# Essays on the determinants of sovereign credit ratings and their effect on the corporate sector

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in the

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# DECLARATION

I, Periklis Boumparis, declare that this thesis titled, "Essays on the determinants of sovereign credit ratings and their effect in the corporate sector" and the work presented in it are my own. I confirm that:

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- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged the main sources of help.
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<u>Refereed Publications:</u>

An earlier version of chapter 2 has been published in *Journal of International Money and Finance,* 2017, 79, 39-71 (joint with Prof Costas Milas and Dr. Theodore Panagiotidis)

An earlier version of chapter 3 has been published in *International Review of Financial Analysis,* 2019 (joint with Prof Costas Milas and Dr. Theodore Panagiotidis)

<u>Conference Presentations:</u>

An earlier version of chapter 2 has been presented in the 3rd International Conference in Applied Theory, Macro and Empirical Finance in Thessaloniki, Greece and the 49th Money, Macro and Finance Research Group Annual Conference in King's College, London

An earlier version of chapter 3 has been presented in the 4th International Conference in Applied Theory, Macro and Empirical Finance in Thessaloniki, Greece, in the 50th Money, Macro and Finance Research Group Annual Conference in Edinburgh, in the NWSSDTP Ph.D. Conference in Economics in Liverpool and in the NWSSDTP Ph.D. Conference in Accounting and Finance in Manchester where it won the best paper award.

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| Periklis Boumparis | Main idea, Literature review, collection of data, empirical estimation, interpretation of results and writing up |
| Prof Costas Milas | Intellectual guidance and suggestions with reference to the writing up and interpretation of results |
| Dr Theodore Panagiotidis | Intellectual guidance on methodological issues and interpretation of results |
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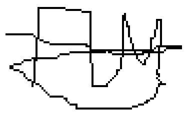
| Periklis Boumparis |  | 07/03/2020 |
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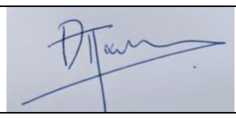
| Dr Theodore Panagiotidis |  | 07/03/2020 |
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| Prof Costas Milas | Intellectual guidance and suggestions with reference to the writing up and interpretation of results |
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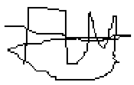
| Periklis Boumparis |  | 07/03/2020 |
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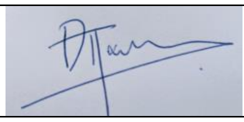
| Dr Theodore Panagiotidis |  | 07/03/2020 |
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## ABSTRACT

The following thesis investigates the determinants of sovereign credit ratings and their effect on the corporate sector.

Chapter 2 examines the effect of economic policy uncertainty on sovereign credit rating decisions made by the three leading rating agencies, namely Moody's, S&P's and Fitch by implementing a panel quantile regression. We find that regulatory quality and competitiveness have a more substantial impact on low rated countries whereas GDP per capita is a major driver of high rated countries. A reduction in the current account deficit leads to a rating or outlook upgrade for low rated countries. Economic policy uncertainty impacts negatively on credit ratings across the conditional distribution; however, the impact is stronger for the lower rated countries. In other words, the creditworthiness of low rated countries takes a much bigger 'hit' than that of high rated countries when European policy uncertainty is on the rise.

Chapter 3 examines the joint behaviour of sovereign ratings and their macroeconomic/financial determinants (namely economic policy uncertainty, GDP growth, government debt-to-GDP ratio, investment-to-GDP ratio and the fiscal balance-to-GDP ratio) in a multivariate Panel Vector Autoregressive (PVAR) framework. We reveal another channel of interconnection between sovereign and banking credit risk by identifying a two-way relationship between non-performing loans (NPLs) and sovereign ratings. Generalized impulse response functions (GIRFs) provide evidence of significant effects from NPLs on sovereign rating decisions over and above the impact of the remaining economic/financial variables. At the same time, sovereign rating decisions impact on NPLs and all other variables.

Chapter 4 works on the adverse consequences of sovereign rating downgrades on firms' operational efficiency. We approach our main question by exploiting exogenous variation in sovereign credit ratings through the so-called sovereign ceiling rule. We then trace our main effect by comparing the differential effect of sovereign rating changes on firms that are limited by the sovereign ceiling (treated firms) and on other firms in the same country that are not limited by the sovereign ceiling (nontreated firms). In particular, we compare firms that have a rating equal to or above the corresponding sovereign (treated firms) with similar firms that have a lower rating than the corresponding sovereign (nontreated firms). We match treated and non treated firms in several categorical and non categorical covariates, namely firm size, investment, Tobin's Q, cash flow, cash, leverage, Country of Domicile and Year. Our difference in difference estimation in the matched sample analysis shows that Sales growth of firms with a rating equal to or above the corresponding sovereign drop by 1.38% more than Sales growth of firms rated below their corresponding sovereign following a sovereign rating downgrade. Finally, chapter 5 concludes this thesis by summarizing the empirical results, pointing out their implications and developing ideas for future research.

# 1. INTRODUCTION

"*You could almost say that we live again in a two-superpower world. There is the U.S. and there is Moody's. The U.S. can destroy a country by leveling it with bombs; Moody's can destroy a country by downgrading its bonds*".

Thomas L. Friedman 22/2/1995 New York Times[1]

The abovementioned phrase is very representative of the power of rating agencies in financial markets. The following thesis is primarily motivated by the role of credit rating agencies during the global financial crisis and the eurozone sovereign debt crisis. It examines their determination and their impact on financial markets, the banking sector and the real economy. It consists of three essay-style chapters covering both sovereign and corporate credit ratings.

There is a very growing empirical literature that has discussed several quantitative and qualitative factors affecting the decisions of CRAs. However, an increasingly large number of decisions appear to remain unexplained. For instance, some of the downgrades of peripheral European debt which took place in 2010 and beyond have been scrutinized by the downgraded peripheral countries and by leading European policymakers. Speaking to the European parliament in May 2010, Jose Manuel Barroso, then the European Union Commission President, criticized the three main CRAs noting that "deficiencies in their working methods has led to ratings being too cyclical, too reliant on the general market mood rather than on fundamentals-regardless of whether market mood is too optimistic or too pessimistic" (Barroso, 2010).

David Beers, Standard & Poor's (at that time) Global head of sovereign ratings, defended the record of the CRAs. In a letter published in March 2011 by *The Economist*, he noted that credit ratings "provide a robust ranking of the risk of sovereign default" and "are independent opinions of creditworthiness based on fundamental analysis and therefore should be expected to change as credit risk evolves over the cycle." Gärtner and Griesbach (2012) argued that "sovereign ratings, their meaning and their underlying procedures are rather opaque." They also went on to argue that "the set of relevant fundamental variables is an open one, and the interpretation of ever evolving political institutions and processes in unprecedented environments are a dime a dozen." Moritz Kraemer, Global Chief Rating Officer of Standard & Poor's, dismissed the arguments of Gärtner and Griesbach (2012) as "simply wrong" and went on to note that S&P's sovereign rating decisions are accompanied by comprehensive published rationales and, often, press releases that explain their reasoning and approach. Kraemer (2012) also pointed out that S&P's explain on their website how they arrive at their ratings and how their ratings perform over time (see www.understandingratings.com) which makes their publications as transparent and complete as possible.

[1] https://www.nytimes.com/1995/02/22/opinion/foreign-affairs-don-t-mess-with-moody-s.html

The growing dissatisfaction across Europe about some of the recent credit rating decisions has given rise to talks amongst Eurozone member states about setting up a European credit rating agency which will increase competition in the rating business. Nevertheless, the European Central Bank (ECB) has been very cautious about how quickly such a project could be deployed. In February 2011, the ECB pointed out that a new credit rating agency will have to rely on extensive data, a number of models, experienced staff and go through building a sound track record for several years before it establishes itself as a credible agency in the rating business (Tait, 2011). In 2016, the European Securities and Markets Authority (ESMA), which is the authority competent for the supervision of CRAs, published a report on sovereign rating processes which noted that because of a "switch to a regulated industry with a focus on the integrity of process…ESMA has driven significant changes in the credit rating process and the methodology…thereby strengthening their integrity, independence, quality, and transparency (ESMA 2016 Report, page 16).

In chapter 2, we examine the effect of economic policy uncertainty on sovereign credit rating decisions made by the three leading rating agencies namely Moody's, Standard and Poors and Fitch for the Eurozone Economies from 2002 to 2015. This chapter is mostly motivated by the unprecedented S&Ps' decision to remove AAA from the US economy for the first time in history in 2011. The biggest rating agency highlights economic policy uncertainty as one of the main drivers of this highly scrutinized decision. The chapter contributes to the growing literature of the determinants of sovereign credit ratings (see Afonso et al., 2011, Reusens and Croux, 2017 among others). We employ a panel quantile framework that allows us to observe the relative importance of quantitative and qualitative factors across the conditional distribution of sovereign credit ratings. We also augment the information set considered in previous studies by examining and identifying the significant impact of competitiveness and the European economic policy uncertainty index on the Eurozone sovereign credit ratings. Our results show that Economic policy uncertainty impacts negatively on credit ratings across the conditional distribution; however, the impact is more substantial on the lower rated countries. In addition, the unemployment rate, regulatory quality, and competitiveness have a stronger impact on low rated countries, whereas GDP per capita is a significant driver of high rated countries. In particular, the impact of an improvement in regulatory quality on credit ratings is almost two times higher for countries rated at A1 and below for Moody's than those rated at Aa3 and almost eight times higher than those rated at Aa1 or Aaa. Additionally, a reduction in the current account deficit or an increase in the current account surplus leads to a rating or outlook upgrade for low rated countries. In our main analysis, we incorporate Baker et al. 2016 economic policy uncertainty index. However, our results are robust to alternative uncertainty indices.

We finally quantify our results the effects of uncertainty on credit ratings by using estimates of our model under uncertainty to infer what credit ratings would have been had uncertainty remained at its 2002-2007 pre-financial and pre-European debt crisis average value. We find that economic policy uncertainty in the Euro area has reduced Greece's credit rating by some three notches at the height of the Eurozone crisis in 2011 and 2012; the impact of uncertainty has been substantial but somewhat less severe for the remaining GIIPS and Cyprus. In other words, our empirical analysis suggests a pivotal role that economic policy uncertainty in the Euro area has played in downgrading the credit profile of Eurozone's periphery.

From a policy point of view and noting the higher relative importance of the competitiveness and regulatory quality indices for Eurozone countries with low credit ratings, our results suggest that structural reforms and improvements in the competitiveness profile of these very countries will improve significantly their low rating profile and therefore reduce their borrowing costs in financial markets. This is in line with policy recommendations recently put forward by the European Commission.

In chapter 3, we reveal another channel of interconnection between sovereign and banking credit risk by identifying a two-way relationship between non-performing loans (NPLs) and sovereign credit ratings. This chapter is primarily motivated by the dramatic increase of non-performing loans in Eurozone periphery economies following the massive sovereign rating downgrades between 2010 and 2015. It contributes to two different strands of the literature. Firstly, it creates a new channel of interconnection between banking and sovereign credit risk (see Acharya et al., 2014, Adelino and Ferreira, 2016, Gennaioli et al., 2014 among others). Secondly, it sheds some new light on what determines sovereign credit ratings (see Afonso et al., 2011, Reusens and Croux, 2017 among others).

In this chapter, we extend the literature by implementing a Panel Vector AutoRegressive (PVAR) model for 72 countries from 1998 to 2016 which allows us to examine the behaviour of sovereign ratings, non-performing loans and a number of macroeconomic/financial variables in a multivariate framework jointly. We find a significant role for NPLs as a measure of banking risk in affecting sovereign credit rating decisions and vice versa. In particular, we rely on Generalized Impulse Response Functions to identify a significant and persistent effect of NPLs on sovereign credit ratings over and above the impact of other drivers, namely economic policy uncertainty, GDP growth, government debt-to-GDP ratio, investment-to-GDP ratio, and the fiscal balance-to-GDP ratio. Second, we find that economic policy uncertainty shocks trigger a negative and persistent effect on sovereign rating decisions, following the financial turmoil and the subsequent Eurozone crisis. Our results are robust to a logistic transformation of sovereign ratings to numbers and alternative measures of uncertainty and banking risk.

This chapter provides additional insight towards understanding how CRAs make sovereign credit rating decisions by flagging the importance of NPLs in driving these decisions. With this in mind, our results should be useful to regulators like the European Securities and Markets Authority (ESMA) who monitor CRAs in order to understand their rating methodology and assess the quality of their ratings.

In chapter 4, we move to the corporate sector by examining the adverse consequences of sovereign rating downgrades on firms' operational efficiency through the so-called sovereign ceiling channel. Sovereign rating downgrades lead to an asymmetric effect on corporate ratings through the sovereign ceiling rule. In that sense, the probability of being downgraded is much higher for firms with a rating equal to or above their sovereign (treated firms) than firms rated below their sovereign (control firms). The chapter adds additional information on the very recent literature of the real effect of rating downgrades on firm outcomes (see Almeida et al., 2017, Wang and Yang, 2019).

From a theoretical point of view, credit rating downgrades might directly affect operational efficiency by changing the profitability of available projects and through changes in capital structure under the agency costs hypothesis (Berger and Di Patti, 2006). They can also affect operational efficiency since the management team learns from credit rating decisions and adjust their strategy following them. We examine the question by incorporating a novel dataset of 482,289 firm-year observations and 49,449 different firms from 81 developed and emerging market countries. We perform difference-in-differences estimations by comparing changes in the outcome variables between firms which have a rating equal to or above the corresponding sovereign (treated firms) and similar firms which have a lower rating than the corresponding sovereign (nontreated firms). Our linear regressions identify an adverse effect from credit rating downgrades on sales growth and Return on Assets, while we do not find any evidence from credit rating downgrades on the ratio of Sales to the Book value of Assets, the ratio of Sales to the book value of assets in place and the ratio of Selling, General and Administrative Costs to Sales. Moreover, our difference in difference estimation in the matched sample analysis shows that Sales growth of firms with a rating equal to or above the corresponding sovereign drop by 1.38% more than Sales growth of firms rated below their corresponding sovereign following a sovereign rating downgrade. However, the rest of the operational efficiency measures are not affected by a sovereign rating downgrade using the matched sample analysis. This chapter might be of interest for corporations since they show whether and how rating downgrades do matter for their efficiency, over and above the effect of macroeconomic fundamentals. It is also of interest for governments that should always consider the negative externalities of their sovereign downgrade in the corporate sector.

The rest of the thesis proceeds as follows. In chapter 2, we examine the effect of economic policy uncertainty on sovereign credit rating decisions in a panel quantile framework, while in chapter 3, we investigate the two-way effect between sovereign credit ratings and non-performing loans in a multivariate framework. In chapter 4, we investigate the effect of sovereign rating downgrades on firm operational efficiency through the sovereign ceiling channel. Finally, chapter 5 offers concluding remarks and directions for further research. Chapters

2, 3 and 4 are self-contained in the sense that we (re)introduce variables, notations, and acronyms in each of them. Where possible, we use the same acronyms across chapters to aid readability. The purpose of this strategy is to enhance readability.

# 2. ECONOMIC POLICY UNCERTAINTY AND SOVEREIGN CREDIT RATING DECISIONS: PANEL QUANTILE EVIDENCE FOR THE EUROZONE

## 2.1 Introduction

During the global financial crisis of 2007-2009 and the subsequent recession, Central Banks and governments responded by injecting additional liquidity into the system and pursuing expansionary fiscal policies, respectively. With the world economy in (the process of returning to) normality, fiscal positions are also being tightened up. Nevertheless, the significant deterioration of public finances post-2007[2] has put on alert Credit Rating Agencies (hereafter CRAs). For instance, Moody's Investor Services, a major credit rating agency, has downgraded over the 2008-2013 period the debt rating of a number of peripheral European countries, namely Greece, Ireland, Italy, Portugal, and Spain (hereafter the GIIPS) and Cyprus by 63 notches in total.[3] Similar decisions have been implemented by the other two main CRAs, namely Standard & Poor's (S&P's) and Fitch Ratings, respectively.[4]

Sovereign credit ratings provide a measure of the probability that a country will default on its debt obligations. In that sense, they set the tone for borrowing costs in international markets both for a sovereign state and the financial institutions operating in that sovereign state (for recent evidence, see Drago and Gallo, 2017a). This is vital for stimulating investments and supporting economic growth. Chen et al. 2013, show that a one-notch upgrade (downgrade) causes an increase (decline) of about 0.6% (0.3%) in re-rated countries' five-year average annual growth rates after accounting for other determinants of economic growth. Changes in country rating affect economic growth via the interest-rate and capital-flow channels: narrower sovereign bond yield spreads and increased capital inflows are associated with upgrades, which stimulate re-rated countries' economic performance, and the converse holds for downgrades.

Reputational concerns do discipline the decisions made by CRAs (see e.g. Bar-Isaac and Shapiro, 2013 and Mariano, 2012). However, the value of reputation depends on economic fundamentals that vary over the business cycle. Using a theoretical model of credit ratings with endogenous reputation, Bar-Isaac and Shapiro (2013) relate credit rating decisions to the economic cycle. They find that CRAs are more likely to issue less accurate ratings when fee-income is high, the economy is booming and securities' default probabilities are low. Indeed, during booms, hiring skilled analysts becomes more expensive for CRAs. At the same

[2] For instance, the International Monetary Fund estimates that gross debt in thirty-nine advanced economies deteriorated from 71.2% of GDP in 2007 to 107.5% in 2016 whereas gross debt in the Euro area deteriorated from 64.9% of GDP in 2007 to 91.7% of GDP in 2016. Data available from: https://www.imf.org/external/pubs/ft/weo/2016/02/weodata/weoselagr.aspx.

[3] In particular, Greece, Ireland, Italy, Portugal, Spain and Cyprus have been downgraded by 14, 10, 6, 10, 9 and 14 notches, respectively by Moody's.

[4] The three main CRAs have a total EU market share of 92.85% (see https://www.esma.europa.eu/sites/default/files/library/20161662_cra_market_share_calculation.pdf).

time, CRAs can potentially charge higher fees and since bond issues are less likely to default, monitoring a CRA activity becomes less effective.

This chapter attempts a comprehensive assessment of credit rating decisions made by the three main CRAs for the Eurozone economies in light of the ongoing criticism discussed above. The existing literature on the determinants of sovereign credit ratings has focused on several macroeconomic, qualitative and risk factors. Recent studies focus on time-varying models of credit ratings (Reusens and Croux, 2017) and models with debt levels conditional on debt being above or below endogenously determined debt threshold levels (Hmiden et al., 2016). Prior to this, Afonso et al. (2011) examine differentiations across rating levels by splitting their dataset into two groups according to the ratings level, namely high-rated countries with credit grades BBB+ and above and low rated countries with credit grades BBB and below.

Arguably, however, the actual degree of importance of the different explanatory variables across the conditional distribution of sovereign credit rating has not been explored in detail as most of the studies focus on the average responses.

We fill the gap in the literature by implementing panel quantile estimation with nonadditive fixed effects as proposed by Powell (2016). The main advantage of Powell's (2016) method relative to other quantile methods is that it provides point estimates which can be interpreted in the same way as the ones coming from cross-sectional regression. Our contribution to the existing literature is summarised as follows: First, we employ a panel quantile framework that allows us to observe the relative importance of quantitative and qualitative factors across the conditional distribution of sovereign credit ratings. Second, we augment the information set considered in previous studies by examining and identifying the significant impact of competitiveness and the European economic policy uncertainty index on the Eurozone sovereign credit ratings.

The implementation of Economic policy uncertainty is mostly motivated by the unprecedented S&Ps' decision to remove AAA from the US economy for the first time in history in 2011. Characteristically, S&P's (2011) states "*More broadly, the downgrade reflects our view that the effectiveness, stability, and predictability of American policymaking and political institutions have weakened at a time of ongoing fiscal and economic challenges to a degree more than we envisioned when we assigned a negative outlook to the rating on April 18, 2011*". Consequently, economic policy uncertainty captures the ability of policymakers to act quickly and decisively to face new economic and political challenges.

The motivation for using competitiveness indicator arises from policymakers that have highlighted competitiveness as one of the main weaknesses of Eurozone periphery countries and from past studies that have connected weak competitiveness to high sovereign spreads. De Santis (2014) show that sovereign spreads of Eurozone countries with weaker fiscal fundamentals, a lower degree of competitiveness and a higher need of foreign financing were more exposed to spillover effects from Greece. Moreover, Maltritz (2012) finds that the most likely country specific drivers of yield spreads are fiscal variables such as budget balance and government debt, as well as external sector variables, such as terms of trade, trade balance and openness. All things considered, it is possible that competitiveness affect directly sovereign credit ratings.

Among our findings, the unemployment rate, regulatory quality, and competitiveness have a stronger impact on low rated countries whereas GDP per capita is a major driver of high rated countries. A reduction in the current account deficit or an increase in the current account surplus leads to a rating or outlook upgrade for low rated countries. Economic policy uncertainty impacts negatively on credit ratings across the conditional distribution; however, the impact is stronger on the lower rated countries. We quantify the effects of uncertainty on credit ratings by using estimates of our model under uncertainty to infer what credit ratings would have been had uncertainty remained at its 2002-2007 pre-financial and pre-European debt crisis average value. We find that economic policy uncertainty in the Euro area has reduced Greece's credit rating by some 3 notches at the height of the Eurozone crisis in 2011 and 2012; the impact of uncertainty has been substantial but somewhat less severe for the remaining GIIPS and Cyprus. In other words, our empirical analysis suggests a pivotal role that economic policy uncertainty in the Euro area has played in downgrading the credit profile of Eurozone's periphery.

The structure of the chapter is as follows. Section 2.2 provides a review of the literature. Section 2.3 discusses the data. Section 2.4 introduces the model and Section 2.5 presents the empirical estimates. Section 2.6 provides a discussion of our findings and offers some policy implications. Finally, Section 2.7 offers some concluding remarks.

## 2.2 Literature Review

The determinants of sovereign credit ratings were firstly monitored in the literature by Cantor and Packer (1996). A set of macroeconomic variables such as GDP per capita, GDP growth, inflation, fiscal balance, external balance, external debt, economic development and default history used to explain the variation in sovereign credit ratings implementing Ordinary Least Squares for a set industrial and emerging countries. That set of variables managed to explain 92% of the variation of sovereign credit ratings. Eliasson (2002), using the same set of explanatory variables, implements both a static and a dynamic panel model to explain sovereign ratings and concludes that the dynamic model had greater explanatory power than the static one. Attention has also been given to the fit of alternative econometric models. Afonso et. al. (2009) compare ordered response models and conclude that the random effects ordered probit model is more preferable than the ordered probit and ordered logit models as it takes into account the additional cross-section error.

Recent studies also shed some light on the behaviour of CRAs across rating levels and over time. Afonso et al. (2011) include time year averages to differentiate between short and long run effects. Moreover, they examine differentiations across rating levels by splitting their dataset into two groups according to the ratings level, namely high-rated countries with credit grades BBB+ and above and low rated countries with credit grades BBB and below. They also check differentiations through time by cutting their sample into two dub periods, before and after the East Asian crisis. Regarding their findings, per capita GDP, real GDP growth, government debt, and government deficit had a short-run impact on a country's credit rating. On the other hand, government effectiveness, external debt, foreign reserves, and sovereign default dummies had only a long-run impact. Besides, the East Asian crisis had no fundamental change in the CRAs assessment method. Reusens and Croux (2017) estimate a multi-year ordered probit model by applying the composite marginal likelihood approach in order to examine the relative importance of explanatory variables over time. They find, among others, that financial balance, economic development, and external debt gain greater significance after 2009. The impact of Eurozone membership turned out from positive to negative and the GDP growth rate became more crucial from highly indebted countries after 2009.

Dimitrakopoulos and Kolossiatis (2016) examine the presence of persistence on sovereign credit ratings. They also check if sovereign credit ratings were sticky or procyclical for the Eurozone Debt Crisis and the East Asian Crisis. They find statistical evidence of stickiness and rating persistence by estimating a dynamic panel ordered probit model with autocorrelated disturbances and nonparametrically distributed random effects. Finally, Hmiden and Cheick (2016) test the existence of a debt threshold level on sovereign credit ratings. The appropriate level is estimated endogenously by implementing a nonlinear panel smooth transition model. They conclude that sovereign credit rating determinants vary across different debt levels. In that sense, GDP per capita, Inflation rate, and External Debt have a stronger impact on highly indebted countries.

Sovereign credit ratings are one of the most crucial drivers of sovereign spreads. Thus, we should also be aware of what drives sovereign spreads for Eurozone countries. That kind of dependence analysed above exists not only on macroeconomic variables but also on sovereign spreads. De Santis (2014) finds a spillover effect on sovereign spreads from Greece to countries with higher fiscal deficits, a lower degree of competitiveness and a greater need for financing from abroad. He also concludes that the risk of sovereign spreads in the Euro area is differentiated on aggregate, country-specific, liquidity and contagion risk. De Grauwe and Ji (2014) study and compare the determinants of sovereign spreads between the Eurozone and the European Monetary System, that existed between 1979 and 1999.

On the one hand, government debt, current account balance and changes in the exchange rate affect sovereign spreads for the EMS from 1987 to 1999. On the other hand, for the case of the Eurozone, government debt has a nonlinear effect on sovereign spreads, GDP growth a linear one, while the accumulated current account balance has an impact only after 2008. Maltritz (2012), by estimating a Bayesian Model Averaging (BMA) for 10 EMU member countries with annual data from 1999 to 2009, concludes that fiscal balance terms of trade, trade balance, and countries' openness are the most significant country-specific drivers of sovereign yield spreads. Attinasi et al., (2009) emphasize the role of fiscal fundamentals and government announcements of substantial bank rescue packages. They use a dynamic panel approach in selected euro area countries during the period between July 2007 and March 2009. They find, among others that the announcement of bank bailout programs has led investors to a reconsider of the sovereign credit risk. In that sense, a part of the risk is transferred from the private financial sector to the public sector. They also support that higher expected fiscal deficit and higher expected government debt have led to higher sovereign bond spreads, with the impact of the former being more robust.

## 2.3 Data

We use annual data from 2002 to 2015 for nineteen Eurozone countries (266 observations in total). Our dependent variable is the sovereign credit rating published by the three main international rating agencies, Moody's, Standard & Poor's (S&P's) and Fitch Ratings (attributed at the end of each calendar year). A linear transformation of credit ratings to numerical scale is implemented starting from 21 for the highest quality with a stable outlook (AAA for Fitch and S&P's and Aaa for Moody's) and ending to 1 for Default (D for Fitch and S&P's and C for Moody's). The difference between two continuous ratings with the same outlook is always equal to 1. Not only we account for changes in credit ratings, but we also consider changes in credit outlooks.[5] The difference between two continuous outlooks is always equal to 1/3, so the difference between two continuous ratings with the same outlook is still equal to one. Table 2.1 reports the linear transformation of credit ratings.

We adopt a set of explanatory variables previously used in the literature (see Reusens and Croux, 2017; Dimitrakopoulos and Kolossiatis, 2016, Aizenman et al., 2013 and Afonso et al., 2011), namely GDP per capita, Government Debt, Current Account Balance, Inflation Rate, Unemployment Rate, and Regulatory Quality Index. Further, we consider two new explanatory variables. The first one is the Competitiveness Indicator; an increase in the index implies lower

[5] We do not account for watch positive and watch negative outlooks for two reasons. First, we assume that the positive (negative) outlook is conceptually very close to watch positive (watch negative) outlook and, second, the number of watch positive and watch negative observations in our dataset is very small.

competitiveness, which impacts negatively on credit rating decisions.[6] Weak competitiveness is often highlighted by government authorities and international organizations such as the International Monetary Fund (IMF), the European Commission (EC) and the European Central Bank (ECB) as one of the main drawbacks of the Eurozone's periphery relative to Eurozone's core. The second explanatory variable is the European Policy Uncertainty Index. It captures the impact of uncertainty, generally on the behaviour of rating agencies over time and more specifically, on the cumulative downgrades of periphery's bonds during the recent Eurozone sovereign debt crisis. The index is constructed based on newspaper articles regarding policy uncertainty from 10 leading European newspapers. It counts the number of newspaper articles containing the terms uncertain or uncertainty, economic or economy, and one or more policy-relevant terms; for more information see Baker et al. (2016) and http://www.policyuncertainty.com/index.html. Table 2.2 provides details on our data definitions and sources.

Next, we discuss the expected impact of each explanatory variable on credit ratings:

GDP per capita – positive response: Higher GDP per capita coincides with a larger tax base and, therefore, an increased ability of the government to repay its obligations. This variable can also reflect economic development. The positive response has also been found in the literature (see Cantor and Packer, 1996, Afonso et al., 2011, Reusens and Croux, 2017, among others)

Government debt – negative response: A high stock of government debt implies higher interest rates to accommodate it. Therefore, additional financial resources are needed to repay debt obligations. Higher government debt can increase the risk of default. The negative effect is also justified from past studies (see Cantor and Packer, 1996, Afonso et al., 2011, Reusens and Croux, 2017, among others)

Current account balance – uncertain response: On the one hand, a higher current account deficit can signal overconsumption, undermining prosperity in the long run. On the other hand, it might have a positive effect, taking into account the productivity of the additional investments and their potentially positive economic impact in the short run. The theoretically uncertain response of credit ratings on current account balance changes is also justified from the existing literature. Cantor and Packer (1996) find a positive effect, while Afonso et al. (2011) and Reusens and Croux (2017) find a negative and an insignificant effect respectively.

Inflation rate – uncertain response: Higher inflation rates are a sign of structural and macroeconomic imbalances in the government's finances. On the other hand, meager inflation might lead to a deflationary spiral (Reusens and Croux, 2017). If

[6] This is the harmonised competitiveness indicator based on unit labour costs indices for the total economy; available from:

https://www.ecb.europa.eu/stats/ecb_statistics/escb/html/table.en.html?id=JDF_EXR_HCI_ULCT&period=index.

we were dealing with debt in domestic currency, high inflation reduces the real stock of government debt in domestic currency and partially offsets the negative impact of high inflation. However, previous studies (Cantor and Packer 1996, Afonso et al. 2011, Reusens and Croux 2017) find a predominantly negative impact of Inflation Rate on sovereign credit ratings

Unemployment rate – negative response: A country with lower unemployment has an efficient labour market. The lower is the unemployment, the greater is overall taxable income and the lower the fiscal burden for unemployment subsidies. Past studies (Cantor and Packer, 1996, Afonso et al., 2011, Reusens and Croux 2017, among others) also find a negative impact

Regulatory quality[7] – positive response: A high value of regulatory quality index reflects the ability of the government to implement necessary regulations that can boost private sector development and increase investment and GDP. Moreover, it can be a qualitative quantification of the government's willingness to repay its obligations. Afonso et al. (2011) find a positive impact, in line with the theoretical argument.

Competitiveness indicator – negative response: Competitiveness reflects a country's ability to attract private investments in an international environment.

European policy uncertainty – negative response: Higher uncertainty worsens the economic environment, makes consumers and investors more cautious and reduces future consumption and investment. In addition, economic policy uncertainty captures the ability of policymakers to act quickly and decisively against new economic challenges.

