uncertainty index proposed in this chapter. More closely related to my index is a government bond yield volatility measure. This may be the case because bond yield spreads react to uncertainty about sovereign credit risk and future discretionary policy, i.e. uncertainty reflected in my forecast-based index. *Ex post* forecast errors, however, appear to be driven by somewhat different factors and may not always reflect uncertainty about the forecast variable.

2.4 Conclusion

This chapter proposes a measure of fiscal uncertainty based on the disagreement between official forecasts of the fiscal deficit and a common uncertainty shock faced by forecasters. The resulting index captures uncertainty about fiscal policy in one year-ahead forecasts and nowcasts as faced by the OECD, IMF and European Commission forecasting departments. It is comparable across a set of 31 advanced economies and reflects uncertainty about the path of fiscal policy in real time. This index therefore provides an insightful complement to existing measures of uncertainty about the macroeconomy, like those proposed by Jurado et al. (2015) and Rossi and Sekhposyan (2015), uncertainty on financial markets, such as the VIX, and uncertainty about economic policy, e.g. the EPU by Baker et al. (2016). The index is shown to provide a direct proxy of uncertainty about fiscal outcomes in the near term.

A regression analysis finds that both fiscal and macroeconomic fundamentals as well as non-fundamental variables, like financial sector risk and political economy factors, are correlated with uncertainty about the fiscal deficit. However, fiscal uncertainty appears to decrease as the debt stabilisation motive imposes constraints on fiscal policy, or externally enforced adjustment programmes limited fiscal policy during the euro area crisis. I also find that the index is more closely related to those drivers than more indirect proxies, such as forecast errors or the volatility on markets for sovereign debt.

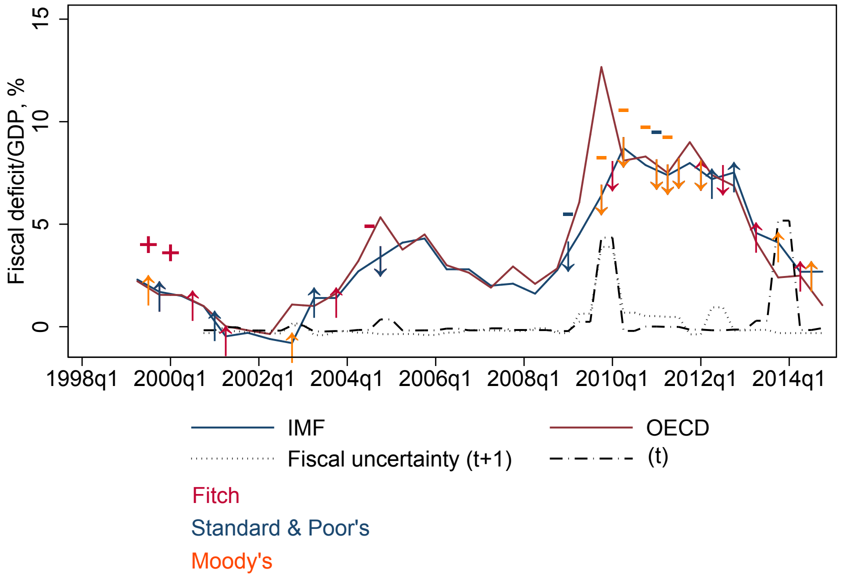
The evolution of the index over time suggests that fiscal uncertainty increased to unprecedented levels in the aftermath of the global financial crisis. This raises the question of potential effects on economic outcomes, which the following two chapters address.

Chapter 3

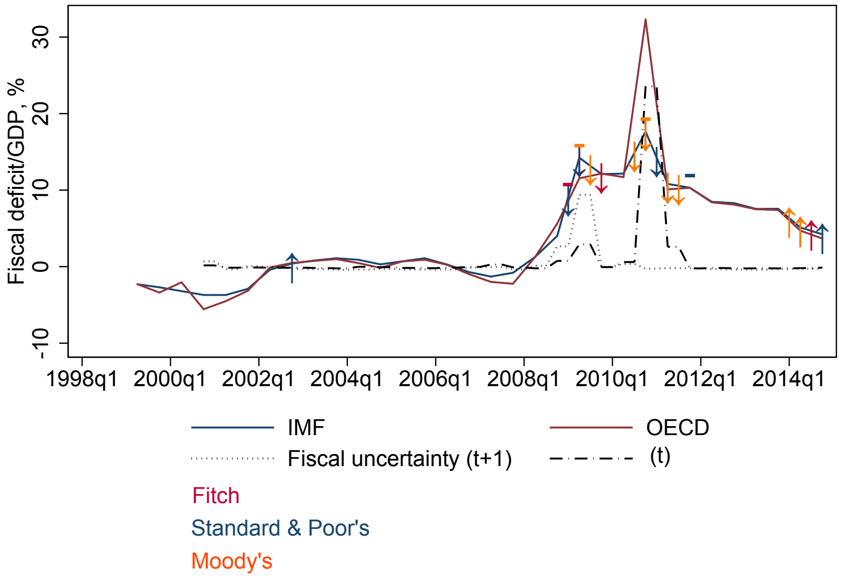
Sovereign Credit Ratings under Fiscal Uncertainty

3.1 Introduction

The recent global financial and European government debt crisis was characterised by a substantial deterioration of public finances. In many advanced economies, the fiscal deficit relative to GDP saw double-digit percentage increases, which had not been experienced in decades. In Greece and Ireland, this increase was among the most pronounced as both countries tipped into a severe sovereign debt crisis after the global financial turmoil of 2008. Figure 3.1 shows that official forecasts of the government budget deficit published by the IMF (blue line) and the OECD (red line) rose to levels just below 10 percent of GDP for Greece and substantially above 10 percent for Ireland. Concerns about sovereign debt heightened not only because fiscal deficits rose in absolute terms. Equally salient was the fact that uncertainty about the fiscal position surged significantly, as indicated by the newly constructed fiscal uncertainty index (dotted and dashed lines) in Figure 3.1.



(a) Greece



(b) Ireland

Figure 3.1: Official fiscal forecasts, uncertainty and sovereign rating migration

In Greece, the rise in fiscal uncertainty at the end of 2009 was aggravated by revelations made by the newly elected Papandreou government about the misreporting of past deficit figures. In Ireland, uncertainty about banks' balance sheets spilled over to the public sector when bank rescues were undertaken by the government in 2010.

Investors in sovereign debt can rely on a number of experts to provide them with information about future fiscal positions, including independent national auditing units, central banks, investment banks and fund managers. In this thesis, 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. Figure 3.1 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). By raising the stock of public sector debt, an increase in the deficit may weaken the future ability of the government to service its debt. The deficit-to-GDP ratio is therefore considered one important sovereign credit risk factor by credit rating agencies, alongside the stock of sovereign debt and the expected state of the macroeconomy. 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 (2014) and 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 much 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, using the methodology of Moody's, and a subjective component that enters ratings as a form of expert opinion. They find that for crisis-hit euro area countries, the subjective component appears to be too optimistic before the crisis, but too pessimistic during and after. Figure 3.1 also seems to suggest that the frequency of rating announcements increases when there is higher fiscal uncertainty (the dotted line is the fiscal uncertainty index based on year-ahead forecasts, the dash-dotted line is the index version based on current-year forecasts). In this chapter, I analyse to what extent fiscal uncertainty can explain the pro-cyclicality of sovereign ratings during crises.

In particular, I test two hypotheses about the effect of fiscal uncertainty on sovereign credit ratings. A first hypothesis is concerned with the effect of fiscal uncertainty on sovereign credit risk. Following surges in fiscal uncertainty in advanced economies during the recent crisis, a new literature emerged that analyses the effects of uncertainty about fiscal policy. Fernández-Villaverde et al. (2015) find that fiscal policy uncertainty reduces economic activity. Political uncertainty during election years often negatively affects domestic and foreign direct investment (Julio and Yook, 2012, Julio and Yook, 2016) while uncertainty about fiscal consolidation measures seems to determine whether these measures are expansionary, or not (Croce et al., 2012, Bi et al., 2013). Likewise, noisy communication of fiscal policy blurs agents' expectations and reduces fiscal multipliers (Ricco et al., 2016). An accurate assessment of sovereign credit risk should take these adverse effects of fiscal uncertainty on country fundamentals and risk premia premia into account. However, the link between fiscal uncertainty and sovereign credit risk has not been given much attention. Sovereign ratings have been shown to react to crises (Monfort and Mulder, 2000, Gärtner et al., 2011), world stock market volatility (Hill et al., 2010) and consumer sentiment (Schumacher, 2014). Yet the direct effect of country-specific fiscal uncertainty has not been analysed in detail. This chapter tries to fill this gap. Using the slowly-moving index developed in chapter 2.2

allows me to identify the effect of fiscal uncertainty, once it has been realised, on decisions taken by credit rating agencies across countries and over time, independent of potential feedback effects rating announcements may arguably have on the degree of uncertainty. I find that for a sample of advanced economies and the three main credit rating agencies Fitch, Standard & Poor's and Moody's, fiscal uncertainty increases the probability of a rating downgrade. A pro-cyclical movement of credit ratings during crises may therefore be justified if it reflects adverse effects of uncertainty on sovereign credit risk.

The second hypothesis is concerned with changes in the behaviour of credit rating agencies that cannot be explained by accurate reflections of sovereign credit risk alone. Fiscal uncertainty creates an information asymmetry between financial market participants and rating agencies as credit risk experts. It is argued that this asymmetry may sometimes be exploited by rating agencies, for instance if they were to seek public attention to increase their publicity. Publicity may be gained by announcing a rating change that cannot be entirely justified by movements in sovereign credit risk. I find that sovereign ratings are changed more frequently during periods of fiscal uncertainty than suggested by fundamentals related to sovereign credit risk. This holds independently of the effect fiscal uncertainty has on such movements of sovereign credit risk. I conclude that rating pro-cyclicality may therefore not be fully explained by the fundamental effect of fiscal uncertainty on sovereign credit risk. Rating agency behaviour not only appears to be driven by the incentive to provide an accurate risk assessment but other incentives related to publicity also play a role.

A number of characteristics in data on advanced economies' sovereign ratings make the estimation of rating determinants difficult. Given that advanced economies generally enjoy investment-grade ratings, not all rating categories along the ordinal rating scale are observed. In addition, sovereign ratings are very stable over time. Rating stability can result from three sources. First, credit ratings are measures of relative credit risk. Sovereign ratings change only if the relative movement in sovereign credit risk exceeds certain thresholds defined by rating agencies. Second, ratings at the upper end of the rating scale are by construction changed less frequently than below-investment grade ratings, i.e. as a technical feature of the rating process some rating categories are more stable. Finally, ratings are assigned using categories along a bounded ordinal scale. A rating at the top end of the rating scale cannot be improved further. Similarly, a rating at the bottom end of the scale cannot be reduced. This renders ratings at the boundary of the rating scale more stable, relative to all other rating categories. This chapter proposes a new empirical framework for the analysis of sovereign rating determinants that accounts for these features. The new framework 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. This chapter therefore also adds to an empirical strand of literature that aims to assess the determinants of sovereign ratings assessed by credit rating agencies (Cantor and Packer, 1996, Afonso et al., 2011, Hill et al., 2010). Monte Carlo simulations show that standard estimation techniques generate biased estimates if rating stability is not taken into account. In addition, the new empirical strategy proposed in this chapter is better able to predict rating changes compared to an estimation of a simple model of rating changes by Ordered Probit that has previously been employed in the literature.

The rest of the chapter is organised as follows. The next section provides the theoretical background and derives the two empirical hypotheses related to fiscal uncertainty as a credit risk, and rating attention. Section 3.3 develops the empirical framework and provides results from a Monte Carlo experiment. Empirical findings for the effect of fiscal uncertainty on sovereign rating transition are presented in Section 3.4. Section 3.5 concludes this chapter.

3.2 Theory and hypotheses

3.2.1 Hypothesis of fiscal uncertainty as a credit risk

When credit rating agencies assign sovereign ratings, they evaluate the capacity and willingness of a sovereign entity to meet its financial obligations at the time of the rating announcement and in the future, fully and on time (FitchRatings, 2010; see also Standard and Poor's, 2011b, Moody's, 2013, IMF, 2010). This definition encompasses various types of sovereign default such as the repudiation of debt, restructuring and renegotiations – events more likely in the context of sovereign issuers than actual defaults (Duffie and Singleton, 2003, pp. 147). Rating agencies claim to take a wide range of quantitative and qualitative information into account to determine the sovereign rating (e.g. FitchRatings, 2010, Standard and Poor's, 2011b, Moody's, 2013). This includes measures of macroeconomic performance, the soundness of public finances, external financial strength, the stability of the financial sector and contingent liabilities as well as the strength of political and economic institutions. Transparency about rating determinants has improved in recent years, partly as a result of financial regulation (e.g. European Union, 2013). Moody's (2013), for instance, now claims that its sovereign rating levels are predictable with a three-notch accuracy. That the degree of fiscal uncertainty guides rating agencies' decisions often becomes clear more indirectly than through stated descriptions of their methodology, for instance in the form of statements justifying particular rating actions (e.g. Standard and Poor's, 2011a).

According to theory, rating agencies care about their reputation in the long run. To earn reputation, they have to provide an accurate assessment of sovereign credit risk based on movements in underlying fundamentals (cf. Mariano, 2012, Bar-Isaac and Shapiro, 2013, and others).

Following the seminal paper by Cantor and Packer (1996), empirical studies have tried to relate sovereign credit ratings to economic variables. Table 3.1 provides an overview. Most studies show that a relatively parsimonious set of macroeconomic and fiscal fundamentals associated with sovereign credit risk can explain a significant part of the variation in sovereign ratings across countries and time.

In particular during crises, sovereign ratings appear to deviate from these fundamentals. For the Asian crisis of the 1990s, Ferri et al. (1999) and Eliasson (2002) find that ratings significantly moved away from what movements in fundamentals would have implied. A model-based indicator of sovereign credit risk proposed by Polito and Wickens (2014) and Polito and Wickens (2015) reacted much earlier than official ratings to deteriorations in governments fiscal positions in the aftermath of the recent financial crisis. Sovereign ratings seem to react to crises (Monfort and Mulder, 2000), as well as world stock market volatility (Hill et al., 2010) and consumer sentiment (Schumacher, 2014), rather than to anticipate these crises. It is argued that this made rating changes pro-cyclical leading to self-fulfilling deteriorations, which could have aggravated pressure on sovereign borrowers.[1]

However, ratings may appear pro-cyclical if fiscal uncertainty, which often increases during crises, is considered a risk determinant to which agencies react. Given that uncertainty about fiscal policy has itself been found to have adverse effects on growth (Fernández-Villaverde et al., 2015, Croce et al., 2012), consumption, investment (Johannsen, 2014) and risk premia on financial markets (Sialm, 2006, Pástor and Veronesi, 2013), an accurate assessment of sovereign credit risk should also take fiscal uncertainty

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[1] Mora (2006), by contrast, finds that during the Asian crisis ratings were stickily reacting to news rather than being pro-cyclical.

as a credit risk factor into account. In what follows, I refer to this as the credit risk hypothesis: as fiscal uncertainty increases, the probability of a rating downgrade is expected to increase.

Given that fiscal uncertainty does not directly enter the reported objective rating component that is based on the level of fundamentals associated with sovereign credit risk, rating agencies likely consider it in a subjective part of their risk assessment. D'Agostino and Lennkh (2016) decompose Moody's ratings into an objective and a subjective component and find that the latter increased substantially during the European sovereign debt crisis. The increase in fiscal uncertainty may explain this finding. Similarly, fiscal uncertainty is likely captured by the arbitrary non-fundamental that Gärtner et al. (2011) show drives ratings of those euro area countries that were most severely hit by the crisis. De Vries and de Haan (2016) 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. This may have been due to persistent levels of fiscal uncertainty. Policies that promote fiscal transparency have been shown to have a positive effect on sovereign ratings by Arbatli and Escolano (2015). This indirectly implies that, as fiscal outcomes become more uncertain, rating agencies react with downgrades.

Another channel through which fiscal uncertainty may affect sovereign credit risk, and which may hence be considered by credit rating agencies who aim for an accurate assessment of this risk in the long run, is the following: Bonfiglioli and Gancia (2015) show that economic uncertainty can be conducive to structural reforms, which in turn would support sovereign creditworthiness. Likewise, uncertainty about fiscal fundamentals may be the result of budgetary reforms, which are beneficial in the long run. In both cases, rating agencies might reward governments with higher fiscal uncertainty and the downgrade probability falls.

Table 3.1: Previous findings on the determinants of sovereign credit ratings

Reference	Sample	Main determinants
Linear regression model of rating levels		
Cantor and Packer (1996)	S&P, Moody's, 49 countries (advanced and developing), 1995	GDP per capita, GDP growth, inflation, fiscal deficit, external debt, development indicator, default history
Ferri et al. (1999)	Moody's, 17 countries (advanced and developing), 1989-1998	GDP growth, fiscal deficit, current account balance, development indicator, external debt, current account and short-term debt relative to foreign reserves
Monfort and Mulder (2000)	S&P, Moody's, 20 emerging markets, 1994-1999	GDP growth, inflation, fiscal deficit, debt over exports, rescheduling history, terms of trade, export growth, investment
Borio and Packer (2004)	S&P, 52 countries (advanced and developing), 1996-2003	GDP per capita, inflation, GDP growth, corruption indicator, political risk indicator, default history, "original sin" measure (foreign currency debt), GDP, currency mismatch
Butler and Fauver (2006)	Institutional Investor, 86 countries (advanced and developing), 2004	GDP per capita, inflation, foreign debt, development indicator, legal and political environment indicators
Non-linear regression model of rating levels		
Hu et al. (2002)	S&P, 62 countries (advanced and developing), 1981-1998	debt, reserves, inflation, default history
Block and Vaaler (2004)	S&P, Moody's, Fitch, IBCA, DCR, Thompson, 19 developing countries, 1987-1998	inflation, fiscal deficit, external balance, external debt, default history, election year indicator
Mora (2006)	S&P, Moody's, 105 countries (advanced and developing), 1989-2001	GDP per capita, GDP growth, fiscal deficit, current account balance, external debt, default history, sovereign bond yield spread
Mellios and Paget-Blanc (2006)	S&P, Moody's, Fitch, 86 countries (advanced and developing), 2003	GDP per capita, government revenue, real exchange rate, inflation, default history, corruption indicator, political risk indicator
Depken et al. (2006)	S&P, 57 countries (advanced and developing), 1995-2003	GDP per capita, inflation, fiscal deficit, external balance, default history, trade openness indicator, corruption indicator
Afonso et al. (2011)	S&P, Moody's, Fitch, 130 countries (advanced and developing), 1970-2005	GDP per capita, GDP growth, unemployment, inflaiton, debt, fiscal deficit, government effectiveness indicator, external debt, current account balance, external debt, default history
Regression model of rating changes		
Hill et al. (2010)	S&P, Moody's, Fitch, 129 countries (advanced and developing), 1990-2006	GDP per capita, GDP growth, external debt, international risk premium

3.2.2 Asymmetric information and attention hypothesis

Investors, for instance in government debt, base their investment decision on publicly available information about fundamental factors related to the credit risk of the investment. The role for rating agencies arises from the fact that public information may be noisy. Theories of rating agency behaviour hypothesise that rating agencies receive a private signal about the true state of fundamentals, for instance as a result of their expert analysis (Mariano, 2012, Bar-Isaac and Shapiro, 2013, Manso, 2013). They can decide to make the signal public in the form of a credit rating. The information made available by rating agencies is taken into account by investors and the general public if it adds value to publicly available information. If ratings provide additional information to market participants, then, on sufficiently efficient markets as described by Fama (1970), rating announcements will have a measurable impact on financial indicators shortly after being made public. Theoretical contributions suggest that, while rating agencies may be concerned about their reputation in the long run, they may nevertheless have incentives to deviate from fundamentals in the short run. Mariano (2012) shows theoretically that agencies may want to conform with market expectations if the private signal they receive is itself noisy, for instance because the agency is not capable of making a good assessment of credit risk. Such a "low-skilled" agency loses reputation from publishing potentially wrong private information. It may therefore decide to contradict its signal and conform with public information to make short-term reputational gains. In a different scenario by Manso (2013), credit ratings have an impact on the survival of the debtor while agencies' pay-offs depend on this survival. Agencies may then also want to publish a softer assessment of credit risk than suggested by the private signal they receive about fundamentals. In a model by Bar-Isaac and Shapiro (2013), producing assessments of credit risk becomes more costly during economic upturns as wages for rating analysts increase. Agencies then compromise on rating quality and publish ratings that deviate from fundamentals.

By the same token, agencies may trade off long-term reputational concerns for the short-term publicity of sovereign rating changes, for instance to draw the attention of customers in other business areas, like the corporate rating sector (Attention Hypothesis). In the following section, a model is presented that introduces publicity pay-offs to a simple theory of rating agency behaviour. It is shown that publicity can provide a short-term benefit that is traded off against long-run reputational concerns. It can provide rating agencies with the incentive to change sovereign ratings more often than justified by movements in underlying fundamentals. In particular, the model shows that the probability of changing ratings more frequently than justified is greater than zero if reputational and publicity concerns enter the agency's utility function with equal weight. The model is related to a theory by Laster et al. (1999) in which macroeconomic forecasters gain from publicity and therefore have an incentive to deviate from consensus forecasts.

Model

Set-up Let there be two players, the Credit Rating Agency A and the Public P.[2] The game consists of two stages. In the first stage, Nature determines the dynamics of sovereign credit risk $x \in \{0, 1\}$. Sovereign credit risk changes, $x = 1$, with probability $\pi_x \in [0, 1]$, or not, $x = 0$, with probability $(1 - \pi_x)$. In the second stage, the Agency observes x and can decide to adjust its sovereign credit rating R accordingly. In particular, it can choose the probability of a change in the rating $R = 1$ conditional on $x = 1$, $\pi_1 = \text{Prob}\{R = 1|x = 1\} \in [0, 1]$. The Agency may also decide to contradict Nature by reporting a rating change even though x does not change. Let us denote the probability of contradicting Nature $\pi_0 = \text{Prob}\{R = 1|x = 0\} \in [0, 1]$. The Public has an interest in the dynamics of sovereign credit risk, for instance to adjust its sovereign debt portfolio. It therefore seeks information about the true value of x. The Public can

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[2] I am grateful to Xueheng Li for his help with this section.

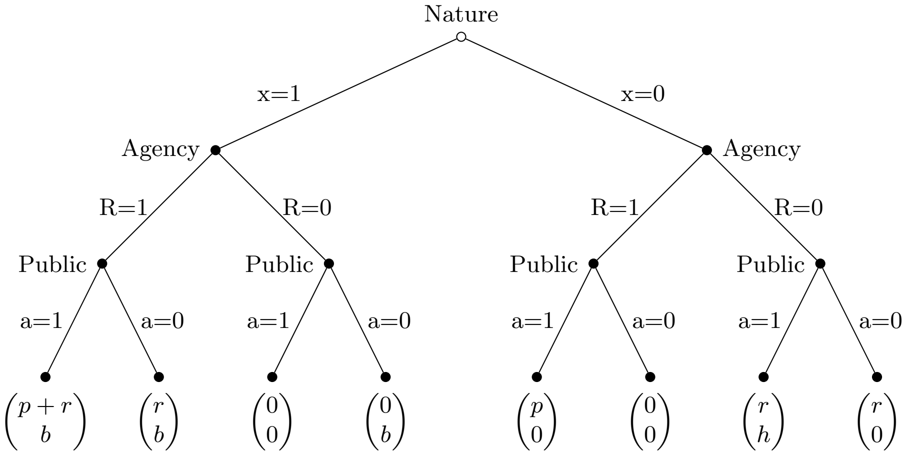

Figure 3.2: Rating game and pay-offs

decide to pay attention to the rating change $a \in \{0, 1\}$, where $a = 1$ denotes paying attention while $a = 0$ means the Public ignores whether a rating change occurs. The Agency and the Public make decisions simultaneously.

Pay-offs and fiscal uncertainty The set-up and pay-offs are summarised in Figure 3.2. The Public earns $b > 0$ if $x = 1$ as a result of portfolio readjustments, and 0 otherwise. If the Public believes the Agency instead of basing decisions on x, it receives a pay-off of zero if no rating change is issued although fundamentals change ($\{R = 0|x = 1\}$), or if ratings change even though fundamentals do not ($\{R = 1|x = 0\}$). The Public gains a pay-off h if $R = 0$ correctly indicates $x = 0$.

The Agency has two objectives. First, it receives a reputational benefit r in the long run if its rating action corresponds to the true value of x, i.e. $r > 0$ for $\{R = 1|x = 1\}$ and $\{R = 0|x = 0\}$. r could also be interpreted as a benefit that indirectly translates into monetary gains in the corporate sector. Second, the Agency gains a publicity pay-off $p > 0$ every time the Public pays attention to its rating change.

If there was complete information, both the Agency and the Public would observe x. Information is available to the Public without cost and it's pay-off from observing

$\{R = 0|x = 0\}$ is $h = 0$. The Public neither gains nor loses from paying attention to rating changes and could therefore ignore them, i.e. $a^* = 0$. Its pay-off is either b or 0 for sure. Given $a^* = 0$, the Agency always provides information that is in line with true movements in sovereign credit risk. It earns r.

Under asymmetric information, the information set for the Agency remains unchanged. However, the Public can no longer observe the true value of x in the short run when it is relevant for investment decisions. It only holds the *ex ante* belief π_x. Only in the long run, x will be observed by both players and reputation r be realised. h now becomes greater than 0. The intuition behind this is that uncertainty generates a cost of information acquisition. Having normalised losses to zero, h becomes the Public's gain from knowing for sure that portfolio readjustments are not necessary.

Equilibrium under asymmetric information The Agency will always report truthfully if fundamentals change $x = 1$ given that the Public observes its rating change $a^* = 1$, i.e. $\pi_1^* = 1$. $a^* = 1$ is the Public's best response to $\pi_1^* = 1$ and π_0^* if rating changes contain more information than the Public's prior belief over the probability of $x = 1$, π_x. In fact, the Public will know for sure that $x = 0$ if it observes $R = 0$. So as long as $\pi_0^* < 1$ and the Public values knowing $x = 0$, i.e. $h > 0$, it will be better off paying attention to the rating change. Unless the Agency always reports $R = 1$ given $x = 0$, a rating change conveys some information to the Public. The Public's trade-off boils down to not gaining any knowledge and gaining at least certainty over $x = 0$ through the (second-best) action $a^* = 1$. Finally, given $a^* = 1$, the Agency adjusts its response to $x = 0$ by maximising its expected pay-off. Mixing between reporting $x = 0$ truthfully and untruthfully issuing a rating change $R = 1$ is only then the best response, if publicity and reputational pay-offs are exactly equal, i.e. $p = r$. The Agency has an incentive to report rating changes more often than justified by movements in credit risk if it gains exactly as much in the form of short-run publicity than it gains reputation in the long run. If long-run reputational pay-offs are higher than publicity gains, it would not pay off to mislead the public. *Vice versa*, if publicity matters more, the Agency would have an incentive to set $\pi_0^* = 1$ which would make the rating change not credible.

Let us define the Public's belief that $x = 1$ if $R = 1$ is issued $\mu = \text{Prob}\{x = 1|R = 1\}$. The following formal proposition then summarises the argument made:

Proposition: *Under asymmetric information there exists a Bayesian Nash equilibrium* $(\pi_0^*, \pi_1^*, a^*, \mu)$ *such that the Agency changes the rating with non-zero probability despite there being no change in fundamentals* $0 < \pi_0^* < 1$*, the Agency always changes the rating if fundamentals change* $\pi_1^* = 1$*, the Public always observes the rating* $a^* = 1$ *and the Public believes* $x = 1|R = 1$ *with probability* $\mu = \frac{\pi_x}{\pi_x + (1-\pi_x)\pi_0^*}$.

A formal derivation is provided in Technical Appendix A2.

This simple model of rating agency behaviour is too abstract to test empirically, and pay-offs are not observed in practice to enable a direct test. The model can nevertheless provide the motivation for the Attention Hypothesis of this chapter. Fiscal uncertainty can generate an asymmetry between the information set of rating agencies and the information held by financial market participants. Rating agencies may exploit this information asymmetry by changing ratings more frequently than justified by underlying fundamentals, if they care about their reputation as well as about their publicity. Differences across rating agencies in the effect of fiscal uncertainty on the frequency of rating changes may therefore reflect differences in reputational concerns. In practice, it seems reasonable to assume that the degree of information asymmetry will be proportional to the degree of uncertainty about the future state of fiscal fundamentals.[3]

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[3] Chapter 4 picks up this argument and tests to what extent attention to rating announcements can be linked to fiscal uncertainty.

3.3 Empirical strategy

3.3.1 Sovereign rating data

The dataset 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 3.2 shows the number of end-of-quarter observations per rating category.

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. As a result, 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 excluding non-OECD countries from the analysis may exacerbate econometric challenges as this reduces the variation in credit ratings. 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 problematic as well. As the interest in this chapter lies in recent developments in advanced economies, a focus on OECD countries is justified. Furthermore, data on macroeconomic and fiscal fundamentals related to credit risk are more readily available for advanced economies. Data at higher frequency (quarterly or semi-annual instead of

Table 3.2: 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.

annual) allows more directly for an analysis of the effect of relatively frequent events on sovereign ratings. For instance, the index of fiscal uncertainty constructed in the previous chapter only covers the sample of OECD countries.

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 3.2 (bottom) shows that sovereign ratings of advanced economies are particularly stable. 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 downgrade (likewise for upgrades). Between 2.4 and 3 percent are rating downgrades, between 2.3 and 2.5 percent are upgrades. Four countries in my 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, have been downgraded only once or twice very recently following the financial crisis. 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 3.2 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 are very stable. Transition matrices show that upgrades and downgrades happen more often for lower than higher rating categories (Tables A5, A6, and A7 in the Appendix). AAA (Aaa) ratings exhibit the highest persistence.

A theoretical argument for why agencies have rating stability in their objective function, 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. Corporate credit risk is subject to fiscal and economic policies as well as the probability of bailouts by the government and therefore partly a function of sovereign credit risk. Gaillard (2011) attributes the higher frequency of rating changes in speculative-grade categories relative to investment grade ratings to the sensitivity of high credit-risk countries to the business cycle (p. 133). 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.

3.3.2 A regression model with two processes

In order to test the two hypotheses about the effect of fiscal uncertainty on the way sovereign ratings are determined by rating agencies, I propose a regression model that consists of two latent processes which jointly determine the probability of rating changes. This approach allows me to separately estimate the determinants of the frequency of rating changes and the determinants of their direction.

Stage 1: credit risk process 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:

$$\Delta R^*_{ct} = \beta_0 + (\Delta X_{ct} - \Delta \overline{X}_{ct})'\beta_2 + \beta_3(\Delta U_{ct} - \Delta \overline{U}_{ct}) + \varepsilon_{ct} \tag{3.1}$$

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 (Credit Risk Hypothesis). 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 (3.1). 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 (cf. discussion in Chapter 2 on cross-sectional dependence in the linear regression context). 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'. It can be thought of as one of the sources of rating stability.

Stage 2: stability process 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 remains unobserved to 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:

$$s^*_{ct} = \beta^S_0 + C^{'}_{ct}\beta^S_1 + \beta^S_2 U_{ct} + \epsilon_{it} \tag{3.2}$$

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 controls 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, or conversely, if during periods of high uncertainty, ratings are changed more frequently (Attention Hypothesis). β^S_j are the coefficients assigned by the rating agency to both types of stability determinants. ϵ_{it} is the error term of the stability process. It is assumed to be independent of the error term ε_{it} of the credit risk 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 (3.1) and the stability process (3.2):

$$\Delta R_{ct} = \begin{cases} \text{`downgrade'} & if \quad \Delta R^*_{ct} \leq c_1 \text{ and } s_{ct} = 1 \\ \text{`no change'} & if \quad c_1 < \Delta R^*_{ct} \leq c_2 \text{ and } s_{ct} = 1 \text{ OR } \quad if \quad s_{ct} = 0 \\ \text{`upgrade'} & if \quad c_2 < \Delta R^*_{ct} \text{ and } s_{ct} = 1 \end{cases} \tag{3.3}$$

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.

3.3.3 An adjusted ordered outcome estimator

Sovereign rating stability Section 3.3.1 implies that an estimator of sovereign rating determinants has to take into account the dominant features of sovereign rating data. This includes the limited number of ratings in some rating categories and high rating stability, in particular at the upper end of the rating scale. Rating stability may result from limited movements in relative credit risk ('through-the-cycle approach'), technical factors inhibiting the frequency of rating changes (stability process), and observations at the boundary of the rating scale (especially 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) (see also Table 3.1). 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 (3.1), 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 3.3.1. 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 3.3 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 (3.2), 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 3.2) 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.

By contrast, it is well established that maximum likelihood estimation is subject to considerable small sample biases because of the restrictive distributional assumption it imposes (e.g. Shenton and Bowman, 1977; Griffiths et al., 1987). Peduzzi et al. (1996) and Vittinghoff and McCulloch (2007) find that a high number of regressors – like in the context of rating determinants – can also generate biases in standard categorical data estimators.

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. Their approach can directly be applied to the two-process model outlined above.

Using equations (3.2) and (3.1), the probability function of the Middle-Category

Inflated Ordered Probit estimator can be written as:

$$\Pr(\Delta R_{ct}) = \begin{cases} \Pr(\Delta R_{ct} = \text{`downgrade'}|C_{ct}, U_{ct}, X_{ct}) & = & \Phi(s^*_{ct})\Phi(c_1 - (\Delta R^*_{ct})) \\ & & \\ \Pr(\Delta R_{ct} = \text{`no change'}|C_{ct}, U_{ct}, X_{ct}) & = & [1 - \Phi(s^*_{ct})] + \Phi(s^*_{ct})[\Phi(c_2 - (\Delta R^*_{ct})) \\ & & -\Phi(c_1 - (\Delta R^*_{ct}))] \\ \Pr(\Delta R_{ct} = \text{`upgrade'}|C_{ct}, U_{ct}, X_{ct}) & = & \Phi(s^*_{ct})[1 - \Phi(c_2 - (\Delta R^*_{ct}))] \end{cases} \tag{3.4}$$

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 (3.4) reduces to the standard Ordered Probit likelihood function for three outcomes.

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^{AAA}_{ct} and D^{D}_{ct}. D^{AAA}_{ct} (D^{D}_{ct}) 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'). The Probit-based outcome probabilities of such a Boundary-Adjusted Middle-Category Inflated Ordered Probit estimator (BAM) then become:

$$\Pr(\Delta R_{ct}) = \begin{cases} \Pr(\Delta R_{ct} = \text{‘downgrade’}|C_{ct}, U_{ct}, X_{ct}, D_{ct}^{D}, D_{ct}^{AAA}) & = & (1 - D_{ct}^{D})\Phi(s_{ct}^{*})\Phi(c_1 - (\Delta R_{ct}^{*})) \\ \\ \Pr(\Delta R_{ct} = \text{‘no change’}|C_{ct}, U_{ct}, X_{ct}, D_{ct}^{D}, D_{ct}^{AAA}) & = & [1 - \Phi(s_{ct}^{*})] + \Phi(s_{ct}^{*})[\Phi(c_2 - (\Delta R_{ct}^{*})) \\ & & -\Phi(c_1 - (\Delta R_{ct}^{*}))] \\ & & +D_{ct}^{AAA}\Phi(s_{ct}^{*})[1 - \Phi(c_2 - (\Delta R_{ct}^{*}))] \\ & & +D_{ct}^{D}\Phi(s_{ct}^{*})\Phi(c_1 - (\Delta R_{ct}^{*})) \\ \\ \Pr(\Delta R_{ct} = \text{‘upgrade’}|C_{ct}, U_{ct}, X_{ct}, D_{ct}^{D}, D_{ct}^{AAA}) & = & (1 - D_{ct}^{AAA})\Phi(s_{ct}^{*})[1 - \Phi(c_2 - (\Delta R_{ct}^{*}))]. \end{cases} \tag{3.5}$$

Note that the presence of dummy indicators D_{ct}^{AAA} and D_{ct}^{D} allows me to take directly into account the third potential source of rating stability, alongside technical stability due to the stability process (3.2) and stability from limited, relative movements in fundamentals of the credit risk process (3.1): stability due to the boundary of the rating scale. For ratings that would see a change according to equations (3.2) and (3.1), this change will not be observed if these ratings lie at the boundary of the rating 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 (3.2) and (3.1) to be estimated by the BAM estimator. Using the probabilities from (3.5), the log likelihood function, that the ML algorithm maximises, becomes:

$$\log\mathcal{L}(\theta) = \begin{cases} \log[\prod_{i=1}^{N}\prod_{t=1}^{T} [\Pr(\Delta R_{ct} = \text{'downgrade'})]] & if \quad \Delta R_{ct} = \text{'downgrade'} \\ \log[\prod_{i=1}^{N}\prod_{t=1}^{T} [\Pr(\Delta R_{ct} = \text{'no change'})]] & if \quad \Delta R_{ct} = \text{'no change'} \\ \log[\prod_{i=1}^{N}\prod_{t=1}^{T} [\Pr(\Delta R_{ct} = \text{'upgrade'})]] & if \quad \Delta R_{ct} = \text{'upgrade'}. \end{cases} \tag{3.6}$$

Marginal effects A number of different marginal effects can be obtained to evaluate the economic significance of stability and credit risk determinants: marginal effects of changes in the determinants of the stability process or the credit risk process. Marginal effects may be unconditional, conditional on $s_{ct} = 1$ in equation (3.2), or conditional on $D_{ct}^{AAA} = 0$ and $D_{ct}^{D} = 0$. One might want to calculate marginal effects at average values of stability and credit risk determinants, average marginal effects, or marginal effects on the probability of 'downgrade', 'no change', or 'upgrade'. 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:

$$\underset{\Pr(\Delta R_{ct}=\text{'downgrade'})}{ME} = \frac{\partial \Pr(\Delta R_{ct} = \text{'downgrade'})}{\partial x} = \phi(-\widehat{\beta}\overline{x})\widehat{\beta} \tag{3.7}$$

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 (3.5) 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':

$$\hat{R_{ct}} = \begin{cases} \text{'downgrade'} & \text{if } \hat{\Pr}(\Delta R_{ct} = \text{'downgrade'}) > \tau_{\text{'downgrade'}} \\ \text{'no change'} & \text{if } \hat{\Pr}(\Delta R_{ct} = \text{'no change'}) > \tau_{\text{'no change'}} \\ \text{'upgrade'} & \text{if } \hat{\Pr}(\Delta R_{ct} = \text{'upgrade'}) > \tau_{\text{'upgrade'}}. \end{cases} \tag{3.8}$$

To calculate the sensitivity and specificity for all three possible outcomes, I set threshold parameters τ_l to the unconditional probability of each outcome $\tau_k = \frac{1}{N}\sum_{c=1}^{C}\sum_{t=1}^{T} R^k_{ct}$, 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.