## 2.4 Methodology

Quantile regression is appropriate when the variables of interest potentially have varying effects at different points of the conditional distribution of the outcome variable. In recent years, there has been a growing literature that combines quantile estimation with panel data. In mean regression, panel data allow for the inclusion of fixed effects to capture within-group variation. Many quantile panel data estimators use an analogous method and include additive fixed effects. However, the additive fixed effects change the underlying model. We implement the quantile regression estimator for panel data (QRPD) with nonadditive fixed effects introduced by Powell (2016). The main advantage of this method relative

[7] Regulatory quality index is a combination of several individual variables such as investment and financial freedom, business regulatory environment, competition policy, tax inconsistency, financial institution's transparency, public sector openness to foreign bidders and easiness to start new business. See: http://info.worldbank.org/governance/wgi/pdf/rq.pdf.

to the existing quantile estimators with additive fixed effects ($\alpha_i$) is that it provides estimates of the distribution of $Y_{it}$ given $D_{it}$ instead of $Y_{it} - \alpha_i$ given $D_{it}$.[8]

Powell (2016) notes that in many empirical applications the latter is undesirable. This is because observations at the top of the ($Y_{it} - \alpha_i$) distribution may be at the bottom of the $Y_{it}$ distribution and therefore additive fixed effect models cannot provide information about the effects of the policy variables on the outcome distribution. Thus, Powell's (2016) method provides point estimates which can be interpreted in the same way as the ones coming from cross-sectional regression. It is also consistent for small $T$. The underlying model is:

$$Y_{it} = \sum_{j=1}^{8} D_{it}^{'}\beta_j(U^{*}_{it}), \tag{2.1}$$

where $Y_{it}$ is the sovereign credit rating for each CRA, $\beta_j$ is the parameter of interest, $D_{it}$ is the set of explanatory variables and $U^{*}_{it}$ is the error term that may be a function of several disturbance terms, some fixed and some time-varying. The model is linear in parameters and $D_{it}^{'}\beta(\tau)$ is strictly increasing in $\tau$. In general, for the $\tau^{th}$ quantile of $Y_{it}$, quantile regression relies on the conditional restriction:

$$P(Y_{it} \le D_{it}^{'}\beta(\tau) \mid D_{it}) = \tau \tag{2.2}$$

Equation (2.2) states that the probability the outcome variable is smaller than the quantile function is the same for all $D_{it}$ and equal to $\tau$. Powell's (2016) QRPD estimator allows this probability to vary by individual and even within-individual as long as such variation is orthogonal to the instruments. Thus, QRPD relies on a conditional restriction and an unconditional restriction, letting $D_i = (D_{i1}, \ldots, D_{iT})$:

$$\begin{aligned} &P(Y_{it} \le D_{it}^{'}\beta(\tau) \mid D_i) = P(Y_{is} \le D_{is}^{'}\beta(\tau) \mid D_i), \\ &P(Y_{it} \le D_{it}^{'}\beta(\tau)) = \tau \end{aligned} \tag{2.3}$$

Powell (2016) develops the estimator in an instrumental variables context given instruments $Z_i = (Z_{i1}, \ldots, Z_{iT})$ but notes that if the explanatory variables are exogenous (in which case $D_i = Z_i$) many of the identification conditions are met

[8] That is due to the different structural quantile functions (SQF). The SQF of QRPD is $d^{'}\beta(\tau)$. In contrast, the SQF of models using additive fixed effects is $\alpha_i + d^{'}\bar{\beta}(\bar{\tau})$ where $d$ denotes potential values of $D_{it}$ and $\tau$ is the relevant quantile of $Y_{it}$. The notation $\bar{\beta}(\bar{\tau})$ for the additive fixed effect model is used to highlight that these parameters are different than those used in the nonadditive fixed effects model.

trivially. The estimation uses the Generalized Method of Moments. Sample moments are defined as:

$$\hat{g}(b) = \frac{1}{N}\sum_{i=1}^{N} g_i(b) \text{ with } g_i(b) = \frac{1}{T}\{\sum_{i=1}^{T}(Z_{it} - \bar{Z}_i)[1(Y_{it} \leq D_{it}^{'}b)]\}, \tag{2.4}$$

where $\bar{Z}_i = \frac{1}{T}\sum_{i=1}^{T} Z_{it}$ .

Using (2.3), the parameter set is defined as:

$$\mathrm{B} \equiv \{b \left| \tau - \frac{1}{N} \leq \frac{1}{N}\sum_{\iota=1}^{N} 1(Y_{it} \leq D_{it}^{'}b) \leq \tau\} \right. \text{ for all } t. \tag{2.5}$$

Then, the parameter of interest is estimated as

$$\hat{\beta}(\tau) = \arg\min_{b \in \beta} \hat{g}^{'}(b)\hat{\mathrm{A}}\hat{g}(b) \tag{2.6}$$

for some weighting matrix $\hat{\mathrm{A}}$ . The model is estimated using the Markov Chain Monte Carlo (MCMC) optimization method.[9]

## 2.5 Empirical results

### 2.5.1 Main estimates

We capture the varying effects on credit ratings by estimating the model for the 0.05, 0.10, 0.15,..., 0.75 quantiles for each of the three CRAs (the model also estimates time fixed effects).[10] In order to control for potential endogeneity, we re-run the same model treating all explanatory variables as endogenous and using first-order lags as instruments. Estimated results (reported in Tables 2.9-2.11) are very similar to those reported below. Mean regressions are also reported in the (Table 2.18)

Tables 2.3-2.5 report estimated coefficients, associated *p*-values, the pseudo-$R^2$ and the Akaike Information Criterion (AIC) for each quantile and each CRA. All explanatory variables have the expected signs and are statistically significant at almost all quantiles. The impact of the unemployment rate, regulatory quality and competitiveness is stronger at low ratings. For instance, the coefficient of the unemployment rate reduces from -0.4446 at the 0.05 quantile to -0.2201 at the 0.35 quantile and then to -0.0069 at the 0.75 quantile for Fitch. The estimates for

[9] All estimations are done in STATA using David Powell's quantile estimator with nonadditive fixed effects available at:

https://sites.google.com/site/davidmatthewpowell/quantile-regression-with-nonadditive-fixed-effects.

[10] Almost 25% of the observations are in the highest quality AAA. That is the reason why 0.75 is the highest quantile we employ in this chapter.

Moody's and S&P's follow a similar pattern. Based on the quantile distribution, the impact of an improvement in regulatory quality on credit ratings is almost two times higher for countries rated at A1 and below for Moody's than those rated at Aa3 and almost 8 times higher than those rated at Aa1 or Aaa (Appendix Figures 2.4-2.6 map the sovereign credit ratings to the quantile distribution for the three CRAs; these should be read together with Table 2.1). Additionally, *ceteris paribus*, an annual decrease in the cost competitiveness index by seven points of the index (such a move is not unusual in our dataset) brings about one half ($\approx 7*0.0687$) of a notch upgrade at the 0.05 quantile for S&P's, one quarter ($\approx 7*0.0324$) of a notch upgrade at the 0.35 and only 0.05 ($\approx 7*0.0061$) of a notch upgrade at the 0.75 quantile. The impact of government debt on credit ratings is almost equally important for countries rated at adequate payment capacity and below and for those rated at high and highest quality, but impressively enough, is less strong for countries rated at strong payment capacity (that is, A1, A2, and A3 ratings for Moody's, and A+, A, and A- ratings for S&P's and Fitch) for all three CRAs. For example, the coefficient of Government Debt for S&P's is -0.0398 at the 0.15 quantile, -0.0370 at the 0.70 quantile but only -0.0209 and -0.0069 at the 0.45 and 0.50 quantiles, respectively.

CRAs attribute a higher weight on GDP per capita[11] for high rated countries; the impact of GDP per capita on sovereign credit rating is almost five times higher for the 0.65 quantile relative to the 0.15 one and almost two times higher relative to the 0.30 and 0.35 quantiles for Fitch. Therefore, the high level of GDP per capita provides a 'safety net' safeguarding (to some extent) against downgrades in the case of high rated countries.

The significance of the inflation rate varies across the rating distribution but without any specific trend pattern. Economic policy uncertainty impacts negatively on credit ratings across the quantile distribution and the impact is stronger on the lower rated countries; in other words, when European uncertainty kicks in, low rated countries take a much bigger 'hit' than high rated countries. Further, the uncertainty effect is stronger for Moody's and weaker for Fitch at all quantiles.

The impact of the current account balance is positive at the 0.05, 0.10 and 0.15 quantiles for all agencies and remains positive at the 0.20, 0.25, and 0.30 quantiles for S&P's and at the 0.20 and 0.30 quantiles for Fitch. The impact of the current account turns negative at all other quantiles for all CRAs. Hence, we find an asymmetric impact of the current account over the quantile distribution of sovereign ratings. Noting that the impact of the current account balance on sovereign credit ratings is theoretically uncertain, our analysis shows that a

[11] Moody's GDP per capita coefficients at the 0.05 and 0.10 part of the distribution are counter-intuitive as is the S&P's GDP per capita coefficient at the 0.05 one. This, however, does not apply to Fitch. One possibility for this result is that countries at this very low part of the distribution, mainly Greece after 2010 and Cyprus after 2012, have witnessed persistent recession in the second half of the sample.

reduction in the current account deficit or an increase in the current account surplus leads to a rating or outlook upgrade for low rated countries which have historically recorded high current account deficits.[12] The effect is entirely different for countries with strong payment capacity, high and highest quality. In this case, a higher current account deficit or a lower current account surplus is associated with either higher creditworthiness or positive economic prospects of the economy and consequently a higher sovereign rating (Afonso et al., 2011). But why low rated countries (namely the GIIPS and Cyprus) are downgraded when they record higher current account deficits? Recalling that current account deficits reflect net borrowing from abroad, one might argue that there is nothing intrinsically wrong with current account imbalances if countries borrow from abroad to invest in capacity which consequently allows them to satisfy their debt obligations. Rather than doing this, Eurozone's periphery funds from abroad largely ended up in non-traded sectors (like government consumption and housing); see, for instance, the discussion in Baldwin and Giavazzi (2015).

### 2.5.2 Robustness checks

As alternatives to the European policy uncertainty index, we use (a) the US policy uncertainty index of Baker et al. (2016) and (b) the Euro area uncertainty proxy of Girardi and Reuter (2017). Like the European policy uncertainty index, the US one captures the policy-related economic uncertainty by counting the number of newspaper articles containing the terms uncertain or uncertainty, economic or economy, and one or more policy-relevant terms of ten leading newspapers (including *The Washington Post*, *The New York Times* and *The Wall Street Journal*) and can be thought of as capturing spillover US economic policy effects to the Eurozone area. On the other hand, the Girardi and Reuter (2017) uncertainty measure pools information from 22 forward-looking business and consumer survey questions contained in the EU Business and Consumer Surveys program (see Girardi and Reuter, 2017).

The correlation between the European and US policy indices is equal to 0.80 whereas the correlation between the European policy index and the survey-based uncertainty measure of Girardi and Reuter (2017) is much weaker and equal to 0.20. Figure 2.1 plots together with the three uncertainty measures. Notice that European policy uncertainty is much more volatile than the remaining uncertainty measures; it also shows a marked increase following from the 2008-2009 financial crisis and the most recent Eurozone debt crisis in 2011-2012. It drops after ECB

[12] Over 2002-2015, Greece recorded an average current account deficit of 7.61% as a share of its GDP. The corresponding deficit figures for Ireland, Italy, Portugal, Spain and Cyprus were 0.85%, 0.87%, 6.63%, 4.02% and 6.45%. By contrast, the Euro area recorded an average current account surplus of 0.71% as a share of its GDP.

President Mario Draghi pledged in 2012 that the ECB was 'ready to do whatever it takes' to protect the Eurozone from collapse.[13]

Tables 2.12-2.14 report the empirical estimates using the US economic policy uncertainty index. As can be seen from Tables 2.12-2.14, there is a spillover negative impact of US uncertainty on Eurozone's credit ratings but the impact is smaller compared to the European uncertainty impact reported in Tables 2.3-2.5. There is mixed evidence in terms of whether the model using the European policy uncertainty index dominates the model using the US one. In the case of Moody's, the model using the European uncertainty index delivers a lower Akaike Information Criterion (AIC) than the model using the US index in 7 out of the 15 quantiles of the rating distribution. In the case of S&P's, the model using the European uncertainty index delivers a lower AIC than the model using the US index in 6 out of the 15 quantiles of the rating distribution. In the case of Fitch, however, the dominance of the European index is much stronger; indeed, the model using the European uncertainty index delivers a lower AIC than the model using the US index in 11 out of the 15 quantiles of the rating distribution. To save space, we do not report our estimates using the uncertainty survey-based measure of Girardi and Reuter (2017); these estimates are available on request. We note, however, that the statistical evidence in favour of a negative impact of the uncertainty survey-based measure is much weaker (for Moody's, this happens in 6 out of the 15 quantiles of the rating distribution; the corresponding figures for S&P's and Fitch are 7 and 8, respectively).

Compared to the alternative uncertainty measures, the stronger impact of the European policy uncertainty index should not necessarily come as a surprise. Policymakers have arguably been rather slow in putting together a workable plan dealing with the Eurozone crisis as planning requires in general parliamentary approval from all member states. In addition, the major institutions (nick-named as the 'Troika' of the International Monetary Fund, the European Commission and the European Central Bank) have not always agreed on how to deal with issues of the crisis, therefore, fuelling policy uncertainty in the Euro area.[14] Indeed, Eurozone's institutional infrastructure was not prepared to deal with the crisis. Baldwin and Giavazzi (2015, page 21) noted critically that "judging from market reactions, each policy intervention made things worse" and that it was only in the summer of 2012 with the 'whatever it takes' assertion by ECB President Mario Draghi that the corner was turned.

Moreover, Girardi and Reuter (2017) Index captures uncertainty from the perception of businesses, which is different from the uncertainty arising from policymakers' decisions. Furthermore, that Index is much less volatile than the European and the American Economic Policy Uncertainty Index. All the above

[13] See e.g. http://www.telegraph.co.uk/finance/financialcrisis/9428894/Debt-crisis-Mario-Draghi-pledges-to-do-whatever-it-takes-to-save-euro.html.

[14] See e.g. http://www.bbc.co.uk/news/business-33531845.

things considered might explain the less pronounced effect of Girardi and Reuter (2017) uncertainty Index. As a direction of further research, it would be interesting to study the effect of economic uncertainty on sovereign rating decisions by using more refined and superior measures of uncertainty such as that of Jurado et al. (2015). The use of more accurate measures of uncertainty could potentially contribute to improve the accuracy of sovereign rating models.

In the preliminary analysis, we added the growth rate of GDP as an extra explanatory variable but found very weak evidence of a positive and statistically significant impact on credit ratings; this might have to do with the persistently weak GDP growth rates observed in the Euro area over the recent years. Arguably, however, the impact of GDP growth on credit ratings is indirectly captured by the impact of the unemployment rate through an Okun's-law type of approximation (in which case there is an inverse relationship between unemployment and GDP growth).

Fiscal discipline has been on the agenda of policymakers in the Euro area after 2009. Fiscal balance to-GDP-ratio was not a major concern for CRAs in making credit rating decisions for developed countries until the recent Eurozone debt crisis; Reusens and Croux (2017) identify a significant positive effect from the fiscal balance-to-GDP ratio on credit ratings only after 2009. In our case, we could only find some statistical evidence using the lagged fiscal balance-to-GDP ratio as an explanatory variable. Arguably, such a finding has to do with continuous revisions in the fiscal balance variable as well as the disagreement between authorities not only on the predicted fiscal balance but also on the actual outcome[15] [16]; to this end, we mention the study of De Castro et al. (2013) who find that most preliminary European Union government balance data releases "are biased and non efficient predictors of subsequent releases, with later vintages of data tending to show lower budget balances than indicated by earlier data releases on average" (De Castro et al., 2013, page 1207). In light of this, CRAs might have been reluctant to monitor current fiscal balance for credit rating decisions which, in turn, might explain why lagged fiscal balance might play more of a role. Tables 2.15-2.17 suggest that there is a positive effect of the lagged fiscal balance throughout the distribution for Moody's, whereas, for S&P's and Fitch, we find a negative effect at the 0.10 and 0.15 quantiles of distribution (estimates on the remaining variables are qualitatively similar to what we report in Tables 2.3-2.5).

Our quantile panel model offers valuable and additional information compared to a standard panel model with fixed individual and time effects; detailed estimates of the latter model for all three CRAs are given in table 2.18. We illustrate some differences between the two models by focusing on the impact of regulatory quality in Figure 2.2 and on the impact of competitiveness in Figure 2.3. Figure 2.2 plots the estimated impact of regulatory quality for Moody's across the conditional distribution of credit ratings (based on the quantile panel model reported in Table

[15] See, for instance: http://www.reuters.com/article/us-eu-deficits-idUSTRE63L1G420100422.
[16] See: http://ec.europa.eu/info/files/winter-2017-economic-forecast-greece_en.

2.3) together with the estimated impact of regulatory quality for a standard panel model with fixed individual and time effects (based on the fixed effect model presented on table 2.18); the latter focuses on the conditional mean response of credit ratings. Figure 2.3 plots the estimated impact of competitiveness for Fitch across the conditional distribution of credit ratings (based on the quantile panel model reported in Table 2.5) together with the estimated impact of competitiveness for the standard panel model with fixed individual and time effects (based on the fixed effect model presented on table 2.18). As can be seen from Figures 2.2 and 2.3, relying on the impact of the model with fixed effects misses valuable information across the quantile distribution that can only be captured by the quantile panel model discussed throughout this chapter.

## 2.6 Discussion of results and policy implications

From a policy point of view, and noting the higher relative importance of the competitiveness and regulatory quality indices for Eurozone countries with low credit ratings, our results suggest that structural reforms and improvements in the competitiveness profile of these very countries will improve significantly their low rating profile and therefore reduce their borrowing costs in financial markets. This is in line with policy recommendations recently put forward by the European Commission.[17] In addition, a decrease in policy uncertainty in the Eurozone area could favour all countries, but low rated would gain more in terms of their credit rating score. We also note the potential of indirect spillover effects from sovereign credit rating decisions on low rated countries to Eurozone's sovereign bond yields; for instance, De Santis (2014) identifies spillover effects in terms of the direct impact of a Greek credit rating downgrade on other Eurozone sovereign yields.

We can illustrate the effects of European uncertainty on credit ratings by using estimates of our credit rating model under uncertainty to infer what credit ratings would have been had uncertainty remained at its 2002-2007 average value. To do this, we construct the difference between the fitted values of the estimates of credit rating model (2.1) for each CRA (as reported in Tables 2.3-2.5) and the fitted values of the counterfactual model (2.1) which sets the post-2007 values of the uncertainty variable equal to its 2002-2007 average.

Tables 2.6-2.8 report the difference between the fitted and the counterfactual values for Eurozone's periphery, namely all GIIPS (that is, Greece, Ireland, Italy, Portugal, and Spain) and Cyprus where a negative value of this difference indicates that credit ratings are lower because of the increased uncertainty.

Our estimates suggest that economic policy uncertainty has impacted negatively on the credit ratings of all GIIPS and Cyprus during the 2008-2015 period. The impact has been more prolonged for Greece. Notice that uncertainty has reduced

[17] See: http://ec.europa.eu/europe2020/pdf/csr2016/cr2016_comm_en.pdf.

Greece's credit rating by some 3 notches at the height of the Eurozone crisis in 2011 and 2012 (the impact is higher in the case of Moody's and Fitch and slightly lower in the case of S&P's). This is not surprising. Greece has witnessed successive bail-outs and remains (at the time of writing this chapter) on bail-out support.[18]

From Tables 2.6-2.8, the impact of uncertainty on the remaining GIIPS and Cyprus is still substantial but, in general, less severe than what Greece witnessed (Portugal suffered, due to uncertainty, the same rating downgrades as Greece in 2011-2014; Cyprus suffered, due to uncertainty, the same rating downgrades as Greece in 2012-2015).[19] Again, this should not come as a surprise as the remaining GIIPS and Cyprus witnessed less 'expensive' and 'smoother' bail-outs; in fact, all these countries are now off bail-out support.[20]

Earlier work by Livingston et al. (2010) suggests that Moody's is more conservative (in the sense that it gives more inferior ratings) than S&P's using data on US corporate bond rating decisions. From Tables 2.6-2.8, the impact of uncertainty on the GIIPS and Cyprus is, in general, more severe for Moody's than for S&P's and Fitch. Hence, our findings support the work of Livingston et al. (2010) in the sense that, since the recent financial and Eurozone crises, Moody's have remained more conservative than the other CRAs because of European policy uncertainty concerns.

Returning to Greece, we note that the Boards of Directors of the European Stability Mechanism (ESM) and European Financial Stability Facility (EFSF) [21] adopted, in January 2017, a set of short-term debt relief measures for Greece aiming at a

[18] Greece, which was bailed-out twice (for €110bn in 2010 and then again for €109bn in 2011), negotiated, in February 2012, a new €130bn rescue package involving a voluntary haircut of some 53.5% on the face value of its bonds held by the private sector. Eurozone ministers agreed (in November 2012) to cut Greece's debt by a further €40bn. In July 2015, Greece was bailed-out for a third time for €86bn.

[19] Notice, in Tables 2.6-2.8, some overlapping for a number of countries in a number of years. This should not come as a surprise. For a given quantile, the difference between the fitted values of the estimates of our credit rating model and the fitted values of the counterfactual model is equal to the estimated coefficient on uncertainty (for the quantile in question) times the difference between uncertainty in time period $t$ and mean uncertainty (over 2002-2007). Recall that European uncertainty does not vary at the cross-sectional dimension. When two (or more countries) are placed in the same quantile of the rating distribution for a given time period $t$, the difference between the fitted values of the estimates of our credit rating model and the fitted values of the counterfactual model is the same.

[20] Ireland was bailed-out for €85bn in November 2010. Portugal was bailed-out for €78bn in May 2011. Spain was granted, in July 2012, financial assistance from the European Stability Mechanism (ESM) for up to €100bn. Cyprus was bailed-out for €10bn in March 2013. See, for instance, the discussion in Dergiades et al., 2015 and *The Financial Times* 'dedicated' website (at https://www.ft.com/topics/themes/Greece_Debt_Crisis).

[21] ESM is a European Union permanent agency that provides financial assistance, in the form of loans, to Eurozone countries or as new capital to banks in difficulty. It has replaced the temporary EFSF.

cumulative reduction of Greece's debt-to-GDP ratio of around 20 percentage points until 2060.[22]

Policymakers from the so-called 'Troika' have repeatedly pointed out that Greece needs to proceed with structural reforms and improve its competitiveness as prerequisites for getting substantial 'medium-term relief'. At the time of writing, Greece stood at the 0.05 quantile of the rating distribution of S&P's (and the remaining CRAs), some 5 notches deep into 'junk status territory' [23] faced with a 7% servicing cost for its 10-year debt; this was some 3 percentage points higher than the 10-year Portuguese yield and 5 percentage points higher than the 10-year Spanish yield. Future rating upgrades of Greece (triggered, for instance, by accelerating structure reforms) will definitely push down Greek borrowing costs.[24]

Although a deep front 'voluntary' haircut on Greek debt is not on the 'negotiating table', our estimates (in Table 2.4 for S&P's) suggest that a haircut of as many as 36 percentage points in the debt-to-GDP ratio (that is, from 179.7% in 2016 to 143.7% in 2017) will, *ceteris paribus*, raise Greece's credit rating by only 1 notch ($\approx 36 * 0.0277$; results are similar using the estimates in Table 2.2 for Moody's and in Table 2.5 for Fitch, respectively). A speedier and much more realistic (since debt haircut is not on the 'negotiating table') Greek exit from the 'junk status territory' would indeed be triggered by structural reforms (and an improvement in competitiveness). For instance, our estimates (in Table 2.4 for S&P's) suggest that Greece would witness an upgrade of almost 3 notches[25] by S&P's if it were to implement structural reforms that would raise its regulatory quality index to the level observed for Portugal.

## 2.7 Conclusions

This chapter examines the determinants of sovereign credit ratings for the Eurozone countries from 2002 to 2015 in a panel quantile framework which allows the relative significance of the explanatory variables to vary across the quantile distribution of sovereign ratings. Our results are summarised as follows: First, the impact of the unemployment rate, regulatory quality and competitiveness is stronger for low rated countries whereas GDP per capita is a major driver of high rated countries; in other words, the high level of GDP per capita provides a 'safety net' safeguarding (to some extent) against downgrades

[22] See: https://www.esm.europa.eu/press-releases/esm-and-efsf-approve-short-term-debt-relief-measures-greece.

[23] In 2017, the S&P's, Moody's and Fitch credit rating scores for Greece were B-, Caa3, and CCC, respectively. From Table 2.1, junk (or high credit risk) sovereign bonds carry a credit rating of BB+ or lower for S&P's and Fitch and a credit rating of Ba1 or lower for Moody's.

[24] Gibson et al. (2017) discuss in detail the strong interaction between sovereign ratings, sovereign borrowing costs and bank ratings in the Eurozone area.

[25] We derive 3 notches as $\approx[(0.940-0.397)*5.075]$; 5.075 is the estimated coefficient on regulatory quality and 0.947 and 0.397 refer to the regulatory quality values for Portugal and Greece, respectively.

in the case of high rated countries. Second, a reduction in the current account deficit or an increase in the current account surplus leads to a rating or outlook upgrade for low rated countries which have historically recorded high current account deficits whereas, for countries with strong payment capacity, a higher current account deficit or a lower current account surplus is associated with either higher creditworthiness or positive economic prospects of the economy and consequently a higher sovereign rating. Third, economic policy uncertainty impacts negatively on credit ratings across the quantile distribution; however, the impact is stronger on the lower rated countries. In other words, the creditworthiness of low rated countries takes a much bigger 'hit' than that of high rated countries when European uncertainty is on the rise.

Our model, which allows for differential impact across the rating distribution, could arguably go some way towards shedding some light on how CRAs assign sovereign credit ratings. For instance, our counterfactual analysis suggests the pivotal role that economic policy uncertainty in the Euro area has played in driving down sovereign credit ratings in Eurozone's periphery. We believe that our empirical analysis and results provide valuable information that can potentially be used by a new credit rating agency towards making credit rating decisions if indeed European policymakers decide to set up such an agency soon.

# 3. NON-PERFORMING LOANS AND SOVEREIGN CREDIT RATINGS

## 3.1 Introduction

In its January 2019 World Economic Outlook, the International Monetary Fund (IMF) noted that while global growth of 3.7% in 2018 remained close to post-crisis highs, the global expansion will somewhat weaken to 3.5% in 2019. [26] In fact, policymakers around the world have little room for complacency about future economic growth; for instance, (former) IMF Economic Counsellor and Director of Research Maurice Obstfeld (2018) noted that "as important as they have been to the recovery, easy financial conditions and fiscal support have also left a legacy of debt – government, and in some cases, corporate and household – in advanced and emerging economies alike." [27]

The ongoing debt hangover brings again into focus the issue of assessing the probability of a (sovereign) default. This remains an important and unresolved issue, not least because of the difficulty of providing an accurate estimate of such probability that can create information asymmetry between governments, banks, corporations, and investors. This information gap has been traditionally filled by Credit Rating Agencies (hereafter CRAs) that publish sovereign credit ratings as measures of the probability that a country will repay its debt in full and on time. Therefore, sovereign ratings influence to a large extent borrowing costs in international markets both for a sovereign state and the financial institutions operating in that sovereign state (see e.g. Drago and Gallo, 2017a) which, in turn, affects the lending supply of banks (Drago and Gallo, 2017b) as well as investment decisions and ultimately economic growth (see e.g. Chen et al., 2016).

With so much at stake in terms of future financial repayments and investment planning, it is not surprising that the way CRAs assess credit scores has received increasing attention. Criticism has focussed on the inability of CRAs to predict corporate defaults that took place in the US during 2007-2008 (see e.g. Baghai et al., 2014), their potential role in the acceleration of the sovereign debt crisis by massively downgrading Eurozone periphery bonds and on the effect of subjectivity in their assessment methods (see De Moor et al., 2018). [28] Decisions by CRAs have indeed been questioned by policymakers. In 2012, for instance, both European Central Bank (ECB) President Mario Draghi and (at the time) Bank of

[26] See https://blogs.imf.org/2019/01/21/a-weakening-global-expansion-amid-growing-risks/.

[27] According to the IMF World Economic Outlook Database, general government gross debt in advanced economies, at 102.8% of Gross Domestic Product (GDP) in 2018, will remain some 32 percentage points above its pre-crisis level in 2007. General government gross debt in emerging market and developing economies, at 51.0% of GDP in 2018, will remain some 15 percentage points above its pre-crisis level.

[28] Herding bahavior issues are also at play. For instance, Lugo et al. (2015) assess the herding behavior of CRAs in the US Home Equity Loan market to find that since the start of the subprime crisis, rating convergence is more likely when Fitch rather than the rival (Moody's or S&P's) has to adjust its evaluation downwards.

England Governor Mervyn King urged investors to pay less attention to CRAs and to make up their own minds about how much the region's debt is worth.[29]

This chapter takes the issues raised above to the data by modelling the behavior of sovereign ratings in the case of the three main CRAs, namely Moody's Investor Services, Standard & Poor's (S&P's) and Fitch Ratings.[30] We extend recent literature (see e.g. Reusens and Croux, 2017and references therein) by identifying a feedback loop between sovereign credit ratings and non-performing loans (NPLs) as a measure of banking risk over and above the impact of macroeconomic and financial determinants, namely economic policy uncertainty, GDP growth, government debt-to-GDP ratio, investment-to-GDP ratio, and the fiscal balance-to-GDP ratio. This is done within a Panel Vector AutoRegressive (PVAR) model which allows us to tackle endogeneity issues that arise since sovereign ratings respond to but also cause country-specific macroeconomic and financial developments.

There are good reasons to suggest a strong connection between sovereign and bank credit risk. In Acharya et al. (2014), for instance, a distressed financial sector induces government bailouts, whose cost increases sovereign credit risk. Increased sovereign credit risk, in turn, weakens the financial sector by eroding the value of its government guarantees and bond holdings. Adelino and Ferreira (2016) show that the rating score of banks with a profile equal to or higher than that of their sovereign state is affected more by sovereign downgrades compared to banks with a lower rating profile than their sovereign state. Mäkinen et al. (2019) link sovereign risk to bailouts in the banking sector and note that rising policy uncertainty weakens the ability of governments to provide bailouts. Gennaioli et al. (2014) focus on the dire consequences of sovereign default on aggregate financial activity in the defaulting country; the impact is stronger in countries where domestic banks hold more public debt. Altavilla et al. (2017) flag the amplification effect of sovereign stress on bank lending to domestic firms for a sample of euro-area banks. All these point to a strong feedback loop between sovereign and banking risk.

It, therefore, comes as no surprise that banking risk has recently appeared on the radar of CRAs. For instance, S&P's recent update of its assessment methodology (S&P's Global Ratings, 2017) refers to contingent liabilities and their potential impact on sovereign ratings. Among these liabilities that have the potential to become government debt, or more broadly affect a government's fiscal profile,

[29] In January 2012, Mario Draghi told the European Parliament in Strasbourg that "we should learn to do without ratings, or at least we should learn to assess creditworthiness" adding that "certainly one needs to ask how important are these ratings for the marketplace overall, for investors", whereas Mervyn King stressed (also in January 2012) in a parliamentary committee in London that one should "put less focus directly on what the ratings agencies say and more on what the market as a whole is saying in terms of sovereign debt" adding that "what we need to do is to move to a point, and I think markets have gone some way towards that, where they pay less attention to the verdicts of the ratings agencies". See http://www.nytimes.com/2012/01/18/business/global/european-central-bankers-criticize-role-of-rating-agencies.html.