3.3.4 Monte Carlo experiment

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 Monte Carlo simulations.

Experimental design The data for simulations is generated using the stability process (3.2) and the credit risk process (3.1). When generating fundamentals X_{ct}, I face a trade-off. On one hand, I want to simulate results that are most relevant to my application. Ideally, I would therefore use actual data. On the other hand, there is a need for a 'controlled lab environment'. Results for different Monte Carlo set-ups need to be comparable with each other. They should not be driven by patterns in the data I do not control for. A more general set-up also yields the benefit of yielding results that are relevant in a broader context. To maintain full control over data patterns, I generate regressors artificially but orient as closely as possible towards moments of actual fiscal and macroeconomic series (cf. Table 2.7). Abstracting from moments of these actual series, I generate ten regressors x_{jct}^{gen}:

$$x_{jct}^{gen} = \rho_j x_{jct-1}^{gen} + e_{jct}, \tag{3.9}$$

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. A different set of parameters could have been chosen but ultimately results remain unaffected by this choice as first differences are taken. I set all elements of vector β in the credit risk process (3.1) 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 (3.2) 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 (3.2) is 4. The error terms of the credit risk and stability processes, ε_{ct} and ϵ_{ct} in equations (3.1) and (3.2), 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 (3.3) 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.

Table 3.3: 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

Table 3.3 summarises which data characteristics will be varied across Monte Carlo

set-ups. This yields 48 different Monte Carlo set-ups, for each of which $I = 2,000$ iterations 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).

Simulation results Simulation results for the baseline set-up are reported in the top panel of Table 3.4.[4] Ordered Probit, MIOP and BAM perform almost identically if observations are balanced across outcome categories (middle-category inflation of 34.8%). Estimates contain a small, positive baseline bias, which can be interpreted as a small-sample bias. This baseline bias is marginally larger for MIOP and BAM compared to Ordered Probit. Standard errors are small and correctly reflect the standard deviation of estimates.

Increasing the number of observations in the middle category significantly increases

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[4] Monte Carlo simulations were conducted in Stata/SE 14.0. The programme's *ml* and *oprobit* commands were used for maximum likelihood estimation. For evaluation, only those Monte Carlo results were considered for which Ordered Probit, MIOP, and BAM all converged within less than 100 maximum likelihood iterations. This reduces the overall number of results from $2,000 \times 48 = 96,000$ to 70,408 (73.34%). For instance, under the econometrically most challenging set-up – 93% 'pure' inflation/ stability process 'on'/ boundary observations 'on'/ sample size 1,800/ 10 regressors – convergence was achieved with less than 100 ML iterations by all estimators in 71.3% of all Monte Carlo iterations. For MIOP and BAM estimation, Ordered Probit estimates were used as initial values which improved convergence rates. Without initial values set, overall convergence was achieved in 66.0% of all iterations (54.3% in the most challenging set-up).

Table 3.4: 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.

baseline biases. This occurs to a larger extent for the complex estimators MIOP and BAM than for standard Ordered Probit. Simultaneous increases in standard errors seem to account for this, which ensures that inference remains valid. That 'pure' inflation leads to biased estimates confirms earlier findings by King and Zeng (2001). The presence of upward biases instead of downward biases can be explained by the fact that I consider middle-category inflation: opposed biases in estimates for 'upgrade' and 'downgrade' seem to partially cancel out but the normalised measure RMSE increases substantially.

If middle-category inflation is generated partly by an unobserved stability process (second panel of Table 3.4), Ordered Probit estimates are severely biased downwards, as previously shown by Harris and Zhao (2007). However, the variation in Ordered Probit estimates remains relatively limited and standard errors remain small. Hence inference becomes highly problematic as biased coefficient estimates likely show up as statistically significant. Results from MIOP and BAM estimation, by contrast, remain valid. Only if 'pure' inflation is very high do MIOP and BAM fail to distinguish between the two sources of middle-category inflation and biases increase.

If, on the other hand, asymmetric outcome probabilities, i.e. observations at the boundary of the rating scale, generate inflation in middle-category observations (third panel of Table 3.4), BAM clearly outperforms Ordered Probit and MIOP, both of which yield significantly downward-biased and widely dispersed estimates.

The fourth panel of Table 3.4 provides Monte Carlo results for a set-up in which middle-category inflation results from a combination of 'pure' inflation, the unobserved stability process and observations for which one outcome is infeasible (boundary observation). BAM yields estimates that are somewhat upward-biased if the contribution of 'pure' inflation is high but outperforms MIOP and standard Ordered Probit, which yield substantially downward-biased estimates. In particular, Ordered Probit estimates remain characterised by relatively small standard deviations and standard errors, which makes inference problematic as wrong estimates will remain unrejected by standard significance tests (type II error).

Turning to the effect of sample size on estimator performance, I find that working with a larger sample can considerably reduce baseline biases (Table 3.5). ‘Pure’ inflation still generates biases but these remain small. A larger sample also ensures that MIOP and BAM estimates are less diffuse; their standard deviation is considerably reduced compared to the moderate-sample set-up.

If increasing the sample size is not feasible in practical applications, reducing the number of regressors can have a similar effect on estimator performance. As previously shown by Peduzzi et al. (1996) and Vittinghoff and McCulloch (2007), and confirmed by Table 3.6, employing one regressor instead of 10 reduces Ordered Probit baseline biases by a half. The performance of MIOP and BAM is also considerably improved throughout.

To summarise simulation results, three different sources of middle-category inflation can significantly impair the performance of Ordered Probit estimation in a three-category set-up. While biases that stem from a high degree of ‘pure’ inflation cannot be sufficiently eliminated within the realm of standard maximum likelihood estimation, inflation that stems from an unobserved stability process, given that ‘pure’ inflation is moderate, can be dealt with by using the MIOP estimator instead of standard Ordered Probit.

Table 3.5: 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 3.6: 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.

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 new boundary-adjusted estimator BAM, proposed in this chapter, can yield sufficiently unbiased estimates. This, however, comes at the cost of relatively large standard errors. In addition, small sample biases associated with maximum likelihood estimation make the use of data with high frequency, long time series, or pooled datasets indispensable if the cross-sectional dimension is by nature limited. 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.

3.3.5 Fundamentals data

Section 3.3.1 introduces a dataset on sovereign rating changes, which is also used for the empirical analysis. I consider major (across-letter notch), minor (within-letter notch) rating changes and changes in the watch or outlook status between the end of the quarter and the end of the previous quarter. The countries included are Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Luxembourg, New Zealand, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, United Kingdom, and the United States. Note that the use of quarterly rating changes is the result of a trade-off. Hill et al. (2010), for instance, use changes over a 6-months interval instead. Using data of lower frequency, like semi-annual or annual frequency, may lead to a loss of information if ratings are changed several times per year, as happened during the recent global financial and European government debt crisis. Hill et al. (2010) therefore define a fourth category 'credit crisis', in addition to the three outcomes in equation (3.3), to capture multiple-notch downgrades. In light of the discussion on the estimation of rare events in the previous section, I refrain from defining another category and instead use quarterly rating data.

The limitations of quarterly data are set by the availability of data on rating determinants. To capture information available in real time to credit rating agencies and the public, I use projections published in the OECD *Economic Outlook* and IMF *World Economic Outlook*, similar to data used in Chapter 2. For the variables deficit/GDP (government net lending per GDP, OECD, multiplied by -1), 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. Empirical analyses show 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 the deficit/GDP, debt/GDP, real GDP growth and unemployment. 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.[5] 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 de-

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[5] 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.

veloped in Chapter 2, which I employ as a regressor in the stability and credit risk equation. In contrast to existing measures of uncertainty, this index has a number of characteristics that allow a direct identification of uncertainty effects on rating changes. First, unlike measures of market volatility, such as the standard deviation of government bond yields, it captures more directly uncertainty about the future path of the fiscal deficit, which is a key variable taken into account by credit rating agencies (see also discussion in Chapter 2). Second, in contrast to forecast error-based measures, the fiscal uncertainty index developed in this study captures uncertainty experienced in real time, by credit rating agency staff, financial market participants and the general public. Third, by construction, the fiscal uncertainty index is exogenous to rating changes that occur after official deficit publications have been made public. It is more of a slowly changing measure of the uncertainty that prevails compared to more frequent news-based indices like the Baker et al. (2016) Economic Policy Uncertainty index.

3.4 Results

3.4.1 Baseline results

Table 3.7 reports baseline results for the determinants of changes in sovereign credit ratings. To increase the sample size and reduce potential small-sample biases, baseline results are obtained for data pooled across the three credit rating agencies Fitch, S&P and Moody's. BAM estimates for the set of fiscal and macroeconomic controls (lower panel of column II) are compared to Ordered Probit results (lower panel of column I) whereby Ordered Probit estimates are obtained from separate, unconditional estimations of the stability and credit risk process. Results show that debt/GDP and unemployment have the expected positive effect on credit risk and 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. Table 3.7 reports marginal effects in percent on the probability of a downgrade. 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).

Table 3.7: Baseline results for rating determinants

	I	II	III	IV	V
	OP	BAM	BAM	BAM	BAM
Stability:					
Fiscal uncertainty			0.08**	0.015*	1.16
			[0.04]	[0.01]	[5.66]
Rating level	-0.03***	-0.02***	-0.02*	-0.005	-0.24***
	[0.00]	[0.00]	[0.01]	[0.00]	[0.05]
Momentum	2.38	1.64	-0.96	-0.24	217***
	[1.49]	[1.19]	[0.60]	[0.17]	[11.5]
Credit risk:					
Fiscal uncertainty				0.70**	1.64***
				[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*	0.30**	0.29**	0.37
	[0.05]	[4.22]	[0.15]	[0.15]	[0.26]
GDP growth	-0.87***	-23.7***	-1.35***	-1.43***	-3.68***
	[0.30]	[9.04]	[0.48]	[0.48]	[0.85]
Unemployment	1.97***	40.7**	3.77***	3.61***	4.85***
	[0.48]	[16.2]	[1.06]	[1.02]	[1.48]
Observations	4,859	4,859	4,304	4,128	4,128
Sensitivity ↓	73.8%	66.7%	81.2%	81.3%	75.2%
Specificity ↓	72.3%	87.4%	71.9%	71.9%	81.0%
Sensitivity =	82.7%	62.2%	54.2%	54.8%	71.2%
Specificity =	44.6%	82.1%	92.8%	93.0%	73.2%
Sensitivity ↑	64.6%	100.0%	92.1%	93.0%	76.9%
Specificity ↑	67.2%	50.9%	63.6%	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, considered as rating changes in column V. Fiscal uncertainty measure: U_{ct1}.

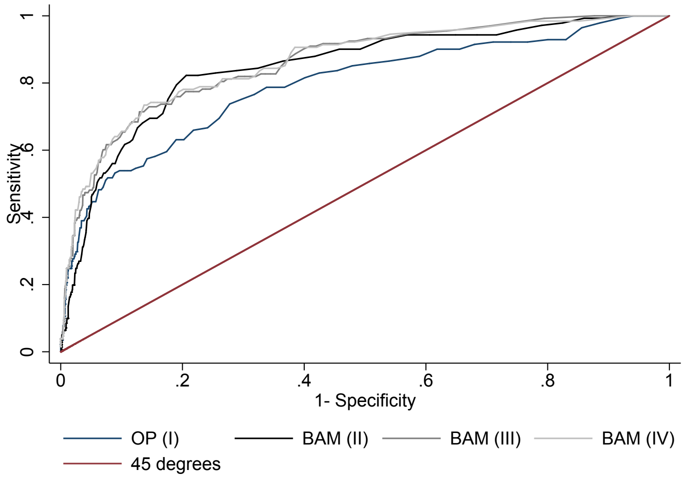
As expected from Monte Carlo simulations in section 3.3.4, OP estimates are substantially smaller in absolute terms compared to BAM estimates, which take into account the effects of the boundary of the rating scale and the stability process on the stability of sovereign ratings. Comparing estimates reported in columns I and II in the lower panel of Table 3.7, I find that BAM estimates are all substantially larger in absolute terms. This suggests that standard Ordered Probit estimates are likely to be biased. In fact, the rating level is found a significant determinants of rating changes independent of movements in fundamentals related to credit risk (see top panel of Table 3.7 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 3.7). BAM correctly 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, compared to 82.1 percent for BAM.

The advantage of BAM over OP is illustrated more clearly by the ROC curves in Figure 3.3. A larger area under the ROC curve indicates a larger true positive rate at a given false positive rate, i.e. a higher goodness-of-fit. For downgrades (Figure 3.3a), OP (blue line) and BAM (black line) curves are similar, with OP only marginally underperforming BAM. By contrast, the area under the ROC curve is substantially larger for BAM compared to OP with respect to 'no change' observations and upgrades (Figures 3.3b, c).

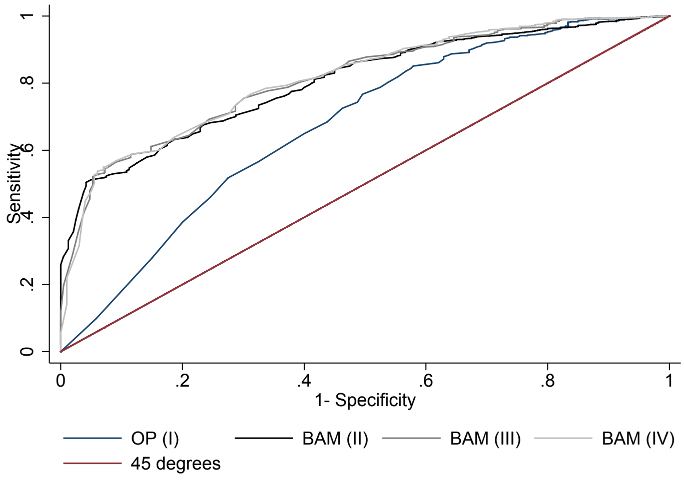
Figure 3.3 also shows that accounting for fiscal uncertainty in the credit risk and stability process improves the goodness-of-fit, although only marginally (grey lines). In particular, the prediction of downgrades improves (higher sensitivity in columns III and IV of Table 3.7). This result comes at the expense of poorer 'no change' predictions.

Fiscal uncertainty has a significantly positive effect on the frequency of rating changes. The coefficient on fiscal uncertainty in the stability process is statistically significant and lies between 0.015 and 0.08 (top panel of Table 3.7). In economic terms, this suggests that a one-standard deviation increase in fiscal uncertainty increases the probability of a rating change by up to 0.08 percent, independent of movements in credit risk. Given that the unconditional probability of rating changes lies only at around 5 percent, this is a substantial effect. A one-standard deviation increase in fiscal uncertainty 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 finding supports the Attention Hypothesis. Credit rating agencies seem to change ratings more frequently during periods of higher uncertainty than what would be justified by movements in credit risk. This may be due to an increase in publicity, which agencies may want to exploit.

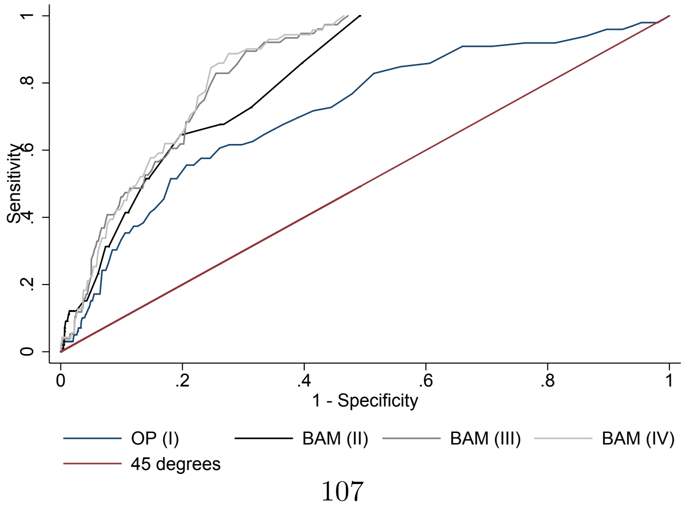
While the effect of fiscal uncertainty on rating frequency remains significant, uncertainty is also considered a credit risk factor by rating agencies. The coefficient for fiscal uncertainty in the credit risk process is positive and statistically significant in column IV and the lower panel of Table 3.7. A one-standard deviation increase in fiscal uncertainty increases the probability of a downgrade by 0.7 percent. I infer that credit rating agencies take fiscal uncertainty into account as a second-moment effect when assessing a country's credit risk. This supports the Credit Risk Hypothesis.



(a) Downgrade



(b) No change



(c) Upgrade

Figure 3.3: ROC curves for OP and BAM estimates

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 only as fundamentals change. On the contrary, fiscal uncertainty loses its explanatory power in the stability process, when watch changes are considered amongst rating change observations. This could suggest that publicity incentives to credit rating agencies are larger for actual movements along the rating scale.

Table A8 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.

3.4.2 Agency-specific results

To gauge differences in rating agency behaviour, I estimate the model for agencies separately. Results are reported in Table 3.8, for the forward-looking and current-year version of the fiscal uncertainty index. Given that this reduces the sample size relative to the pooled specification, a note of caution is warranted that reported standard errors may be somewhat too large. 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 on 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 3.8. 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.

Table 3.8: 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 not considered as rating changes.

3.4.3 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 3.9). Results suggest that rating agencies somewhat changed their focus 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 more important after the global financial crisis and during the European sovereign debt crisis. By contrast, the evidence for an effect of fiscal uncertainty on the frequency of rating changes (Attention Hypothesis) is smaller for the sub-sample post-2009, compared to before (upper panel of Table 3.9). Reputational concerns seem to have gained importance after the crisis.

To test more directly whether publicity considerations matter for the timing of rating announcements, I check whether a rating agency's action depends on actions taken by other rating agencies. For that, I define a dummy variable that takes the value of one if in a certain period other agencies announce rating changes. I include this dummy variable as a regressor of the stability process, instead of fiscal uncertainty

Table 3.9: 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 not considered as rating changes.