[30] These CRAs collectively control around 95% of the market. See http://www.bbc.co.uk/news/business-36629099.

bank NPLs[31] have increased rapidly after 2008 not least in the Euro area adding to regulatory concerns.[32] In 2016, for instance, the European Banking Authority (EBA) flagged high NPLs as one of the main risks for EU banks, whereas in 2017, the ECB stressed that high NPLs harm bank lending to the economy as a result of profitability and capital constraints and also flagged the benefits of a reduction of NPLs to the economy from both a microprudential and a macroprudential perspective.[33] Thus, it is not surprising that CRAs consider changes in NPLs as an important driver of rating changes. For example, S&P's latest report on Greece notes "Another potential trigger for an upgrade would be a marked reduction in nonperforming assets in Greece's impaired banking system".[34]

In recent work, Brůha and Kočenda (2018) examine the link between banking sector quality and sovereign risk to show that rising NPLs is the single most influential sector-specific variable that is associated with increased sovereign risk in the European Union. Besides, rising NPLs have often been considered the consequence of weak economic growth but, at the same time, negatively feedback themselves to the banking sector and the wider economy. Indeed, NPLs have been shown to be a significant predictor of bank failures (see Barr et al., 1994, Gonzalez-Hermosillo et al., 1997, Lu and Whidbee, 2013). But even in the case where banks avoid failure, rising NPLs have a negative impact on the cost structure and efficiency of banks as well as their willingness to lend (see e.g. Balgova et al., 2016) and, as a result, undermine future economic growth.

This very discussion indicates that NPLs are an appropriate measure of banking risk and opens up the possibility that developments in NPLs affect sovereign rating decisions over and above the impact of other control variables. On the other hand, sovereign ratings impact negatively on NPLs through banking ratings and lending supply. This is because sovereign rating downgrades lead to banking rating downgrades through the sovereign ceiling rule (Adelino and Ferreira, 2016) which in turn lead to a reduction in lending supply and, at the same time, increase the burden of refinancing existing loans, therefore, making it more likely than not that NPLs will increase. This two-way feedback is examined within a panel VAR of 72 countries over the 1998-2016 period.

First, we identify a significant negative effect of NPLs on sovereign credit ratings and vice versa. Second, economic policy uncertainty shocks trigger a negative effect on sovereign rating decisions following the financial turmoil and the

[31] These are loans where the full repayment of the principal and interest may no longer be expected. Typically, the principal or interest would be at least 90 days in arrears, although the precise definition of NPLs varies across jurisdictions.

[32] For instance, NPLs increased from 4.67% of total gross loans in 2008 to 36.29% in 2016 in Greece and from 3.59% in 2008 to 48.67% in 2016 in Cyprus. For the Euro area NPLs increased from 2.80% in 2008 to 4.05% in 2016.

[33] See https://www.eba.europa.eu/documents/10180/1315397/EBA+Risk+Assessment+Report_December+2016.pdf and https://www.bankingsupervision.europa.eu/ecb/pub/pdf/guidance_on_npl.en.pdf.

[34] See https://www.standardandpoors.com/en_US/web/guest/article/-/view/type/HTML/id/2075495.

subsequent Eurozone crisis. Indeed, economic policy uncertainty is firmly now on the radar of CRAs; Moody's, for instance, notes (in May 2018) policy uncertainty in Italy as a reason for a credit rating review.[35] From a theoretical point of view, uncertainty shocks could undermine the expected profitability of firms, which puts upward pressure on their perceived riskiness. In this context, investors demand higher interest rates be compensated for the higher risk and consequently that issuance of additional debt becomes more costly and adversely affects investments (see e.g. Gilchrist et al., 2014).

Our results provide additional insight towards understanding how CRAs make sovereign credit rating decisions by flagging the importance of NPLs in driving these decisions. With this in mind, our results should be useful to regulators like the European Securities and Markets Authority (ESMA) who monitor CRAs in order to understand their rating methodology and assess the quality of their ratings. Our results should also be informative for investors who can rely on our findings to get additional clarity on how CRAs reach their sovereign assessment decisions. This will go some way towards restoring part of the investor confidence towards CRAs which was undermined following the recent financial crisis and the heavy criticism CRAs received (and indeed continue to receive) by policymakers during the Eurozone crisis and beyond.

The structure of this chapter is as follows. Section 3.2 discusses our dataset. Section 3.3 introduces the panel VAR model and Section 3.4 presents and discusses the empirical estimates. Finally, Section 3.5 offers some concluding remarks.

## 3.2 Data description

We use $T$= 19 annual observations over the 1998-2016 period for a panel of $N$= 72 countries.[36] Our main variable of interest is the sovereign credit rating published by the three main international rating agencies, Moody's, S&P's and Fitch Ratings (attributed on the 31st of December of each calendar year). In our main model, we implement a linear transformation of credit ratings to numerical scale, starting from 21 for the highest quality with a stable outlook (AAA for Fitch and S&P's and Aaa for Moody's) and ending to 1 for Default (D for Fitch and S&P's

[35] Something that triggered the reaction of Five Star leader Di Maio who wrote that "governments are decided by the credit rating agencies". See https://www.bloomberg.com/news/articles/2018-05-27/italy-s-president-vetoes-candidacy-of-euroskeptic-savona.

[36] The countries included are: United Arab Emirates, Argentina, Armenia, Australia, Austria, Belgium, Bulgaria, Bolivia, Brazil, Canada, Switzerland, Chile, China, Colombia, Costa Rica, Cyprus, Czech Republic, Germany, Denmark, Dominican Republic, Ecuador, Spain, Estonia, Finland, France, Gabon, The United Kingdom, Georgia, Ghana, Greece, Hong Kong, Croatia, Hungary, Indonesia, India, Ireland, Iceland, Israel, Italy, Japan, Korea Republic, Lithuania, Luxembourg, Latvia, Morocco, Moldova, Mexico, F.Y.R.O.M., Malta, Malaysia, The Netherlands, Norway, New Zealand, Pakistan, Philippines, Poland, Portugal, Paraguay, Romania, Russian Federation, Saudi Arabia, Singapore, Slovak Republic, Slovenia, Sweden, Thailand, Tunisia, Turkey, Ukraine, Uruguay, The United States and South Africa. Due to missing observations, our dataset includes 1226 observations for Moody's, 1253 observations for S&P's and 1190 observations for Fitch.

and C for Moody's). We consider both changes in credit ratings and changes in credit outlooks. For our sovereign rating variable, the difference between two continuous outlooks is always equal to 1/3, so the difference between two continuous ratings with the same outlook is always equal to one. Table 3.1 reports the linear transformation of credit ratings and provides details on the frequencies of the ratings per category. We also consider the logistic transformation of ratings in the robustness section of the chapter.

Our PVAR framework (details of the theoretical model are given in the next section of the chapter) allows us to examine jointly sovereign ratings and a number of factors. In particular, we implement a PVAR model which includes Economic Policy Uncertainty, GDP growth rate, total investments (as % of GDP), gross government-debt (as % of GDP), fiscal balance (as % of GDP), NPLs (non-performing loans as % of total gross loans) and sovereign credit ratings as endogenous variables and the shadow interest rate as predetermined variable.

Endogenous variables selection is based on economic theory and prior empirical studies. Following the current literature, we incorporate variables that have been found to affect and be affected from sovereign credit ratings. On the one hand the literature on the determinants of sovereign credit ratings (see Cantor and Packer, 1996, Afonso et al., 2011, Reusens and Croux, 2017, among others) shows that variables selected do affect credit ratings. On the other hand, sovereign credit ratings impact on those variables, as well. For instance, Chen et al. (2016) show that sovereign credit ratings affect gdp growth rate and Chen et al. (2013) show that sovereign ratings matter for investments. Moreover, Duygun et al. show that sovereign ratings do impact on government debt and fiscal balance. The theoretically expected impact of those variables is discussed below.

Economic Policy Uncertainty is an index constructed based on newspaper articles regarding policy uncertainty from leading newspapers. It counts the number of newspaper articles containing the terms uncertain or uncertainty, economic or economy, and one or more policy-relevant terms.[37] Increased uncertainty is expected to trigger sovereign rating downgrades as it makes consumers and investors more cautious and reduces consumption and investment. For example, S&P's lists policy uncertainty as one of the main reasons driving its unprecedented decision to downgrade the US in 2011.[38] On the other hand, a rating downgrade creates weaker economic conditions which, in turn, increases policy uncertainty. This is because governments are more likely to change their policy to deal with weak economic conditions and it, therefore, becomes increasingly uncertain which of the potential new policies will be adopted (Pástor and Veronesi, 2013).

[37] For more information see Baker et al. (2016) and http://www.policyuncertainty.com/index.html. Because of data unavailability, a country specific index is only employed for 22 countries. For European countries without a country specific index, the aggregate European index is employed. In the case of non-European countries without a country specific index, the Global policy uncertainty index is employed.

[38] See https://www.reuters.com/article/us-usa-sp-downgrade-text/sp-lowers-united-states-credit-rating-to-aa-idUSTRE7750D320110806.

GDP growth impacts positively on sovereign ratings and vice versa (see e.g. Chen et al., 2016 and Reusens and Croux, 2017, and references therein). An increase in investments triggers sovereign rating upgrades as they enhance the country's economic prospects. On the other hand, a rating downgrade reduces investments by affecting the cost of capital and changing the net present value of some projects from positive to negative (see Chen et al., 2016 and Chen et al., 2013). An increase in government debt triggers sovereign rating downgrades because a high stock of government debt implies higher interest rates to service it. Hence, additional financial resources are needed to repay debt obligations and therefore, higher government debt should increase the risk of default. On the other hand, the impact of sovereign ratings on government debt is uncertain. This is because rating upgrades decrease sovereign spreads and make debt repayment cheaper which might reduce the pile of debt. At the same time, however, political business cycle considerations suggest that governments might exploit the opportunity of the positive sentiment in financial markets following a rating upgrade and adopt expansionary fiscal policies to increase the probability of an electoral victory.[39] A fiscal surplus or very low fiscal deficit indicates strong fiscal performance which, in turn, triggers sovereign rating upgrades. On the other hand, the impact of the sovereign rating on the fiscal balance is uncertain. This is because rating upgrades decrease sovereign spreads and reduce the amount needed to be paid on interest rates each year. At the same time, however, political business cycle considerations might trigger expansionary fiscal policies leading to a deterioration of the fiscal balance.

We expand the information set by including NPLs in the specification. Rising NPLs lead to sovereign rating downgrades as they increase the possibility of a bailout to the banking sector that sets an additional fiscal burden and undermines the country's economic prospects. On the other hand, sovereign downgrades lead to a rise in NPLs. This is because sovereign rating downgrades lead to banking rating downgrades which in turn lead to a reduction in lending supply and, at the same time, increase the burden of refinancing existing loans, therefore, making it more likely than not that NPLs will increase. Table 3.2 provides details of the data definitions and sources and Table 3.3 reports the data summary statistics.

We also take into account monetary policy by including the shadow interest rate in our model. In response to the financial crisis, policymakers brought policy interest rates down to their zero lower bound (hereafter ZLB) and authorised Quantitative Easing policies. To assess the impact of the presence of these types of policies, we use the shadow interest rate proposed by Wu and Xia (2016). Noting that the prime focus of our chapter is on sovereign ratings and its determinants, the shadow rate enters our information set as a pre-determined variable that is, a variable which is potentially correlated with past errors (see e.g. the discussion in

[39] Duygun et al. (2016) find that a rating upgrade is likely to increase sovereign debt because of sovereign ratings' procyclicality and path dependence. Nevertheless, they also find that the impact of sovereign rating decisions on debt varies with the degree of the country's institutional quality; in particular, rating upgrades in countries with higher institutional quality are followed by debt reductions and an improvement in the fiscal balance.

Sigmund and Ferstl, 2019); this allows monetary policy to react to past shocks in the remaining variables of the model. Estimated from an affine term structure model, the shadow interest rate is the nominal interest rate that would prevail in the absence of its effective lower bound. Therefore, the shadow interest rate has the advantage that it is not constrained by the ZLB and thus allows us to combine the monetary policy rate data from the ZLB (or unconventional) period with the non-ZLB (or conventional) period. For the US, Eurozone and the UK, we use the corresponding shadow rates available at Wu's website (https://sites.google.com/view/jingcynthiawu/shadow-rates). For the remaining countries in our sample, we construct and use a 'global' shadow interest rate as a weighted average of the shadow interest rates for the US, Eurozone, and the UK.[40] Figure 3.1 plots the shadow rates for the US, UK and Eurozone economies together with the 'global' measure; these drop to negative territory post-2008 (and the US one reverts to positive territory after 2015 due to QE 'tapering').

### 3.3 Methodology

We follow the estimation approach of Binder et al. (2005) and the implementation and extension by Sigmund and Ferstl (2019) and consider a PVAR model with fixed effects:

$$y_{i,t} = \mu_i + \sum_{l=1}^{p} A_l \, y_{i,t-1} + B x_{i,t} + \varepsilon_{i,t}, \tag{3.1}$$

where $y_{i,t} \in \mathbb{R}^m$ is an ($m$ x 1) vector of endogenous variables for the $i$-th cross-sectional unit ($i$ = 1,2,…,$N$) at time $t$ ($t$ = 1,2,…,$T$), $x_{i,t} \in \mathbb{R}^k$ is a ($k$x1) vector of predetermined variables that are potentially correlated with past errors, $\boldsymbol{\varepsilon}_{i,t} \in \mathbb{R}^m$ is an ($m$ x 1) vector of disturbances, $\mu_i$ is an ($m$ x 1) vector of individual-specific effects, and $p$ is the lag length of the PVAR model. Stationarity requires all unit roots of the model to lie inside the unit circle. Parameter homogeneity for the ($m$ x $m$) $A_l$ matrix and the ($m$ x $k$) $B$ matrix is assumed. A PVAR model is hence a combination of a single equation dynamic panel model (DPM) and a vector autoregressive model (VAR).

[40] Based on the share of US, Eurozone and UK GDP output in the sum of their output using GDP (Purchasing Power Parity, constant 2011 international $), the US accounts for 52.47%, while the Eurozone and the UK account for 39.70% and 7.83% respectively.. Notice that the shadow rate for the Eurozone is available from 2004 onwards. From Wu's website, this tracks well the ECB main refinancing rate prior to the financial crisis. With this in mind, we use the ECB main refinancing rate as a proxy for the Eurozone shadow rate over the 1999-2003 period and Bundesbank's discount rate for 1998.

Applying the first difference transformation to (3.1) we get:

$$\Delta y_{i,t} = \sum_{l=1}^{p} A_l \, \Delta y_{i,t-l} + B\Delta x_{i,t} + \Delta\varepsilon_{i,t}, \tag{3.2}$$

where Δ refers to the first difference operator.[41]

Following Binder et al. (2005), the moment conditions for the lagged endogenous and the predetermined variables are:

$$E\left[\Delta\varepsilon_{i,t} y_{i,j}^T\right] = 0 \tag{3.3}$$
$$E\left[\Delta\varepsilon_{i,t} x_{i,j}^T\right] = 0$$

with $j \in \{1,\dots,T-2\}$ and $t \in \mathbb{T}_\Delta$. By stacking over $t$, (3.2) is written as:

$$\Delta Y_i = \sum_{l=1}^{p} \Delta Y_{i,l} A_l^T + \Delta X_i B_l^T + \Delta E_i, \tag{3.4}$$

where $\Delta Y_i$, $\Delta Y_{i,l}$ and $\Delta E_i$ are $((T - 1 - p) \text{ x } m)$ matrices and $\Delta X_i$ is a $((T\text{-}1\text{ - }p) \text{ x } k)$ matrix. Thus, the stacked moment conditions for each $i$ is as follows:

$$E[Q_i^T(\Delta E_i)] = 0, \tag{3.5}$$

where $Q_i$ is the stacked form of $q_{i,t}$ with $q_{i,t}^T := (y_{i,t-p-1}^T, y_{i,t-p-2}^T, \dots, y_{i,1}^T, x_{i,t-1}^T, x_{i,t-2}^T, \dots, x_{i,1}^T)$,

for $t \in \{p+2,\dots,T\}$ and

$$Q_i := \begin{pmatrix} q_{i,p+2}^T & 0 & \cdots & 0 \\ 0 & q_{i,p+3}^T & & 0 \\ \vdots & & \ddots & \vdots \\ 0 & 0 & \cdots & q_{i,T}^T \end{pmatrix} \tag{3.6}$$

[41] The first difference transformation exists for $t \in \{p+2,\dots,T\}$. We denote the set of indexes $t$, for which the transformation exists by $\mathbb{T}_\Delta$. Using the forward orthogonal transformation of Arellano and Bover (1995) produced qualitatively similar results to what we report below (these results are available on request).

Based on the moment conditions (3.5), the minimization problem is:

$$\min_{\Phi}\{\sum_{i=1}^{N} Z_i^T(\Delta Y_i - [\Delta Y_{i,-1}\Delta X_i]\Phi)^T \Lambda_z^{-1} \sum_{i=1}^{N} Z_i^T(\Delta Y_i - [\Delta Y_{i,-1}\Delta X_i]\Phi)\}, \tag{3.7}$$

where $\Phi$ delivers the Generalized Method of Moments (GMM) estimates of the model (3.2) and $\Lambda_z$ is the weighting matrix based on the one-step estimation procedure of Binder et al. (2005); see also the detailed technical discussion in Sigmund and Ferstl (2019).

The choice of the optimal weighting matrix reduces the asymptotic bias in the estimation. Fixed effects are removed by implementing the first differences.

There are $m = 7$ endogenous variables in our PVAR model such that the vector $y_{i,t}$ is given by $y_{i,t}$ = [Uncertainty, GDP growth, Investments, Debt, Fiscal Balance, NPLs, rating] using a lag length of $p = 2$ and employing 3 lags of all endogenous variables as instruments.[42] The choice of the lag length is based on the Andrews and Lu (2001) model and moment selection criteria (MMSC).[43] A choice of 2 lags appears justified also on economic grounds as there is evidence of persistence and stickiness in rating decisions (Dimitrakopoulos and Kolossiatis, 2016); considerable persistence also shows up in some of the impulse responses reported in the following section of the chapter.

To examine the response of one (endogenous) variable to an impulse in another (endogenous) variable, we rely on Generalized Impulse Response Functions (GIRFs) of Pesaran and Shin (1998); contrary to Orthogonalized Impulse Response Functions (OIRFs; where the underlying shocks to the model are orthogonalized using the Cholesky decomposition before calculating impulse responses), GIRFs are not affected by the ordering of the variables in the PVAR model and fully take account of the historical patterns of correlations observed amongst the different shocks. The justification of GIRFs over OIRFs is twofold. First, the theoretical framework for this strand of the empirical literature is

[42] The literature on sovereign ratings (see e.g. Afonso et al., 2011) often models ratings as a function of GDP growth and the unemployment rate. To keep the dimensionality of the PVAR model as manageable as possible, we use GDP growth in our model. In any case, the impact of the unemployment rate on sovereign ratings is indirectly captured by the impact of GDP growth through an Okun's-law type of approximation (in which case there is an inverse relationship between unemployment and GDP growth).

[43] For instance, using Moody's model and implementing the first difference transformation, the MMSC-HQIC (Hannan-Quinn Information Criterion) is equal to 993110.5 using 2 lags and equal to 1054326 using 1 lag. All MMSC-HQIC, MMSC-BIC (Bayesian Information Criterion) and MMSC-AIC (Akaike Information Criterion) selection criteria suggest 2 lags for all PVAR models employed in our chapter.

limited at best[44] and, second, the large number of variables we employ makes an appropriate ordering almost impossible.[45] In what follows, we report GIRFs with 95% confidence intervals estimated using bootstrap cross-sectional resampling (Kapetanios, 2008).[46]

## 3.4 Empirical results

### 3.4.1 Main estimates

We calculate and report GIRFs to one standard error shocks for all CRAs based on the first difference transformation (stability condition is satisfied in all cases). Figures 3.2 to 3.4 report GIRFs for the three CRAs using the first difference transformation.

An economic policy uncertainty shock impacts negatively on the sovereign ratings assigned by all CRAs; the impact is statistically significant (slightly less so for S&P's) but lasts only for 1-2 years for all CRAs (see Figures 3.2-3.4). A positive GDP growth rate shock impacts positively on CRA decisions; the effect lasts for almost 8 years for Moody's and 5 years for S&P's and Fitch. A positive investment shock leads to sovereign rating upgrades. The duration of the effect varies from 5 years for Moody's to 3 years for S&P's and to 1 year for Fitch. The latter results suggest that Moody's assigns a higher weight on investments than the remaining rating agencies.

A positive shock to government debt has a negative and persistent effect on sovereign ratings. A positive shock to fiscal balance has a positive and persistent effect on sovereign ratings. The impact of a government debt shock is statistically important for up to 8 years while a shock on fiscal balance impacts on sovereign ratings for more than 10 years. Therefore, fiscal considerations in terms of fiscal balance trigger a longer impact on the rating decisions made by the three CRAs compared to government debt developments. The persistence of the effect is arguably not surprising given the stickiness of sovereign ratings and the importance of fiscal variables on default risk.

Turning our attention to NPLs, our model confirms their importance for sovereign rating decisions. A positive shock to NPLs leads to sovereign rating downgrades with the impact being statistically stronger and economically more prolonged for Moody's (up to 6 years).

From Figures 3.2-3.4, we also note that positive shocks to sovereign ratings do have a very temporary impact on economic policy uncertainty and trigger a positive effect on GDP growth for all CRAs. The impact on GDP growth, which is similar for all CRAs, reaches its peak after 2 years and remains statistically

[44] See Holden at al. (2018) for an equilibrium theory that allows for the possibility that ratings affect the performance of the rated objects.
[45] Granger causality tests within our PVAR model (available on request) do not provide clear guidance on the ordering of the variables as they indicate bidirectional causality.
[46] We use 500 bootstrap replications in all calculations.

significant for up to 9 years. Investments also respond positively to positive sovereign rating shocks. The impact is maximized after 2 years for all agencies and lasts (from a statistical point of view) for almost 9 years after the shock in the case of Moody's and slightly less so (7 to 8 years) for Fitch and S&P's. Positive shocks to sovereign ratings do have a positive impact on fiscal balance and government debt. The impact on government debt is persistent and statistically significant for up to 8 years for Moody's and slightly less so (up to 7 years) for S&P's and Fitch, while, for all CRAs, a positive sovereign rating shock exerts a statistically significant and positive impact on the fiscal balance for up to 4 years. Consequently, or GIRFs show that governments do not exploit the opportunity of the positive sentiment in financial markets following a rating upgrade to adopt expansionary fiscal policies and increase the probability of an electoral victory (see Duygun et al. 2016).

Last but not least, positive shocks to sovereign ratings reduce NPLs. The impact reaches its peak after 3 years and is long lasting (up to 9 years for Moody's, up to 10 years for S&P's and up to 8 years for Fitch) and the magnitude of the impact of the shock at peak (after 3 years) is stronger for Moody's (that is, a negative change of approximately 1.3 percentage points following a one standard error positive shock in the equation for sovereign ratings).

To sum up, GIRFs provide evidence of significant effects from NPLs on sovereign rating decisions over and above the effects of the remaining economic/financial variables; at the same time, sovereign ratings impact on NPLs and all other variables. We also note that sovereign rating changes trigger a stronger response at peak (after 3 years) on NPLs in the case of Moody's. Moody's sovereign rating decisions exert a longer-lasting impact on investment decisions compared to decisions made by S&P's and Fitch. Livingston et al. (2010) find that, in the case of corporate bond rating decisions, Moody's has become more conservative (in the sense that it gives more inferior ratings) than S&P's post-1998 and that investors value "more" decisions made by Moody's than decisions made by S&P's. If indeed, investors value "more" decisions made by Moody's, one would expect Moody's decisions to exert a longer-lasting impact on investment decisions compared to the remaining CRAs which is what the results of our GIRFs point to.

Finally, fiscal considerations in terms of fiscal balance rather than government debt trigger a longer-lasting impact on the sovereign rating decisions made by the three CRAs. The next section examines how the impact of sovereign rating determinants on the assessment of CRAs has varied over time.

### 3.4.2 Impulse response functions over time

Using a multi-year probit analysis, Reusens and Croux (2017) documented that CRAs changed their sovereign credit rating assessment after the start of the European debt crisis in 2009. From a theoretical viewpoint, Holden at al. (2018) showed that it is possible that CRAs were too lenient before the 2007-8 period but not afterwards. We incorporate this into the context of PVAR models by examining how GIRFs change over time. In particular, we consider GIRFs over the pre-crisis 1998-2006 period. We then expand our sample to include the 1998-2009 period which allows us to account for the effect of the global financial crisis. We further expand our sample to include the 1998-2012 period so that the Eurozone crisis is also allowed. GIRFs over the expanding time windows discussed above are plotted together with the previously reported GIRFs over the full 1998-2016 sample period in Figures 3.5, 3.6 and 3.7 for Moody's, S&P's and Fitch, respectively using the first difference transformation.[47]

Expanding window sample analysis reveals some interesting findings. Policy uncertainty was not a major concern for Moody's up until 2009; a controversial positive effect (but not always statistically significant) appears for S&P's and Fitch up to 2009. On the other hand, as we expand our sample to include the Eurozone debt crisis and beyond, policy uncertainty exerts a negative and statistically significant impact for up to 2 years. This should not necessarily come as a surprise. Eurozone policymakers have arguably been fairly slow in responding to the Eurozone crisis because planning involves general parliamentary approval from all member states; at the same time, the so-called 'Troika' of the IMF, the European Commission, and the ECB have had their differences in dealing with the crisis[48] , therefore, adding to policy uncertainty in the Euro area.[49]

Prior to the financial crisis, the impact of GDP growth rate shocks on sovereign ratings was slightly smaller and less persistent for Moody's whereas the opposite is true for S&P's and Fitch. For all CRAs, the impact of investments shocks on sovereign ratings was less persistent before the crisis. In line with Reusens and Croux (2017), fiscal variables received greater attention from the three CRAs after 2009; indeed, the effect of government debt and fiscal balance shocks became economically and statistically more important after the financial crisis and during the Eurozone crisis and beyond. As mentioned earlier on, the interaction between sovereign and bank credit risk was highlighted by the financial and the sovereign debt crisis. Taking that into account, it is not surprising that the sovereign rating assigned by Fitch was not affected by a shock to NPLs prior to 2007. The effect of a shock to NPLs on the rating of Fitch becomes economically stronger following from the financial crisis and up to the end of our sample period. On the other hand, Moody's and S&P's ratings were affected by shocks to NPLs even prior to the financial crisis.

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[47] We pursue expanding rather than rolling window sample analysis due to the relatively short time dimension of our sample. Given the broad consensus of our earlier empirical results in terms of the first difference and the forward orthogonal deviation transformation, we focus only on expanding time windows using the former transformation.

[48] See e.g. http://www.bbc.co.uk/news/business-33531743.

[49] In the context of sovereign credit spreads rather than sovereign credit ratings, Jeanneret (2015) shows that the global market uncertainty (proxied by the US option-implied volatility index; VIX) drives emerging markets sovereign spreads but also notes that the disagreements among European leaders on policies to prevent contagion in the default crisis, for example, are factors likely to affect European sovereign spreads beyond the level of volatility in financial markets.

Turning our attention to sovereign rating shocks we note that these affect policy uncertainty and more so (economically and statistically) through the period which includes the Eurozone crisis and beyond. Therefore, our model reveals a feedback from policy uncertainty to sovereign ratings and vice versa especially over the period which includes the Eurozone debt crisis; our results complement the results of Pástor and Veronesi (2013) who predict that uncertainty about the government's future policy choice is generally larger in weaker economic conditions because that is when the government is more likely to change its policy.

The impact of sovereign rating shocks on GDP growth and investments became economically and statistically more significant following the Eurozone debt crisis; this highlights to some extent the adverse effect of massive sovereign downgrades on GDP growth rates recorded especially in Eurozone's periphery since the debt crisis. [50] At first sight, these effects might appear counterintuitive especially if one bears in mind the increased criticism CRAs attracted in the aftermath of the 2007-2008 financial crisis. This criticism was based on their inability to foresee corporate failures during the period leading to the financial crisis and questioning their decisions received from policymakers during the Eurozone crisis. That said, there are encouraging signs that CRAs have responded to the increasing criticism by subsequently improving their valuation assessment. Indeed, some encouraging evidence towards this end was provided, for instance, by the European Securities and Markets Authority (ESMA), the European authority competent for the supervision of CRAs. In fact, the 2016 ESMA Report noted that since the beginning of the supervision of CRAs in 2011, "ESMA's supervisory work has triggered improvements in the empowerment and effectiveness of CRA's internal control functions" and that "ESMA has driven significant changes in the credit rating process and the methodology and business development process thereby strengthening their integrity, independence, quality and transparency" (ESMA, 2016, pages 16-17). The very fact that CRAs have adjusted their methodology to reflect ESMA guidelines might explain why we find an increasing influence of CRA decisions on GDP growth and investments over the most recent period. In recent work, Drobetz et al. (2018) find that rising policy uncertainty reduces the sensitivity of investments to the cost of capital. To the extent that policy uncertainty (which has been more elevated post rather than pre-2007) distorts the relationship between investments and market-based interest rates, it should not come as a surprise that investors have arguably turned to CRAs and, consequently, investment decisions have been more responsive to rating decisions over the most recent period.

With reference to the fiscal variables, the response of government debt and fiscal balance to shocks on sovereign ratings became economically more important during the period covering the Eurozone debt crisis especially for S&P's. The impact of shocks to sovereign rating decisions on debt was statistically

[50] Eurozone's periphery (namely Greece, Ireland, Italy, Portugal, Spain and Cyprus) recorded an average GDP growth rate of 2.24% per annum over the 1998-2011 period. Eurozone's periphery average GDP growth rate dropped to 0.74% per annum over the 2012-2016 period.

insignificant prior to 2007 for Moody's and S&P's (there is some weak evidence of statistical significance for Fitch). The impact of shocks on rating decisions on the fiscal balance was statistically insignificant prior to 2009 for S&P's and prior to 2007 for Fitch. Finally, NPLs decrease in response to positive shocks to rating decisions only after 2009. The impact is statistically and economically insignificant before that year. This is in line with our earlier discussion that the interaction between sovereign and bank credit risk was highlighted by the financial and the sovereign debt crisis.

### 3.4.3 Robustness checks

So far, our results have been based on the linear transformation of sovereign ratings from letters to numbers. This implies that the distance between two subsequent ratings is always the same. Among others, Afonso et al. (2011) have considered a logistic transformation of sovereign ratings instead of a linear one. The logistic transformation is given by $L_l = \ln[R_l / (1 - R_l)]$, where $R_l = (2l - 1)/(2n_c)$, the number of categories, $n_c$, equals 21 and (from the last column of Table 3.1) the rating grades are $l = 1, 2, \ldots, 21$. Figure 3.8 plots together with the linear and logistic transformation for Moody's sovereign credit ratings.

In the logistic transformation, the differences between categories are not constant but are still imposed *a priori*. Consequently, we perform again our analysis using the logistic transformation of sovereign ratings. We report in Figure 3.9 GIRFs for Moody's over the 1998-2016 period using the first difference transformation; these are broadly in line with our main results reported earlier on. However, minor differences can be observed. For instance, a comparison of Figure 3.9 with Figure 3.2 shows that the impact of sovereign rating shocks on NPLs based on the logistic transformation against the linear transformation is statistically most long-lived (10 years for the former as opposed to 9 years for the latter case) and the impact of sovereign rating shocks on investments based on the linear transformation against the logistic transformation is statistically most long-lived (9 years for the former as opposed to 8 years for the latter case).

Rather than using policy uncertainty in our PVAR model, we have tried country-specific stock price volatility.[51] Our GIRFs (see Figure 3.10) throughout the entire sample period for Moody's based on the first difference transformation are broadly in line with our main results reported earlier on. Notice, however (by comparing Figure 3.10 with Figure 3.2), that the impact of stock price volatility on sovereign ratings and vice versa is more profound (i.e. 6 years and 4 years respectively) than the impact of policy uncertainty on sovereign ratings and vice versa (i.e. 2 years).

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[51] Volatility of stock price index is the 360-day standard deviation of the return on the national stock market index. (Bloomberg). This is available from the Federal Reserve Bank of St Louis database.

As a further robustness check, rather than capturing banking risk considerations by NPLs, we have constructed for each country a 'banking risk' factor measure using principal component analysis (PCA). PCA is pooling information from a 4-variable dataset, namely NPLs, bank credit to bank deposits, bank capital to risk-weighted assets and bank Z-score which contribute 22.42%, 26.11%, 23.99%, and 27.48% to the 'banking risk' factor, respectively, while the 'banking risk' factor contributes 53.67% to the total variation of the 4-variable dataset (these are average numbers across countries).[52] The bank capital to risk-weighted assets is a measure of bank solvency and resiliency which shows the extent to which banks are able to 'weather the storm' of unexpected losses. The bank credit to bank deposits is a measure of liquidity (see e.g. the discussion in Klomp and de Haan, 2012). The bank Z-score captures the (inverse of the) probability of default of a country's banking system, calculated as a weighted average of the Z-scores of a country's individual banks where a bank-specific Z-score compares a bank's buffers (capitalization and returns) with the volatility of those returns. From Figure 3.11, there is a statistically insignificant impact of shocks to the 'banking risk' factor on sovereign ratings and vice versa. Overall, these results suggest that NPLs dominate pooling-based information from measures of banking risk in driving credit rating decisions.[53]

We have also explored the impact of regulatory quality; this pools information from a number of variables such as investment and financial freedom, business regulatory environment, competition policy, tax inconsistency, financial institution's transparency, public sector openness to foreign bidders and easiness to start a new business.[54] To keep the dimensionality of the PVAR manageable, and noting that regulatory quality is a policy variable (more likely to affect than be affected by other economic or financial variables), we let it enter as an exogenous one. Doing so made no qualitative difference to the results reported earlier.[55]

## 3.5 Conclusions

This chapter examines the joint behavior of sovereign ratings and its macroeconomic/financial drivers within a multivariate Panel Vector AutoRegressive framework. Using a panel of 72 countries over the 1998-2016 period, several findings stand out. First, our model finds an important role for NPLs in affecting sovereign rating assessment over and above the effects of economic policy uncertainty, GDP growth, government debt-to-GDP ratio,

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[52] To ensure that an increase in the 'banking risk' factor indicates additional risk across countries, we have applied (at the country level) PCA to NPLs, bank credit to bank deposits, the inverse of bank capital to risk weighted assets and the inverse of bank Z-score.

[53] An alternative to PCA would involve running a country-specific dynamic factor model which relies, for instance, on the 4-variable dataset mentioned above to derive a latent banking risk factor. The country-specific time series information set is too short to pursue this option.

[54] For more details see http://info.worldbank.org/governance/wgi/pdf/rq.pdf.

[55] Jeanneret (2018) finds that government effectiveness as a measure of the ability of governments to collect and use fiscal revenues effectively leads to a reduction of sovereign credit spreads.

investment-to-GDP ratio, and the fiscal balance-to-GDP ratio. At the same time, sovereign rating decisions themselves affect NPLs. Intuitively, sovereign rating downgrades trigger bank rating downgrades which in turn lead to a reduction in lending supply and, at the same time, increase the burden of refinancing existing loans, therefore, triggering a rise in NPLs. Second, economic policy uncertainty shocks trigger sovereign rating downgrades following the financial turmoil and the subsequent Eurozone crisis.

By flagging the importance of rising NPLs as a vital banking risk factor, our model provides additional insight towards understanding how CRAs make their sovereign rating assessments. Both rising NPLs and increased policy uncertainty trigger sovereign rating downgrades that 'hit' investments and economic growth. With this in mind, it is in the interest of policymakers to be tackling policy uncertainty and NPLs, especially since rising NPLs, have been found themselves to undermine future economic growth (Balgova et al., 2016). This could be achieved by improving, for instance, governance indicators; indeed, Balgova et al. (2016) note that improved governance (as a measure of the quality of institutions) helps reduce NPLs and strengthen economic growth.

# 4. DO CREDIT RATINGS AFFECT FIRM OPERATIONAL EFFICIENCY? EVIDENCE FROM SOVEREIGN RATING DOWNGRADES

## 4.1 Introduction

A rating change, especially a downgrade, is always a concern for sovereigns, banks, and corporations. Despite the mass criticism related to their role in the global financial crisis and the Eurozone Debt crisis, investors still pay great attention to credit ratings in making their investment decisions. Anecdotal evidence shows that credit ratings affect corporate investment (Almeida et al., 2017) and innovation (Wang and Yang, 2019). What is not answered yet is whether credit ratings affect operational efficiency. Thus, the purpose of this chapter is to analyse the effect of credit rating downgrades on operational efficiency.

Firms always monitor credit rating agencies' decisions since the latter affect their access to financial markets and rating downgrades do not always remain unanswered from their chief staff. For example, Miguel Viana, CEO of EDP Energias de Portugal in 2011 conference call said: "*In terms of credit ratings, EDP recently suffered from downgrades by S&P and Moody's, penalized by the maximum notch differential allowed between EDP and Portugal Sovereign, so right now EDP is one notch above Portugal by S&P and two notches above Portugal by Moody's. Nevertheless, we consider that these by-the-book credit agencies methodologies are unable to reflect EDP's distinct credit profile, namely the geographical diversification, the high quality of our generation fleet, our resilient EBITDA, and the fact that our operations in Portugal have low sensitivity to the economic cycle.*" EDP Energias de Portugal was downgraded by S&P's from A- to BBB on March 28, 2011, following Portugal's sovereign rating downgrade from A- to BBB on the same day. EDP Energias de Portugal was unambiguously affected by the sovereign ceiling rule. On January 27 of the same year, S&P's downgraded Japan's sovereign rating from AA to AA-. Toyota Motor Corporation, one of the largest firms in the country, was affected, facing a rating downgrade from AA to AA- on March 4 of the same year. Mike Michels, Toyota spokesman said in a statement: "*The downgrade by S&P is regrettable and we do not take this rating change lightly. We aim to improve our rating by making the best management decisions we can while continuing to take care of our customers as our top priority. This will help us improve our profitability over the long-term*" (MarketWatch, 2011).[56] Both examples provide evidence that there is a link between sovereign and corporate rating downgrades and firms adjust their decisions and plans following credit rating downgrades. Moreover, Almeida et al. (2017) show that there is a clear discontinuity at the sovereign bound, in the sense that the probability a corporate issuer will be downgraded within a month following a sovereign downgrade is much higher for corporations rated equal to or above the corresponding sovereign relative to those rated below. Firms affected by a sovereign rating downgrade through the sovereign ceiling rule reduce their

[56] https://www.marketwatch.com/story/toyotas-profit-path-trips-sp-downgrade-2011-03-04

investment and reliance on credit markets due to a rising cost of debt (Almeida et al., 2017).

Performance measurement is at the heart of strategic management research. It is and should be one of the main priorities for every enterprise. It is also very important for every society that prioritizes the best use of available resources. Efficiency is typically defined as the maximization of outputs for a fixed level of inputs, or alternatively a minimization of inputs for a fixed level of outputs (Demerjian 2018). It encompasses several strategies and techniques used to accomplish the fundamental goal of delivering quality goods to customers in the most cost-effective and timely manner. Resource utilization, production, distribution, and inventory management are all common aspects of operational efficiency.

As mentioned above, the purpose of this chapter is to analyse the effect of credit rating downgrades on operational efficiency. We examine our main question by exploiting exogenous variation in credit ratings through the so-called sovereign ceiling rule. According to this policy, corporate credit ratings were bound by their corresponding sovereign rating, in the sense that sovereign rating acted as an upper bound for corporations and banks operating in that state. Although rating agencies moved officially away from this rule in the late ’90s, data and recent evidence (Almeida et al., 2017) show that corporate ratings are still bound to a large extent by sovereign ratings. Thus, sovereign rating downgrades lead to an asymmetric effect on corporate ratings through the sovereign ceiling rule. In that sense, the probability of being downgraded is much higher for firms bounded by the sovereign ceiling (treated firms) than those rated below their sovereign (control firms).

We then trace our main effect by comparing changes between firms with a rating equal or above their sovereign (treated firms) and firms rated below their sovereign (control firms) around a sovereign downgrade. We find some weak evidence of an adverse effect from credit rating downgrades on sales growth and ROA. More specifically, our difference in difference estimation in the matched sample analysis shows that Sales growth of firms with a rating equal to or above the corresponding sovereign (treated firms) drops by 1.38% more than Sales growth of firms rated below their corresponding sovereign (control firms) following a sovereign rating downgrade. However, we do not find any evidence from credit rating downgrades on the ratio of Sales to the Book value of Assets, the ratio of Sales to the book value of assets in place and the ratio of Selling, General and Administrative Costs to Sales.

Our results can be of interest for corporations since they show how and whether rating downgrades do matter for their efficiency, over and above the effect of macroeconomic fundamentals. They are also of interest to governments which should always consider the negative externalities of their sovereign downgrades on the corporate sector.

Rating agencies behaviour has not been stable over time. Baghai et al. (2014) show that rating agencies have become more conservative in assigning corporate credit ratings over the period 1985 to 2009; holding firm characteristics constant, average ratings have dropped by three notches. Firms affected more by conservatism issue less debt, have lower leverage, hold more cash, are less likely to obtain a debt rating, and experience lower growth. Furthermore, Alp (2013) provides evidence of a divergent pattern between investment-grade and speculative-grade rating standards from 1985 to 2002 as investment-grade standards tighten and speculative-grade loosen. She also shows a structural shift occurs toward more stringent ratings in 2002.

The chapter contributes to the very recent literature on the real effects of credit ratings on firm outcomes. Almeida et al. (2017) show that firms reduce their investment and reliance on credit markets due to a rising cost of debt capital following a sovereign rating downgrade. They find that firms with a rating equal or above their sovereign (treated firms) reduce investment significantly more than firms rated below their sovereign (control firms) following a sovereign downgrade. More specifically, average investment drops from 26.6% to 17.7% of capital, a reduction of 8.9 percentage points for treated firms while investment decreases only slightly from 19.2% to 16.6% of capital, a reduction of 2.6 percentage points. Investment is therefore reduced 6.4 percentage points more for treated firms than control firms, which is statistically and economically significant. They identify these effects by exploiting exogenous variation in corporate ratings due to rating agencies' sovereign ceiling policies, which require that firms' ratings remain at or below the sovereign rating of their country of domicile. Following the same identification strategy, Wang and Yang (2019) show that a sovereign downgrade leads to significant reductions in innovation among firms that have a rating at the sovereign bound ex-ante. The effect is more prolonged among firms with external finance dependence

The sovereign ceiling channel has also been prolonged in the banking sector. Adelino and Ferreira (2016) study the causal effect of bank credit rating downgrades on the supply of bank lending. They exploit the asymmetric impact of sovereign downgrades through the sovereign ceiling rule on bank ratings at the sovereign bound and they show that this asymmetric effect leads to more significant reductions in ratings-sensitive funding and lending of banks at the bound relative to other banks.

This chapter examines whether credit rating downgrades affect firm operational efficiency of firms rated at or above their corresponding country through the sovereign ceiling rule. A credit rating downgrade might affect operational efficiency through various channels. One the one hand, it might affect the weighted average cost of capital (WACC) a company faces and might turn new projects' net present value (NPV) from positive to negative. Moreover, it can create a substitution effect between bigger and smaller projects since the former might require funds that would not be approachable in a period of financial stress. Furthermore, credit rating downgrades can affect operational efficiency through capital structure. Almeida et. (2017) show that following rating downgrades companies issue less debt and more equity. Under the agency costs hypothesis, high leverage or a low equity/asset ratio reduces the agency costs of outside equity and increases firm value by constraining or encouraging managers to act more in the interests of shareholders (Berger and Di Patti, 2006). On the other hand, given the higher expected costs, firms would be more careful when deciding which project to invest in. Moreover, companies may also interpret a rating downgrade as a signal from rating agencies to change their main strategy. Bennett et al. (2019) show that management, directly or indirectly, learn from its own firm's stock price. In the same sense, management can also learn from credit rating changes and adjust its strategy accordingly. Based on the proceeding discussion, the effect of credit rating downgrades on operational efficiency is theoretically uncertain.

The chapter is structured as follows. Section 4.2.1 discusses the primary content of the sovereign ceiling rule, while section 4.2.2 explains our identification strategy. Section 4.2.3 provides details regarding the matching approach. Section 4.3 provides information regarding the dataset, whereas in section 4.4, we discuss the results of the linear regressions (4.4.1) and the difference in difference estimation (4.4.2). Finally, 4.5 contains concluding remarks.

## 4.2 Methodology

### 4.2.1 Sovereign Ceiling Rule

Credit ratings provide a measure of the probability that an entity will repay its debt obligations in full and on time. CRAs have been firstly criticized for not predicting Enron's default in 2001. In fact, they rated Enron's bonds as investment-grade—safe for many pension funds, that is—until shortly before the firm collapsed. They also failed to flag problems at WorldCom and Parmalat before they went bankrupt. They have also faced mass criticism for not predicting corporate defaults during the 2008 financial crisis and for accelerating the Eurozone sovereign debt crisis by massively downgrading Eurozone periphery bonds. Although they have been heavily criticized they are still broadly considered as a credible measure of countries', banks' and companies' financial performance and consequently set the tone for borrowing costs in international markets both for a sovereign state and the financial institutions operating in that sovereign state. Ratings are categorized into short and long term depending on the entity's maturity and into foreign and local depending on currency denomination. Following the previous literature, we focus on foreign currency long-term issuer ratings, which are most likely to be bound by the sovereign rating. There are three leading credit rating agencies, namely Standard & Poor's (S&P's), Moody's, and Fitch which control more than 90% of the market.

Credit rating agencies implemented a strict strategy of not providing a private company a foreign currency credit rating above the corresponding sovereign rating. This so-called "sovereign ceiling rule" was officially abandoned firstly by

S&P’s in April of 1997 for a number of dollarized Latin American economies. Fitch and Moody’s incorporated the same policy in 1998 and 2001 respectively. However, corporate ratings exceeding their corresponding sovereign rating are not commonly observable even after rating agencies relaxed the sovereign ceiling rule.

Credit rating agencies do not use only a firm’s ability and willingness to repay its debt in full and on time. Still, they also take into consideration other factors that can affect the issuer’s ability to fulfill its financial obligations in foreign currency. They consider the probability that capital and exchange controls might be imposed following a sovereign default. Two factors can lead to a corporate rating above the corresponding sovereign: strong adaptability to financial and economic disruptions typically following sovereign stress, as well as some degree of insulation and independence from the sovereign. For instance, firms with higher foreign sales, foreign assets, and foreign ownership are less likely to be bounded by the sovereign ceiling rule.

Globalization, financial integration, and innovation have led to multinational corporate world. A more significant percentage of corporations become more export-oriented, hold more foreign assets in other countries, are owned and sometimes managed by foreign investors. That explains why CRA has recently updated its methodologies to address some of the limitations of the previous approach. For instance, The Standard & Poor’s Rating Services (2013) methodology can be summarized as follows. An entity can be rated above the sovereign foreign currency rating if, in their view, there is a significant likelihood that it would not default if the sovereign were to default. They first determine the entity's potential rating, which they compare with the sovereign foreign currency rating on the country (or countries) where the entity has material exposure(s). Standard & Poor's clearly states that the sovereign rating does not act as a "ceiling" for ratings. However, when rating an entity above the sovereign foreign currency rating, Standard & Poor's (2013) is expressing its view that the entity has sufficient creditworthiness to withstand a sovereign default. Therefore, they apply a hypothetical sovereign foreign currency default stress scenario (stress test). This stress test is applied with respect to the country (or countries) where the entity has material concentration(s) of exposure and where the potential rating would exceed the foreign currency rating on the sovereign. Firms that pass the stress test can be rated up to two or four notches above the sovereign rating, depending on whether S&P’s views their sector’s sensitivity to country risk as high or moderate, respectively. As a result of the updated methodology, Standard & Poor's (2013) expects a few entities to be affected by corporate and project finance ratings. This suggests that S&P’s issued conservative ratings to some firms due to the sovereign ceiling before the recent revision of the methodology (Almeida et al. 2017).

### 4.2.2 Identification Strategy

The main challenge in examining the effect of sovereign credit ratings on operational efficiency and more broadly on firm outcomes is the inherent endogeneity among the sovereign's creditworthiness, a firm's credit quality and firm outcomes. In other words, the credit rating may affect operational efficiency and other firm outcomes, but at the same time, it may be affected by them. Endogeneity is, arguably, one of the most critical and pervasive issues confronting studies in empirical corporate finance. Endogeneity leads to biased and inconsistent parameter estimates that make reliable inference virtually impossible. In many cases, endogeneity can be severe enough to reverse even qualitative inference (Roberts and Whited 2013). Three primary sources can lead to endogeneity; omitted variable bias, simultaneity, and measurement error. Omitted variables bias refers to those variables that should be included in the vector of explanatory variables, but for various reasons are not. Simultaneity bias occurs when the dependent variable and one or more of the independents are determined in equilibrium so that it can plausibly be argued either that one of the independents causes the dependent or that dependent causes one of the independents. Finally, a measurement error occurs when one or more of the variables are measured imperfectly. It arises due to the fact that most empirical studies in corporate finance use proxies for unobservable or difficult to quantify variables. When variables are measured imperfectly, the measurement error becomes part of the regression error.

Following Almeida et al. (2017) we tackle endogeneity in our empirical analysis by examining the differential effect of sovereign rating changes on firms that are limited by the sovereign ceiling (treated firms) and on other firms in the same country that are not limited by the sovereign ceiling (nontreated firms). In particular, we compare firms which have a rating equal to or above the corresponding sovereign (treated firms) with similar firms which have a lower rating than the corresponding sovereign (nontreated firms).

Almeida et al. (2017) show that there is a clear discontinuity at the sovereign bound, in the sense that the probability a corporate issuer will be downgraded within a month following a sovereign downgrade is much higher for corporations rated equal to or above the corresponding sovereign relative to those rated below. Consequently, treated firms have a significantly higher probability of being downgraded than nontreated firms following a sovereign downgrade. For example, our dataset includes 230 treated and 1873 non treated firm-year observations from the same countries in a year of a sovereign downgrade. If the sovereign ceiling didn't hold, following a sovereign downgrade, the probability of being downgraded would not have been different between treated and non treated firms. However, 141 of treated firms (62%) are downgraded within one year while only 238 of non treated firms (13%) are downgraded during the same period. Thus, our dataset confirms an apparent discontinuity because of the sovereign ceiling rule. To test even further the robustness of our identification strategy, we compare changes on corporate ratings between treated and non treated firms around sovereign rating downgrade. Following Almeida et al., we transform credit ratings from letters to numbers using a linear transformation, starting from 22 for the highest rated companies (AAA) to 1 for default (SD/D). Table 4.1 presents the linear transformation of credit ratings from letters to numbers, while Table 4.2 displays the difference in difference estimation on corporate ratings around a sovereign rating downgrade. Following a sovereign downgrade, treated firms experience an average drop of 2.7 notches, while non treated firms face only a decline of 0.3 notches. The difference between them (2.4 notches) is statistically an economically significant and enhances our hypothesis. A reasonable concern is that this discontinuity may be driven by factors other than the sovereign ceiling rule. For instance, it could be argued that the deterioration of economic conditions is responsible for that discontinuity. It can only happen if macroeconomic changes increase credit risk only for bound firms. In fact, if there were any differential macroeconomic effects, better-quality firms (treatment group) should be less affected than poorer-quality firms (control group) (Almeida et al. 2017).

To sum up, data show that sovereign ceiling rule is still implemented, at least to some extent, following a sovereign downgrade. So, the effect on operational efficiency across treated and nontreated firms following a sovereign downgrade should derive from changes in ratings and not from differences in firm fundamentals.

### 4.2.3 Matching Approach

We examine whether sovereign rating downgrades affect the operational efficiency of bounded firms around a sovereign rating downgrade through the sovereign ceiling channel. We incorporate the Abadie and Imbens (2011) estimator, as introduced by Abadie et al. (2004). We follow this estimator in order to take into consideration the fact that treated and nontreated firms may have different observable characteristics. The main idea of the matching estimator can be summarized as follows. The set of counterfactuals is restricted to the matched controls, that is, in the absence of the treatment (in our context, sovereign downgrades), the treatment group would behave similarly to the control group (Almeida et al., 2017).

The matching procedure works as follows. The first step is to isolate firms which prior to the sovereign downgrade had a rating equal or above the corresponding sovereign rating (treated firms). The second step is to look for identical firms from the same country which before the sovereign downgrade rated below the relevant sovereign rating (control firms). So, we then match each treated firm with an identical control firm along multiple categorical (year and country) and non-categorical (firm size, investment, Tobin’s Q, cash flow, cash, leverage) variables. We require a perfect match on categorical and a less exact but very close match on noncategorical variables[57]. We then compare the differences in the outcome variables between the matched treated and control group around a sovereign rating downgrade.

### 4.3 Data construction and summary statistics

The sample consists of firms from 81 countries from 1990 to 2017. Financial firms (SIC Code 6000-6999) are excluded because they follow different financial policies. More specifically, we cannot compare leverage ratios between financial and non-financial firms. We obtain firm accounting data from WRDS Compustat, Compustat Global and Datastream and sovereign and corporate credit ratings (foreign currency long-term issuer ratings) from Bloomberg. We match firms between databases using International Securities Identification Number (ISIN), Stock Exchange Daily Official List (SEDOL), Committee on Uniform Securities Identification Procedures (CUSIP) and Company Name. In particular, we match US and Canadian firms using CUSIP and Company Name and International firms using ISIN, SEDOL, and Company name. The initial sample consists of 482,289 firm-year observations and 49,449 different firms. Only a small percentage of these companies has a rating (37,948 firm-year observations for 3,953 unique firms).

Table 4.3 presents the total number of treated firm-year observations by country and year. There is initially a total of 230 treated firms from 25 individual countries. Treated firms appear both in developed markets (such as Italy and Japan) and emerging market countries (such as Argentina, Brazil, and Russia). Many countries have faced multiple sovereign rating downgrades from 2000 to 2017. For example, Italy has been downgraded 6 times, Portugal 3 times and Brazil 5 times. Thus, some firms have been affected more than once from a sovereign rating downgrade through the sovereign ceiling rule.

We measure operational efficiency with the following six proxies broadly incorporated in the literature (Mitton 2006). Asset turnover defined as the ratio of total sales to total assets. We also incorporate the ratio of Sales to the value of assets in place (VAIP) as calculated in Loderer et al. (2017) and the ratio of Selling, general and administrative costs to total sales. Moreover, we employ Sales growth defined as the natural logarithmic difference of total sales, Return on Assets defined as the ratio of Earnings before interest, taxes, depreciation and amortization to total assets and finally Operating return on Assets defined as the ratio of Earnings before interest and taxes to total assets.

[57]We implement the matching estimator using the Stata command nnmatch. A detail we need to treat very carefully regarding exact matching in categorical variables is that the code does not automatically limit the match to be exact, but instead gives a weight of 1,000 (instead of one) for the categorical variables for which we request an exact match. For instance, the code may find an observation from the control group from Argentina in 2001 that minimizes the (Mahalanobis) distance for the vector of observed covariates for one treated observation from Brazil during the same year. In our application, we drop treated firms for which we are unable to find a perfect match in the same country and year.

We match treated and non treated firms in several covariates namely firm size, investment, Tobin's Q, cash flow, cash, and leverage. Size is defined as the logarithm of total assets(Compustat item AT - Datastream item WC02999), Investment is defined as the ratio of annual capital expenditures (Compustat item CAPX - Datastream item WC04601) to lagged net property, plant, and equipment (Compustat item PPENT - Datastream item WC02501), Tobin's Q is defined as the ratio of total assets plus market capitalization minus common equity (Compustat item CEQ - Datastream item WC03501) to total assets and Cash Flow is defined as the ratio of annual operating income (Compustat item OIBDP - Datastream item WC18155) plus depreciation and amortization (Compustat item DP - Datastream item WC01151) to lagged total assets. A detailed explanation of every variable is provided in table 4.4

In addition, we require firms to match on year and country of domicile perfectly. In other words, we ensure that treated and control firms are exposed to the same sovereign rating downgrade and any other country-level shocks. Finally, we only match treated firms with rated non-treated firms. This is essential because we cannot assume that non rated firms would have been in the control group if they had a rating.

We drop observations with missing values and treated firms that do not match exactly with a firm from the control group of the same country during the same year. As a result, we end up with 64 treated firm-year observations. The list of perfectly matched treated firm-year observations is presented in table 4.5 whereas summary statistics are provided in table 4.6. We compare mean and median between treated and control firms, but we also report summary statistics of all rated and non rated firms. In general, rated firms are bigger, more leveraged and have higher investment ratios. The goal of the matching estimator is to take into account those distributional differences, which could bias posttreatment outcomes. The Abadie–Imbens matching estimator identifies a match for each firm-year observation in the treatment group. We thus have 64 firm-year observations in both groups, but because matching is done with replacement, in the sense that one observation can be used more than once as a control in matching, we have 40 unique firm-year observations in the control group. The similarity of the mean and the median of the covariates between treated and control firms guarantees the appropriateness of the matched treated control sample. All the above things considered, we ensure that changes in the outcome variable are driven by sovereign rating downgrades.

## 4.4 Results

### 4.4.1 Linear Regression results

We examine the effect of credit rating downgrades on the operational efficiency of treated firms using the following regression model.

$$Efficiency_{i,t}=\alpha+\beta_1*SovereignDowngrade_{i,t}+\beta_2*Bound_{i,t-1}+\beta_3*SovereignDowngrade_{i,t}*Bound_{i,t-1}+\gamma X_{i,t-1}+\delta_i+\delta_t+\varepsilon_{i,t} \quad (4.1)$$

Where *i* indexes firm and *t* indexes year. Efficiency is one of the six measures we incorporate in year *t*.[58] *Sovereign Downgrade* is a dummy variable that takes the value of 1 in the year of the sovereign downgrade and *Bound* is a dummy variable that takes the value of 1 if the firm has a rating equal or above its country of domicile. *Sovereign Downgrade*Bound* is the product of the sovereign rating downgrade dummy and the lag of the bound firm dummy since we examine the effect on firms that had a rating equal or above their country of domicile *prior* to the sovereign rating downgrade. Finally, $X_{i,t-1}$ is the vector of firm-level control variables, $\delta_t$ captures year fixed effects and $\delta_i$ firm fixed effects.

The coefficient of interest is the interaction term *SovereignDowngrade*Bound*, representing the difference in difference in operational efficiency between treated firms and nontreated firms following a sovereign downgrade relative to the difference before the downgrade. We also include a set of control variables commonly used in the corporate finance literature to account for the time-varying differences across firms. We control for firm Size, Tobin's Q, Investment, Cash, Cash Flow, and Leverage.

Tables 4.7 – 4.12 report the estimates of equation 4.1 for each measure of operational efficiency. Each table incorporates 5 columns. Column1 presents the simple DiD effect without Firm/Year fixed effects. Column 2 shows the effects of using only Firm FE, whereas column 3 includes both Firm and Year fixed effects. Moreover, column 4 presents the results, including Firm fixed effects and control variables and column 5 includes Firm and Year fixed effects as well as control variables.

Table 4.7 presents the effect of sovereign rating downgrades on Asset Turnover of treated firms. The coefficient of interest is always positive and statistically insignificant, showing that there is no effect of sovereign rating downgrades on Asset turnover of treated firms through the sovereign ceiling channel. Table 4.8 examines the impact of credit rating downgrades on Sales growth. *The SovereignDowngrade*Bound* variable of interest is negative and statistically important in column 2. For instance, column 2 suggest that sales growth of treated firms drop by 24% relative to non treated firms following a sovereign rating downgrade. However, the effect disappears once we add Year fixed effects and/or control variables.

In table 4.9, we display the result of the linear regression on Sales to Value of Assets in Place of firms that have a pre-downgrade rating at or above the sovereign bound (i.e., treated firms) relative to non treated firms. Not surprisingly, the

[58] We have also examined the effect in year $_{t+1}$, in the sense that rating downgrades might affect operational efficiency with a lag, but the results do not differ significantly.

coefficient of the variable of interest is insignificant, indicating no evidence of the sovereign ceiling rule effect on Sales to VAIP.

Next, we examine the effect of sovereign downgrades on SGA to Sales ratio. This ratio usually employed as a proxy of agency cost in the literature (Florackis, 2008), serves as a proxy of the inverse of operational efficiency. In that sense, an increase in the SGA to sales ratio means that a firm becomes less efficient since its expenses increase more for every extra unit of sales. The coefficient of interest in column 1 of Table 4.10 shows that Selling, General and Administrative Expenses to Sales increase more for treated firms relative to non-treated, following the sovereign rating downgrade. However, the impact does not exist when we add Firm/Year fixed effects and or control variables.

Finally, tables 4.11 and 4.12 display the effect of the coefficient of interest on Return on Assets and Operating Return on Assets respectively. Column 1 in both tables shows that ROA/OROA of treated firms drops by around 7% more relative to nontreated firms. Unfortunately, the effect is opaque since it disappears once we add Firm/Year fixed effects and or control variables.

### 4.4.2 Difference in difference results on the treated-control matched sample

Our linear regressions reported some weak evidence of an effect of rating downgrades on operational efficiency. However, the linear regression results might be affected from the differences between treated and non treated firms. Consequently, we perform a matched sample analysis in order to take into consideration these concerns. We match each treated firm with an identical control firm along multiple categorical (year and country) and non-categorical (firm size, investment, Tobin's Q, cash flow, cash, leverage) variables. We require a perfect match on categorical and a less exact but very close match on noncategorical variables, and we then compare the differences in the outcome variables between the matched treated and control group around a sovereign rating downgrade.

Tables 4.13 – 4.18 report the difference in difference estimates in each proxy of operational efficiency around a sovereign rating downgrade between treated and control firms. In line with linear regression results, we do not find statistically significant differences in 5 out of 6 operational efficiency measures between treated and control firm-year observations around a sovereign downgrade. We only see a differential effect in Sales growth between treated and control firms around a sovereign downgrade. Table 4.14 presents a difference-in-differences matching estimator in Sales growth around a sovereign downgrade. For firms in the treatment group, average Sales growth drops from 8.6% to 7.85%, a reduction of 0.75 percentage points. For control firms, Sales growth increases slightly from 7.07% to 7.70%, an upgrade of 0.63 percentage points. Sales growth is therefore reduced by 1.38% more for treated firms than control firms, which is statistically and economically significant.