(Table 3.10, variable 'Other'). The fact that another rating agency changes its rating in a given period has a significantly positive effect on the frequency of rating changes by S&P and Moody's (columns III, IV), independent of movements in credit risk. This could suggest that agencies may want to make rating announcements around the time announcements of other agencies are made, possibly in order to also gain publicity. This would support the Attention Hypothesis.[6]

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[6] Gomes (2011), by contrast, proposes a piggy-backing hypothesis according to which rating agencies may change ratings shortly after another rating agency announces a rating change. This is explained with the costs of rating production which may incentivise agencies to spend less effort on their own analysis but wait until other agencies publish their findings. Given that my analysis is based on

Table 3.10: Other agencies' actions as a rating determinant

	I Full sample	II Fitch	III Standard & Poor's	IV Moody's
Stability:				
Other agency	28.6***	57.4	32.8***	16.3***
	[8.69]	[92.5]	[11.8]	[2.80]
Rating level	-0.09***	-0.16**	-0.10***	-0.038***
	[0.02]	[0.08]	[0.03]	[0.01]
Momentum	-4.11	-21.2	-4.17	0.38
	[5.78]	[60.7]	[10.0]	[3.75]
Credit risk:				
Fiscal uncertainty	2.23**	1.00	1.91**	8.35***
	[0.94]	[1.38]	[0.85]	[3.03]
Deficit/GDP	0.34	0.52*	0.60	-0.39
	[0.34]	[0.29]	[0.38]	[0.64]
Debt/GDP	0.95	0.54	0.43	3.70*
	[0.82]	[0.42]	[0.47]	[2.00]
GDP growth	-4.21***	-2.22**	-4.94***	-5.87
	[1.57]	[1.05]	[1.50]	[4.00]
Unemployment	9.08***	5.13***	5.46	28.5***
	[2.99]	[1.75]	[4.81]	[9.70]
Observations	4,128	1,418	1,429	1,281
Sensitivity ↓	80.5%	79.5%	78.8%	86.5%
Specificity ↓	82.3%	83.2%	77.9%	88.0%
Sensitivity =	73.6%	73.0%	69.3%	80.1%
Specificity =	75.9%	75.8%	73.7%	75.4%
Sensitivity ↑	74.6%	70.4%	79.2%	90.0%
Specificity ↑	73.4%	72.7%	71.5%	77.3%

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 not considered as rating changes. Fiscal uncertainty measure: U_{ct1}.

3.4.4 Application to sovereign rating downgrades during the global financial and European government debt crisis

A question of high policy relevance is whether sovereign credit ratings were changed more often during the financial and European government debt crisis than model-implied rating changes (e.g. Polito and Wickens, 2014, Polito and Wickens, 2015, D'Agostino and Lennkh, 2016). I therefore compute model-implied downgrade proba-

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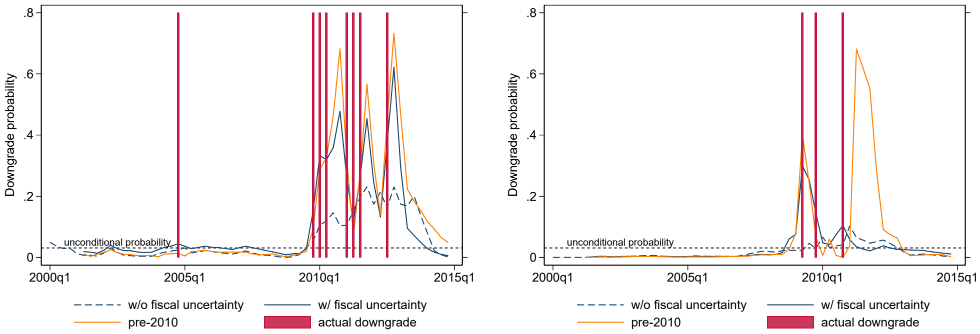
quarterly rating changes and abstracts from the exact timing, results in Table 3.10 are consistent with both the Attention and 'piggy-backing' hypothesis.

bilities using equation (3.5) and BAM estimates of model parameters. Parameters are taken from three model specifications: one that excludes fiscal uncertainty (corresponding to column II in Table 3.7), one that includes fiscal uncertainty (corresponding to column IV in Table 3.7), and one that includes fiscal uncertainty but is estimated only up to 2009 (corresponding to column I in Table 3.9). This also provides an additional check of the predictive power that fiscal uncertainty adds to a model of sovereign rating changes. Estimates from the specification for the period after 2009 can be thought of as out-of-sample predictions.

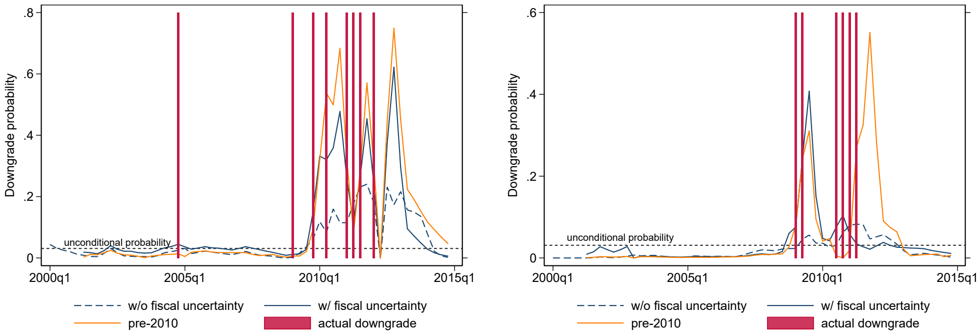
Results are plotted in Figure 3.4 for Greece and Ireland and in Figure 3.5 for Spain and Portugal, i.e. countries most severely affected by the European government debt crisis, as well as for the three agencies Fitch, Standard & Poor's and Moody's. They are contrasted in Figure 3.6 with results for Germany, where no rating changed was announced over the sample period, and the United States that experienced only one downgrade by Standard & Poor's in the aftermath of the financial 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 over time implied by a model that includes fiscal uncertainty as a measure. Yellow lines capture predicted downgrade probabilities from a full specification estimated until 2009, which after that point in time can be interpreted as out-of-sample predictions. 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 the model that accounts for fiscal uncertainty (solid blue lines) fares surprisingly well in predicting rating downgrades of the countries hit by the European sovereign debt crisis. In a number of cases, the probability estimate exceeds the unconditional threshold shortly before a series of actual rating downgrades occurs. This confirms that the model could be used 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. 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.

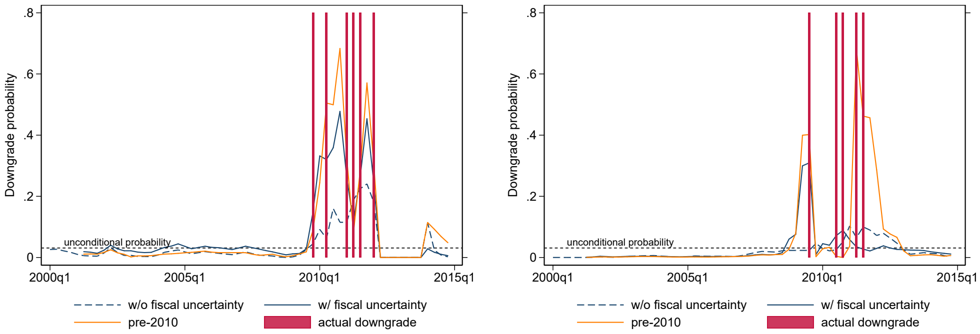
Comparing the estimates from a model specification that includes the fiscal uncertainty index (solid blue lines) to one that does not (dashed blue lines), Figures 3.4 and 3.5 illustrate that the latter specification provides a substantially poorer prediction of rating downgrades. For most of the examples, 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. Only for the safe haven countries Germany and the United States, this specification yields superior estimates. Figure 3.6 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.



(a) Greece, Fitch (b) Ireland, Fitch

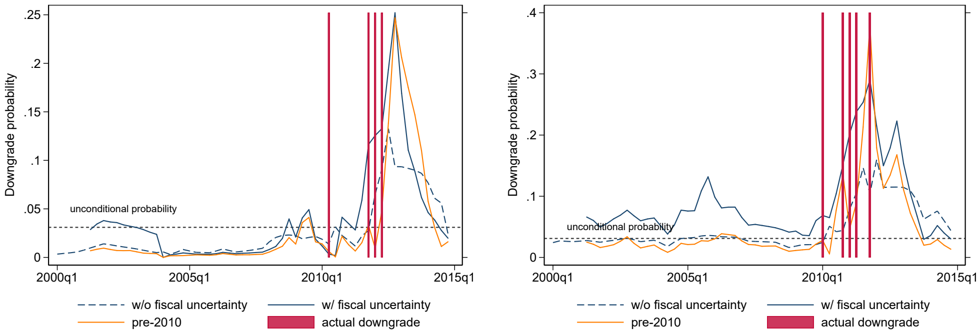


(c) Greece, S&P (d) Ireland, S&P

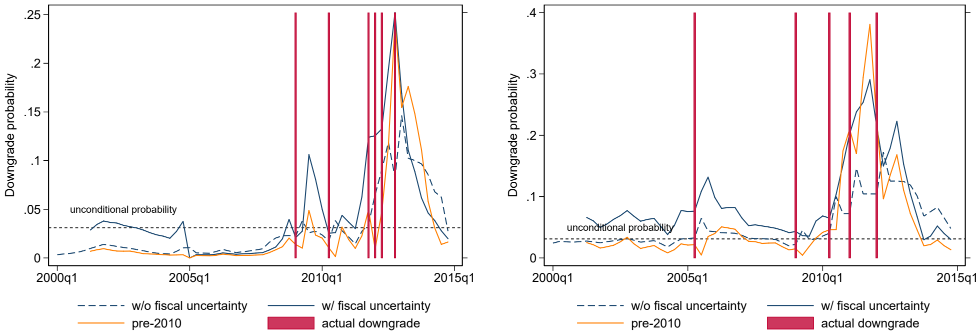


(e) Greece, Moody's (f) Ireland, Moody's

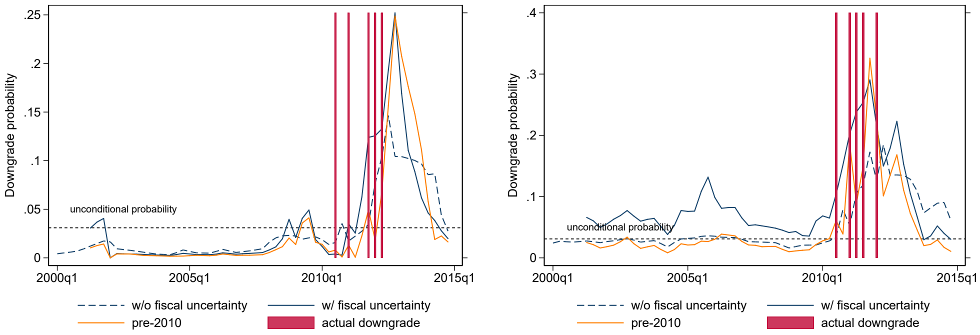
Figure 3.4: Estimated downgrade probabilities, Greece and Ireland



(a) Spain, Fitch (b) Portugal, Fitch

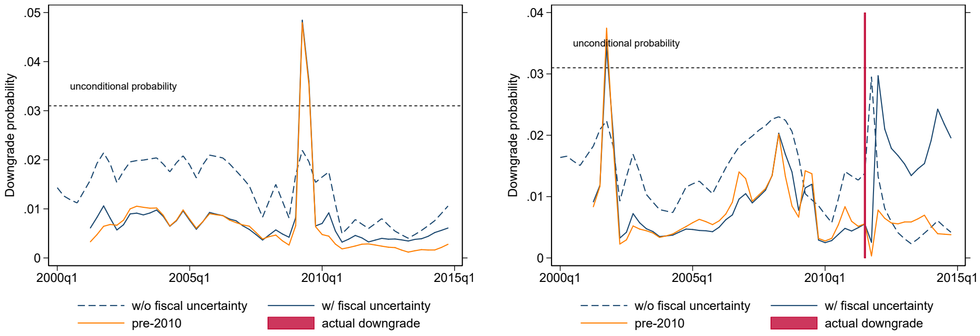


(c) Spain, S&P (d) Portugal, S&P



(e) Spain, Moody's (f) Portugal, Moody's

Figure 3.5: Estimated downgrade probabilities, Spain and Portugal



(a) Germany, S&P

(b) United States, S&P

Figure 3.6: Estimated downgrade probabilities, Germany and United States

Figures 3.4 to 3.6 show further that 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.

Model-implied downgrade predictions are therefore much in line with actual rating changes undertaken by credit rating agencies. 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.

3.5 Conclusion

This chapter develops a new empirical framework for the analysis of sovereign rating determinants. The framework accounts for high levels of rating stability over time. Rating stability may result from the approach adopted by credit rating agencies of looking through the business cycle, technical factors that determine the rating process, and a large number of observations at the boundary of the rating scale. Monte Carlo simulations and an application to data on advanced economies' sovereign credit ratings show that empirical approaches not accounting for rating stability can yield biased estimates and over-predict rating changes.

The empirical framework is applied to test whether fiscal uncertainty affects sovereign ratings. I find that credit rating agencies consider high levels of uncertainty about the future path of fiscal policy a credit risk determinant. In addition, my results show that credit rating agencies tend to change sovereign ratings more frequently than suggested by movements in credit risk. I interpret this as a result of increased publicity from which agencies benefit. To confirm the assumption that underlies this hypothesis, namely that fiscal uncertainty increases the attention to rating announcements, chapter 4 proceeds with an analysis of announcement effects.

Chapter 4

Attention to Sovereign Rating Announcements

4.1 Introduction

Having established in Chapter 3 that fiscal uncertainty significantly affects sovereign credit risk as measured by credit ratings, this chapter turns to the effect fiscal uncertainty can have on the attention paid to rating announcements. Behavioural research finds that uncertainty changes the way economic agents make decisions. As public information becomes more noisy, agents may become cognitively over-burdened (Kahneman, 1973). They may then revert to simple heuristics rather than analysing public data as thoroughly as they would in more certain times (Tversky and Kahneman, 1974). For investors in sovereign debt, such a heuristic may be the use of sovereign credit ratings as a benchmark. One of the assumptions in the previous chapter is that credit rating agencies provide information to market participants that they do not previously possess. Therefore, more attention may be given to announcements about sovereign ratings, the noisier the public information about sovereign credit risk, in particular as noisy information often coincides with dramatic events during crises.

Indirect evidence suggests that sovereign credit ratings indeed gain more attention during periods of economic crisis in the form of larger price reactions on financial markets. Crises are associated with downgrades, which, Reisen and von Maltzan (1999) find, cause larger movements in sovereign bond yield spreads than upgrades. Exchange rates respond more sharply to sovereign rating announcements when fiscal fundamentals are weak (Alsakka and ap Gwilym, 2012), while stock market reactions are stronger when global volatility is high (Hill and Faff, 2010). Yet the direct effect of country-specific uncertainty about variables that determine sovereign credit risk, like the fiscal deficit, has not been analysed. This is the gap this chapter tries to fill.

I conduct an event study for a set of advanced economies to investigate the impact of announcements about sovereign ratings. I find that greater fiscal uncertainty significantly increases the attention to rating announcements by institutional investors in sovereign debt: sovereign CDS spreads, i.e. the price paid to insure against sovereign default, increase more after the announcement of a negative rating event, the higher the degree of uncertainty about the future path of the fiscal deficit.

The use of CDS spreads to measure the price impact of events on sovereign debt markets is popular in the literature (e.g. Ismailescu and Kazemi, 2010, Kiff et al., 2012). In contrast to sovereign bond yields or stock market indices, CDS prices are available as country-specific spreads and no benchmark needs to be identified. Figure 4.1 shows for the example of Spain that the sovereign CDS spread spikes every time Standard & Poor's announce a change of the country's sovereign rating (red arrows). However, event study analyses require the estimation of 'normal' returns – counterfactual returns that would arise without the event. In the sovereign context, this is particularly difficult as announcements about other countries' ratings may spill over (Afonso et al., 2012), especially since rating agencies often announce rating changes simultaneously for a set of countries. In addition, the mechanism by which prices, like CDS spreads, instantaneously incorporate the new information provided by rating announcements

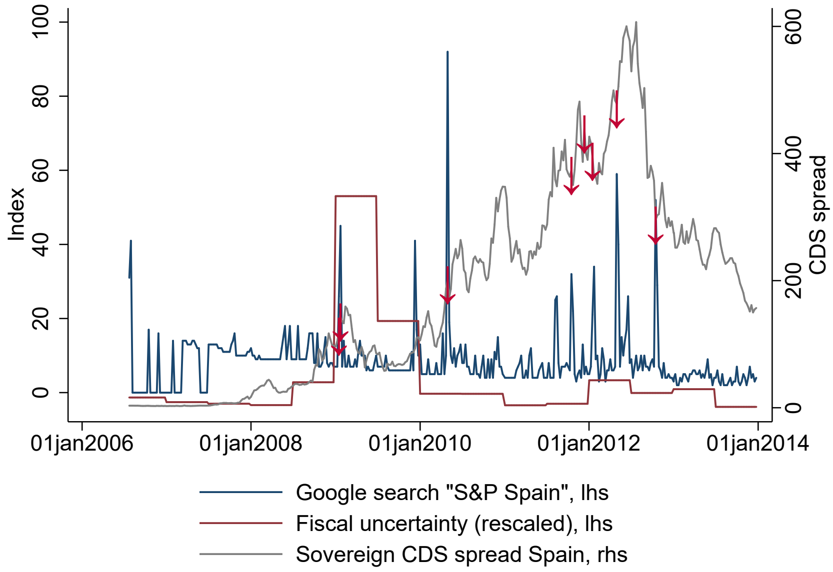


Figure 4.1: Spain's sovereign CDS spread, Google search volume and fiscal uncertainty

rests on the assumption that financial markets are efficient (Fama, 1970). The efficient market hypothesis might fail if investors are cognitively overburdened with information, in particular during crisis periods (Kahneman, 1973).

To address these shortcomings of financial market indicators, like CDS spreads, the second contribution of this chapter lies in introducing to the literature on rating impact an attention measures that is based on internet search volume. Da et al. (2011) find that the frequency of stock-related search terms on Google captures attention more timely and directly than market prices. The Google search frequency can also capture attention not just of sophisticated institutional investors but the general public more widely. In addition, by using the frequency of country- and rating agency-specific search terms, I obtain an attention measure that is cleaner from other news than sovereign CDS spreads. Figure 4.1 illustrates that the search term 'S&P Spain' is looked up considerably more frequently in weeks during which Standard & Poor's announced rating changes for Spain. Figure 4.1 shows further that spikes in search volume tend to be larger when the fiscal uncertainty index lies above its average of zero. Overall, I find that attention measured using Google search volume increases significantly more when fiscal uncertainty is high.

The chapter proceeds as follows. Section 4.2 reviews the existing literature on rating impact. The event study set-up and attention measures are explained in Section 4.3. Results are presented in Section 4.4 and Section 4.5 concludes this chapter.

4.2 Existing literature on rating impact

The market impact of credit ratings has been estimated in a number of event studies. From work on corporate ratings we know that the impact of downgrades on stock returns (Goh and Ederington, 1993, Dichev and Piotroski, 2001), bond yields and CDS spreads (Daniels and Shin Jensen, 2005) is generally significant. On the other hand, upgrades seem not to have a significant effect. The impact of rating announcements depends on the credit rating agency that issues it as well as on the rating level (Norden and Weber, 2004). Announcements are often anticipated (Hull et al., 2004), which mitigates the direct market impact.