Tables 4.13 and 4.15-4.18 report very small differences between treated and control firms around the sovereign downgrade but these differences are not statistically and economically important. For example, table 4.17 shows that Return on Assets of treated firms drops by 2.6% from 15 to 12.4 percentage points. At the same time, Return on Assets of control firms drops by 2.3% from 13.2 to 10.9 percentage points. As a result, Return on Assets drops by only 0.3% more for treated firms than control firms, which is neither economically nor statistically significant.

To conclude, linear regression results and differences in differences matching estimators present only opaque evidence of an effect of sovereign rating downgrades on operational efficiency.

## 4.5 Conclusion

Our work examines a novel channel through which financing might affect operational efficiency. We only find weak evidence that sovereign rating downgrades can affect operational efficiency through the sovereign ceiling channel. In particular, we show that Sales growth of firms with a rating equal to or above the corresponding sovereign drop by 1.38% more than Sales growth of firms rated below their corresponding sovereign following a sovereign rating downgrade. We exploit exogenous variation on corporate ratings from sovereign rating downgrades through the sovereign ceiling rule. This exogenous variation lets us identify a causal relationship between credit ratings and operational efficiency.

The absence of robust evidence may arise from several reasons. First of all, as mentioned above, there are theoretically 3 different channels through which credit ratings affect operational efficiency. Thus, it possible that these channels neutralize each other and make the total effect insignificant. Secondly, the result may also be driven by the small number of treated firms. Finally, the results may be affected from the financial ratios used as proxies of operational efficiency

Future work in this area could focus on more advanced operational efficiency measures to tackle the latter. For example, Stochastic Frontier Analysis and Data Envelopment Analysis which belong to the group of frontier methodologies can be incorporated to clarify the effect of credit rating downgrades on operational efficiency. Moreover, future work could also examine whether sovereign downgrades affect other corporate policies. Managers may use earnings management to dampen the adverse consequences of rating downgrades. It is also possible that firms affected by sovereign rating downgrades focus on their economic and financial performance setting aside environmental and corporate policies.

# 5. CONCLUSION AND DIRECTIONS FOR FURTHER RESEARCH

## 5.1. Conclusion

This thesis consists of three essay-style chapters in sovereign and corporate credit ratings. Chapter 2 studies the impact of economic policy uncertainty on sovereign credit rating decisions made by the three leading rating agencies namely Moody's, Standard and Poor's and Fitch for the Eurozone Economies from 2002 to 2015. In doing so, we implement a panel quantile regression that allows us to observe the relative importance of quantitative and qualitative factors across the conditional distribution of sovereign credit ratings. Our results can be summarized as follows. Economic policy uncertainty negatively affects credit ratings across the conditional distribution; however, the impact is more prolonged on the lower rated countries. Moreover, the unemployment rate, regulatory quality and competitiveness have a stronger impact on low rated countries whereas GDP per capita is a major driver of high rated countries. We then quantify the negative effects of uncertainty on credit ratings by using estimates of our model under uncertainty to infer what credit ratings would have been had uncertainty remained at its 2002-2007 pre-financial and pre-European debt crisis average value. We find that economic policy uncertainty in the Euro area has reduced Greece's credit rating by around 3 notches at the height of the Eurozone crisis in 2011 and 2012; the impact of uncertainty has been substantial but somewhat less severe for the remaining GIIPS and Cyprus.

Chapter 3 analyses the bidirectional relationship between sovereign credit ratings and non-performing loans over and above the impact of their remaining fundamentals namely economic policy uncertainty, GDP growth, Investments, Government Debt and Fiscal Balance in a Panel VAR for 72 countries from 1998 to 2017. Our generalized impulse response functions identify a significant and persistent effect of NPLs on sovereign credit ratings and vice versa. Our results are robust to a logistic transformation of sovereign ratings to numbers and alternative measures of uncertainty and banking risk.

Finally, in chapter 4, we examine the adverse consequences of sovereign rating downgrades on firms' operational efficiency. We approach our main question by exploiting exogenous variation in sovereign credit ratings through the so-called sovereign ceiling rule. We then trace our main effect by comparing the differential effect of sovereign rating changes on firms that are limited by the sovereign ceiling (treated firms) and on other firms in the same country that are not limited by the sovereign ceiling (nontreated firms). In particular, we compare firms which have a rating equal to or above the corresponding sovereign (treated firms) with similar firms which have a lower rating than the corresponding sovereign (nontreated firms). We match treated and non treated firms in several categorical and non categorical covariates namely firm size, investment, Tobin's Q, cash flow, cash, leverage, Country of Domicile and Year. Our linear regressions identify a negative effect from credit rating downgrades on sales growth and ROA, while we do not find any evidence from credit rating downgrades on the ratio of Sales to the

Book value of Assets, the ratio of Sales to the book value of assets in place and the ratio of Selling, General and Administrative Costs to Sales. Moreover, our difference in difference estimation in the sample analysis shows that Sales growth of firms with a rating equal to or above the corresponding sovereign drop by 1.38% more than Sales growth of firms rated below their corresponding sovereign following a sovereign rating downgrade.

## 5.2 Directions for further research

We now discuss some directions for further research that extend the work that has been done during this thesis.

### 5.2.1 The possible impact of liquidity injections

What we have not considered in chapter 2 is the possible impact (if any at all) of liquidity injections put forward by the ECB in terms of purchases and holdings of securities for monetary policy purposes from 2009 onwards (see the discussion in Lo Duca et al., 2016) and post-2014 Quantitative Easing support (see e.g. the discussion in Koijen et al., 2016) on Eurozone's sovereign credit ratings. If, for instance, these types of policies provide a 'signal' that Eurozone's economic recovery is, at best, shaky, CRAs might become more reluctant to proceed with a number of sovereign upgrades. The counter-argument, of course, is that ECB's policies might have safeguarded against deteriorating economic conditions, therefore preventing additional sovereign downgrades over the recent years. We intend to explore these issues in future research.

### 5.2.2 Using CDS instead of credit ratings

The focus of chapter 3 has been on sovereign ratings. Credit Default Swaps provide a market-based measure of sovereign risk which is available at a higher frequency. Whether this links in the same manner as sovereign ratings to the lower frequency information set of fundamentals employed in our chapter is an interesting avenue of future research that could be addressed through e.g. mixed data sampling (MIDAS) models. [59] Future research could also focus on the potential role of state-owned versus private banks. For instance, Gonzalez-Garcia and Grigoli (2013) find that a larger presence of state-owned banks in the banking system is associated with more credit to the public sector, larger fiscal deficits, higher public debt ratios, and higher NPLs because these tend to be more sensitive to political interests if governance in these banks is weak. In addition, state-owned banks appear to have a higher fraction of NPLs loans than privately-owned banks and tend to display a higher likelihood of default (see the discussion in Cull et al., 2017 and references therein). These findings open up the possibility of exploring the interconnections among debt, NPLs and ultimately credit rating decisions in a panel VAR model which controls for governance indicators and a distinction

[59] Berndt et al. (2018) show that CDS in the US corporate sector comove with macroeconomic indicators (namely the 5-year Treasury rate and the University of Michigan consumer sentiment index).

between state-owned and private banks. Finally, it could be interesting to try to identify and investigate additional factors that credit rating agencies do not consider in their sovereign rating models but that could be used to further improve their models. For example, models used by sophisticated investors could highlight important factors neglected by rating agencies' models; also, market prices of traded instruments linked to sovereign risk could reflect investors' expectations about changes in the default likelihood of a sovereign. We intend to return to these issues in future research.

### 5.2.3 Using stochastic frontier analysis and data envelopment analysis

In chapter 4 we have incorporated 6 financial ratios as measures of operational efficiency. A potential extension on chapter 4 would be to integrate data envelopment analysis (DEA), which belongs to the group of frontier methodologies, in order to measure operational efficiency. In frontier methodologies, a firm's performance is measured in terms of distance from the industry's efficient frontier. In the DEA program, observations (termed decision-making units or DMUs) are sorted into groups based on commonality in production technology or operations (termed the calculation group) (Demerjian 2012). The efficient frontier is a function that indicates the maximum attainable level of output corresponding to a given quantity of input (Cheng et al., 2018). The frontier methodologies have proved particularly useful when firm performance is characterized by multiple dimensions with different units of analysis. A key strength of DEA lies in its capability to simultaneously incorporate multiple inputs and outputs, a requirement for analysis of many industries and for studies that seek to incorporate nonfinancial measures of performance (Cheng et al., 2018). DEA combines the ratio of outputs to inputs to create an efficient frontier of production based on an optimization program to maximize operational efficiency. The main drawback of the DEA approach is that it is not restricted to a definite functional form for the relationship between inputs and outputs. Additionally, it is non-parametric and optimal weightings are derived from the dataset used and are not assigned a priori. The DEA program calculates an efficiency score for each DMU in the calculation group, with scores ranging from zero to one. The operational efficiency of a company is relatively compared to those companies located on the efficient frontier which creates an ordinal ranking of firms. For example, the most efficient firm is that one that produces the maximum level of output given the level of inputs or uses the minimum level of inputs given the level of outputs. After solving an optimization program for each firm within an estimation group, the DEA analysis standardizes efficiency scores so that the most (least) efficient firms are assigned a value of one (zero) (Cheng et al. 2018). All in all DEA could shed some extra light on the question examined in chapter 4.

### 5.2.4 Sovereign rating downgrades and earnings management.

In chapter 4, we have shown have how operational efficiency can be affected by sovereign rating downgrades through the sovereign ceiling channel. However, operational efficiency is not the only firm outcome or policy that can be affected by credit rating downgrades. Examples provided above show that firms take rating downgrades very seriously into their strategies. Firms may look for options that could dampen the harmful effects of rating downgrades. Earnings management is one option that could abbreviate the adverse impact of rating downgrades of firm performance.

Earnings management may be defined as "reasonable and legal management decision making and reporting intended to achieve stable and predictable financial results. Stein and Wang (2016) document that firms report more negative discretionary accruals when financial markets are less certain about their prospects. The period following a rating downgrade is usually a period with high uncertainty, so firms may opportunistically shift earnings following a rating downgrade. This project can highlight a new channel through credit rating decisions affect earnings management.

#### 5.2.5 Sovereign rating downgrades and corporate social responsibility.

During recent decades our world has realized to a vast extent the necessity to protect the environment. Within this framework, a new aspect of Finance has erased. The so-called sustainable finance has exploded, with a strong appetite from investors and policymakers. Firms are now taking actions to protect the environment and benefit the society. Among these actions is the bond issuance for environmental projects, the so-called green bonds. Flammer (2018) documents that green bonds yield positive announcement returns, improvements in long-term value and operating performance, gains in environmental performance, increases in green innovations, and an increase in ownership by long-term and green investors. As a result, firms are now assessed by independent organizations that report environmental and social scores for them. As mentioned above, the period following a rating downgrade is usually a period with high uncertainty. Firms usually put more emphasis on their financials. So we can hypothesize that rating downgrades would lead to a substitution effect between financials and corporate social responsibility in the sense that firms put less emphasis on their environmental and social actions following a credit rating downgrade. The effect might be more prolonged for firms with lower institutional ownership since recent research shows that across 41 countries, institutional ownership is positively associated with environmental and social performance (Dyck et al., 2019).

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## Table 2.1: Linear transformation of sovereign ratings

| | Rating Agency | | | | Rating Grades (1-21) |
|---|---|---|---|---|---|
| | Fitch | S&P's | Moody's | Outlook | |
| Highest quality | AAA | AAA | Aaa | Stable | 21 |
| | | | | Negative | 20.67 |
| | | | | Positive | 20.33 |
| | AA+ | AA+ | Aa1 | Stable | 20 |
| | | | | Negative | 19.67 |
| | | | | Positive | 19.33 |
| High quality | AA | AA | Aa2 | Stable | 19 |
| | | | | Negative | 18.67 |
| | | | | Positive | 18.33 |
| | AA- | AA- | Aa3 | Stable | 18 |
| | | | | Negative | 17.67 |
| | | | | Positive | 17.33 |
| | A+ | A+ | A1 | Stable | 17 |
| | | | | Negative | 16.67 |
| | | | | Positive | 16.33 |
| Strong payment | A | A | A2 | Stable | 16 |
| capacity | | | | Negative | 15.67 |
| | | | | Positive | 15.33 |
| | A- | A- | A3 | Stable | 15 |
| | | | | Negative | 14.67 |
| | | | | Positive | 14.33 |
| | BBB+ | BBB+ | Baa1 | Stable | 14 |
| | | | | Negative | 13.67 |
| Adequate payment | | | | Positive | 13.33 |
| capacity | BBB | BBB | Baa2 | Stable | 13 |
| | | | | Negative | 12.67 |
| | | | | Positive | 12.33 |
| | BBB- | BBB- | Baa3 | Stable | 12 |
| | | | | Negative | 11.67 |
| | | | | Positive | 11.33 |
| | BB+ | BB+ | Ba1 | Stable | 11 |
| | | | | Negative | 10.67 |
| Likely to fullfill | | | | Positive | 10.33 |
| obligations, ongoing | BB | BB | Ba2 | Stable | 10 |
| uncertainty | | | | Negative | 9.67 |
| | | | | Positive | 9.33 |
| | BB- | BB- | Ba3 | Stable | 9 |
| | | | | Negative | 8.67 |
| | | | | Positive | 8.33 |
| | B+ | B+ | B1 | Stable | 8 |
| | | | | Negative | 7.67 |
| | | | | Positive | 7.33 |
| High credit risk | B | B | B2 | Stable | 7 |
| | | | | Negative | 6.67 |
| | | | | Positive | 6.33 |
| | B- | B- | B3 | Stable | 6 |
| | | | | Negative | 5.67 |
| | | | | Positive | 5.33 |
| | CCC+ | CCC+ | Caa1 | Stable | 5 |
| | | | | Negative | 4.67 |
| | | | | Positive | 4.33 |
| Very high credit | CCC | CCC | Caa2 | Stable | 4 |
| risk | | | | Negative | 3.67 |
| | | | | Positive | 3.33 |
| | CCC- | CCC- | Caa3 | Stable | 3 |
| | | | | Negative | 2.66 |
| Non default wih | CC | CC | Ca | | 2.33 |
| possibility of recovery | C | | | | 2 |
| Default | DDD | SD | C | | |
| | DD | D | | | 1 |
| | D | | | | |

**Table 2.2: Data definitions and sources**

Data Definitions

| Variable Name | Definition | Source |
|---|---|---|
| Fitch rating | Sovereign rating attributed at 31st December of each year | Fitch |
| S&P's rating | Sovereign rating attributed at 31st December of each year | S&P's |
| Moody's rating | Sovereign rating attributed at 31st December of each year | Moody's |
| GDP per capita | Log GDP per capita, US dollars, constant 2005 prices | World Bank |
| Government debt | General government gross debt as a percent of GDP | IMF WEO |
| Current account balance | Current account balance as a percent of GDP | IMF WEO |
| Unemployment Rate | Unemployment rate as a percent of total labor force | IMF WEO |
| Inflation Rate | Annual growth rate of consumer price index | IMF WEO |
| Regulatory Quality | Aggregate government indicator | World Bank |
| Competitiveness Indicator | Harmonised competitiveness indicator based on unit labour costs indices for the total economy | ECB |
| European Policy Uncertainty | Eurozone's countries average | www.policyuncertainty.com |

**Table 2.3: Estimates for Moody's**

| Dependent Variable: Moody's rating | Log GDP per capita | | Government Debt | | Current Account | | Inflation Rate | | Unemployment Rate | | Regulatory Quality | | Competitiveness | | Uncertainty | | AIC | Pseudo $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| quantile | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | | |
| 0.05 | **-1.1960** | 0.000 | **-0.0264** | 0.000 | **0.1159** | 0.000 | **0.2609** | 0.000 | **-0.3202** | 0.000 | **4.3321** | 0.000 | **-0.0467** | 0.000 | **-0.0325** | 0.000 | 9.207 | 0.585 |
| 0.10 | **-0.6623** | 0.000 | **-0.0384** | 0.000 | **0.0604** | 0.000 | **0.0332** | 0.000 | **-0.3341** | 0.000 | **4.3158** | 0.000 | **-0.0360** | 0.000 | **-0.0158** | 0.000 | 9.072 | 0.594 |
| 0.15 | **0.6975** | 0.000 | **-0.0370** | 0.000 | **0.0077** | 0.000 | **-0.0027** | 0.000 | **-0.2744** | 0.000 | **4.1139** | 0.000 | **-0.0349** | 0.000 | **-0.0119** | 0.000 | 8.804 | 0.608 |
| 0.20 | **3.1277** | 0.000 | **-0.0387** | 0.000 | **-0.0508** | 0.000 | 0.0034 | 0.864 | **-0.2400** | 0.000 | **4.1229** | 0.000 | **-0.0313** | 0.000 | **-0.0117** | 0.000 | 8.049 | 0.627 |
| 0.25 | **4.6216** | 0.000 | **-0.0449** | 0.000 | **-0.0196** | 0.014 | **-0.0680** | 0.000 | **-0.1907** | 0.000 | **3.3931** | 0.000 | **-0.0329** | 0.000 | **-0.0175** | 0.000 | 7.426 | 0.639 |
| 0.30 | **5.4820** | 0.000 | **-0.0372** | 0.000 | **-0.0377** | 0.000 | 0.0410 | 0.203 | **-0.1181** | 0.000 | **4.1231** | 0.000 | **-0.0341** | 0.000 | **-0.0109** | 0.000 | 7.528 | 0.625 |
| 0.35 | **4.8628** | 0.000 | **-0.0412** | 0.000 | **-0.1542** | 0.011 | **-0.1530** | 0.024 | **-0.1286** | 0.000 | **3.2106** | 0.000 | **-0.0251** | 0.000 | **-0.0307** | 0.000 | 7.345 | 0.575 |
| 0.40 | **3.3678** | 0.000 | **-0.0082** | 0.000 | **-0.0739** | 0.001 | 0.0221 | 0.576 | **-0.2136** | 0.000 | **4.4561** | 0.000 | **-0.0484** | 0.000 | **-0.0136** | 0.000 | 7.884 | 0.584 |
| 0.45 | **4.3645** | 0.000 | 0.0089 | 0.153 | **-0.0789** | 0.000 | -0.0111 | 0.694 | **-0.2083** | 0.000 | **4.0718** | 0.000 | **-0.0294** | 0.000 | **-0.0191** | 0.000 | 7.092 | 0.533 |
| 0.50 | **3.7006** | 0.000 | 0.0032 | 0.337 | **-0.0226** | 0.000 | **-0.1233** | 0.000 | **-0.2119** | 0.000 | **2.4526** | 0.000 | **-0.0156** | 0.000 | **-0.0140** | 0.000 | 7.505 | 0.554 |
| 0.55 | **4.4081** | 0.000 | **-0.0097** | 0.000 | **0.0050** | 0.029 | **-0.0834** | 0.000 | **-0.2319** | 0.000 | **1.6651** | 0.000 | **-0.0325** | 0.000 | **-0.0158** | 0.000 | 7.621 | 0.589 |
| 0.60 | **6.7502** | 0.000 | **-0.0272** | 0.000 | **-0.0347** | 0.056 | 0.0363 | 0.213 | **-0.2010** | 0.000 | **1.9421** | 0.000 | **-0.0263** | 0.000 | **-0.0062** | 0.001 | 8.069 | 0.627 |
| 0.65 | **6.9493** | 0.000 | **-0.0168** | 0.000 | **-0.0641** | 0.000 | **-0.2221** | 0.000 | **-0.2727** | 0.000 | **0.6950** | 0.000 | 0.0036 | 0.656 | **0.0091** | 0.070 | 8.414 | 0.519 |
| 0.70 | **8.4967** | 0.000 | **-0.0246** | 0.000 | **-0.0411** | 0.000 | **-0.1600** | 0.000 | -0.0403 | 0.163 | **0.9713** | 0.001 | **-0.0100** | 0.000 | **-0.0042** | 0.000 | 8.736 | 0.519 |
| 0.75 | **9.7634** | 0.000 | **-0.0308** | 0.000 | **-0.0263** | 0.025 | **-0.1112** | 0.011 | 0.0133 | 0.629 | 0.3437 | 0.180 | **-0.0201** | 0.000 | **-0.0076** | 0.002 | 8.889 | 0.495 |

Notes: Figures in bold indicate significance at the 10% level or lower. AIC is the Akaike Information Criterion.

## Table 2.4: Estimates for S&P's

**Dependent Variable: S&P's rating**

| | Log GDP per capita | | Government Debt | | Current Account | | Inflation Rate | | Unemployment Rate | | Regulatory Quality | | Competitiveness | | Uncertainty | | AIC | Pseudo $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| quantile | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | | |
| 0.05 | **-0.1961** | 0.000 | **-0.0277** | 0.000 | **0.0565** | 0.000 | **0.0361** | 0.000 | **-0.3655** | 0.000 | **5.0575** | 0.000 | **-0.0687** | 0.000 | **-0.0219** | 0.000 | 9.101 | 0.620 |
| 0.10 | **2.7722** | 0.000 | **-0.0316** | 0.000 | **0.0156** | 0.000 | **-0.0336** | 0.000 | **-0.2247** | 0.000 | **3.3226** | 0.000 | **-0.0539** | 0.000 | **-0.0112** | 0.000 | 8.414 | 0.663 |
| 0.15 | **4.1889** | 0.000 | **-0.0398** | 0.000 | **0.0424** | 0.000 | **-0.1598** | 0.000 | **-0.2510** | 0.000 | **1.8446** | 0.000 | **-0.0417** | 0.000 | **-0.0118** | 0.000 | 8.019 | 0.681 |
| 0.20 | **4.8046** | 0.000 | **-0.0293** | 0.000 | **0.0194** | 0.049 | **-0.1416** | 0.000 | **-0.2487** | 0.000 | **2.7552** | 0.000 | **-0.0328** | 0.000 | **-0.0206** | 0.000 | 7.397 | 0.684 |
| 0.25 | **3.2558** | 0.000 | **-0.0237** | 0.000 | **0.0540** | 0.000 | **-0.1174** | 0.000 | **-0.2821** | 0.000 | **2.6147** | 0.000 | **-0.0420** | 0.000 | **-0.0159** | 0.000 | 8.292 | 0.675 |
| 0.30 | **4.5407** | 0.000 | **-0.0277** | 0.000 | **0.0555** | 0.000 | **-0.0873** | 0.000 | **-0.2470** | 0.000 | **2.4303** | 0.000 | **-0.0439** | 0.000 | **-0.0109** | 0.000 | 7.616 | 0.682 |
| 0.35 | **5.6193** | 0.000 | **-0.0402** | 0.000 | **-0.0202** | 0.035 | **-0.2705** | 0.000 | **-0.2713** | 0.000 | **2.3127** | 0.000 | **-0.0324** | 0.000 | **-0.0151** | 0.000 | 6.908 | 0.683 |
| 0.40 | **6.2628** | 0.000 | **-0.0270** | 0.000 | 0.0083 | 0.303 | **-0.1976** | 0.000 | **-0.2361** | 0.000 | **1.7445** | 0.000 | **-0.0275** | 0.000 | **-0.0129** | 0.000 | 7.490 | 0.687 |
| 0.45 | **6.5806** | 0.000 | **-0.0209** | 0.000 | **0.0130** | 0.003 | **-0.1212** | 0.000 | **-0.2405** | 0.000 | **1.3283** | 0.000 | **-0.0275** | 0.000 | **-0.0066** | 0.000 | 7.834 | 0.670 |
| 0.50 | **5.4772** | 0.000 | **-0.0069** | 0.046 | -0.0419 | 0.308 | **-0.1020** | 0.000 | **-0.2703** | 0.000 | **1.0692** | 0.000 | -0.0041 | 0.169 | **-0.0153** | 0.000 | 7.345 | 0.636 |
| 0.55 | **8.1589** | 0.000 | **-0.0373** | 0.000 | **-0.0568** | 0.029 | **-0.0810** | 0.000 | **-0.2010** | 0.000 | **1.6103** | 0.000 | **-0.0191** | 0.000 | 0.0007 | 0.810 | 8.576 | 0.671 |
| 0.60 | **8.3574** | 0.000 | **-0.0200** | 0.000 | -0.0129 | 0.315 | 0.0264 | 0.686 | **-0.1562** | 0.000 | **0.4308** | 0.072 | **0.0118** | 0.000 | **-0.0109** | 0.000 | 8.727 | 0.645 |
| 0.65 | **8.8327** | 0.000 | **-0.0211** | 0.000 | **-0.0524** | 0.001 | **-0.3271** | 0.000 | **-0.2436** | 0.000 | **1.1058** | 0.000 | 0.0036 | 0.360 | **0.0137** | 0.000 | 8.896 | 0.567 |
| 0.70 | **11.1976** | 0.000 | **-0.0370** | 0.000 | **-0.0311** | 0.007 | -0.0352 | 0.245 | **-0.0564** | 0.000 | -0.2596 | 0.417 | 0.0009 | 0.460 | **-0.0085** | 0.000 | 9.133 | 0.619 |
| 0.75 | **12.6666** | 0.000 | **-0.0429** | 0.000 | -0.0292 | 0.105 | **-0.0962** | 0.005 | 0.0169 | 0.359 | 0.1282 | 0.343 | **-0.0061** | 0.009 | **-0.0064** | 0.089 | 9.316 | 0.591 |

Notes: Figures in bold indicate significance at the 10% level or lower. AIC is the Akaike Information Criterion.

## Table 2.5: Estimates for Fitch

**Dependent Variable: Fitch rating**

| | Log GDP per capita | | Government Debt | | Current Account | | Inflation Rate | | Unemployment Rate | | Regulatory Quality | | Competitiveness | | Uncertainty | | AIC | Pseudo $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| quantile | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | | |
| 0.05 | **0.8393** | 0.000 | **-0.0237** | 0.000 | **0.0960** | 0.000 | **-0.0463** | 0.000 | **-0.4446** | 0.000 | **1.2453** | 0.000 | **-0.0509** | 0.000 | **-0.0317** | 0.000 | 9.116 | 0.577 |
| 0.10 | **0.7370** | 0.000 | **-0.0179** | 0.000 | **0.0765** | 0.000 | **-0.1005** | 0.000 | **-0.4457** | 0.000 | **2.8360** | 0.000 | **-0.0389** | 0.000 | **-0.0115** | 0.000 | 8.911 | 0.633 |
| 0.15 | **2.3524** | 0.000 | **-0.0253** | 0.000 | **0.0583** | 0.000 | **-0.1070** | 0.000 | **-0.4223** | 0.000 | **2.7182** | 0.000 | **-0.0419** | 0.000 | **-0.0053** | 0.000 | 8.563 | 0.651 |
| 0.20 | **3.4014** | 0.000 | **-0.0203** | 0.000 | **0.0433** | 0.000 | **-0.1092** | 0.000 | **-0.3287** | 0.000 | **2.6176** | 0.000 | **-0.0421** | 0.000 | **-0.0107** | 0.000 | 8.214 | 0.663 |
| 0.25 | **6.5064** | 0.000 | **-0.0294** | 0.000 | -0.0045 | 0.442 | **-0.1364** | 0.000 | **-0.3004** | 0.000 | **1.6866** | 0.000 | **-0.0488** | 0.000 | **-0.0093** | 0.000 | 7.198 | 0.669 |
| 0.30 | **4.7267** | 0.000 | **-0.0554** | 0.000 | **0.0523** | 0.019 | **-0.2287** | 0.000 | **-0.3111** | 0.000 | **1.3404** | 0.000 | **-0.0381** | 0.000 | 0.0040 | 0.441 | 7.729 | 0.634 |
| 0.35 | **5.6993** | 0.000 | **-0.0074** | 0.000 | **-0.0179** | 0.006 | **-0.0578** | 0.000 | **-0.2201** | 0.000 | **2.2305** | 0.000 | **-0.0370** | 0.000 | **-0.0118** | 0.000 | 7.267 | 0.635 |
| 0.40 | **6.5795** | 0.000 | **-0.0120** | 0.000 | **-0.0386** | 0.000 | **-0.1348** | 0.000 | **-0.1908** | 0.000 | **2.3079** | 0.000 | **-0.0388** | 0.000 | **-0.0152** | 0.000 | 7.794 | 0.633 |
| 0.45 | **6.1085** | 0.000 | **-0.0122** | 0.000 | **-0.0202** | 0.000 | **-0.0288** | 0.035 | **-0.2246** | 0.000 | **2.7174** | 0.000 | **-0.0402** | 0.000 | **-0.0098** | 0.000 | 7.632 | 0.647 |
| 0.50 | **5.4025** | 0.000 | **-0.0128** | 0.000 | -0.0241 | 0.144 | **-0.1071** | 0.000 | **-0.2603** | 0.000 | **2.5984** | 0.000 | **-0.0315** | 0.000 | 0.0049 | 0.201 | 7.495 | 0.630 |
| 0.55 | **5.2451** | 0.000 | **-0.0092** | 0.001 | 0.0082 | 0.309 | -0.0148 | 0.259 | **-0.2261** | 0.000 | **2.3528** | 0.000 | **-0.0221** | 0.000 | **-0.0077** | 0.000 | 7.297 | 0.660 |
| 0.60 | **9.3137** | 0.000 | **-0.0249** | 0.000 | **-0.0217** | 0.000 | **-0.0429** | 0.000 | **-0.1646** | 0.000 | **0.1749** | 0.006 | **-0.0177** | 0.000 | **-0.0010** | 0.097 | 8.789 | 0.632 |
| 0.65 | **10.1534** | 0.000 | **-0.0262** | 0.000 | **-0.0306** | 0.000 | **-0.0698** | 0.000 | **-0.1308** | 0.000 | **0.6065** | 0.000 | **-0.0091** | 0.000 | 0.0009 | 0.667 | 9.021 | 0.616 |
| 0.70 | **9.1753** | 0.000 | **-0.0292** | 0.000 | **-0.0575** | 0.000 | **-0.1863** | 0.000 | **-0.0706** | 0.000 | **0.8319** | 0.000 | **-0.0133** | 0.000 | 0.0006 | 0.832 | 8.843 | 0.595 |
| 0.75 | **11.8393** | 0.000 | **-0.0379** | 0.000 | **-0.0449** | 0.000 | **-0.1528** | 0.000 | -0.0069 | 0.193 | **-0.7012** | 0.000 | **-0.0181** | 0.000 | 0.0025 | 0.132 | 9.182 | 0.498 |

Notes: Figures in bold indicate significance at the 10% level or lower. AIC is the Akaike Information Criterion.

**Table 2.6: Impact of European policy uncertainty on ratings for Moody's**

| Year | Greece | Ireland | Italy | Portugal | Spain | Cyprus |
|---|---|---|---|---|---|---|
| 2008 | -0.535 | -0.212 | -0.442 | -0.442 | -0.212 | -0.392 |
| 2009 | -0.314 | -0.112 | -0.283 | -0.250 | -0.135 | -0.250 |
| 2010 | -1.037 | -0.780 | -1.037 | -0.893 | -0.410 | -0.918 |
| 2011 | -3.025 | -1.471 | -1.632 | -3.025 | -2.860 | -1.471 |
| 2012 | -3.521 | -1.712 | -1.712 | -3.521 | -1.712 | -3.521 |
| 2013 | -2.707 | -1.316 | -1.316 | -2.707 | -1.316 | -2.707 |
| 2014 | -1.453 | -0.532 | -0.532 | -0.707 | -0.532 | -1.453 |
| 2015 | -2.010 | -0.736 | -0.736 | -0.977 | -0.736 | -2.010 |

Notes: Table 2.6 illustrates the effects of European policy uncertainty on credit ratings by using estimates of our credit rating model under uncertainty to infer what credit ratings would have been had uncertainty remained at its 2002-2007 average value. To do this, we construct the difference between the fitted values of the estimates of credit rating model (1) for Moody's (as reported in Table 2.3) and the fitted values of the counterfactual model (1) which sets the post 2007 values of the uncertainty variable equal to its 2002-2007 average.

**Table 2.7: Impact of European policy uncertainty on ratings for S&P's**

| Year | Greece | Ireland | Italy | Portugal | Spain | Cyprus |
|---|---|---|---|---|---|---|
| 2008 | -0.4227 | -0.1800 | -0.1855 | -0.4280 | -0.1800 | -0.1855 |
| 2009 | -0.2108 | 0.0128 | -0.1187 | -0.2317 | -0.1954 | -0.1187 |
| 2010 | -0.7379 | -0.7151 | -0.4352 | -1.3492 | 0.0469 | -0.7151 |
| 2011 | -2.0431 | -1.9144 | -1.0146 | -1.0470 | -1.4244 | -1.0470 |
| 2012 | -2.3775 | -1.2761 | -1.2184 | -2.3775 | -1.2184 | -2.3775 |
| 2013 | -1.8281 | -1.7130 | -0.9369 | -1.8281 | -0.9369 | -1.8281 |
| 2014 | -0.9815 | -0.6757 | -0.5030 | -0.9815 | -0.5268 | -0.9815 |
| 2015 | -1.3576 | -0.4103 | -0.6957 | -0.6957 | -0.7287 | -1.3576 |

Notes: Table 2.7 illustrates the effects of European policy uncertainty on credit ratings by using estimates of our credit rating model under uncertainty to infer what credit ratings would have been had uncertainty remained at its 2002-2007 average value. To do this, we construct the difference between the fitted values of the estimates of credit rating model (1) for S&P's (as reported in Table 2.4) and the fitted values of the counterfactual model (1) which sets the post 2007 values of the uncertainty variable equal to its 2002-2007 average.

## Table 2.8: Impact of European policy uncertainty on ratings for Fitch

| Year | Greece | Ireland | Italy | Portugal | Spain | Cyprus |
|---|---|---|---|---|---|---|
| 2008 | 0.1132 | 0.0687 | 0.1382 | -0.2166 | 0.0687 | 0.1382 |
| 2009 | -0.0945 | 0.0884 | 0.0884 | 0.0884 | 0.0439 | 0.0884 |
| 2010 | -0.7522 | -0.7007 | 0.3240 | -0.7734 | 0.0596 | 0.3240 |
| 2011 | -2.9516 | -0.4918 | -1.0974 | -2.9516 | -0.9145 | -1.0673 |
| 2012 | -3.4349 | -0.5723 | -1.1569 | -3.4349 | -1.2420 | -3.4349 |
| 2013 | -2.6411 | -0.8896 | -0.4401 | -2.6411 | -0.9550 | -2.6411 |
| 2014 | -1.4179 | -0.4160 | -0.4776 | -0.5127 | -0.4776 | -1.4179 |
| 2015 | -1.9613 | -0.5754 | -0.6606 | -0.7092 | -0.6606 | -1.9613 |

Notes: Table 2.8 illustrates the effects of European policy uncertainty on credit ratings by using estimates of our credit rating model under uncertainty to infer what credit ratings would have been had uncertainty remained at its 2002-2007 average value. To do this, we construct the difference between the fitted values of the estimates of credit rating model (1) for Fitch (as reported in Table 2.5) and the fitted values of the counterfactual model (1) which sets the post 2007 values of the uncertainty variable equal to its 2002-2007 average.

Table 2.9: Estimates for Moody’s with first order lags as instrumental variables

Dependent Variable: Moody's rating

| | Log GDP per capita | | Government Debt | | Current Account | | Inflation Rate | | Unemployment Rate | | Regulatory Quality | | Competitiveness | | Uncertainty | | AIC | Pseudo $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| quantile | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | | |
| 0.05 | **-0.7718** | 0.000 | **-0.0272** | 0.000 | **0.1196** | 0.000 | **0.2586** | 0.000 | **-0.3085** | 0.000 | **4.2377** | 0.000 | **-0.0476** | 0.000 | **-0.0307** | 0.000 | 9.150 | 0.593 |
| 0.10 | **-0.5901** | 0.000 | **-0.0390** | 0.000 | **0.0580** | 0.000 | **0.0355** | 0.000 | **-0.3339** | 0.000 | **4.2815** | 0.000 | **-0.0361** | 0.000 | **-0.0158** | 0.000 | 9.064 | 0.594 |
| 0.15 | **0.8942** | 0.000 | **-0.0396** | 0.000 | **0.0158** | 0.000 | **-0.0143** | 0.000 | **-0.2801** | 0.000 | **3.7907** | 0.000 | **-0.0376** | 0.000 | **-0.0108** | 0.000 | 8.801 | 0.609 |
| 0.20 | **2.7490** | 0.000 | **-0.0412** | 0.000 | **0.0030** | 0.000 | **-0.0328** | 0.000 | **-0.2265** | 0.000 | **3.7852** | 0.000 | **-0.0367** | 0.000 | **-0.0104** | 0.000 | 8.288 | 0.626 |
| 0.25 | **5.8908** | 0.000 | **-0.0456** | 0.000 | **-0.0179** | 0.008 | **-0.1727** | 0.000 | **-0.1720** | 0.000 | **2.6823** | 0.000 | **-0.0199** | 0.000 | **-0.0165** | 0.000 | 7.401 | 0.638 |
| 0.30 | **4.6627** | 0.000 | **-0.0304** | 0.000 | **-0.1361** | 0.000 | **-0.1292** | 0.000 | **-0.0936** | 0.000 | **6.3281** | 0.000 | **-0.0177** | 0.000 | **-0.0087** | 0.000 | 7.774 | 0.575 |
| 0.35 | **4.2664** | 0.000 | **-0.0223** | 0.000 | **-0.0379** | 0.000 | -0.0257 | 0.283 | **-0.1272** | 0.000 | **4.0622** | 0.000 | **-0.0298** | 0.000 | **-0.0172** | 0.000 | 7.126 | 0.626 |
| 0.40 | **3.9472** | 0.000 | **-0.0056** | 0.015 | **-0.0209** | 0.024 | 0.0234 | 0.454 | **-0.2066** | 0.000 | **3.2522** | 0.000 | **-0.0379** | 0.000 | **-0.0146** | 0.000 | 7.578 | 0.585 |
| 0.45 | **3.0212** | 0.000 | **-0.0035** | 0.014 | **-0.0707** | 0.019 | **0.0439** | 0.018 | **-0.2055** | 0.000 | **4.9529** | 0.000 | **-0.0403** | 0.000 | **-0.0176** | 0.000 | 7.904 | 0.583 |
| 0.50 | **2.7157** | 0.001 | 0.0074 | 0.295 | **-0.0648** | 0.000 | -0.0743 | 0.324 | **-0.2392** | 0.000 | **3.2915** | 0.000 | **-0.0093** | 0.038 | **-0.0106** | 0.000 | 7.792 | 0.554 |
| 0.55 | **8.1312** | 0.000 | **-0.0318** | 0.000 | -0.0003 | 0.978 | **-0.1885** | 0.000 | **-0.0999** | 0.000 | -0.0333 | 0.915 | **-0.0224** | 0.000 | **-0.0122** | 0.000 | 8.358 | 0.570 |
| 0.60 | **5.4859** | 0.000 | **-0.0111** | 0.030 | -0.0309 | 0.159 | **-0.1036** | 0.025 | **-0.1875** | 0.000 | **1.5205** | 0.001 | **-0.0290** | 0.000 | **-0.0091** | 0.000 | 7.258 | 0.568 |
| 0.65 | **8.1615** | 0.000 | **-0.0217** | 0.000 | **-0.0377** | 0.000 | **-0.1567** | 0.012 | **-0.0658** | 0.000 | **0.6343** | 0.000 | **-0.0157** | 0.000 | -0.0037 | 0.307 | 8.608 | 0.509 |
| 0.70 | **9.4343** | 0.000 | **-0.0264** | 0.000 | **-0.0342** | 0.000 | **-0.0781** | 0.021 | **-0.0191** | 0.015 | 0.2237 | 0.299 | **-0.0193** | 0.000 | **-0.0052** | 0.000 | 8.841 | 0.496 |
| 0.75 | **10.5101** | 0.000 | **-0.0357** | 0.000 | **-0.0379** | 0.003 | **-0.1316** | 0.000 | 0.0251 | 0.113 | 0.1774 | 0.398 | **-0.0222** | 0.000 | **-0.0087** | 0.001 | 8.983 | 0.502 |

Notes: Figures in bold indicate significance at the 10% level or lower. AIC is the Akaike Information Criterion.

### Table 2.10: Estimates for S&P’s with first order lags as instrumental variables

**Dependent Variable: S&P's rating**

| | Log GDP per capita | | Government Debt | | Current Account | | Inflation Rate | | Unemployment Rate | | Regulatory Quality | | Competitiveness | | Uncertainty | | AIC | Pseudo $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| quantile | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | | |
| 0.05 | **0.2561** | 0.223 | **-0.0332** | 0.000 | **0.0996** | 0.000 | **0.1097** | 0.000 | **-0.3598** | 0.000 | **5.0597** | 0.000 | **-0.0704** | 0.000 | **-0.0224** | 0.000 | 9.049 | 0.629 |
| 0.10 | **3.1985** | 0.000 | **-0.0336** | 0.000 | **0.0123** | 0.000 | **-0.0188** | 0.000 | **-0.2321** | 0.000 | **3.1895** | 0.000 | **-0.0540** | 0.000 | **-0.0091** | 0.000 | 8.277 | 0.666 |
| 0.15 | **4.1839** | 0.000 | **-0.0403** | 0.000 | **0.0425** | 0.000 | **-0.1568** | 0.000 | **-0.2497** | 0.000 | **1.8321** | 0.000 | **-0.0425** | 0.000 | **-0.0128** | 0.000 | 8.048 | 0.680 |
| 0.20 | **3.8653** | 0.000 | **-0.0317** | 0.000 | **0.0616** | 0.000 | **-0.0849** | 0.006 | **-0.2305** | 0.000 | **2.4660** | 0.000 | **-0.0412** | 0.000 | **-0.0145** | 0.000 | 8.034 | 0.684 |
| 0.25 | **5.2135** | 0.000 | **-0.0386** | 0.000 | **0.0713** | 0.002 | **-0.1237** | 0.000 | **-0.2467** | 0.000 | **1.7475** | 0.000 | **-0.0456** | 0.000 | **-0.0167** | 0.000 | 7.554 | 0.685 |
| 0.30 | **4.5990** | 0.000 | **-0.0285** | 0.000 | **0.0421** | 0.001 | **-0.0986** | 0.000 | **-0.2503** | 0.000 | **2.4420** | 0.000 | **-0.0466** | 0.000 | **-0.0124** | 0.000 | 7.663 | 0.682 |
| 0.35 | **5.0184** | 0.000 | **-0.0234** | 0.000 | **0.0311** | 0.000 | **-0.1279** | 0.000 | **-0.1890** | 0.000 | **2.5447** | 0.000 | **-0.0393** | 0.000 | **-0.0154** | 0.000 | 7.068 | 0.679 |
| 0.40 | **7.0828** | 0.000 | **-0.0235** | 0.000 | -0.0323 | 0.452 | **-0.2229** | 0.000 | **-0.2458** | 0.000 | **1.5197** | 0.000 | **-0.0227** | 0.009 | **-0.0113** | 0.000 | 8.059 | 0.674 |
| 0.45 | **5.8402** | 0.000 | **-0.0189** | 0.000 | **-0.0128** | 0.593 | **-0.1645** | 0.016 | **-0.2379** | 0.000 | **2.0647** | 0.000 | **-0.0289** | 0.000 | **-0.0088** | 0.000 | 7.406 | 0.672 |
| 0.50 | **6.6124** | 0.000 | **-0.0222** | 0.000 | -0.0113 | 0.212 | **-0.2705** | 0.000 | **-0.2465** | 0.000 | **1.5298** | 0.000 | **-0.0210** | 0.000 | **-0.0053** | 0.025 | 7.938 | 0.666 |
| 0.55 | **5.1502** | 0.000 | **-0.0213** | 0.000 | **-0.0181** | 0.029 | 0.0020 | 0.927 | **-0.2167** | 0.000 | **3.6500** | 0.000 | **-0.0184** | 0.000 | -0.0004 | 0.863 | 7.684 | 0.664 |
| 0.60 | **7.9678** | 0.000 | **-0.0281** | 0.000 | **0.0271** | 0.007 | -0.0017 | 0.957 | **-0.1486** | 0.000 | -0.0360 | 0.907 | **-0.0041** | 0.081 | **-0.0056** | 0.000 | 8.517 | 0.661 |
| 0.65 | **8.2714** | 0.000 | **-0.0321** | 0.000 | 0.0111 | 0.416 | **-0.2254** | 0.007 | **-0.1171** | 0.000 | **0.8732** | 0.001 | **-0.0254** | 0.000 | -0.0067 | 0.289 | 8.490 | 0.654 |
| 0.70 | **10.5796** | 0.000 | **-0.0422** | 0.000 | **-0.0138** | 0.002 | **-0.1360** | 0.000 | **-0.0601** | 0.000 | **0.2215** | 0.092 | **-0.0039** | 0.009 | **-0.0071** | 0.007 | 9.033 | 0.640 |
| 0.75 | **11.5694** | 0.000 | **-0.0378** | 0.000 | -0.0127 | 0.122 | **-0.1121** | 0.000 | **-0.0254** | 0.000 | **0.3859** | 0.054 | -0.0028 | 0.161 | -0.0048 | 0.383 | 9.209 | 0.605 |

Notes: Figures in bold indicate significance at the 10% level or lower. AIC is the Akaike Information Criterion.

## Table 2.11: Estimates for Fitch with first order lags as instrumental variables

Dependent Variable: Fitch rating

| | Log GDP per capita | | Government Debt | | Current Account | | Inflation Rate | | Unemployment Rate | | Regulatory Quality | | Competitiveness | | Uncertainty | | AIC | Pseudo $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| quantile | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | | |
| 0.05 | **0.5366** | 0.000 | **-0.0204** | 0.000 | **0.1048** | 0.000 | **-0.0159** | 0.000 | **-0.4264** | 0.000 | **1.6633** | 0.000 | **-0.0492** | 0.000 | **-0.0297** | 0.000 | 9.113 | 0.587 |
| 0.10 | **-0.4317** | 0.000 | **-0.0093** | 0.000 | **0.0646** | 0.000 | **-0.1265** | 0.000 | **-0.4788** | 0.000 | **3.5251** | 0.000 | **-0.0380** | 0.000 | **-0.0052** | 0.000 | 9.028 | 0.611 |
| 0.15 | **1.9404** | 0.000 | **-0.0240** | 0.000 | **0.0662** | 0.000 | **-0.1173** | 0.000 | **-0.4323** | 0.000 | **2.6932** | 0.000 | **-0.0421** | 0.000 | **-0.0042** | 0.000 | 8.662 | 0.645 |
| 0.20 | **3.7112** | 0.000 | **-0.0213** | 0.000 | **0.0246** | 0.000 | **-0.1000** | 0.000 | **-0.3350** | 0.000 | **2.6471** | 0.000 | **-0.0437** | 0.000 | **-0.0091** | 0.000 | 8.086 | 0.663 |
| 0.25 | **4.4816** | 0.000 | **-0.0185** | 0.000 | -0.0020 | 0.756 | **-0.1843** | 0.000 | **-0.3376** | 0.000 | **2.3379** | 0.000 | **-0.0379** | 0.000 | **-0.0095** | 0.000 | 7.643 | 0.664 |
| 0.30 | **4.4702** | 0.000 | -0.0026 | 0.245 | **-0.0674** | 0.000 | **-0.1153** | 0.001 | **-0.2963** | 0.000 | **3.8467** | 0.000 | **-0.0235** | 0.000 | **-0.0046** | 0.000 | 6.999 | 0.633 |
| 0.35 | **6.3135** | 0.000 | -0.0052 | 0.112 | -0.0613 | 0.287 | **-0.0742** | 0.047 | **-0.2090** | 0.000 | **2.7420** | 0.000 | **-0.0297** | 0.005 | **-0.0107** | 0.000 | 7.962 | 0.625 |
| 0.40 | **6.5421** | 0.000 | **-0.0082** | 0.001 | -0.0443 | 0.164 | -0.1001 | 0.131 | **-0.2181** | 0.000 | **2.3106** | 0.000 | **-0.0397** | 0.000 | **-0.0154** | 0.000 | 7.765 | 0.626 |
| 0.45 | **5.9594** | 0.000 | **-0.0117** | 0.000 | -0.0195 | 0.146 | **-0.1031** | 0.063 | **-0.2269** | 0.000 | **2.6819** | 0.000 | **-0.0372** | 0.000 | -0.0039 | 0.284 | 7.676 | 0.637 |
| 0.50 | **5.9069** | 0.000 | **-0.0177** | 0.000 | **-0.0405** | 0.000 | **-0.2021** | 0.000 | **-0.2611** | 0.000 | **2.1313** | 0.000 | **-0.0374** | 0.000 | **0.0053** | 0.000 | 7.589 | 0.627 |
| 0.55 | **7.3734** | 0.000 | **-0.0133** | 0.000 | **-0.0199** | 0.000 | **-0.0637** | 0.000 | **-0.2130** | 0.000 | **1.8956** | 0.000 | **-0.0221** | 0.000 | **-0.0048** | 0.000 | 8.382 | 0.647 |
| 0.60 | **6.1613** | 0.000 | **-0.0178** | 0.000 | **0.0217** | 0.000 | **-0.1767** | 0.000 | **-0.2968** | 0.000 | **0.3757** | 0.000 | **0.0073** | 0.012 | **-0.0087** | 0.000 | 7.809 | 0.665 |
| 0.65 | **7.9307** | 0.000 | **-0.0205** | 0.000 | -0.0029 | 0.756 | **-0.0691** | 0.002 | **-0.2220** | 0.000 | **0.9636** | 0.000 | **-0.0079** | 0.013 | **0.0073** | 0.010 | 8.627 | 0.623 |
| 0.70 | **9.5834** | 0.000 | **-0.0344** | 0.000 | **-0.0781** | 0.000 | **-0.1846** | 0.000 | **-0.0804** | 0.000 | 0.1674 | 0.263 | **-0.0190** | 0.000 | **-0.0055** | 0.013 | 8.806 | 0.625 |
| 0.75 | **11.6596** | 0.000 | **-0.0355** | 0.000 | **-0.0642** | 0.000 | **-0.1174** | 0.008 | -0.0070 | 0.426 | -0.1257 | 0.591 | **-0.0129** | 0.000 | -0.0025 | 0.476 | 9.184 | 0.566 |

Notes: Figures in bold indicate significance at the 10% level or lower. AIC is the Akaike Information Criterion.

Table 2.12: Estimates for Moody's using the US policy uncertainty index

Dependent Variable: Moody's rating

| | Log GDP per capita | | Government Debt | | Current Account | | Inflation Rate | | Unemployment Rate | | Regulatory Quality | | Competitiveness | | US Uncertainty | | AIC | Pseudo $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| quantile | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | | |
| 0.05 | **-1.0811** | 0.000 | **-0.0463** | 0.000 | **0.0798** | 0.000 | **0.1869** | 0.000 | **-0.3495** | 0.000 | **4.2204** | 0.000 | **-0.0390** | 0.000 | **-0.0105** | 0.000 | 9.125 | 0.553 |
| 0.10 | **-0.0365** | 0.000 | **-0.0510** | 0.000 | **0.0451** | 0.000 | **0.0346** | 0.000 | **-0.3460** | 0.000 | **3.5093** | 0.000 | **-0.0454** | 0.000 | **-0.0090** | 0.000 | 9.039 | 0.570 |
| 0.15 | **2.4221** | 0.000 | **-0.0460** | 0.000 | **-0.0298** | 0.000 | **-0.0239** | 0.000 | **-0.2643** | 0.000 | **3.6139** | 0.000 | **-0.0364** | 0.000 | **-0.0011** | 0.000 | 8.360 | 0.602 |
| 0.20 | **2.1861** | 0.000 | **-0.0416** | 0.000 | **-0.0049** | 0.000 | **0.0104** | 0.000 | **-0.2914** | 0.000 | **4.0044** | 0.000 | **-0.0434** | 0.000 | **-0.0050** | 0.000 | 8.476 | 0.608 |
| 0.25 | **2.8051** | 0.000 | **-0.0318** | 0.000 | **-0.0276** | 0.000 | -0.0144 | 0.324 | **-0.2250** | 0.000 | **4.3131** | 0.000 | **-0.0399** | 0.000 | **-0.0102** | 0.000 | 8.166 | 0.610 |
| 0.30 | **4.2157** | 0.000 | **-0.0295** | 0.000 | **-0.0348** | 0.003 | **0.0851** | 0.001 | **-0.1798** | 0.000 | **5.0614** | 0.000 | **-0.0479** | 0.000 | 0.0032 | 0.335 | 7.060 | 0.588 |
| 0.35 | **3.8584** | 0.000 | **-0.0245** | 0.000 | **-0.0717** | 0.000 | 0.0248 | 0.116 | **-0.1511** | 0.000 | **4.7225** | 0.000 | **-0.0504** | 0.000 | **-0.0128** | 0.000 | 7.579 | 0.586 |
| 0.40 | **4.2968** | 0.000 | **-0.0250** | 0.000 | **-0.0368** | 0.000 | **-0.0411** | 0.006 | **-0.1663** | 0.000 | **3.7575** | 0.000 | **-0.0468** | 0.000 | -0.0013 | 0.569 | 7.228 | 0.586 |
| 0.45 | **4.5009** | 0.000 | **-0.0082** | 0.001 | **-0.0256** | 0.001 | -0.0305 | 0.220 | **-0.2563** | 0.000 | **3.5760** | 0.000 | **-0.0272** | 0.000 | **-0.0097** | 0.001 | 7.050 | 0.577 |
| 0.50 | **6.4926** | 0.000 | **-0.0153** | 0.000 | **-0.0811** | 0.000 | **-0.0845** | 0.000 | **-0.1773** | 0.000 | **1.9668** | 0.000 | **-0.0326** | 0.000 | **0.0087** | 0.009 | 8.152 | 0.533 |
| 0.55 | **6.7314** | 0.000 | **-0.0196** | 0.000 | -0.0078 | 0.120 | **-0.0476** | 0.000 | **-0.1232** | 0.000 | **1.0435** | 0.000 | **-0.0358** | 0.000 | -0.0034 | 0.189 | 7.994 | 0.527 |
| 0.60 | **5.9102** | 0.000 | **-0.0152** | 0.000 | **0.0328** | 0.000 | 0.0019 | 0.842 | **-0.2000** | 0.000 | **0.9797** | 0.000 | **-0.0174** | 0.000 | **-0.0127** | 0.000 | 7.585 | 0.569 |
| 0.65 | **7.5368** | 0.000 | **-0.0163** | 0.001 | -0.0560 | 0.363 | -0.0246 | 0.267 | **-0.0631** | 0.000 | 0.8085 | 0.148 | **-0.0128** | 0.050 | -0.0054 | 0.407 | 8.510 | 0.516 |
| 0.70 | **8.2166** | 0.000 | **-0.0201** | 0.000 | **-0.0393** | 0.000 | **-0.1358** | 0.000 | **-0.0800** | 0.000 | **0.4679** | 0.005 | **-0.0192** | 0.000 | -0.0009 | 0.569 | 8.612 | 0.486 |
| 0.75 | **9.5034** | 0.000 | **-0.0257** | 0.000 | **-0.0445** | 0.000 | **-0.1482** | 0.000 | -0.0332 | 0.463 | **0.1742** | 0.012 | **-0.0156** | 0.000 | 0.0140 | 0.174 | 8.951 | 0.420 |

Notes: Figures in bold indicate significance at the 10% level or lower. AIC is the Akaike Information Criterion.

**Table 2.13: Estimates for S&P's using the US policy uncertainty index**

**Dependent Variable: S&P's rating**

| | Log GDP per capita | | Government Debt | | Current Account | | Inflation Rate | | Unemployment Rate | | Regulatory Quality | | Competitiveness | | US Uncertainty | | AIC | Pseudo $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| quantile | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | | |
| 0.05 | **1.0733** | 0.000 | **-0.0455** | 0.000 | **0.0714** | 0.000 | **0.0970** | 0.000 | **-0.3025** | 0.000 | **4.1584** | 0.000 | **-0.0764** | 0.000 | **-0.0198** | 0.000 | 8.965 | 0.615 |
| 0.10 | **4.1456** | 0.000 | **-0.0398** | 0.000 | -0.0020 | 0.453 | **-0.1039** | 0.000 | **-0.2420** | 0.000 | **2.2753** | 0.000 | **-0.0398** | 0.000 | 0.0008 | 0.849 | 7.707 | 0.668 |
| 0.15 | **7.3733** | 0.000 | **-0.0542** | 0.000 | **-0.0238** | 0.034 | **-0.1443** | 0.000 | **-0.1919** | 0.000 | **0.9407** | 0.000 | **-0.0364** | 0.000 | -0.0019 | 0.375 | 7.971 | 0.672 |
| 0.20 | **4.3276** | 0.000 | **-0.0414** | 0.000 | **0.0767** | 0.000 | **-0.1416** | 0.000 | **-0.3205** | 0.000 | **2.6185** | 0.000 | **-0.0213** | 0.000 | **-0.0251** | 0.000 | 7.819 | 0.658 |
| 0.25 | **3.7672** | 0.000 | **-0.0248** | 0.000 | **0.0519** | 0.000 | **-0.0537** | 0.000 | **-0.2790** | 0.000 | **3.0710** | 0.000 | **-0.0452** | 0.000 | **-0.0125** | 0.000 | 7.985 | 0.665 |
| 0.30 | **5.3187** | 0.000 | **-0.0250** | 0.000 | **0.0143** | 0.022 | -0.0288 | 0.118 | **-0.1949** | 0.000 | **3.5621** | 0.000 | **-0.0434** | 0.000 | -0.0016 | 0.595 | 7.281 | 0.660 |
| 0.35 | **4.4419** | 0.000 | **-0.0306** | 0.000 | **-0.0248** | 0.013 | **-0.2510** | 0.000 | **-0.2719** | 0.000 | **2.8031** | 0.000 | **-0.0437** | 0.000 | **-0.0065** | 0.000 | 7.605 | 0.666 |
| 0.40 | **5.3021** | 0.000 | **-0.0213** | 0.000 | **0.0171** | 0.006 | **-0.1674** | 0.000 | **-0.2376** | 0.000 | **2.1254** | 0.000 | **-0.0342** | 0.000 | -0.0049 | 0.159 | 6.948 | 0.661 |
| 0.45 | **7.2741** | 0.000 | **-0.0229** | 0.000 | **-0.0190** | 0.079 | **-0.1977** | 0.000 | **-0.2624** | 0.000 | **1.9839** | 0.000 | **-0.0313** | 0.000 | **-0.0075** | 0.001 | 8.166 | 0.658 |
| 0.50 | **5.8615** | 0.000 | **-0.0177** | 0.000 | 0.0046 | 0.840 | **-0.0878** | 0.000 | **-0.2357** | 0.000 | **2.3395** | 0.000 | -0.0001 | 0.991 | -0.0002 | 0.918 | 8.089 | 0.666 |
| 0.55 | **7.4878** | 0.000 | **-0.0125** | 0.006 | -0.0181 | 0.487 | **-0.1858** | 0.000 | **-0.2607** | 0.000 | **1.8494** | 0.000 | **-0.0280** | 0.000 | **-0.0128** | 0.024 | 8.271 | 0.624 |
| 0.60 | **10.7138** | 0.000 | **-0.0381** | 0.000 | **-0.0661** | 0.046 | **-0.0819** | 0.011 | **-0.1080** | 0.000 | **0.6225** | 0.000 | **0.0086** | 0.001 | **-0.0283** | 0.003 | 9.038 | 0.610 |
| 0.65 | **9.8143** | 0.000 | **-0.0343** | 0.000 | **-0.0123** | 0.000 | **-0.1153** | 0.013 | **-0.0898** | 0.000 | **0.9291** | 0.000 | **-0.0075** | 0.002 | -0.0048 | 0.160 | 8.953 | 0.639 |
| 0.70 | **10.7290** | 0.000 | **-0.0310** | 0.000 | **-0.0453** | 0.000 | **-0.2093** | 0.000 | **-0.0967** | 0.000 | 0.4517 | 0.229 | 0.0012 | 0.819 | **-0.0046** | 0.082 | 9.105 | 0.610 |
| 0.75 | **11.3388** | 0.000 | **-0.0399** | 0.000 | -0.0016 | 0.873 | **-0.0665** | 0.000 | -0.0346 | 0.212 | **0.3835** | 0.026 | **-0.0056** | 0.009 | -0.0114 | 0.331 | 9.147 | 0.614 |

Notes: Figures in bold indicate significance at the 10% level or lower. AIC is the Akaike Information Criterion.