These general findings have been confirmed by event studies of sovereign credit ratings. Cantor and Packer (1996), in an early study, look at the response of sovereign bond yield spreads to rating announcements. They find significant 90 basis point increases after negative announcements and 130 basis point decreases following positive news. Response effects are highly significant for sovereigns with low, speculative-grade ratings but are found insignificant for high, investment grade ratings. Reisen and von Maltzan (1999) find that, on average across advanced economies and emerging markets, the impact of rating news on sovereign yield spreads is insignificant. Rating news, and in particular downgrades, however, do significantly affect spreads of emerging market sovereigns. This confirms that ratings matter when fundamentals are weak. It may also have to do with poorer quality of information about the state of the economy in emerging markets, i.e. uncertainty. Brooks et al. (2004) come to the conclusion that downgrades have significant negative effects on domestic stock markets and the dollar value of the country's currency. Gande and Parsley (2005) show that there are significant spillover effects across countries: rating downgrades in one country significantly affect sovereign yield spreads in other countries. Ferreira and Gama (2007) find that news about sovereign downgrades spill over to foreign stock markets, especially if the foreign country is an emerging market economy and geographically close. Focusing on emerging markets only, Ismailescu and Kazemi (2010) provide evidence on responses of sovereign CDS spreads to rating changes that contrast responses of other financial market indicators. In particular positive rating news seems to trigger larger domestic responses in the authors' sample, as well as spillover effects, compared to negative announcements, which are anticipated more often. In line with previous findings, Böninghausen and Zabel (2015) find strong evidence for bond market spillovers from downgrades, especially if countries lie in the same geographic area. Kiff et al. (2012), who assess the impact on sovereign CDS spreads, confirm that negative credit warnings (reviews, outlooks, watches) have significant effects, whereas actual rating changes do not. If upgrades or downgrades move ratings in and out of the investment grade class of rating categories, their impact becomes statistically significant however. Afonso et al. (2012) focus on countries of the European Union rather than emerging markets. They find that rating news spill over from countries that were more severely affected by the financial and European government debt crisis to less affected countries. Differences in the market impact across developing and developed countries are found by Alsakka and ap Gwilym (2012), who study effects on domestic and international foreign exchange markets. Hill and Faff (2010) find differences in the market impact of ratings across rating agencies. Standard & Poor's is found to provide more new information while Moody's has more of an impact with ratings for advanced economies. Changes in the ‘outlook’ or ‘watch’ status are found to be more influential than actual downgrades or upgrades. The authors also conclude that market reactions are stronger during crises.

In summary, the literature on the impact of sovereign rating announcements finds that market responses are stronger for downgrades, for countries with weak fundamentals and during crises. This suggests that uncertainty about whether the future path of fundamentals may lead the country into default, or not, affects the way rating announcements are internalised by market participants. This chapter is the first to study explicitly the effect of uncertainty around fiscal fundamentals on the market impact of sovereign rating announcements.

4.3 Event study set-up

In line with the event study literature, I employ the following approach to analyse the effect of fiscal uncertainty on the attention to sovereign rating announcements. If A_i^m is the movement of an attention variable m around the time an event i takes place, such as a sovereign rating change for a particular country on a particular day, then the average attention to such events can be estimated as:

$$A_i^m = \beta_0 + \beta_1 U_i + \beta_2 C_i + \epsilon_i \tag{4.1}$$

Note that subscript i denotes an identifier for every rating event, i.e. every country-time combination for which a rating announcement is made. β_0 is the constant term. U_i is the level of fiscal uncertainty for each country- and time-specific event, C_i is a matrix with control variables, β_1 and β_2 are coefficients to be estimated, ϵ_i is the error term, which may be correlated across observations for each country.

Regressing A_i^m on the constant term β_0 constitutes a simple t-test of whether the average attention response is significantly different from zero. β_1 yields an estimate of the additional effect an increase in fiscal uncertainty has on the attention to rating announcements. A coefficient estimate that is positive and significantly different from zero supports the hypothesis that uncertainty about fiscal policy increases the attention to sovereign rating announcements. By measuring uncertainty using projections of the fiscal deficit published prior to rating announcements, I make sure the fiscal uncertainty index remains uncorrelated with the error term ϵ_i.

Gande and Parsley (2005) and Alsakka and ap Gwilym (2012), by contrast, identify responses using so-called comprehensive credit ratings: a linearised scale of major rating changes, minor (intra-category) rating changes and outlook/watch status. Small changes serve as the benchmark, whereas larger rating changes are defined as event and their impact is estimated. Similarly, Böninghausen and Zabel (2015) define the difference between single-notch and multi-notch changes as event and estimate if this triggers a significant response. A problem with this approach may occur if small events, like the change in the watch status, have a bigger impact than those defined as a major event. For instance, findings by Kiff et al. (2012) for sovereign rating changes and CDS spread responses suggest that changes in credit warnings (outlook/watch status) can have larger effects than changes of rating categories.

I therefore refrain from a comprehensive credit rating procedure. Instead, I consider a set of control variables in matrix C_i. It includes a dummy for the direction of rating changes, which takes the value of one if the announcement is positive, i.e. constitutes an upgrade or a withdrawal of a watch or outlook status. Positive announcements are expected to lead to a smaller response in attention. I further control for agency fixed effects and the level of the previous rating. The former allows some agencies to raise more attention than others. The latter captures differences in attention across the rating scale. I linearly transform sovereign ratings by assigning a value of 21 to AAA/Aaa ratings, 20 to AA+/Aa1 ratings, etc. to 1 for Default ratings. Changes at the upper end of the rating scale are expected to cause smaller responses.

4.3.1 Sovereign credit rating announcements

To estimate the effect of fiscal uncertainty on rating attention, I employ a sub-sample of the dataset on sovereign rating announcements introduced in Chapter 3. The scope of the dataset used for this event study is constrained by the availability of data on CDS spreads and Google search volumes. The resulting database contains 203 announcements about major (across-letter category) rating changes, minor (within-letter category) rating changes, and announcements of a change in the watch or rating outlook status (145 for the Google Trends sub-sample). It covers announcements for 22 advanced economies during the period 2000 to 2013. Table 4.1 provides the total number of rating announcements by country, for the overall sample (fourth column) and the sub-sample for which Google Trends data is available (last column). The highest number of observations are obtained for Greece, Ireland, Spain and Portugal – countries most affected by the global financial and European government debt crisis. No Google Trends data could be obtained for rating announcements made about Czechia, Estonia, Finland, Slovakia, Slovenia and Sweden, which drop out of the sub-sample. Table 4.1 also summarises the number of rating events by type of announcement – whether the announcement was negative (downgrade or watch or outlook status imposed) or positive (upgrade or watch or outlook status lifted). The majority of events are negative rating announcements (163 out of 203) owing to the large impact of the crisis on sovereign credit risk.

4.3.2 CDS returns

Like Ismailescu and Kazemi (2010), Afonso et al. (2012) and Kiff et al. (2012), I use daily data on sovereign CDS spreads as a response measure. CDS are credit derivatives that protect against the default of – in this case sovereign – debt issuers. Spreads are periodic payments from a buyer to the seller of the insurance and expressed as a percentage of the amount insured. In contrast to bond yields, for which an appropriate risk-free

Table 4.1: Sovereign credit rating announcements

Country	Positive announcements	Negative announcements	Total	Google Trends sub-sample
Australia	1	0	1	1
Austria	0	2	2	2
Belgium	1	6	7	2
Czech Republic	3	0	3	0
Estonia	1	0	1	0
Finland	1	1	2	0
France	0	5	5	5
Germany	1	1	2	2
Greece	2	29	31	29
Hungary	0	17	17	7
Ireland	3	21	24	24
Italy	0	16	16	16
Japan	1	2	3	3
Korea	9	0	9	2
Netherlands	1	2	3	3
New Zealand	0	2	2	1
Portugal	0	22	22	22
Slovakia	13	3	16	0
Slovenia	0	10	10	0
Spain	2	21	23	23
Sweden	1	0	1	0
United Kingdom	0	3	3	3
Total	40	163	203	145

Source: Bloomberg financial database.

benchmark rate needs to be identified to construct a spread measure, CDS prices are recorded as credit spreads (Hull et al., 2004). The market for sovereign CDS has been growing over the last decade, in particular since the financial crisis. Around 75 percent of sovereign CDS are bought and sold by global market-making financial institutions; much smaller shares are traded by other banks and securities firms, insurance companies and hedge funds.[1] Movements in CDS spreads on event days hence reflect the attention of professional investors at these institutions to sovereign rating announcements.

Ideally, attention is measured as the abnormal CDS return around the event day, where normal returns are returns on a benchmark portfolio. In event studies on corporate data, the average relationship between the response variable and the benchmark

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[1] Source: Bank for International Settlements OTC Derivatives Statistics, averaged over multiple years.

portfolio is often estimated for a so-called estimation window: a period before the event that is uncontaminated by the event of interest and other influential news. In the sovereign rating context, where announcements by other agencies, rating announcements for other countries as well as various other news affect CDS spreads at a constant rate, it is hard to argue that such a clean estimation window can be identified. Instead, I use raw returns to capture baseline effects and follow the literature on the market impact of sovereign rating announcements (Gande and Parsley, 2005, Afonso et al., 2012, Böninghausen and Zabel, 2015) by using a relatively short event window of 2 trading days $t \in [0, 1]$, the day of the announcement and the subsequent day. A short event window ensures that market responses remain unaffected by news that appear shortly before or after the rating announcement. It also facilitates a causal interpretation: while in theory rating agencies may react to new information conveyed by movements in CDS spreads, a short event window helps to mitigate the risk of reverse causality. The empirical measure for A_i^{CDS} is the cumulative rate of return (percentage change) on the CDS contract for the country the rating of which changes, between the end of the trading day preceding the announcement day $t = -1$ and the end of the trading day after the announcement day $t = 1$:

$$A_i^{CDS} = \begin{cases} 100 \times \frac{p_{t=1}^{CDS} - p_{t=-1}^{CDS}}{p_{t=-1}^{CDS}} & if \quad \Delta R_{ct} < 0 \\ -100 \times \frac{p_{t=1}^{CDS} - p_{t=-1}^{CDS}}{p_{t=-1}^{CDS}} & if \quad \Delta R_{ct} > 0 \end{cases} \tag{4.2}$$

Negative rating announcements are expected to lead to an increase in sovereign CDS spreads as they signal to financial markets that sovereign credit risk has increased. Positive announcements, on the other hand, are expected to have a zero or negative effect as they signal an improvement in creditworthiness. To increase the size of the estimation sample and thereby efficiency, I estimate attention responses jointly. To do so, I multiply CDS returns after positive announcements by minus one to make them comparable to CDS returns after negative announcements. Compared to absolute return values, such an approach ensures that spread movements in an unexpected direction are taken into account as such.

As other news may affect sovereign CDS spreads even on the day of the announcement, I also provide a robustness check using two measures of abnormal returns. The first proxy is based on equally-weighted average CDS spreads of all other countries in the sample and follows Ismailescu and Kazemi (2010) and Afonso et al. (2012). The second measure consists of innovations to CDS spreads that cannot be explained by slowly changing macroeconomic and fiscal variables. Details are provided in section 4.4.2.

Data on daily CDS spreads are obtained from Bloomberg's financial database. More specifically, I work with end-of-day price, bid and ask price data for 5-year USD-denominated sovereign CDS spreads, priced in New York. Data is available from the mid-2000s, which is when trading in most sovereign CDS began, and earlier for some countries, like Hungary, Korea or Slovakia. Dickey-Fuller tests reported in Table 4.2 suggest that the large majority of daily CDS spread series are integrated of order 1. The relatively strong persistence of CDS spreads is economically relevant as innovations introduced to the series by sovereign rating announcements are likely to affect spreads over a long time, rather than constituting only a transitory shock.

Over the whole period, two-way cumulative CDS returns on non-announcement days are on average 0.138 percentage points (Table 4.3). On days of negative rating announcements, mean cumulative returns are 2.35, which is significantly larger than non-announcement day returns. However, on days of positive rating announcements, mean cumulative returns decrease on average by 0.357 percent but the standard deviation is large and the mean is not significantly different from non-announcement day mean returns. This is also illustrated by Figure 4.2. For each rating announcement the cumulative evolution of CDS spreads from 10 days prior to the announcement to 10 days after is calculated. For all negative events, the average evolution of CDS spreads

Table 4.2: Unit root tests of sovereign CDS spread data

Country	Observations	Without trend	With trend
Australia	1,397	0.200	0.316
Austria	2,327	0.225	0.473
Belgium	2,826	0.522	0.798
Czech Republic	1,986	0.276	0.655
Estonia	1,387	0.711	0.610
Finland	1,592	0.391	0.837
France	2,806	0.551	0.695
Germany	2,826	0.449	0.589
Greece	2,826	0.605	0.693
Hungary	3,077	0.547	0.555
Ireland	1,622	0.626	0.966
Italy	2,826	0.530	0.518
Japan	2,866	0.528	0.545
Korea	3,088	0.091	0.247
Netherlands	1,387	0.287	0.691
New Zealand	1,208	0.063	0.225
Portugal	2,806	0.679	0.841
Slovakia	3,181	0.414	0.418
Slovenia	2,274	0.769	0.537
Spain	2,534	0.521	0.591
Sweden	2,594	0.200	0.412
United Kingdom	1,407	0.237	0.066

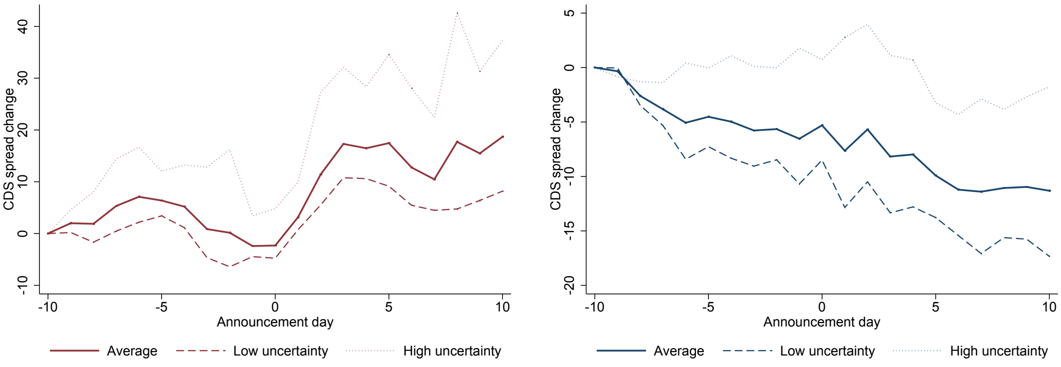
Note: Augmented Dickey-Fuller tests of the null hypothesis that the variable has a unit root. Approximate p-values for the relevant test statistic are reported.

Table 4.3: Cumulative 2-day returns on sovereign CDS

	N	Mean	*t*-test	Std Dev
Non-event day	50,636	0.138		7.523
Negative announcement	163	2.350	0.000	6.941
Positive announcement	40	-0.357	0.707	8.261

Note: Estimation sample, *t*-test of difference in means relative to non-event days, p-value reported.

around the announcement is depicted by the solid line in 4.2a; for positive events the solid line in panel (b) draws the corresponding average movement. Figure 4.2a illustrates that around 5 days prior to negative rating announcements, spreads somewhat widen on average, then decrease a little but increase sharply during the first four days after the announcement. By contrast, spreads appear to decrease gradually during days preceding positive rating announcements (Figure 4.2b). Average spreads then appear to increase somewhat on the announcement day, and drop further the day after. This suggests that positive announcements are anticipated more often by financial market



(a) Negative announcements (b) Positive announcements

Figure 4.2: Average response of CDS spreads to sovereign rating announcements

participants. Figure 4.2 also suggests that fiscal uncertainty alters the way announcements about sovereign ratings impact financial markets. Dotted lines depict the average evolution of spreads by type of announcement for the subcategory of events for which fiscal uncertainty is high, defined as $U_{ct1} > 0$, i.e. whenever the index version based on year-ahead forecasts lies above the overall sample average. During periods of high fiscal uncertainty, spread changes are larger on average. Spreads increase much more sharply after negative rating announcements but also seem to increase prior to positive rating announcements. During periods of below-average uncertainty (dashed lines, defined as $U_{ct1} < 0$), average spread changes are somewhat less pronounced.

4.3.3 Internet search volume

Given that spillover effects from announcements about other countries' ratings and other news about sovereign credit risk may attenuate CDS returns, I use an additional measure of attention to sovereign rating announcements: the rating news-related Google search volume obtained from Google Trends. Internet search volume has been shown to improve forecasts of consumption activity (Vosen and Schmidt, 2011, Choi and Varian, 2012, Carrière-Swallow and Labbé, 2013), unemployment (Askitas and

Zimmermann, 2009) and inflation (Guzman, 2011) by providing real-time information. Da et al. (2011) argue with Kahneman (1973) that the efficient market hypothesis might fail if investors are cognitively overburdened with information, hence attention may be limited and prices do not reflect all available information. This may also be true for ratings announcements if they are accompanied by a number of other relevant news about sovereign credit risk, in particular during crises. Da et al. (2011) propose as a direct measure of investor attention the frequency of stock-related search terms on Google, which, they find, correlates with existing attention measures (albeit at low levels), captures attention in a more timely way, reflects the attention of less sophisticated individual investors and can predict stock prices in the short run. In Cunha et al. (2017), the frequency of the search term ‘credit ratings’ on Google is used to measure public attention to announcements by credit rating agencies about the credit risk of local government debt across US states.

I construct an attention measure of sovereign rating-related Google search requests as follows. For every country in the sample and the three main credit rating agencies Fitch, Standard & Poor’s and Moody’s, I obtain the weekly search volume of the search term ‘[agency] [country]’ from Google Trends in the English language.[2] Compared to CDS returns, rating news-related search volume is likely capturing the attention by the (informed) general population to sovereign rating announcements, rather than sophisticated investors, who will access this information through other channels, like Bloomberg or Reuters terminals. The measure therefore reflects a more widely defined type of attention that may be relevant to credit rating agencies, if they care about their reputation among the general public. It measures attention more directly than movements in CDS spreads given that it is country- and rating agency-specific. Furthermore, Google search volume defined this way is robust to spillover effects from

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[2] [country] is one of ‘austria’, ‘belgium’, ‘germany’, ‘spain’, ‘france’, ‘greece’, ‘hungary’, ‘ireland’, ‘israel’, ‘italy’, ‘japan’, ‘korea’, ‘netherlands’, ‘new zealand’, ‘portugal’, ‘uk’. [agency] is one of ‘fitch’, ‘s&p’, ‘moodys’. Google search terms are not case-sensitive.

announcements about other countries' ratings.

The search volume-based attention measure is defined as the frequency of the country and agency-specific search term in the week of the rating announcement w. The search volume from Google Trends is given as an index value on a 1 to 100 scale relative to other search requests in the respective week, and relative to the history of the search volume of the term. Following Da et al. (2011), I use the natural log of search volume as the attention measure and control for country-agency fixed effects in equation (4.1). Given the relative nature of Google Trends series, I check the robustness of the results using a scaled version.[3] To do so, I divide the search volume during the announcement week by the average search volume across the whole search volume series for each agency- and country-specific search term:

$$A_i^{Google} = \frac{SV_i(\text{`country' `agency'})}{\frac{1}{W}\sum_{w=1}^{W} SV_w(\text{`country' `agency'})} \tag{4.3}$$

for announcement week i and all other weeks w.