Table 2.14: Estimates for Fitch using the US policy uncertainty index

**Dependent Variable: Fitch rating**

| | Log GDP per capita | | Government Debt | | Current Account | | Inflation Rate | | Unemployment Rate | | Regulatory Quality | | Competitiveness | | US Uncertainty | | AIC | Pseudo $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| quantile | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | | |
| 0.05 | **1.6295** | 0.000 | **-0.0408** | 0.000 | **0.0589** | 0.000 | **-0.2168** | 0.000 | **-0.4458** | 0.000 | **1.1758** | 0.000 | **-0.0329** | 0.000 | **-0.0126** | 0.000 | 8.871 | 0.603 |
| 0.10 | **1.6581** | 0.000 | **-0.0250** | 0.000 | **0.0282** | 0.000 | **-0.2082** | 0.000 | **-0.4687** | 0.000 | **2.6636** | 0.000 | **-0.0468** | 0.000 | **-0.0029** | 0.000 | 8.766 | 0.631 |
| 0.15 | **1.9947** | 0.000 | **-0.0266** | 0.000 | **0.0478** | 0.000 | **-0.1543** | 0.000 | **-0.4698** | 0.000 | **2.7098** | 0.000 | **-0.0367** | 0.000 | **0.0032** | 0.000 | 8.595 | 0.638 |
| 0.20 | **2.9458** | 0.000 | **-0.0229** | 0.000 | **0.0318** | 0.000 | **-0.1051** | 0.000 | **-0.3810** | 0.000 | **3.0963** | 0.000 | **-0.0410** | 0.000 | **-0.0056** | 0.000 | 8.305 | 0.653 |
| 0.25 | **4.4844** | 0.000 | **-0.0155** | 0.000 | **-0.0428** | 0.007 | **-0.1952** | 0.000 | **-0.3602** | 0.000 | **2.8791** | 0.000 | **-0.0391** | 0.000 | **-0.0129** | 0.009 | 7.594 | 0.644 |
| 0.30 | **3.0192** | 0.000 | **-0.0124** | 0.000 | **0.0251** | 0.000 | **-0.0799** | 0.000 | **-0.3332** | 0.000 | **3.3293** | 0.000 | **-0.0371** | 0.000 | **-0.0040** | 0.000 | 8.100 | 0.647 |
| 0.35 | **4.5063** | 0.000 | **-0.0224** | 0.000 | -0.0132 | 0.727 | **-0.0882** | 0.000 | **-0.1951** | 0.000 | **3.5161** | 0.000 | **-0.0263** | 0.003 | **-0.0115** | 0.000 | 6.913 | 0.655 |
| 0.40 | **6.3075** | 0.000 | **-0.0125** | 0.000 | **-0.0371** | 0.000 | **-0.1339** | 0.000 | **-0.1951** | 0.000 | **2.4441** | 0.000 | **-0.0405** | 0.000 | -0.0037 | 0.385 | 7.840 | 0.617 |
| 0.45 | **6.6617** | 0.000 | **-0.0101** | 0.000 | **-0.0317** | 0.000 | **-0.0819** | 0.000 | **-0.2160** | 0.000 | **2.9831** | 0.000 | **-0.0413** | 0.000 | **-0.0104** | 0.000 | 8.010 | 0.619 |
| 0.50 | **5.8961** | 0.000 | **-0.0154** | 0.000 | -0.0149 | 0.280 | **-0.1328** | 0.000 | **-0.2610** | 0.000 | **2.2834** | 0.000 | **-0.0234** | 0.000 | -0.0002 | 0.951 | 7.761 | 0.655 |
| 0.55 | **8.9905** | 0.000 | **-0.0320** | 0.000 | -0.0097 | 0.399 | **-0.1322** | 0.000 | **-0.2261** | 0.000 | 0.2419 | 0.682 | **-0.0257** | 0.000 | **-0.0029** | 0.068 | 8.670 | 0.660 |
| 0.60 | **9.4244** | 0.000 | **-0.0222** | 0.000 | **-0.0320** | 0.000 | -0.0241 | 0.223 | **-0.2069** | 0.000 | **0.1083** | 0.063 | **-0.0037** | 0.068 | 0.0002 | 0.484 | 8.873 | 0.633 |
| 0.65 | **9.9326** | 0.000 | **-0.0195** | 0.000 | **-0.0603** | 0.000 | **-0.1353** | 0.000 | **-0.1377** | 0.000 | **0.8549** | 0.000 | **-0.0086** | 0.001 | **-0.0015** | 0.090 | 8.989 | 0.604 |
| 0.70 | **10.7658** | 0.000 | **-0.0315** | 0.000 | **-0.0450** | 0.000 | **-0.1552** | 0.000 | **-0.0706** | 0.000 | **0.8198** | 0.000 | **-0.0064** | 0.000 | 0.0006 | 0.513 | 9.121 | 0.598 |
| 0.75 | **12.0175** | 0.000 | **-0.0344** | 0.000 | **-0.0866** | 0.000 | **-0.1331** | 0.000 | 0.0101 | 0.514 | 0.2083 | 0.143 | **-0.0120** | 0.000 | -0.0014 | 0.787 | 9.253 | 0.545 |

Notes: Figures in bold indicate significance at the 10% level or lower. AIC is the Akaike Information Criterion.

**Table 2.15: Estimates for Moody's adding the 1st order lag of fiscal balance**

**Dependent Variable: Moody's rating**

| | Log GDP per capita | | Government Debt | | Lag Fiscal Balance | | Current Account | | Inflation Rate | | Unemployment Rate | | Regulatory Quality | | Competitiveness | | Uncertainty | | AIC | Pseudo $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| quantile | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | | |
| 0.05 | **-1.5290** | 0.000 | **-0.0316** | 0.000 | **0.0381** | 0.000 | **0.0577** | 0.000 | **0.1778** | 0.000 | **-0.3651** | 0.000 | **3.4120** | 0.000 | **-0.0566** | 0.000 | **-0.0251** | 0.000 | 9.448 | 0.568 |
| 0.10 | **-1.3230** | 0.000 | **-0.0318** | 0.000 | **0.0593** | 0.000 | **0.0778** | 0.000 | **0.0315** | 0.000 | **-0.3322** | 0.000 | **4.8095** | 0.000 | **-0.0431** | 0.000 | **-0.0170** | 0.000 | 9.309 | 0.596 |
| 0.15 | **0.9305** | 0.000 | **-0.0333** | 0.000 | **0.1155** | 0.000 | **0.0243** | 0.000 | **0.0452** | 0.000 | **-0.2549** | 0.000 | **4.3205** | 0.000 | **-0.0432** | 0.000 | **-0.0100** | 0.000 | 8.913 | 0.616 |
| 0.20 | **2.7095** | 0.000 | **-0.0373** | 0.000 | **0.1240** | 0.000 | **0.0220** | 0.000 | -0.0012 | 0.646 | **-0.2279** | 0.000 | **3.1784** | 0.000 | **-0.0426** | 0.000 | **-0.0075** | 0.000 | 8.530 | 0.630 |
| 0.25 | **3.7513** | 0.000 | **-0.0428** | 0.000 | 0.0226 | 0.570 | -0.0073 | 0.380 | -0.0077 | 0.743 | **-0.2357** | 0.000 | **3.8349** | 0.000 | **-0.0362** | 0.000 | **-0.0157** | 0.000 | 8.092 | 0.638 |
| 0.30 | **5.2677** | 0.000 | **-0.0239** | 0.000 | **0.1015** | 0.000 | **-0.0313** | 0.001 | 0.0144 | 0.492 | **-0.1063** | 0.000 | **3.3843** | 0.000 | **-0.0321** | 0.000 | **-0.0150** | 0.000 | 7.369 | 0.635 |
| 0.35 | **4.6305** | 0.000 | **-0.0184** | 0.000 | **0.0660** | 0.000 | **-0.0216** | 0.021 | 0.0058 | 0.773 | **-0.1398** | 0.000 | **3.6970** | 0.000 | **-0.0299** | 0.000 | **-0.0143** | 0.000 | 7.133 | 0.631 |
| 0.40 | **5.7900** | 0.001 | -0.0042 | 0.633 | 0.0005 | 0.995 | **-0.0718** | 0.092 | -0.0176 | 0.751 | **-0.1869** | 0.000 | **3.0631** | 0.000 | **-0.0319** | 0.011 | -0.0061 | 0.445 | 8.000 | 0.544 |
| 0.45 | **5.1887** | 0.000 | **-0.0149** | 0.011 | **0.0680** | 0.002 | **-0.1557** | 0.000 | **-0.1527** | 0.000 | **-0.1330** | 0.000 | **3.3001** | 0.000 | **-0.0176** | 0.001 | **-0.0066** | 0.002 | 7.799 | 0.595 |
| 0.50 | **5.8321** | 0.000 | **-0.0134** | 0.000 | **0.0832** | 0.000 | **-0.0706** | 0.000 | 0.0056 | 0.631 | **-0.0980** | 0.000 | **1.7713** | 0.000 | **-0.0517** | 0.000 | **-0.0184** | 0.000 | 7.239 | 0.567 |
| 0.55 | **4.2450** | 0.000 | **-0.0152** | 0.000 | -0.0147 | 0.555 | **0.0201** | 0.064 | -0.0104 | 0.646 | **-0.1958** | 0.000 | **1.6746** | 0.000 | **-0.0273** | 0.000 | **-0.0192** | 0.003 | 7.823 | 0.620 |
| 0.60 | **7.8933** | 0.000 | **-0.0217** | 0.000 | **0.0747** | 0.004 | -0.0212 | 0.201 | -0.0144 | 0.337 | **-0.1929** | 0.001 | **0.4218** | 0.043 | **-0.0157** | 0.009 | 0.0003 | 0.950 | 8.628 | 0.587 |
| 0.65 | **9.1220** | 0.000 | **-0.0219** | 0.000 | **0.0925** | 0.000 | **-0.0277** | 0.011 | **-0.0447** | 0.040 | -0.0205 | 0.111 | **0.3451** | 0.013 | **-0.0137** | 0.001 | -0.0021 | 0.352 | 8.976 | 0.516 |
| 0.70 | **9.0676** | 0.000 | **-0.0237** | 0.000 | 0.0135 | 0.513 | **-0.0205** | 0.000 | **-0.0920** | 0.000 | **-0.0189** | 0.000 | **0.2455** | 0.007 | **-0.0189** | 0.000 | **-0.0050** | 0.000 | 8.919 | 0.487 |
| 0.75 | **10.1590** | 0.000 | **-0.0299** | 0.000 | -0.0120 | 0.415 | **-0.0210** | 0.032 | **-0.0643** | 0.000 | **0.0541** | 0.000 | **0.4887** | 0.000 | **-0.0159** | 0.000 | **-0.0093** | 0.000 | 9.133 | 0.471 |

Notes: Figures in bold indicate significance at the 10% level or lower. AIC is the Akaike Information Criterion.

### Table 2.16: Estimates for S&P's adding the 1st order lag of fiscal balance

**Dependent Variable: S&P's rating**

| | Log GDP per capita | | Government Debt | | Lag Fiscal Balance | | Current Account | | Inflation Rate | | Unemployment Rate | | Regulatory Quality | | Competitiveness | | Uncertainty | | AIC | Pseudo $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| quantile | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | | |
| 0.05 | **-0.2452** | 0.003 | **-0.0228** | 0.000 | **-0.0876** | 0.000 | **0.0641** | 0.000 | **0.0526** | 0.000 | **-0.3479** | 0.000 | **5.8159** | 0.000 | **-0.0553** | 0.000 | **-0.0283** | 0.000 | 9.175 | 0.617 |
| 0.10 | **2.5703** | 0.000 | **-0.0293** | 0.000 | **-0.0218** | 0.000 | **0.0258** | 0.000 | **-0.0359** | 0.000 | **-0.2185** | 0.000 | **3.4540** | 0.000 | **-0.0420** | 0.000 | **-0.0143** | 0.000 | 8.529 | 0.667 |
| 0.15 | **3.5529** | 0.000 | **-0.0259** | 0.000 | 0.0156 | 0.519 | **0.0616** | 0.000 | **-0.0894** | 0.000 | **-0.2615** | 0.000 | **2.2664** | 0.000 | **-0.0380** | 0.000 | **-0.0164** | 0.000 | 8.325 | 0.681 |
| 0.20 | **4.4567** | 0.000 | **-0.0334** | 0.000 | **0.0157** | 0.000 | **0.0572** | 0.000 | **-0.0854** | 0.000 | **-0.2215** | 0.000 | **2.1014** | 0.000 | **-0.0456** | 0.000 | **-0.0135** | 0.000 | 7.971 | 0.684 |
| 0.25 | **3.8314** | 0.000 | **-0.0282** | 0.000 | **0.0225** | 0.000 | **0.0716** | 0.000 | **-0.1017** | 0.000 | **-0.2788** | 0.000 | **2.0795** | 0.000 | **-0.0461** | 0.000 | **-0.0141** | 0.000 | 8.318 | 0.678 |
| 0.30 | **6.7341** | 0.000 | **-0.0455** | 0.000 | **-0.1266** | 0.006 | -0.0109 | 0.800 | **-0.1076** | 0.000 | **-0.1922** | 0.000 | **3.8860** | 0.000 | **-0.0579** | 0.000 | -0.0063 | 0.214 | 7.985 | 0.657 |
| 0.35 | **5.0360** | 0.000 | **-0.0183** | 0.000 | **0.0736** | 0.000 | **0.0457** | 0.000 | **-0.1318** | 0.000 | **-0.2389** | 0.000 | **1.8713** | 0.000 | **-0.0331** | 0.000 | **-0.0119** | 0.000 | 7.211 | 0.680 |
| 0.40 | **5.8972** | 0.000 | **-0.0102** | 0.004 | **0.0994** | 0.000 | **0.0257** | 0.021 | **-0.1852** | 0.000 | **-0.2468** | 0.000 | **1.1568** | 0.000 | **-0.0299** | 0.000 | **-0.0077** | 0.000 | 7.411 | 0.647 |
| 0.45 | **5.7537** | 0.000 | **-0.0132** | 0.000 | **0.1150** | 0.000 | -0.0032 | 0.902 | **-0.1526** | 0.000 | **-0.2221** | 0.000 | **1.6885** | 0.000 | **-0.0169** | 0.043 | **-0.0173** | 0.003 | 7.441 | 0.674 |
| 0.50 | **5.6370** | 0.000 | **-0.0149** | 0.000 | **0.0824** | 0.000 | -0.0080 | 0.109 | **-0.0659** | 0.004 | **-0.2176** | 0.000 | **1.4285** | 0.000 | **-0.0261** | 0.000 | **-0.0067** | 0.072 | 7.410 | 0.675 |
| 0.55 | **5.3905** | 0.000 | **-0.0143** | 0.000 | **0.0511** | 0.000 | 0.0133 | 0.166 | **-0.1355** | 0.004 | **-0.2226** | 0.000 | **1.8670** | 0.000 | **-0.0214** | 0.000 | **-0.0117** | 0.000 | 7.237 | 0.680 |
| 0.60 | **5.5769** | 0.000 | -0.0017 | 0.839 | **0.1248** | 0.000 | -0.0125 | 0.425 | -0.0007 | 0.957 | **-0.2420** | 0.002 | **1.5841** | 0.000 | 0.0014 | 0.840 | **-0.0042** | 0.071 | 8.035 | 0.648 |
| 0.65 | **11.2861** | 0.000 | **-0.0292** | 0.000 | **0.1027** | 0.001 | -0.0411 | 0.102 | **-0.0720** | 0.001 | **-0.0753** | 0.000 | **0.6712** | 0.000 | 0.0008 | 0.748 | **-0.0156** | 0.000 | 9.291 | 0.644 |
| 0.70 | **9.8056** | 0.000 | **-0.0235** | 0.000 | **0.0900** | 0.000 | -0.0173 | 0.529 | **-0.2087** | 0.008 | **-0.0624** | 0.020 | 0.4422 | 0.219 | -0.0088 | 0.247 | **-0.0077** | 0.001 | 9.064 | 0.622 |
| 0.75 | **11.9267** | 0.000 | **-0.0376** | 0.000 | **0.0420** | 0.001 | 0.0004 | 0.985 | -0.0327 | 0.306 | **-0.0212** | 0.026 | -0.0431 | 0.815 | -0.0071 | 0.210 | **-0.0089** | 0.004 | 9.354 | 0.618 |

Notes: Figures in bold indicate significance at the 10% level or lower. AIC is the Akaike Information Criterion.

## Table 2.17: Estimates for Fitch adding the 1st order lag of fiscal balance

**Dependent Variable: Fitch rating**

| | Log GDP per capita | | Government Debt | | Lag Fiscal Balance | | Current Account | | Inflation Rate | | Unemployment Rate | | Regulatory Quality | | Competitiveness | | Uncertainty | | AIC | Pseudo $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| quantile | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | coef. | p-val. | | |
| 0.05 | **-0.3671** | 0.002 | **-0.0163** | 0.000 | **-0.0605** | 0.000 | **0.1055** | 0.000 | **-0.0178** | 0.000 | **-0.4518** | 0.000 | **3.2446** | 0.000 | **-0.0415** | 0.000 | **-0.0263** | 0.000 | 9.273 | 0.599 |
| 0.10 | **0.5267** | 0.000 | **-0.0178** | 0.000 | **-0.0205** | 0.000 | **0.0803** | 0.000 | **-0.0752** | 0.000 | **-0.4514** | 0.000 | **2.9392** | 0.000 | **-0.0408** | 0.000 | **-0.0128** | 0.000 | 9.097 | 0.627 |
| 0.15 | **2.4328** | 0.000 | **-0.0185** | 0.000 | **0.0290** | 0.000 | **0.0561** | 0.000 | **-0.0900** | 0.000 | **-0.3776** | 0.000 | **2.7393** | 0.000 | **-0.0450** | 0.000 | **-0.0069** | 0.000 | 8.669 | 0.653 |
| 0.20 | **2.8415** | 0.000 | **-0.0168** | 0.000 | **0.0350** | 0.000 | **0.0606** | 0.000 | **-0.0887** | 0.000 | **-0.3379** | 0.000 | **2.7900** | 0.000 | **-0.0442** | 0.000 | **-0.0118** | 0.000 | 8.557 | 0.658 |
| 0.25 | **3.8107** | 0.000 | **-0.0156** | 0.000 | -0.0191 | 0.232 | **0.0234** | 0.001 | **-0.1209** | 0.000 | **-0.3329** | 0.000 | **2.7569** | 0.000 | **-0.0392** | 0.000 | **-0.0108** | 0.000 | 8.101 | 0.659 |
| 0.30 | **4.4626** | 0.000 | **-0.0204** | 0.000 | **0.0634** | 0.001 | 0.0042 | 0.843 | **-0.1101** | 0.000 | **-0.2535** | 0.000 | **2.5880** | 0.000 | **-0.0478** | 0.000 | **-0.0050** | 0.090 | 7.724 | 0.662 |
| 0.35 | **5.3301** | 0.000 | **-0.0167** | 0.000 | **0.0465** | 0.029 | 0.0011 | 0.933 | 0.0036 | 0.864 | **-0.2313** | 0.000 | **3.0073** | 0.000 | **-0.0471** | 0.000 | -0.0018 | 0.531 | 7.194 | 0.651 |
| 0.40 | **4.9300** | 0.000 | 0.0006 | 0.641 | **0.1033** | 0.000 | -0.0204 | 0.103 | -0.0093 | 0.524 | **-0.1889** | 0.000 | **2.8000** | 0.000 | **-0.0307** | 0.000 | -0.0024 | 0.278 | 7.383 | 0.626 |
| 0.45 | **4.4089** | 0.000 | -0.0009 | 0.873 | -0.0134 | 0.802 | -0.0330 | 0.183 | **-0.1134** | 0.000 | **-0.2435** | 0.000 | **3.3225** | 0.000 | 0.0096 | 0.584 | **-0.0120** | 0.006 | 7.559 | 0.644 |
| 0.50 | **5.8097** | 0.000 | **-0.0124** | 0.011 | 0.0243 | 0.496 | -0.0113 | 0.406 | **-0.0990** | 0.000 | **-0.2623** | 0.000 | **2.2384** | 0.000 | **-0.0262** | 0.006 | **-0.0021** | 0.818 | 7.780 | 0.657 |
| 0.55 | **6.2886** | 0.000 | **-0.0250** | 0.076 | **-0.0800** | 0.027 | **-0.0873** | 0.017 | **-0.2708** | 0.020 | **-0.3180** | 0.000 | **2.0090** | 0.056 | **-0.0311** | 0.000 | -0.0022 | 0.535 | 7.788 | 0.645 |
| 0.60 | **9.2795** | 0.000 | **-0.0189** | 0.000 | **0.0871** | 0.000 | **-0.0245** | 0.000 | 0.0028 | 0.801 | **-0.1776** | 0.000 | **0.3689** | 0.030 | **-0.0097** | 0.003 | 0.0009 | 0.365 | 8.990 | 0.637 |
| 0.65 | **10.5963** | 0.000 | **-0.0279** | 0.000 | **0.0457** | 0.000 | -0.0116 | 0.234 | **-0.0937** | 0.001 | **-0.0974** | 0.000 | 0.1014 | 0.342 | **-0.0092** | 0.000 | **-0.0078** | 0.001 | 9.160 | 0.628 |
| 0.70 | **9.4169** | 0.000 | **-0.0239** | 0.000 | -0.0045 | 0.779 | **-0.0363** | 0.000 | **-0.1783** | 0.000 | **-0.0703** | 0.000 | **0.6184** | 0.000 | **-0.0076** | 0.001 | **-0.0044** | 0.000 | 9.031 | 0.598 |
| 0.75 | **11.5613** | 0.000 | **-0.0321** | 0.000 | 0.0173 | 0.269 | **-0.0534** | 0.000 | **-0.1193** | 0.000 | **-0.0430** | 0.065 | **-0.3545** | 0.075 | **-0.0060** | 0.000 | 0.0026 | 0.607 | 9.342 | 0.559 |

Notes: Figures in bold indicate significance at the 10% level or lower. AIC is the Akaike Information Criterion.

**Table 2.18: Estimates of mean regressions for Moody's, S&P's and Fitch ratings**

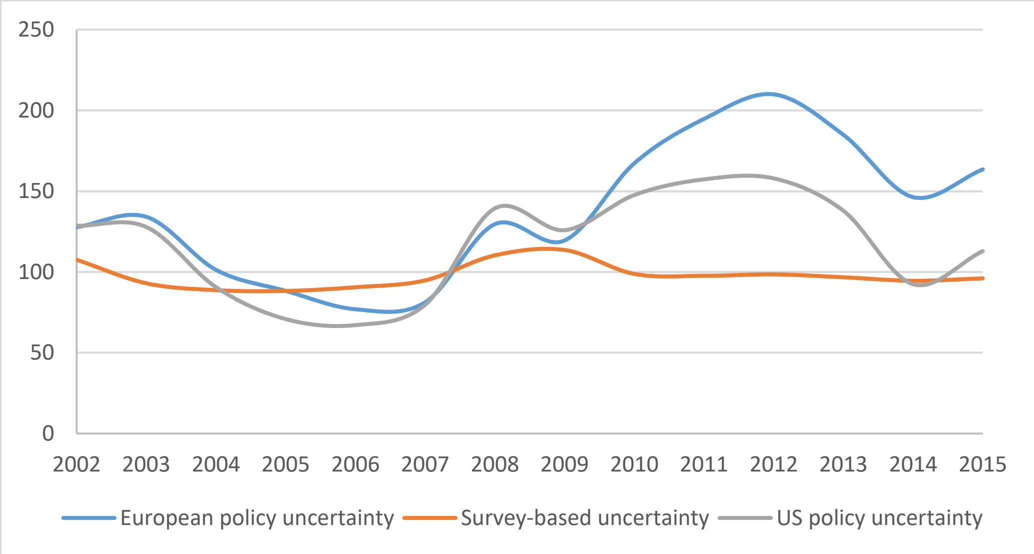
| | Moody's | | S&P's | | Fitch | |
|---|---|---|---|---|---|---|
| | coef. | p-val. | coef. | p-val. | coef. | p-val. |
| Log GDP per capita | **14.7949** | 0.000 | **16.0823** | 0.000 | **16.3700** | 0.000 |
| Government Debt | **-0.1094** | 0.000 | **-0.0727** | 0.000 | **-0.0840** | 0.000 |
| Current Account | **-0.0628** | 0.007 | -0.0328 | 0.114 | **-0.0356** | 0.075 |
| Unemployment Rate | **-0.1386** | 0.006 | **-0.2852** | 0.000 | **-0.2458** | 0.000 |
| Inflation Rate | **-0.1714** | 0.000 | **-0.1946** | 0.000 | **-0.2111** | 0.000 |
| Regulatory Quality | **2.9120** | 0.000 | **2.6319** | 0.000 | **2.1821** | 0.001 |
| Competitiveness | **-0.0416** | 0.000 | **-0.0235** | 0.014 | **-0.0286** | 0.002 |
| Uncertainty | -0.0083 | 0.131 | **-0.0099** | 0.046 | 0.0022 | 0.645 |
| Constant | **-38.2044** | 0.008 | **-46.7757** | 0.000 | **-48.0082** | 0.000 |

| Time effects | coef. | p-val. | coef. | p-val. | coef. | p-val. |
|---|---|---|---|---|---|---|
| 2003 | 0.1657 | 0.621 | 0.1675 | 0.577 | 0.2415 | 0.406 |
| 2004 | -0.2732 | 0.544 | -0.1930 | 0.633 | 0.4167 | 0.286 |
| 2005 | -0.5254 | 0.315 | -0.4935 | 0.293 | 0.1750 | 0.699 |
| 2006 | -0.9529 | 0.113 | -1.1522 | 0.033 | -0.2590 | 0.619 |
| 2007 | -1.3860 | 0.023 | -1.7272 | 0.002 | -0.8070 | 0.127 |
| 2008 | -0.1771 | 0.681 | -0.4662 | 0.228 | -0.3021 | 0.419 |
| 2009 | 1.0514 | 0.025 | -0.4168 | 0.319 | 0.3485 | 0.389 |
| 2010 | 1.5486 | 0.000 | 0.4149 | 0.166 | 0.7237 | 0.013 |
| 2011 | 0.5975 | 0.066 | 0.4120 | 0.157 | 0.2816 | 0.317 |
| 2012 | 0.4528 | 0.137 | 0.3420 | 0.186 | 0.6235 | 0.463 |
| 2013 | 0.2504 | 0.452 | -0.1271 | 0.671 | 0.0961 | 0.739 |
| 2014 | 0.6234 | 0.139 | -0.4244 | 0.262 | 0.2200 | 0.547 |
| 2015 | 0.2562 | 0.503 | -0.5742 | 0.096 | -0.5315 | 0.111 |

| | | | | |
|---|---|---|---|---|
| R^2 | within | 0.877 | 0.849 | 0.864 |
| | between | 0.582 | 0.684 | 0.653 |
| | overall | 0.602 | 0.667 | 0.642 |

Notes: Figures in bold indicate significance at the 10% level or lower.

## Figure 2.1: Uncertainty measures




Note: The survey-based uncertainty is from Girardi and Reuter (2017) and the other two from Baker et al (2016).

## Figure 2.2: Impact of regulatory quality on ratings for Moody's: Quantile panel model versus standard panel model with fixed individual and time effects

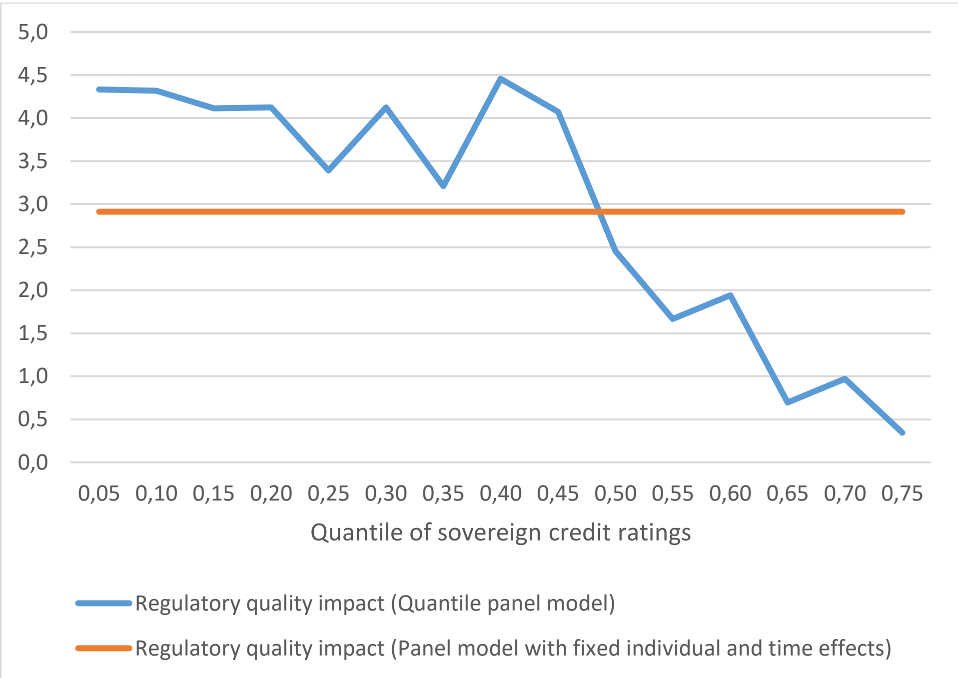


**Figure 2.3: Impact of competitiveness on ratings for Fitch: Quantile panel model versus standard panel model with fixed individual and time effects**

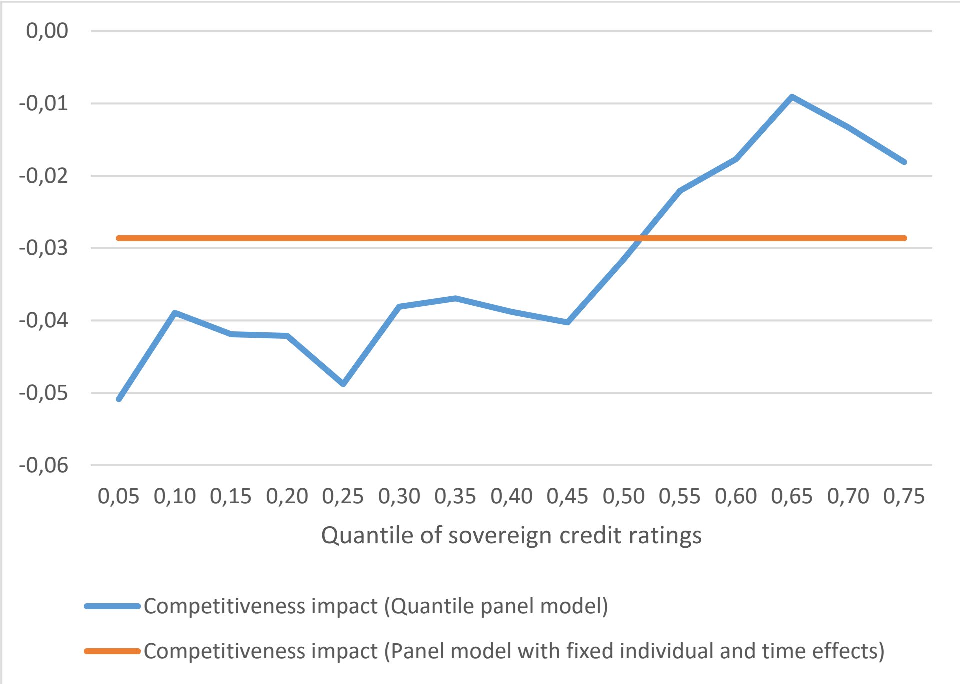



**Figure 2.4: Mapping of sovereign credit ratings to quantile distribution for Moody's**

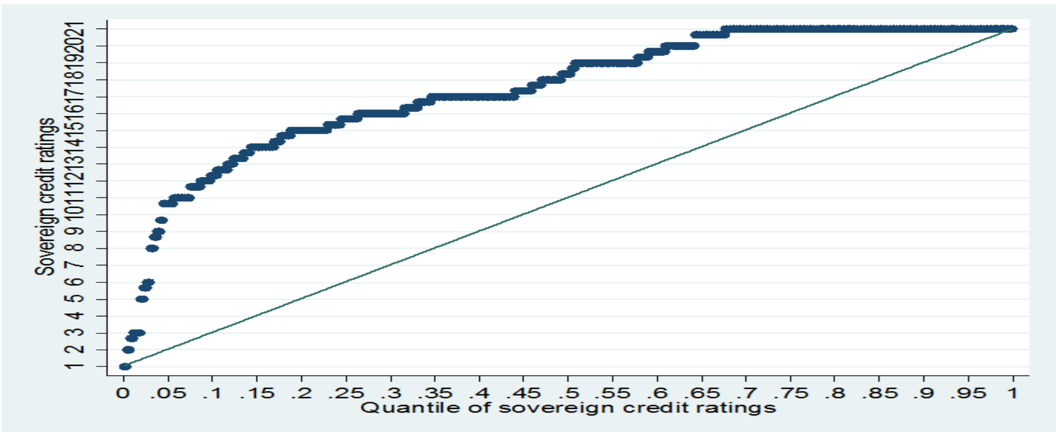


Figure 2.5: Mapping of sovereign credit ratings to quantile distribution for S&P's