4.4 Event study results

4.4.1 Baseline results for CDS returns

Baseline results for cumulative (normal) CDS returns are reported in Table 4.4. As expected, changes in CDS spreads after rating announcements are substantially different from zero as indicated by statistically significant estimates of the constant term. This confirms the findings in the literature. Controlling for agency fixed effects (columns II to V) improves the goodness of fit, which implies that announcements by different agencies receive different attention on financial markets. By contrast, whether the announcement is positive or negative, or whether it is announced for ratings at the

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[3] Bontempi et al. (2016) discuss the comparability of Google Trends volumes across search terms in detail.

Table 4.4: Baseline results for CDS returns

	I	II	III	IV	V
Uncertainty measure:	U_{ct1}	U_{ct1}	U_{ct1}	D_{ct1}	U_{ct0}
Fiscal uncertainty	0.645**	0.663**	0.713***	1.163***	0.127*
	[0.29]	[0.28]	[0.21]	[0.40]	[0.07]
Positive announcement			-1.232	-1.772	-1.420
			[1.29]	[1.43]	[1.34]
Rating level			-0.226	-0.136	-0.182
			[0.15]	[0.17]	[0.15]
Constant	1.814***	3.463***	6.451***	5.609**	6.451***
	[0.56]	[0.77]	[2.07]	[2.57]	[2.07]
Agency FE	no	yes	yes	yes	yes
Observations	203	203	203	203	203
R-squared	0.024	0.049	0.070	0.069	0.048

Note: OLS, standard errors clustered at country level (in brackets), *** p<0.01, ** p<0.05, * p<0.1.

upper or lower end of the rating scale, does not seem to affect CDS spread responses. Coefficients for both variables remain statistically insignificant (columns III to V).

By contrast, fiscal uncertainty significantly increases the absolute response of sovereign CDS spreads. The higher the degree of fiscal uncertainty, the more attention rating announcements receive on markets for sovereign CDS. The impact of a one-standard deviation increase in fiscal uncertainty on the percentage change in CDS spreads over the two days after the rating announcement depends on the uncertainty measure and lies between 0.127 and 0.713 percentage points. The effect for the disagreement component of the fiscal uncertainty index is even larger (column IV). This could imply that financial markets are more sensitive to idiosyncratic uncertainty, rather than common shocks to fiscal policy. The effect of the latter on sovereign credit risk may be more easily gauged without rating information. In other words, the information content of ratings appears to be larger when uncertainty is driven by differences in the assessment of fiscal outcomes across forecasters.

4.4.2 Cumulative abnormal returns

As discussed above, raw CDS returns may respond to other information and therefore be contaminated. However, defining abnormal returns as the difference between raw returns and normal returns is difficult in the sovereign context. Ismailescu and Kazemi (2010) and Afonso et al. (2012) define normal returns as returns of an equally-weighted average CDS spread of all countries in the sample other than the country of interest. Abnormal returns are then defined as cumulative returns on adjusted CDS spreads, the difference between the observed rate of change in the spread and the cross-country average change. I apply their approach to my sample and report results in panel A of Table 4.5. This shows that the effects of uncertainty remain positive but only statistically significant in the case of my forward-looking index version U_{ct1}. Lower statistical significance may result from spillovers of rating news across countries (cf. Gande and Parsley, 2005, and Ferreira and Gama, 2007), in particular as cross-country average returns may also pick up CDS responses of those countries for which rating announcements are made on the same day.

However, while the relatively short event window ensures that CDS returns do not capture a substantial amount of other news, CDS returns may be consistently higher or lower during different periods of time, independent of rating announcements. In particular, fiscal uncertainty or global market volatility may lead to an elevation of average two-day cumulative returns, and so may a deterioration in fiscal and macroeconomic fundamentals. To obtain an alternative proxy of normal cumulative returns, I therefore regress raw returns on a range of slowly-changing variables that themselves do not respond to rating announcements, as well as on year- and country-fixed effects. Table A9 in the Appendix reports results for the three fiscal uncertainty index versions and three different sets of regressors. Specification (1) regresses two-day cumulative CDS returns on year- and country-fixed effects and fiscal uncertainty only. Rather than increasing CDS spreads, fiscal uncertainty is found to have no statistically significant effect, or even a negative effect.

In specification (2), I include changes in the VIX as a measure of global volatility. It has a significantly positive effect. I also include the lagged level of CDS spreads and the VIX to account for an error correction mechanism. In fact, the significantly negative coefficient on the level of CDS spreads and the significant VIX coefficient imply that CDS spreads tend to return to a long-run equilibrium defined by global sentiment. Specification (3) adds as controls the current-year and one-year-ahead forecasts of fiscal and macroeconomic fundamentals. Fiscal variables are found to significantly affect average cumulative CDS returns. Residuals from these regressions are interpreted as cumulative abnormal CDS returns. They are orthogonal to components predictable by fiscal uncertainty, global sentiment, or fiscal and macroeconomic fundamentals. In panels B to D of Table 4.5, I employ cumulative abnormal returns defined in this way as the dependent variable. Results confirm the robustness of the findings based on raw CDS returns. The effect of fiscal uncertainty is statistically significant throughout, independent of the index version employed and the specification used to calculate abnormal returns. In fact, coefficients are somewhat larger than those for raw returns reported in Table 4.4.

Table 4.5: Cumulative abnormal CDS returns

	I	II	III
Uncertainty measure:	U_{ct1}	D_{ct1}	U_{ct0}
A) Normal returns defined as weighted averages			
Fiscal uncertainty	0.358**	0.580	0.057
	[0.17]	[0.42]	[0.04]
Constant	5.777***	5.053**	5.472***
	[1.79]	[2.19]	[1.76]
Observations	203	203	203
R squared	0.067	0.067	0.057
B) Normal returns controlling for fiscal uncertainty (specification 1)			
Fiscal uncertainty	0.856***	1.118**	0.270***
	[0.22]	[0.41]	[0.08]
Constant	7.017***	5.339*	6.336**
	[2.36]	[2.71]	[2.23]
Observations	199	203	199
R squared	0.078	0.064	0.065
C) Normal returns controlling for volatility (specification 2)			
Fiscal uncertainty	0.866**	1.152**	0.167**
	[0.33]	[0.43]	[0.07]
Constant	6.989***	5.319**	6.200***
	[1.73]	[1.88]	[1.70]
Observations	172	174	172
R-squared	0.100	0.084	0.064
D) Normal returns controlling for full set of fundamentals (specification 3)			
Fiscal uncertainty	0.847**	1.154**	0.246***
	[0.31]	[0.42]	[0.07]
Constant	6.269***	4.463**	5.505***
	[1.85]	[1.92]	[1.78]
Observations	172	174	172
R squared	0.093	0.076	0.074

Note: OLS, standard errors clustered at country level (in brackets), *** p<0.01, ** p<0.05, * p<0.1. All specifications control for positive announcement effects, the rating level and agency fixed effects.

4.4.3 Controlling for CDS liquidity

In Table 4.6, I control for the rate of growth of the bid-ask spread relative to the CDS spread within the event window. The change in the bid-ask spread approximates changes in the liquidity of the CDS contract. In contrast to slowly changing fiscal and macroeconomic determinants of sovereign CDS spreads, liquidity may change daily around the rating announcement. This may be because the rating announcement triggers an increase in liquidity (or a decrease in the bid-ask spread) as more investors enter the market. Controlling for short-term liquidity changes is also motivated by work on insider trading in CDS markets and endogenous liquidity. Acharya and Johnson (2007) argue theoretically that in markets that are dominated by banks that serve both as loan providers and as intermediaries in the credit derivatives market – i.e. like in the sovereign CDS market – asymmetric information in the form of insider trading may prevail. Uninformed market makers may then decrease their liquidity before events in order to avoid the exploitation by insiders. This should lead to a decrease in liquidity before, in particular, negative rating announcements and possibly price effects. Acharya and Johnson (2007) fail to find empirical evidence for these theoretical considerations on US corporate CDS markets. Qiu and Yu (2012), by contrast, do find evidence for a positive effect of liquidity on CDS prices if there are many dealers and room for information asymmetries.

Interestingly, the change in the bid-ask spread is only a significant determinant of cumulative CDS returns following positive rating announcements. This can be seen in the interaction between the bid-ask spread and the dummy for positive announcements in columns II, IV and VI of Table 4.6. If liquidity (the bid-ask spread) decreases (increases) during the event period, then the CDS price effect is more pronouncedly negative (multiplying the coefficient by -1 given the definition of CDS returns in equation (4.2)). CDS spreads drop as demand for insurance against sovereign default decreases and investors leave the CDS market. For negative announcements (baseline coefficient on the bid-ask spread), this effect remains statistically insignificant. Two counteracting forces may be at work. Following negative announcements, liquidity increases (the bid-ask spread decreases) as more investors enter the market and demand for CDS increases. In fact, the bid-ask spread decreases on average by 14 percent following negative announcements (whereas it increases by 3 percent following positive announcements). Higher demand increases the CDS spread further; this effect seems to dominate. Yet supply may also increase, which has a countervailing negative effect on spreads. Future work could explore further how these results can be reconciled with findings on insider trading.

Table 4.6: CDS returns controlling for liquidity effects

	I	II	III	IV	V	VI
Uncertainty measure:	U_{ct1}	U_{ct1}	D_{ct1}	D_{ct1}	U_{ct0}	U_{ct0}
Fiscal uncertainty	0.920**	0.951**	1.305***	1.440***	0.139	0.136
	[0.34]	[0.35]	[0.34]	[0.25]	[0.08]	[0.08]
Positive announcement	-1.298	-1.911	-1.961	-2.641*	-1.559	-2.166
	[1.28]	[1.18]	[1.42]	[1.27]	[1.32]	[1.29]
Rating level	-0.211	-0.236*	-0.099	-0.119	-0.147	-0.168
	[0.13]	[0.13]	[0.14]	[0.14]	[0.13]	[0.13]
Bid-ask spread	0.021	0.007	0.020	0.005	0.018	0.004
	[0.02]	[0.02]	[0.02]	[0.02]	[0.01]	[0.02]
*positive ann.		0.186*		0.195*		0.179*
		[0.10]		[0.10]		[0.10]
Constant	6.924***	7.290***	5.171**	5.434**	6.071***	6.393***
	[1.67]	[1.81]	[1.84]	[2.01]	[1.61]	[1.63]
Agency FE	yes	yes	yes	yes	yes	yes
Observations	195	195	195	195	195	195
R-squared	0.098	0.146	0.087	0.140	0.056	0.101

Note: OLS, standard errors clustered at country level (in brackets), *** p<0.01, ** p<0.05, * p<0.1.

4.4.4 Google Trends results

Table 4.7 reports results for the response of Google search volume to sovereign rating announcements. I find that fiscal uncertainty increases the attention of Google users. This supports the hypothesis of higher attention during periods of uncertainty and is in line with findings for CDS spreads. It also suggests that non-professional stakeholders pay more attention to rating changes during periods of higher fiscal uncertainty by increasing the frequency at which they search information about these changes on the internet.

The effect is statistically significant when agency-country-fixed effects are controlled for, i.e. the peculiar nature of Google Trends data is taken into account that arises from the normalisation of search volume time series for each search term. A one-standard deviation increase in fiscal uncertainty increases the volume of internet search by 4.9 percent. For the disagreement component of the index D_{ct1}, results are again higher and lie at 14.3 percent.

Interestingly, the rating level is a statistically significant regressor for Google search volumes. Announcements about ratings at the upper end of the rating scale trigger significantly smaller search frequencies than announcements about lower ratings. Whether the announcement is negative or positive does not have a significant effect.

Overall findings are confirmed by Table A10 in the Appendix, which considers effects on scaled Google Trends data series. Note that, in contrast to results for the impact on CDS spreads, the constant term estimate for Google Trends responses does not carry any meaning and simply reflects the average response of the search volume index during announcement weeks. Given the interest lies solely in the effect of fiscal uncertainty on attention during announcement weeks, I do not attempt to explicitly estimate whether attention during non-announcement weeks is different, although the scaled version of the Google Trends attention measure implicitly accounts for search volume during weeks in which no rating announcement is made.

4.4.5 Other uncertainty measures

Tables A11 and A12 in the Appendix provide results for alternative measures of uncertainty, for CDS spreads and Google search volume respectively. These show that mea-

Table 4.7: Google Trends results

	I	II	III	IV	V
Uncertainty measure:	U_{ct1}	U_{ct1}	U_{ct1}	D_{ct1}	U_{ct0}
Fiscal uncertainty	0.025	0.023**	0.049*	0.143***	0.016***
	[0.01]	[0.01]	[0.03]	[0.04]	[0.00]
Positive announcement			-0.488	-0.506	-0.490
			[0.29]	[0.30]	[0.31]
Rating level			-0.049**	-0.049**	-0.039**
			[0.02]	[0.02]	[0.02]
Constant	3.048***	2.647***	3.659***	3.687***	3.441***
	[0.06]	[0.00]	[0.44]	[0.42]	[0.35]
Agency-Country FE	no	yes	yes	yes	yes
Observations	145	145	145	145	145
R-squared	0.003	0.304	0.334	0.341	0.331

Note: OLS, standard errors clustered at country level (in brackets), *** p<0.01, ** p<0.05, * p<0.1.

sures that do not capture uncertainty about fiscal fundamentals directly, like the EPU and sovereign bond yield volatility, do not significantly affect attention to sovereign rating announcements. From *ex post* observable absolute forecast errors, only the error in year-ahead deficit forecasts appears to have an effect on CDS spreads (Table A11, column IV), but not on Google search volume (Table A12, columns III, IV). This serves as another proof that the index of fiscal uncertainty developed in Chapter 2 captures better the degree of uncertainty related to fiscal outcomes, which are relevant in the context of sovereign credit risk, compared to existing proxies.

4.5 Conclusion

The two event studies conducted in this chapter show that changes in sovereign credit ratings gain more attention on financial markets, and among the wider public, the higher the degree of uncertainty about the future path of the fiscal deficit. Both absolute returns on sovereign CDS as well as the frequency of country- and rating agency-specific search requests on Google are larger after sovereign rating announcements if fiscal uncertainty is high. Results hold independently of the measurement of uncertainty in forecasts of the fiscal deficit, i.e. for different versions of the fiscal uncertainty index. Results are also robust to specifications that control for the effect of slowly moving fiscal and macroeconomic fundamentals on cumulative CDS returns, liquidity on markets for sovereign CDS and the definition of Google Trends search volumes.

By showing that attention to actions taken by credit rating agencies depends on the degree of noise about the information agencies are expected to provide expert analysis on, this chapter confirms empirically one key assumption in models of credit rating agency behaviour. Market participants seek rating news when these news add to the stock of publicly available information. The result may provide one possible explanation for why rating agencies adjust sovereign credit ratings more frequently during periods of higher uncertainty than justified by movements in sovereign credit risk: an increase in attention may correspond to publicity gained by rating agencies.

Chapter 5

Conclusion

The global financial crisis of 2008 and the subsequent 'Great Recession' brought three main themes to the forefront of the academic and policy debate: the importance of uncertainty for economic outcomes, the implications of fiscal policy becoming active, and sovereign credit risk as an issue that can also arise in advanced economies, not only in the developing world. This doctoral thesis provides a joint account of these themes. This final chapter summarises the main methodological advances made and directs to potential future avenues of research. It discusses the findings obtained in individual thesis chapters, discusses their interrelation and outlines potential policy implications.

A first contribution is made to a literature that is concerned with the measurement of economic uncertainty. While the aftermath of the recent crisis brought about a number of new approximations to macroeconomic uncertainty (Jurado et al., 2015, Rossi and Sekhposyan, 2015) and economic policy uncertainty (Baker et al., 2016), a coherent measure of fiscal uncertainty has not been agreed on. Chapter 2 proposes a proxy that is directly related to fiscal outcomes in the near term, comparable across advanced economies and observable in real time. It develops further the uncertainty index Lahiri and Sheng (2010) construct for macroeconomic forecasts to apply it to official projections of the fiscal deficit provided by the IMF, the OECD and the European Commission. The method by Lahiri and Sheng (2010) consists of constructing two index components: forecast disagreement and expectations about the variance of common shocks. The authors argue that disagreement alone does not capture economic uncertainty fully. I confirm this for my sample of fiscal forecasts and find that the variance of common fiscal forecast shocks is particularly important in the aftermath of the financial crisis, i.e. when innovations to fiscal policy came as a surprise to all forecasters. Fiscal forecasts are subject to considerable biases as forecasting institutions are too optimistic about governments' budgetary positions, likely as a result of the data they are provided with by fiscal authorities. I therefore clean the forecast data from predictable components before constructing the disagreement measure. Lahiri and Sheng (2010) obtain an empirical proxy for the variance of aggregate shocks in macroeconomic series from a GARCH estimation. Given that fiscal forecasts are available only at a low frequency and a limited number of years, such an approach cannot be easily applied to fiscal deficit data. Instead, I propose the use of unexpected forecast innovations. These are obtained by stripping forecast revisions from components that are predictable at the time the initial forecast is made. The fiscal deficit relative to GDP is a widely used indicator of the fiscal position. Uncertainty around this indicator therefore has implications for a large number of stakeholders, in the public and the private sector. However, the fiscal deficit subsumes cyclical adjustments made to the government budget balance as well as interest payments, uncertainty about which therefore also enters the index. Future work could consider using a more direct measure of discretionary spending, such as the cyclically-adjusted primary balance, provided the availability of such data improves. A fiscal uncertainty index based on the cyclically-adjusted primary balance would capture more directly the uncertainty about planned fiscal policies. The fiscal deficit is also the fiscal indicator that is most coherently measured across forecasters. As more forecasters, including private sector professionals, report fiscal deficit projections, the index could be extended to include a larger number of point forecasts.

Likewise, if fiscal forecasters were to provide an indication of forecast probabilities, for instance in the form of density forecasts, this could provide a better proxy of fiscal uncertainty. Fiscal deficit forecasts are also only consistently available for a forecast horizon up to one year. The fiscal uncertainty index therefore captures uncertainty about fiscal policy measures that may be adopted within a relatively short time frame. Using fiscal forecasts for longer horizons, where available, may instead shed light on uncertainty about the long-term sustainability of fiscal policy.

The resulting index is closely related to the theoretical concept of fiscal uncertainty, according to which fiscal instruments follow stochastic processes. It allows a more direct analysis of the factors that underlie fiscal uncertainty compared to existing measures of fiscal policy discretion (Sørensen et al., 2001, Galí and Perotti, 2003, Lane, 2003, Cimadomo, 2012), fiscal forecast errors (Jonung and Larch, 2006, von Hagen and Wolff, 2006, de Castro et al., 2013), or fiscal policy volatility (Henisz, 2004, Zhou, 2009, Agnello and Sousa, 2013). I assess the correlation between the new fiscal uncertainty index and factors that the literature identifies as the drivers of fiscal policy discretion and forecast errors. In particular, I estimate the link between fiscal uncertainty and the business cycle, financial sector vulnerabilities and elections. I also look at possible constraints to fiscal policy, which may reduce fiscal uncertainty. More specifically, I estimate the role of institutional constraints, such as the participation in an Economic Adjustment Programme enforced by international institutions, and the role of debt stabilisation, which may reduce fiscal space. The latter is approximated using the level of debt/GDP, which is only an incomplete proxy of fiscal space. It may be worthwhile in future work to estimate linkages between fiscal uncertainty and more direct estimates of fiscal space provided by international institutions (e.g. Blanchard, 1990, Kose et al., 2017), or model-based estimates of fiscal space (e.g. Polito and Wickens, 2012). Another avenue for future work may consist of testing recently proposed theoretical predictions about the effects of fiscal uncertainty on economic activity (e.g. Fernández-Villaverde et al., 2015), the effectiveness of fiscal policy (Ricco et al., 2016) and risk premia (e.g. Sialm, 2006, Pástor and Veronesi, 2013). The fiscal uncertainty proxy proposed in this thesis would be suitable for this type of analysis given its close link to theory and its high comparability across countries.

This thesis focuses on the effects of fiscal uncertainty on sovereign credit ratings and the attention given to rating announcements. A main methodological innovation proposed in Chapter 3 is a new empirical framework for the estimation of sovereign credit rating determinants. Credit ratings of advanced economies are characterised by a high number of observations in investment grade categories. Hence the number of time observations in some rating categories is small. Some authors deal with this data characteristic using Bayesian methods (e.g. Bruha et al., 2017, Dimitrakopoulos and Kolossiatis, 2016). Instead, I estimate a model of rating changes. While the level of the credit rating depends on initial conditions, including slowly-changing institutional factors, the weights assigned to which in the rating process are increasingly made transparent by credit rating agencies, the interest often lies in the timing of rating *changes*. However, given that ratings of advanced economies hardly change over time, estimating the determinants of rating migration proves difficult. In fact, Monte Carlo simulations show that Ordered Probit estimates of a model with three possible outcomes – rating upgrade, no change, or downgrade – tend to be biased downward. This is confirmed in an empirical application to ratings data from Fitch, Standard & Poor's and Moody's. I therefore propose the estimation of a model that explicitly allows for rating stability. Harris and Zhao (2007) develop an adjustment to the Ordered Probit estimator to account for inflation in survey data on consumer choice through an additional latent process. I show that in the rating context, the additional process can be interpreted as a technical process, which is part of the rating methodology and reduces the probability of rating changes. Parameter estimates from the adjusted Ordered Probit estimation of credit risk determinants are associated with smaller biases. In addition, a high number of cross-country, cross-time rating observations sit in the top rating category (AAA). For these observations, it is known *ex ante* that further upgrades have a zero-probability, which further contributes to rating stability; the same argument applies *vice versa* to downgrades away from the bottom rating category. I develop the estimation framework to also account for the boundedness of the rating scale and find that this reduces estimate biases further. Limits on the set of feasible outcomes for some observations, which are known *ex ante*, are not necessarily confined to the context of rating changes. For instance, the number of options given to survey respondents may be different for some respondents than others. The boundary-adjusted ordered outcome estimator proposed in Chapter 3 may therefore find useful applications in fields other than the rating context. The new empirical framework for the estimation of rating migration could be extended and built upon along several lines. Improvements to the maximum likelihood-based estimation approach could reduce relatively large standard error estimates and enhance inference. The framework could be applied to rating data for other countries, in particular in the developing world, as well as to ratings issued by other than the three largest credit rating agencies. Hypotheses about rating determinants in addition to those about fiscal uncertainty, that have been tested in a number of empirical studies, could be cross-checked using the new framework. In general, the framework could be used to inform policy-makers, financial regulators or credit rating agencies about the quality of the rating process and its external replicability.

By introducing an attention measure based on online search volume, I also make a contribution to work on the effects of policy announcements. In the context of sovereign credit ratings, this literature has so far focussed on the effects on market prices like bond yields and spreads, exchange rates or equity price indices (e.g. Cantor and Packer, 1996, Reisen and von Maltzan, 1999, Gande and Parsley, 2005, Ismailescu and Kazemi, 2010, Kiff et al., 2012). Online search volume can capture the attention of stakeholders more directly if the efficient market hypothesis fails and prices do not immediately reflect new information. In addition, in applications to sovereign ratings it is often difficult to identify whether observed price movements are truly driven by rating announcements, or instead caused by other news. Using the search volume that is specific to the rated issuer and rating agency helps to identify the effects more clearly. It can therefore be worthwhile to make use of data on online search volume also within other practically relevant event studies, for instance on the effectiveness of monetary policy announcements.

Turning to a discussion of the empirical results, I find that the recent crisis marked a striking rise of fiscal uncertainty. While the newly constructed index of uncertainty in fiscal deficit forecasts is relatively subdued for the period prior to 2007, it spikes in 2009 as official forecasters fail to gauge the fiscal implications of the financial crisis. In most advanced economies, fiscal policy soon becomes predictable again as the index returns to pre-crisis levels. However, the cross-country heterogeneity in fiscal uncertainty remains elevated as ambiguity rises about the fiscal position of a number of euro area countries during the European government debt crisis of 2010-11. Trying to trace some of the origins of fiscal uncertainty, I find that its rise is driven by the more active role of fiscal policy. As with uncertainty measures in general, statements about causality are difficult to make. I show that the economic downturn as well as financial sector vulnerabilities, to which fiscal policy reacts with a lag, are significantly correlated with fiscal uncertainty. Given that theory suggests that fiscal uncertainty may itself generate a reduction in economic activity (e.g. Fernández-Villaverde et al., 2015), future work should lay a stronger focus on the direction of causality, for example by looking at selected crisis episodes and the timing of events associated with uncertainty. I further show that the election cycle plays an important role. If an election is scheduled in a given year, the uncertainty about that year's fiscal deficit increases *ex ante*. The more heated political climate in the aftermath of the crisis and unanticipated election results across advanced economies have certainly contributed to this. The result is not so much driven by political budget cycles in the original sense, according to which politicians buy votes prior to elections (Nordhaus, 1975, Hallerberg and Strauch, 2002). Instead, the link between elections and fiscal uncertainty is stronger, the smaller the projected deficit, either because governments manipulate the data provided to official forecasters (Brück and Stephan, 2006), or because a smaller deficit reflects more room for fiscal manoeuvre. In fact, I find that a more pressing need to stabilise debt levels, as indicated by high debt/GDP ratios, can decrease fiscal uncertainty. In addition, exogenous constraints on fiscal policy, such as those imposed by international institutions on euro area member states during the European government debt crisis, are also associated with lower fiscal uncertainty.

Given that fiscal uncertainty is strongly linked to adverse fiscal effects from crises and political disruptions, it is not surprising that credit rating agencies appear to consider it a risk to sovereign creditworthiness. I find that elevated levels of uncertainty about future fiscal deficits significantly increase the likelihood of a rating downgrade. The result holds alongside the contribution of fiscal and macroeconomic fundamentals, which rating agencies report to take into account. It can explain why credit ratings deviate from their objective fundamentals-based component during crises (D'Agostino and Lennkh, 2016). If agencies consider fiscal uncertainty, explicitly or implicitly, when they make a subjective judgement, this can provide an explanation for why ratings may sometimes differ from from model-based credit risk measures (Polito and Wickens, 2014, Polito and Wickens, 2015). In fact, as fiscal uncertainty increases at the height of crises, incorporating it can render ratings pro-cyclical and lead to what may seem like excessive downgrades (Ferri et al., 1999, Dimitrakopoulos and Kolossiatis, 2016).

I also find that fiscal uncertainty can affect the way economic agents acquire information. I show that fiscal uncertainty increases the attention to rating announcements. Risk premia priced on financial markets react more strongly to a rating change in an environment of uncertainty. This can explain why rating responses are stronger for rating downgrades (Reisen and von Maltzan, 1999), when fiscal fundamentals are weak (Alsakka and ap Gwilym, 2012), or global market sentiment is high (Hill and Faff, 2010). Likewise, rating-related online search volume is shown to increase substantially more in response to rating announcements if fiscal uncertainty is high, implying that the wider public also gives ratings more attention. Consulting sovereign credit ratings can provide a simple heuristic when the noise about publicly available data increases the cost of information acquisition.

What are the lessons to be drawn for future research on fiscal uncertainty and sovereign credit risk as well as for policy-makers and financial market stakeholders? Given its substantial variation across countries and over time, uncertainty about future fiscal outcomes should feature more prominently in theoretical work. Similarly, future empirical work on the determinants of sovereign credit ratings, but also of other market-based measures of credit risk premia, may want to control more explicitly for market reactions to uncertainty about fiscal and macroeconomic fundamentals. As the index developed in this thesis reflects uncertainty about the fiscal deficit within the horizon of one year, an extended analysis may also consider measures of uncertainty about fiscal outcomes further into the future. Governments have an incentive to improve their rating to reduce the cost of borrowing, which depends to a high degree on sovereign credit ratings. The findings provided here imply that reducing ambiguity about future fiscal deficits can make a substantial contribution. Communicating clearly the fiscal strategy, in particular during downturns, appears to be important. Similarly, constraints set by an economic adjustment programme can be a temporary means to reduce fiscal uncertainty and thereby alleviate sovereign credit risk. At the same time, unforeseen events, such as financial crises, will require unforeseen policy action, which will ratchet up the level of fiscal uncertainty independent of what governments may do to reduce ambiguity about fiscal policy. Similarly, the regular occurrence of elections in a democratic system, that provides voters with clear alternatives, may always lead to a certain degree of unpredictability. A reduction in the credit rating can, however, serve as an incentive for governments to place more weight on a sustainable conduct of fiscal policy. This can reduce fiscal uncertainty and eventually improve sovereign creditworthiness. To this end, it may be beneficial for credit rating agencies to explicitly state that uncertainty is taken into account when sovereign credit risk is assessed. This would not only raise the awareness of fiscal policy-makers to the adverse effects of fiscal uncertainty. It would also resolve some of the criticism faced by rating agencies as procyclical rating changes could be considered justified during periods of high uncertainty. However, if rating agencies partly responded to fiscal uncertainty to raise the attention they receive during the crisis, which could explain why ratings are changed more frequently during periods of uncertainty independent of movements in sovereign credit risk, recent regulatory changes should facilitate higher rating quality in the future (see e.g. European Union, 2013). A higher reliance on credit rating changes by financial market participants and the general public, whether these changes are justified or not, can trigger the self-fulfilling dynamics between sovereign risk and the state of economy that are described in work by Corsetti et al. (2013) and others. More generally, the relation between uncertainty and the role for expert analyses, as well as a discussion of potential incentives faced by the providers of these analyses, is certainly a field that deserves more research. The present application to sovereign credit ratings can be a step in this direction. From the point of view of financial regulation, a lesson to be drawn is that providers of an export opinion may need to be scrutinised more during periods of higher uncertainty, which is when the reliance on these experts increases. Ensuring that market stakeholders, policy-makers and the public are provided with information without bias from a large number of independent sources would help prevent the escalation of periods of uncertainty into self-fulfilling crises.

In summary, the thesis as a whole therefore illustrates the pervasive nature of uncertainty in the area of fiscal policy, in particular since the outbreak of the global financial crisis. An application to sovereign credit risk shows that understanding the effects of fiscal uncertainty is indispensable from an academic point of view as well as from a policy perspective.

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Appendix A

Technical Appendix

A1 Deriving the aggregate measure of uncertainty

To derive an aggregate measure of uncertainty from the variance decomposition $Var(e_{icth}) = \beta_{ich}^2 Var(e_{cth}) + Var(\epsilon_{icth})$, Ozturk and Sheng (2018) follow Campbell et al. (2001) and find an expression of individual forecast errors that does not require estimates of β_{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 $e_{icth} = \beta_{ich} e_{cth} + \epsilon_{icth} + \phi_{ich}$, setting $\phi_{ich} = 0$ and re-arranging yields:

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

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

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

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 β_{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:

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

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 $E(e_{cth}) = 0$:

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

The variance of expression (A2) is $Var(v_{icth}) = (\beta_{ich} - 1)^2 Var(e_{cth}) + Var(\epsilon_{icth})$. 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 β_{ich}, $\sum_{i=1}^{N} (\beta_{ich} - 1)^2$, and the common shock. This can be shown by taking the weighted average of $Var(v_{icth})$:

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

If the variance $(\beta_{ich} - 1)^2$ is small across forecasters, the proxy coincides with the true measure of idiosyncratic uncertainty.

A2 Derivation of the model proposition

(i) If $x = 1$ and $a^* = 1$, the best response by the Agency is a pure strategy in which a rating change $\{R = 1|x = 1, a^* = 1\}$ is issued with $\pi_1^* = 1$ since

$$U_A(R = 1|x = 1, a^* = 1) = \pi_1^*(p + r) > 0 = U_A(R = 0|x = 1, a^* = 1). \tag{A10}$$

(ii) Given $\pi_1^* = 1$, the belief of the Public that $x = 1$ if $R = 1$ is issued, becomes:

$$\mu = \frac{\pi_x \pi_1^*}{\pi_x \pi_1^* + (1 - \pi_x)\pi_0^*} = \frac{\pi_x}{\pi_x + (1 - \pi_x)\pi_0^*}. \tag{A11}$$

Hence μ is greater than π_x unless $\pi_0^* = 1$ and the Agency always misinforms when $x = 0$.

$a^* = 1$ is the best response to $\{\pi_1^* = 1|x = 1\}$ and π_0^* if and only if $U_P(a = 1) \geq U_P(a = 0)$. Plugging the Public's pay-offs into U_P, this condition becomes

$$[\pi_x + (1 - \pi_x)\pi_0^*]\mu b + (1 - \pi_x)(1 - \pi_0^*)h \geq \pi_x b. \tag{A12}$$

Replacing μ with expression A11 and simplifying yields that condition A12 holds for all $\pi_0^* \leq 1$ as long as $h > 0$. In other words, the Public is strictly better off playing $a^* = 1$ if $\pi_0^* < 1$ and there is a gain from getting to know $x = 0$. The mechanism is not the information contained in $R = 1$ but rather the information contained in $R = 0$. If the Public pays attention to $R = 0$, it knows for sure that $x = 0$. .

(iii) Given $a^* = 1$, the Agency maximises its expected pay-off in response to $x = 0$:

$$\max_{\pi_0^*} \pi_0^* p + (1 - \pi_0^*) r \tag{A13}$$

The first-order condition with respect to π_0^* implies that the Agency's equilibrium strategy is mixing between $\{R = 1|x = 0\}$ and $\{R = 0|x = 0\}$, i.e. $0 < \pi_0^* < 1$ if and only if

$$p = r. \tag{A14}$$

Appendix B

Tables and Figures

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: Cross-sectional dependence of fiscal uncertainty index

	U_{ct0}	D_{ct0}	U_{ct1}	D_{ct1}
Overall	45.0***	4.9***	46.5***	8.4***
Before spring 2009	45.3***	6.1***	48.9***	9.4***
After spring 2009	24.1***	3.2***	9.0***	3.2***

Notes: Pesaran (2015) test of weak cross-sectional dependence, CD test statistic, significance level given by *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Determinants of fiscal uncertainty index versions

	I	II	III	IV	V	VI	VII	VIII	IX
Dependent variable:	D_{ct1}	D_{ct1}	D_{ct1}	U_{ct0}	U_{ct0}	U_{ct0}	D_{ct0}	D_{ct0}	D_{ct0}
Deficit/GDP squared	0.002*	0.006***	0.002*	0.011***	0.002***	0.011***	0.008***	0.003***	0.008***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Debt/GDP	-0.002	-0.002	-0.002	-0.005***	-0.001	-0.005***	-0.004**	-0.002	-0.004**
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Unemployment	0.004	-0.008	0.004	0.017	0.002	0.017	0.023*	-0.004	0.024*
	[0.01]	[0.03]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.02]	[0.01]
Bank CDS spread		0.126			-0.074			0.011	
		[0.14]			[0.08]			[0.09]	
Lag 1		0.186			-0.069			-0.087	
		[0.14]			[0.08]			[0.09]	
Lag 2		0.438***			0.150*			-0.087	
		[0.14]			[0.08]			[0.09]	
Election			0.116**			-0.015			-0.023
			[0.05]			[0.04]			[0.05]
Observations	777	357	777	756	355	756	837	357	837
Countries	31	20	31	31	20	31	31	20	31
R-squared	0.575	0.383	0.614	0.812	0.916	0.812	0.700	0.905	0.700
p-value CD statistic	0.675	0.243	0.916	0.000	0.000	0.075	0.825	0.442	0.878

Notes: Common Correlated Effects estimates, cross-sectional averages of fiscal policy uncertainty, deficit/GDP and GDP growth included as well as the crisis dummy. Standard errors in brackets, significance level given by *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Determinants of alternative uncertainty measures

	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
Dependent variable:	EPU	EPU	EPU	Bond vol	Bond vol	Bond vol	$\|e_{ct1}\|$	$\|e_{ct1}\|$	$\|e_{ct1}\|$	$\|e_{ct0}\|$	$\|e_{ct0}\|$	$\|e_{ct0}\|$
Deficit squared	.005***	.004***	.003***	.004***	.000	.004***	-.02***	.003	-.02***	-.01***	-.002	-.01***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Debt/GDP	.006***	.006**	.006***	-.01***	-.001	-.01***	-.02***	.005	-.02***	-.02***	.011***	-.02***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]
Unemployment	-.02**	-.023	-.02*	.085***	.033*	.108***	.060*	.041	.060*	.100***	.046*	.102***
	[0.01]	[0.02]	[0.01]	[0.01]	[0.02]	[0.01]	[0.03]	[0.05]	[0.03]	[0.03]	[0.03]	[0.03]
Bank CDS spread		-.014			.108			.425**			.093	
		[0.08]			[0.07]			[0.18]			[0.11]	
Lag 1		.092			.081			1.162***			.074	
		[0.08]			[0.07]			[0.21]			[0.11]	
Lag 2		.104			.210***			.735***			.079	
		[0.08]			[0.07]			[0.19]			[0.11]	
Election			.017			.089			-.137			-.20**
			[0.04]			[0.06]			[0.11]			[0.10]
Observations	762	326	762	843	359	843	785	359	785	845	359	845
Countries	27	18	27	30	20	30	31	20	31	31	20	31
R-squared	0.815	0.631	0.816	0.584	0.841	0.577	0.673	0.568	0.587	0.483	0.680	0.486
p-value CD stat	0.033	0.000	0.003	0.000	0.000	0.000	0.858	0.002	0.889			

Notes: Common Correlated Effects estimates, cross-sectional averages of fiscal policy uncertainty, deficit/GDP and GDP growth included as well as the crisis dummy. Standard errors in brackets, significance level given by *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Transition matrix Fitch

		Rating (t)															
		AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB-	B+	B	B-	CCC
Rating (t-1)	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 A6: Transition matrix S&P

		Rating (t)																		
		AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC	CC	SD/D
Rating (t-1)	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 A7: 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 A8: 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 considered as rating changes in columns II, IV.

Table A9: Normal CDS returns

	I	II	III	IV	V	VI	VII	VIII	IX
Specification:	1	2	3	1	2	3	1	2	3
Uncertainty measure:	U_{ct1}	U_{ct1}	U_{ct1}	D_{ct1}	D_{ct1}	D_{ct1}	U_{ct0}	U_{ct0}	U_{ct0}
Fiscal uncertainty	-0.246**	-0.119	-0.207	0.123	0.196	0.193	-0.221	-0.006	-0.201
	[0.12]	[0.14]	[0.15]	[0.10]	[0.13]	[0.12]	[0.17]	[0.15]	[0.17]
CDS spread (lagged level)		-0.011***	-0.017***		-0.011***	-0.017***		-0.011***	-0.017***
		[0.00]	[0.00]		[0.00]	[0.00]		[0.00]	[0.00]
VIX (lagged level)		0.111***	0.134***		0.111***	0.135***		0.113***	0.136***
		[0.02]	[0.02]		[0.02]	[0.02]		[0.02]	[0.02]
VIX (difference)		0.145***	0.146***		0.146***	0.146***		0.145***	0.146***
		[0.02]	[0.02]		[0.02]	[0.02]		[0.02]	[0.02]
Deficit/GDP			-0.077**			-0.102***			-0.096***
			[0.04]			[0.03]			[0.03]
Deficit/GDP forecast			-0.140*			-0.156**			-0.133*
			[0.07]			[0.06]			[0.08]
Debt/GDP			0.010			0.016			0.019
			[0.04]			[0.04]			[0.04]
Debt/GDP forecast			0.163***			0.144***			0.146***
			[0.06]			[0.06]			[0.06]
Real GDP growth			0.037			0.055			0.044
			[0.06]			[0.06]			[0.06]
Real GDP growth forecast			0.138			0.141			0.145
			[0.10]			[0.10]			[0.10]
Unemployment			0.050			-0.018			0.029
			[0.10]			[0.09]			[0.10]
Unemployment forecast			-0.114			-0.087			-0.124
			[0.18]			[0.17]			[0.18]
Inflation			-0.025			-0.028			-0.024
			[0.02]			[0.02]			[0.02]
Inflation forecast			-0.010			-0.015			-0.009
			[0.02]			[0.02]			[0.02]
Current account			0.070			0.082*			0.084*
			[0.05]			[0.04]			[0.04]
Current account forecast			0.294***			0.291***			0.298***
			[0.09]			[0.09]			[0.09]
Constant	-0.580**	0.260	1.087	-0.495	-0.592	1.998*	-0.587**	0.043	0.773
	[0.26]	[1.08]	[1.15]	[0.71]	[1.06]	[1.20]	[0.26]	[1.03]	[1.08]
Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	41,643	37,390	37,390	44,198	39,699	38,017	41,643	37,390	37,390
Countries	23	23	23	23	23	23	23	23	23
R-squared	0.009	0.043	0.047	0.008	0.043	0.047	0.008	0.043	0.047

Note: OLS, Driscoll-Kraay standard errors (in brackets), *** p<0.01, ** p<0.05, * p<0.1.

Table A10: Google Trends results (relative search volume)

	I	II	III	IV	V
Uncertainty measure:	U_{ct1}	U_{ct1}	U_{ct1}	D_{ct1}	U_{ct0}
Fiscal uncertainty	0.002	0.019***	0.036**	0.105**	0.015***
	[0.02]	[0.00]	[0.02]	[0.04]	[0.00]
Positive announcement			-0.489	-0.504	-0.482
			[0.30]	[0.30]	[0.31]
Rating level			-0.037**	-0.037**	-0.031**
			[0.01]	[0.01]	[0.01]
Constant	1.087***	-0.448***	0.326	0.343	0.174
	[0.13]	[0.00]	[0.31]	[0.30]	[0.26]
Agency-Country FE	no	yes	yes	yes	yes
Observations	145	145	145	145	145
R-squared	0.000	0.326	0.351	0.355	0.351

Note: OLS, standard errors clustered at country level (in brackets), *** p<0.01, ** p<0.05, * p<0.1.

Table A11: Other uncertainty measures (CDS spreads)

	I	II	III	IV
Uncertainty measure:	EPU	Bond vol	$\|e_{ct0}\|$	$\|e_{ct1}\|$
Fiscal uncertainty	-0.238	-0.239	0.466	0.229**
	[0.51]	[0.25]	[0.32]	[0.09]
Positive announcement	-1.578	-1.824	-1.168	-1.361
	[1.56]	[1.45]	[1.44]	[1.39]
Rating level	-0.206	-0.243	-0.132	-0.222
	[0.15]	[0.15]	[0.14]	[0.16]
Constant	7.169***	7.946***	4.925**	6.689***
	[2.01]	[2.32]	[2.27]	[2.04]
Agency FE	yes	yes	yes	yes
Observations	201	202	203	203
R-squared	0.048	0.043	0.057	0.054

Note: OLS, standard errors clustered at country level (in brackets), *** p<0.01, ** p<0.05, * p<0.1.

Table A12: Other uncertainty measures (Google Trends)

	I	II	III	IV
Uncertainty measure:	EPU	Bond vol	$\|e_{ct0}\|$	$\|e_{ct1}\|$
Fiscal uncertainty	0.002	0.017	0.002	0.000
	[0.13]	[0.04]	[0.06]	[0.02]
Positive announcement	-0.536*	-0.527*	-0.536*	-0.536*
	[0.28]	[0.30]	[0.29]	[0.30]
Rating level	-0.036*	-0.030	-0.037*	-0.037*
	[0.02]	[0.02]	[0.02]	[0.02]
Constant	3.375***	3.264***	3.389***	3.390***
	[0.58]	[0.40]	[0.36]	[0.41]
Agency-Country FE	yes	yes	yes	yes
Observations	144	145	145	145
R-squared	0.326	0.327	0.326	0.326

Note: OLS, standard errors clustered at country level (in brackets), *** p<0.01, ** p<0.05, * p<0.1.

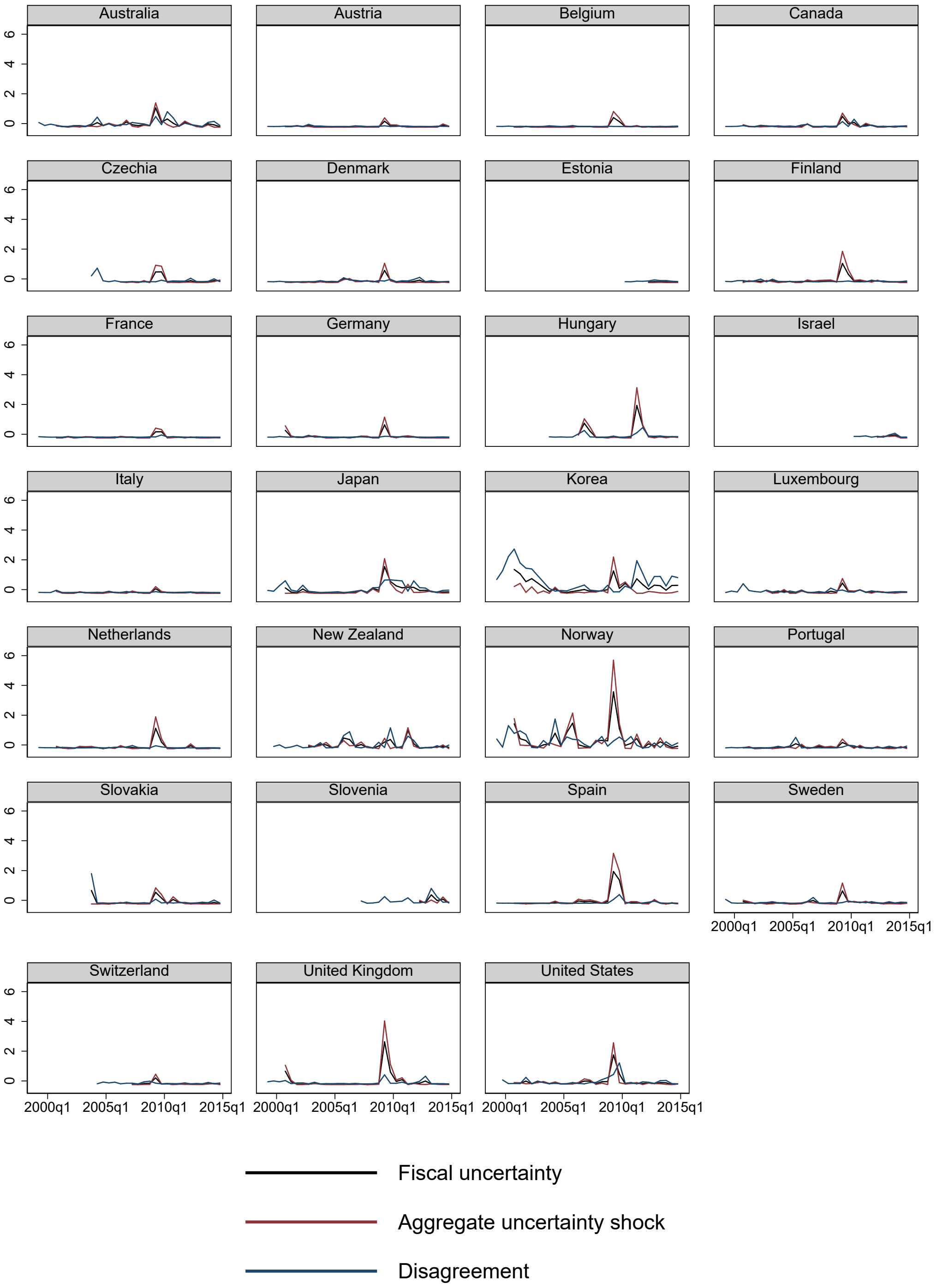

Figure A1: Fiscal uncertainty across countries (standard deviations, current-year index version)

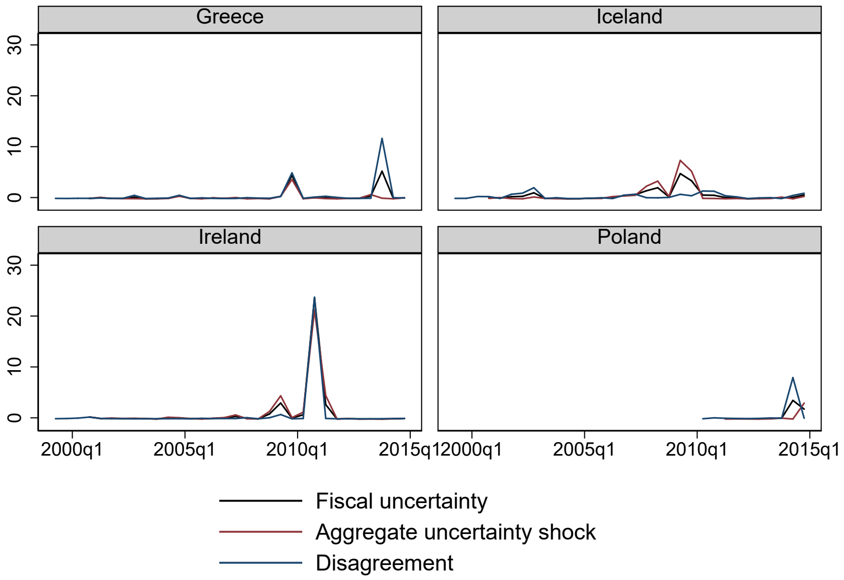

Figure A2: Fiscal uncertainty across additional countries (standard deviations, current-year index version)

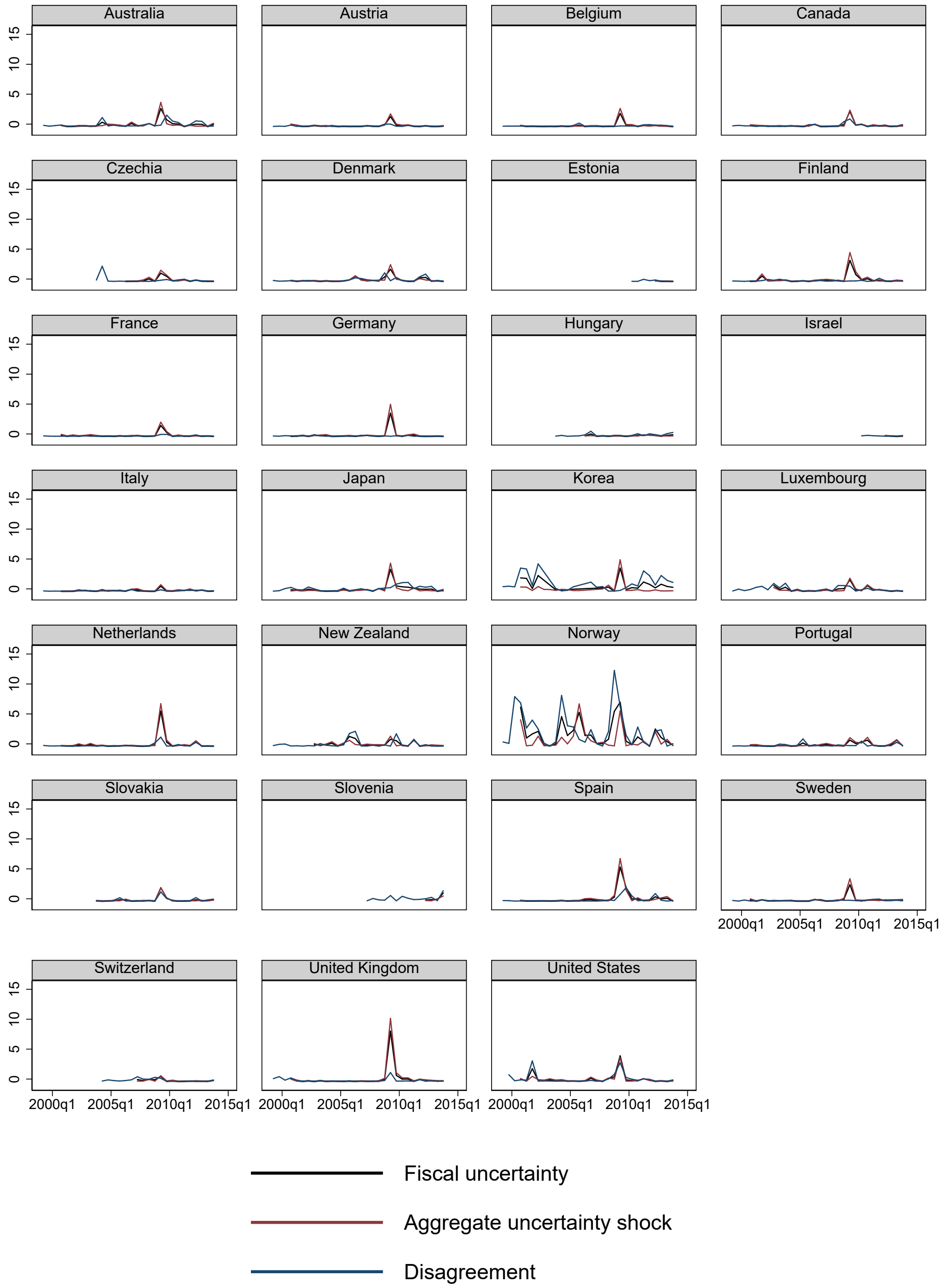

Figure A3: Fiscal uncertainty across countries (standard deviations, year-ahead index version)

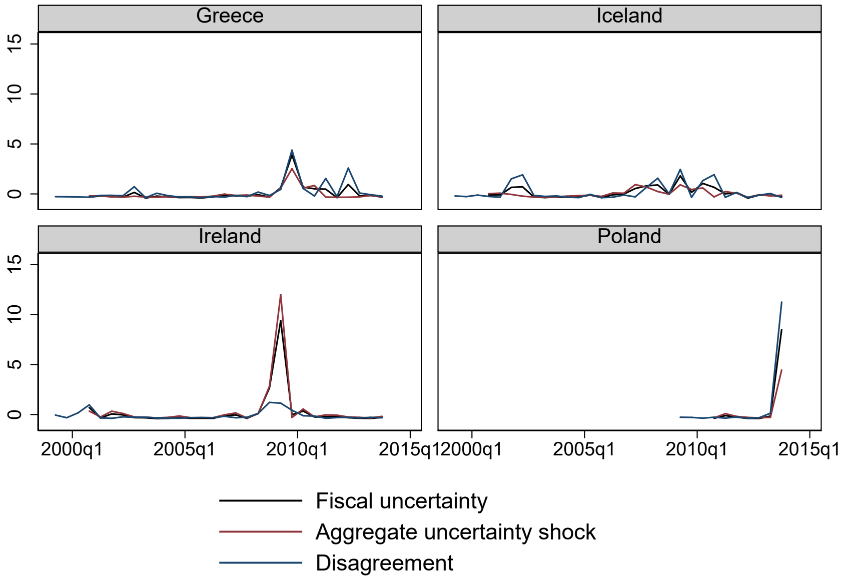

Figure A4: Fiscal uncertainty across additional countries (standard deviations, year-ahead index version)

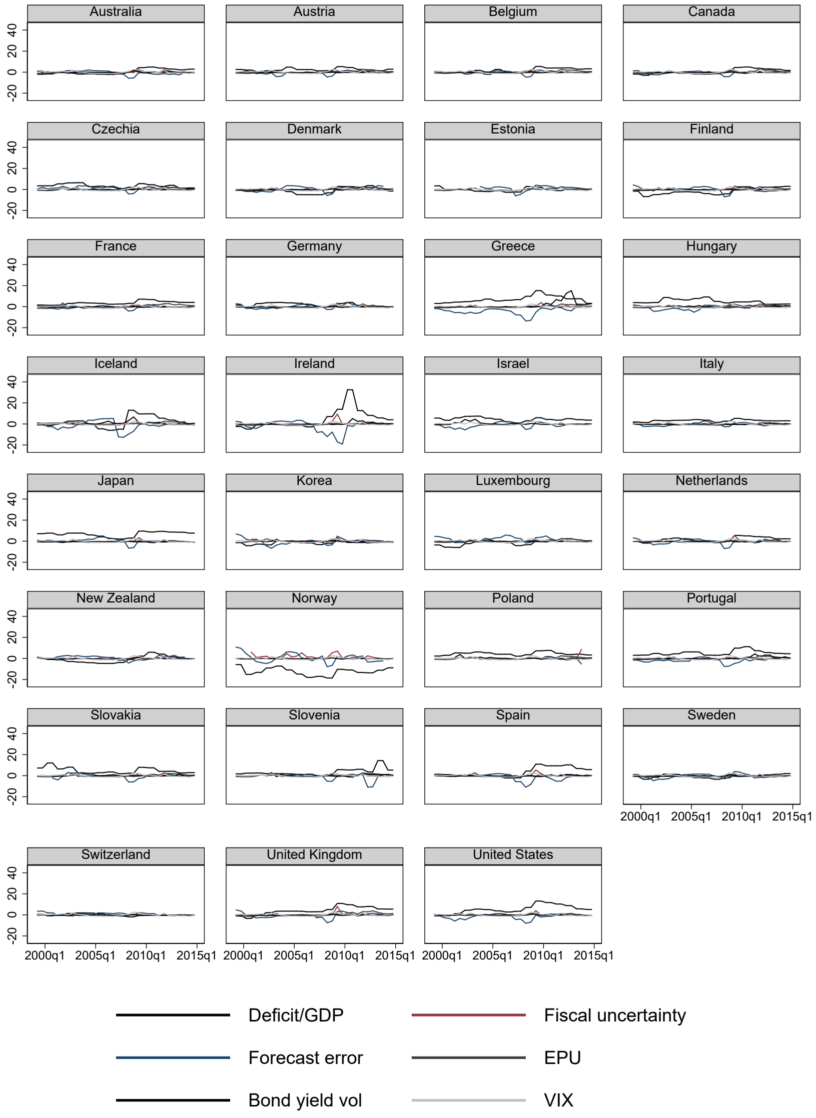

Figure A5: Comparison to other uncertainty measures by country (standard deviations, year-ahead index version)