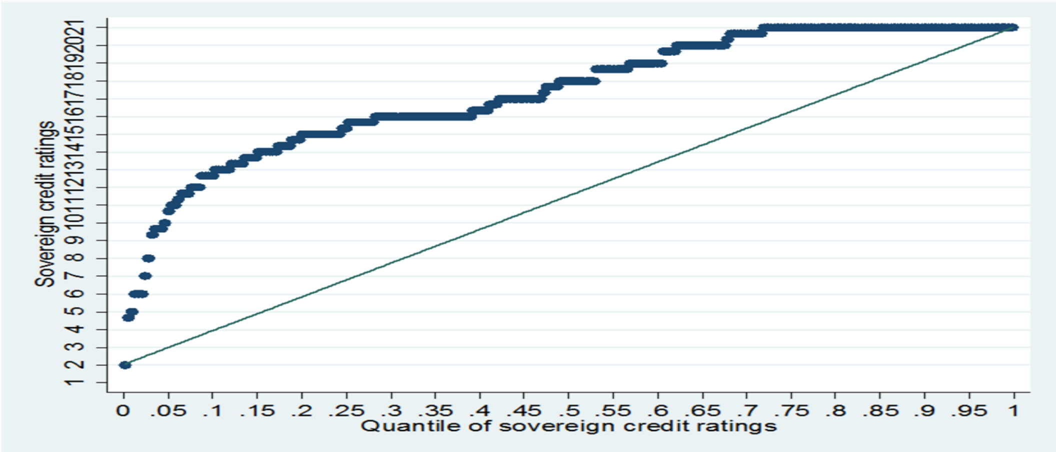
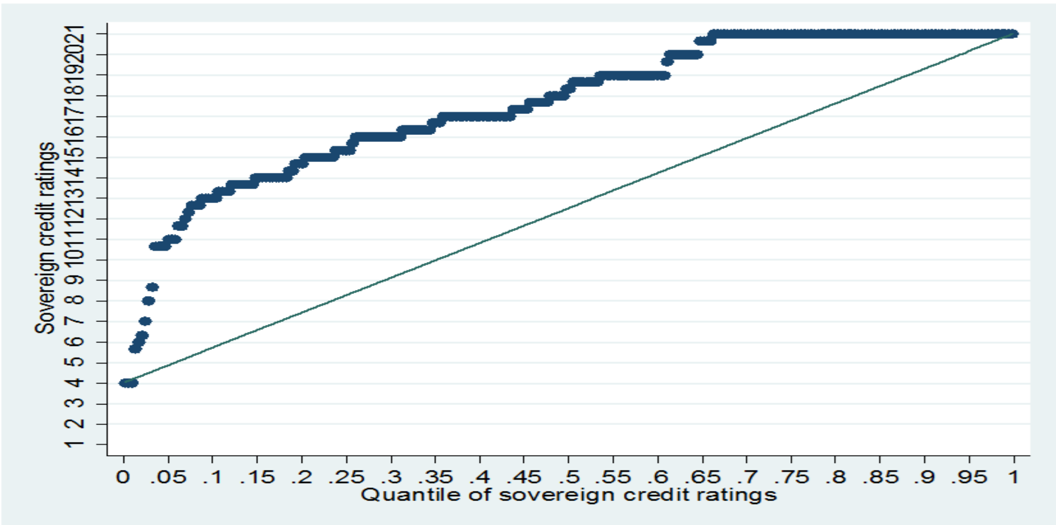



Figure 2.6: Mapping of sovereign credit ratings to quantile distribution for Fitch



## Table 3.1: Linear transformation of sovereign ratings

| | Rating Agency | | | | Frequency | | | Rating Scale |
|---|---|---|---|---|---|---|---|---|
| | Fitch | S&P's | Moody's | Outlook | Fitch | S&P's | Moody's | (1-21) |
| Highest quality | AAA | AAA | Aaa | Stable | 249 | 249 | 291 | 21 |
| | | | | Negative | 8 | 15 | 12 | 20.67 |
| | | | | Positive | - | 11 | 3 | 20.33 |
| | AA+ | AA+ | Aa1 | Stable | 56 | 52 | 35 | 20 |
| | | | | Negative | 3 | 11 | 9 | 19.67 |
| | | | | Positive | 3 | 4 | 7 | 19.33 |
| High quality | AA | AA | Aa2 | Stable | 61 | 40 | 50 | 19 |
| | | | | Negative | 15 | 14 | 2 | 18.67 |
| | | | | Positive | 4 | 2 | 10 | 18.33 |
| | AA- | AA- | Aa3 | Stable | 34 | 41 | 35 | 18 |
| | | | | Negative | 10 | 9 | 4 | 17.67 |
| | | | | Positive | 8 | 9 | 12 | 17.33 |
| | A+ | A+ | A1 | Stable | 57 | 38 | 65 | 17 |
| | | | | Negative | 8 | 7 | 4 | 16.67 |
| | | | | Positive | 13 | 11 | 9 | 16.33 |
| Strong payment capacity | A | A | A2 | Stable | 45 | 66 | 54 | 16 |
| | | | | Negative | 2 | 10 | 7 | 15.67 |
| | | | | Positive | 10 | 11 | 14 | 15.33 |
| | A- | A- | A3 | Stable | 58 | 64 | 45 | 15 |
| | | | | Negative | 9 | 6 | 10 | 14.67 |
| | | | | Positive | 6 | 9 | 5 | 14.33 |
| | BBB+ | BBB+ | Baa1 | Stable | 49 | 42 | 57 | 14 |
| | | | | Negative | 17 | 12 | 10 | 13.67 |
| Adequate payment capacity | | | | Positive | 10 | 15 | 11 | 13.33 |
| | BBB | BBB | Baa2 | Stable | 58 | 57 | 43 | 13 |
| | | | | Negative | 7 | 15 | 10 | 12.67 |
| | | | | Positive | 10 | 7 | 28 | 12.33 |
| | BBB- | BBB- | Baa3 | Stable | 83 | 59 | 64 | 12 |
| | | | | Negative | 18 | 23 | 21 | 11.67 |
| | | | | Positive | 12 | 14 | 15 | 11.33 |
| | BB+ | BB+ | Ba1 | Stable | 46 | 35 | 52 | 11 |
| | | | | Negative | 16 | 16 | 20 | 10.67 |
| Likely to fulfill obligations, ongoing uncertainty | | | | Positive | 4 | 19 | 7 | 10.33 |
| | BB | BB | Ba2 | Stable | 37 | 52 | 23 | 10 |
| | | | | Negative | 12 | 23 | 8 | 9.67 |
| | | | | Positive | 16 | 3 | 3 | 9.33 |
| | BB- | BB- | Ba3 | Stable | 34 | 45 | 28 | 9 |
| | | | | Negative | 6 | 9 | 6 | 8.67 |
| | | | | Positive | 9 | 12 | 11 | 8.33 |
| | B+ | B+ | B1 | Stable | 24 | 32 | 39 | 8 |
| | | | | Negative | 4 | 5 | 7 | 7.67 |
| | | | | Positive | 7 | 11 | 2 | 7.33 |
| High credit risk | B | B | B2 | Stable | 27 | 26 | 24 | 7 |
| | | | | Negative | 8 | 8 | 4 | 6.67 |
| | | | | Positive | 3 | 3 | 6 | 6.33 |
| | B- | B- | B3 | Stable | 24 | 42 | 36 | 6 |
| | | | | Negative | 8 | 9 | 9 | 5.67 |
| | | | | Positive | - | - | 4 | 5.33 |
| | CCC+ | CCC+ | Caa1 | Stable | 2 | 18 | 13 | 5 |
| | | | | Negative | 1 | 4 | 9 | 4.67 |
| | | | | Positive | - | - | - | 4.33 |
| Very high credit risk | CCC | CCC | Caa2 | Stable | 10 | - | 4 | 4 |
| | | | | Negative | - | 2 | - | 3.67 |
| | | | | Positive | - | - | - | 3.33 |
| | CCC- | CCC- | Caa3 | Stable | - | - | 7 | 3 |
| | | | | Negative | - | 3 | 2 | 2.66 |
| Non default with possibility of recovery | CC | CC | Ca | | - | - | - | 2.33 |
| | | | | | | | | 2 |
| | C | | | | 3 | 3 | 4 | |
| Default | DDD | SD | C | | | | | |
| | DD | D | | | 8 | 10 | 1 | 1 |
| | D | | | | | | | |

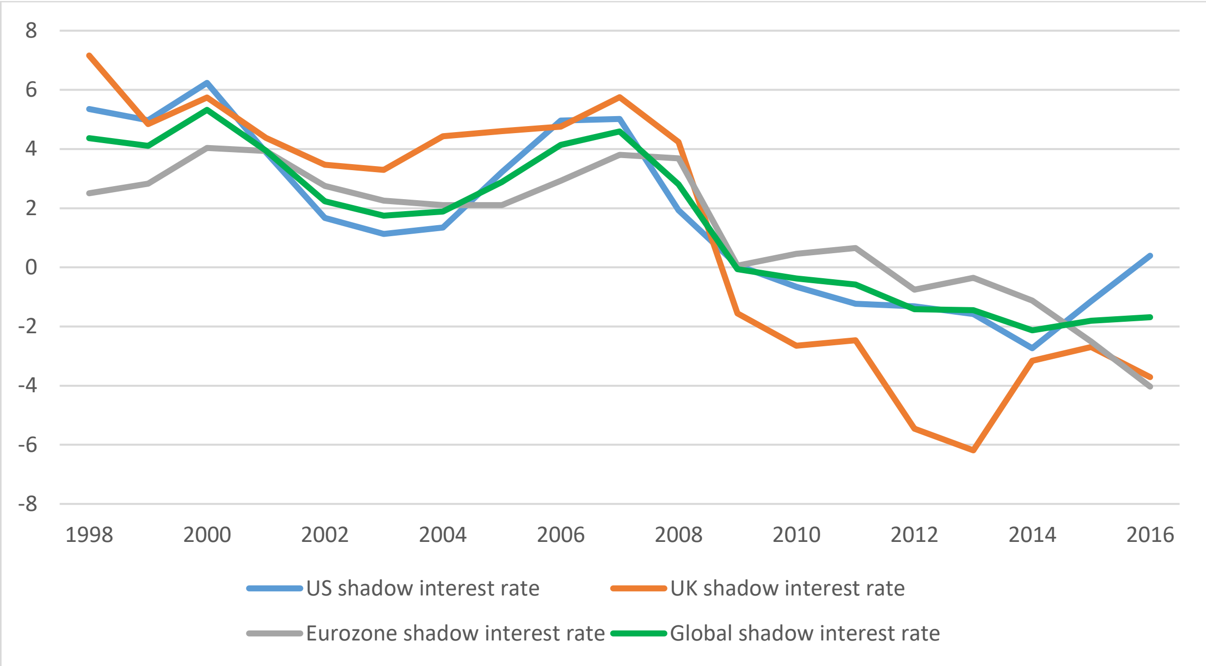
### Table 3.2: Data definitions and sources

| Variable Name | Definition | Source |
|---|---|---|
| Fitch rating | Sovereign rating attributed at 31st December of each year | Fitch |
| S&P's rating | Sovereign rating attributed at 31st December of each year | S&P's |
| Moody's rating | Sovereign rating attributed at 31st December of each year | Moody's |
| Uncertainty | News Index Economic Policy Uncertainty | www.policyuncertainty.com |
| GDP growth rate | Gross domestic product, constant prices Percent change | IMF WEO April 2017 |
| Investments | Total investments as a percent of GDP | IMF WEO April 2017 |
| Government debt | General government gross debt as a percent of GDP | IMF WEO April 2017 |
| Fiscal Balance | General government net lending/borrowing as a percent of GDP | IMF WEO April 2017 |
| Non-performing loans | Non-performing loans as a percent of total gross loans | World Bank; FRED; IMF IFS |

### Table 3.3: Summary statistics of the data variables

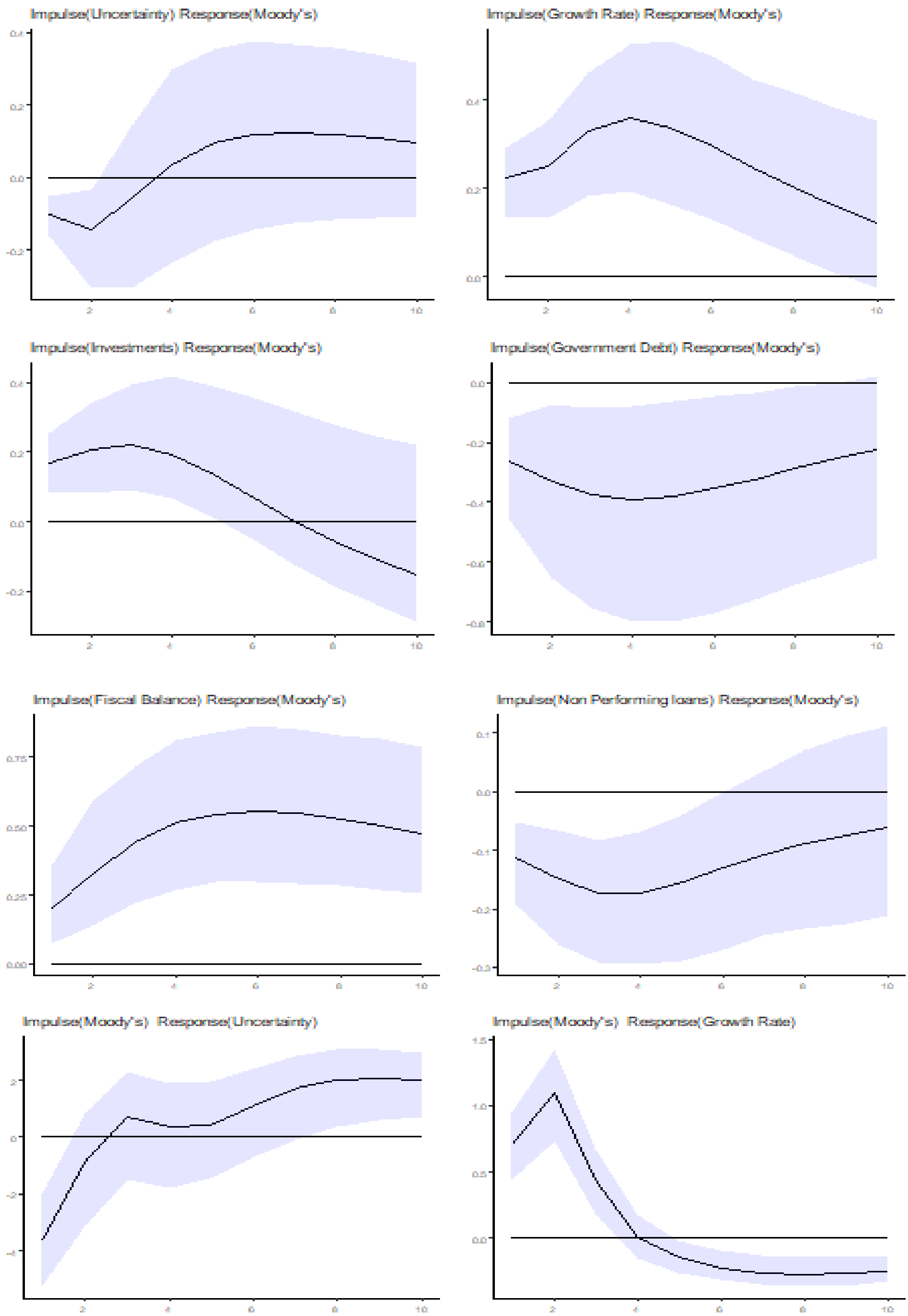
| Variable | Min. | 1st Quartile | Median | Mean | 3rd Quartile | Max. | St. Dev. |
|---|---|---|---|---|---|---|---|
| Moody's ratings | 1 | 11 | 15 | 14.84 | 20 | 21 | 5.10 |
| S&P's ratings | 1 | 10.33 | 15 | 14.46 | 19.67 | 21 | 5.12 |
| Fitch ratings | 1 | 11 | 15 | 14.87 | 20 | 21 | 4.90 |
| Economic Policy Uncertainty | 26.62 | 81.22 | 108.41 | 117.96 | 135.11 | 542.77 | 47.26 |
| GDP growth rate | -15.14 | 1.51 | 3.31 | 3.22 | 5.14 | 26.26 | 3.69 |
| Investments | 4.31 | 20.06 | 22.81 | 23.51 | 26.08 | 48.01 | 5.37 |
| Government debt | 0.06 | 29.48 | 44.13 | 51.48 | 66.89 | 242.11 | 33.51 |
| Fiscal Balance | -32.13 | -4.09 | -2.21 | -1.81 | 0.04 | 29.80 | 4.53 |
| Non-performing loans | 0.08 | 1.79 | 3.61 | 6.61 | 8.60 | 71.70 | 7.81 |

**Figure 3.1: Shadow interest rates (%), 1998-2016**

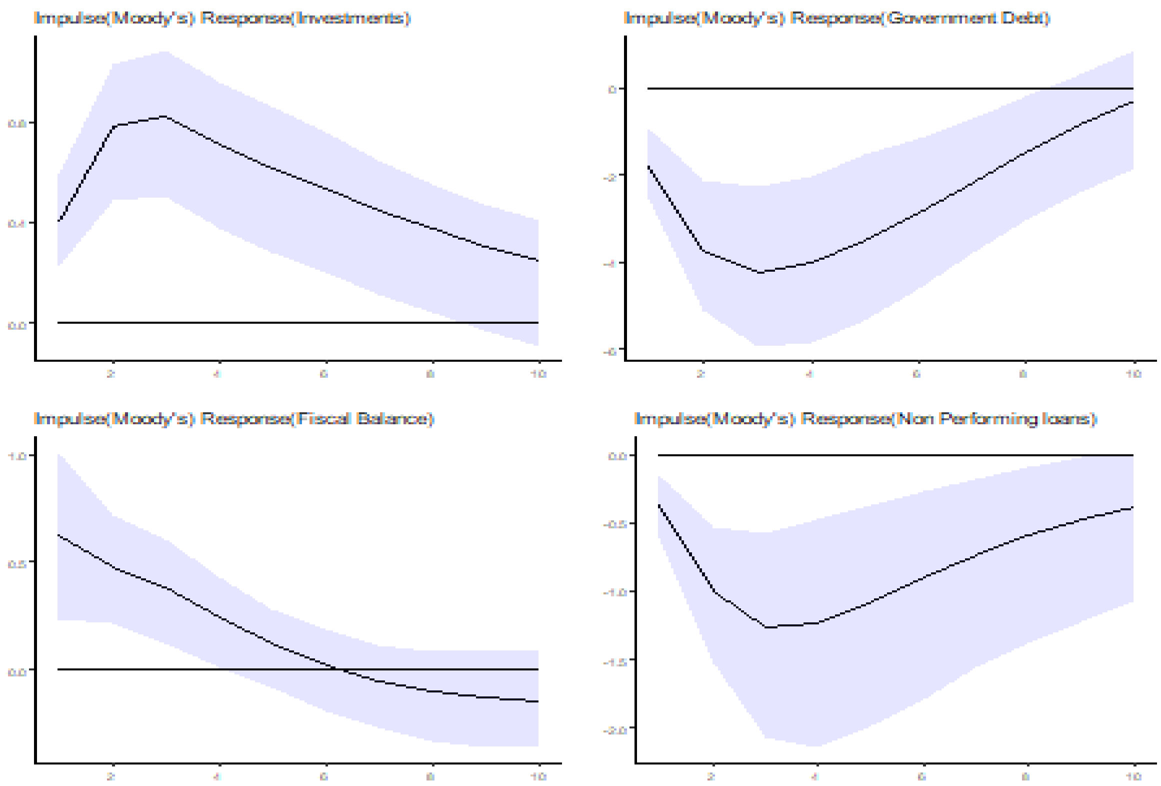



Notes: Shadow interest rates for the US, UK, the Eurozone area and 'global' shadow interest rate. The 'global' shadow interest rate is a weighted average of the shadow interest rates for the US, Eurozone and the UK as discussed in Section 2 of the chapter.

**Figure 3.2: Generalized impulse response functions for Moody's using first difference transformation**



## Figure 3.2 (continued): Generalized impulse response functions for Moody's using first difference transformation




Notes: Shaded areas refer to the 95% confidence intervals based on 500 bootstrap replications. Generalized impulse response functions are based on estimates of the Panel Vector AutoRegressive (PVAR) model (3.2) in Section 3 of the chapter where the endogenous variables in our PVAR model are

$y_{i,t}$ = [Uncertainty, GDP growth, Investments, Debt, Fiscal Balance, NPLs, rating] using the rating of Moody's and the first difference transformation.

**Figure 3.3: Generalized impulse response functions for S&P's using the first difference transformation**

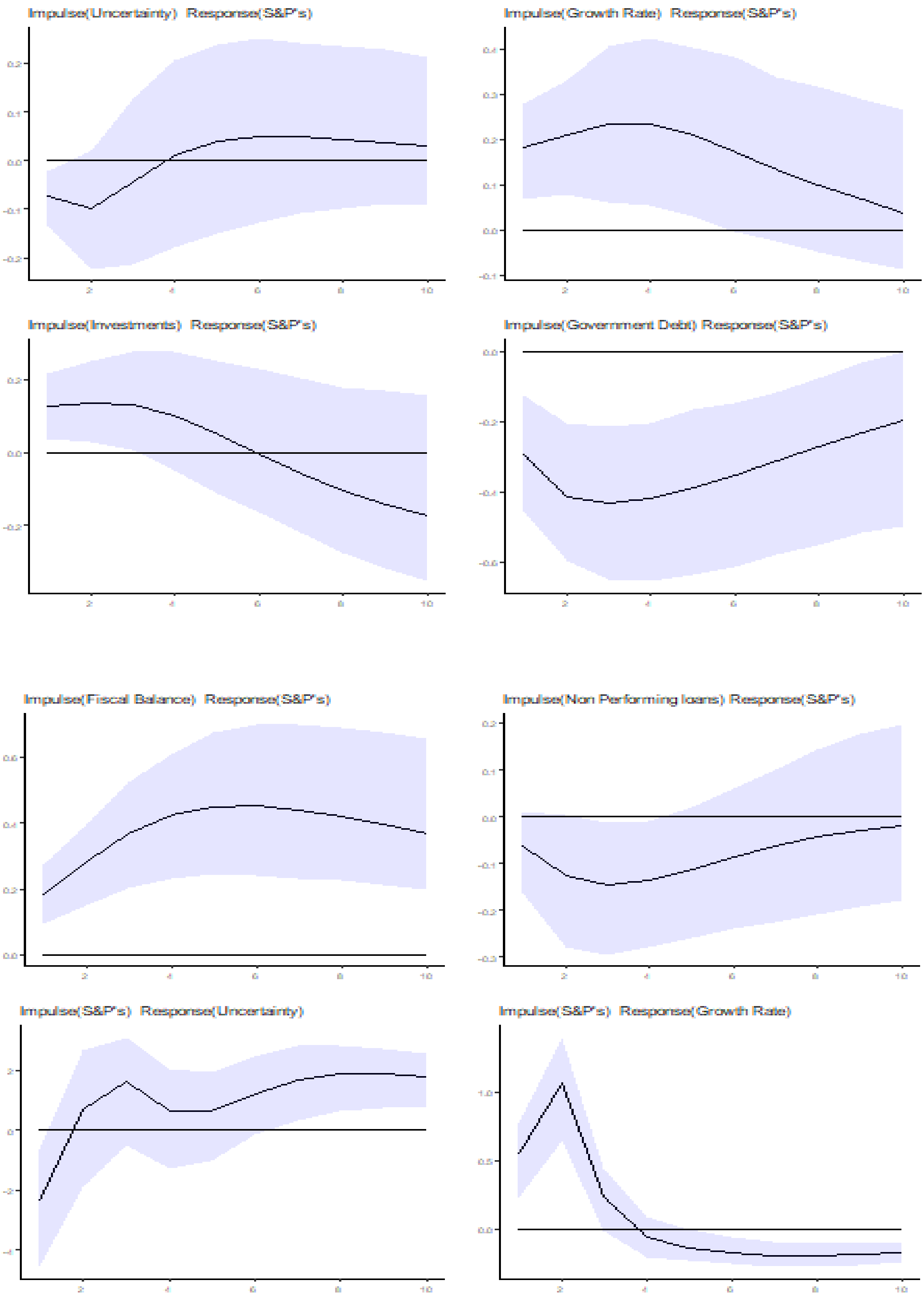
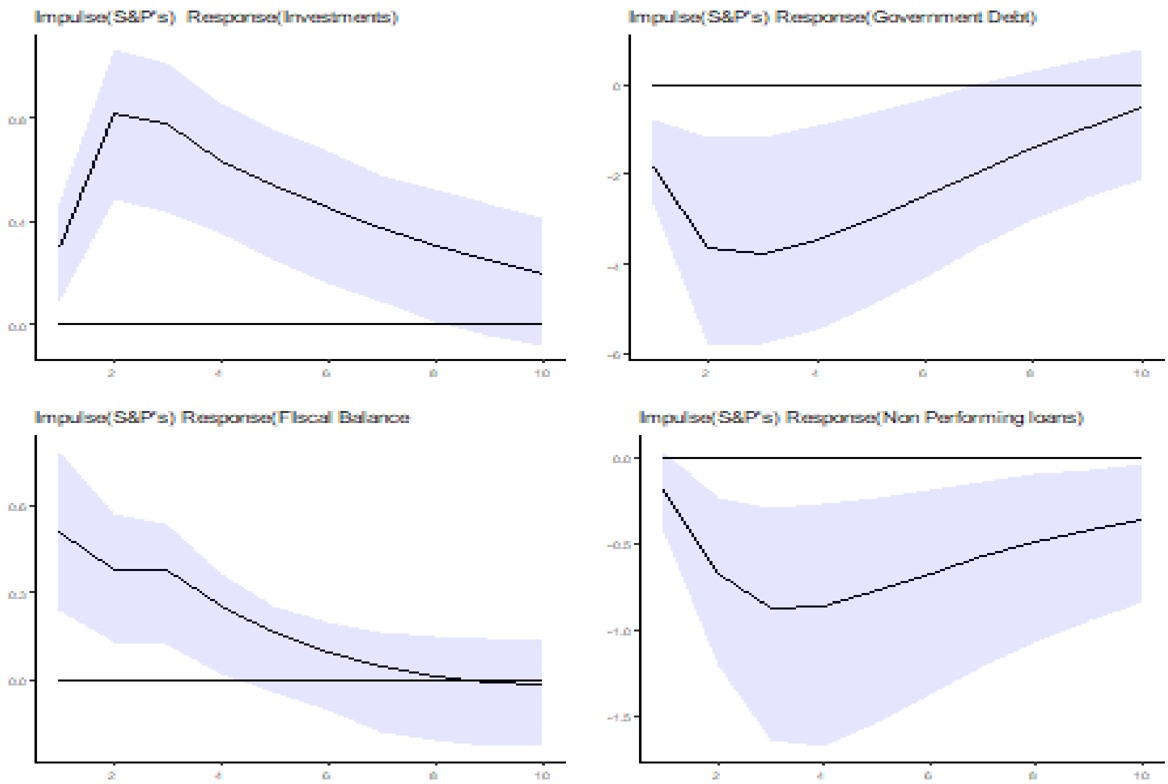


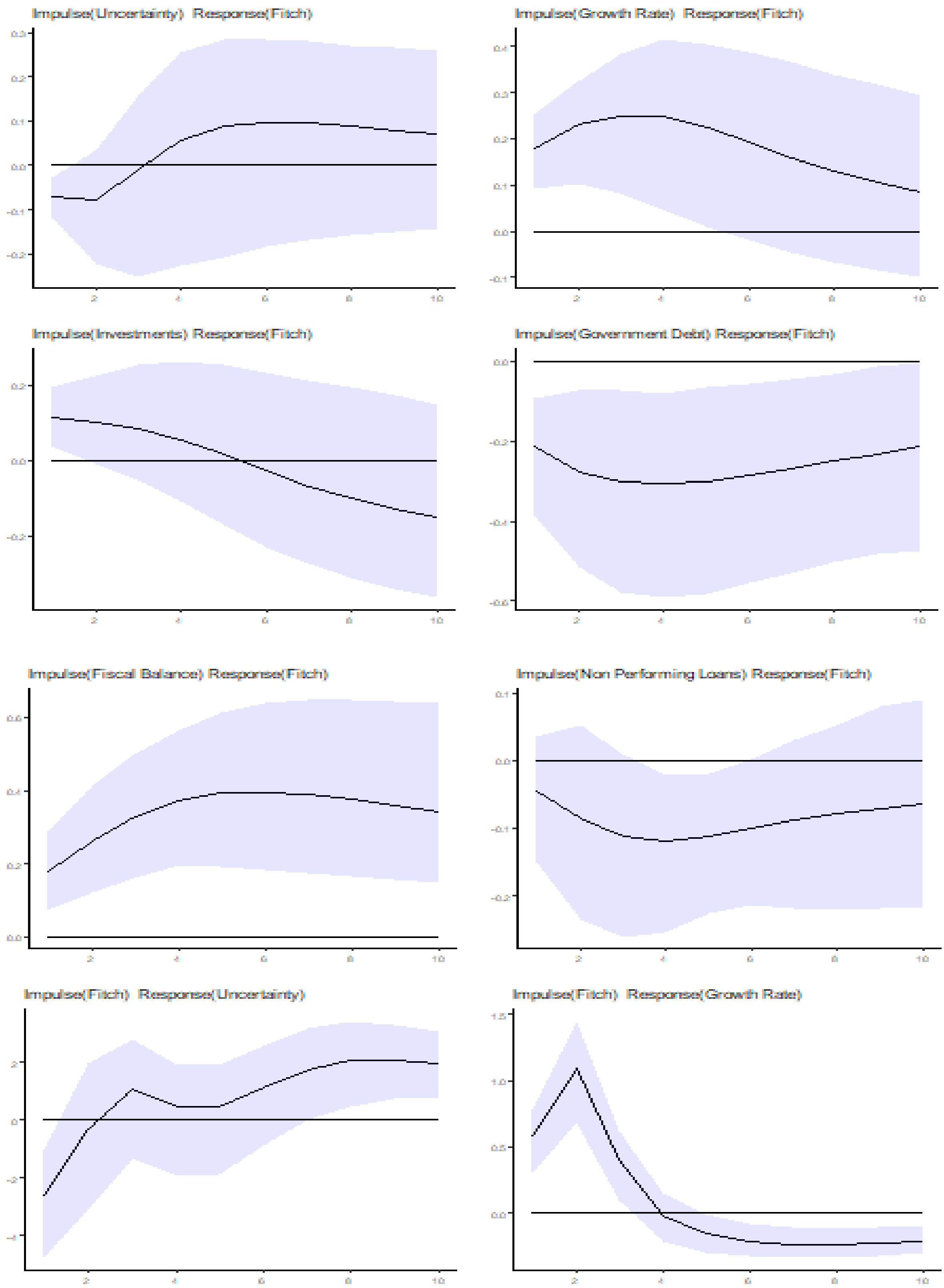
**Figure 3.3 (continued): Generalized impulse response functions for S&P's using the first difference transformation**



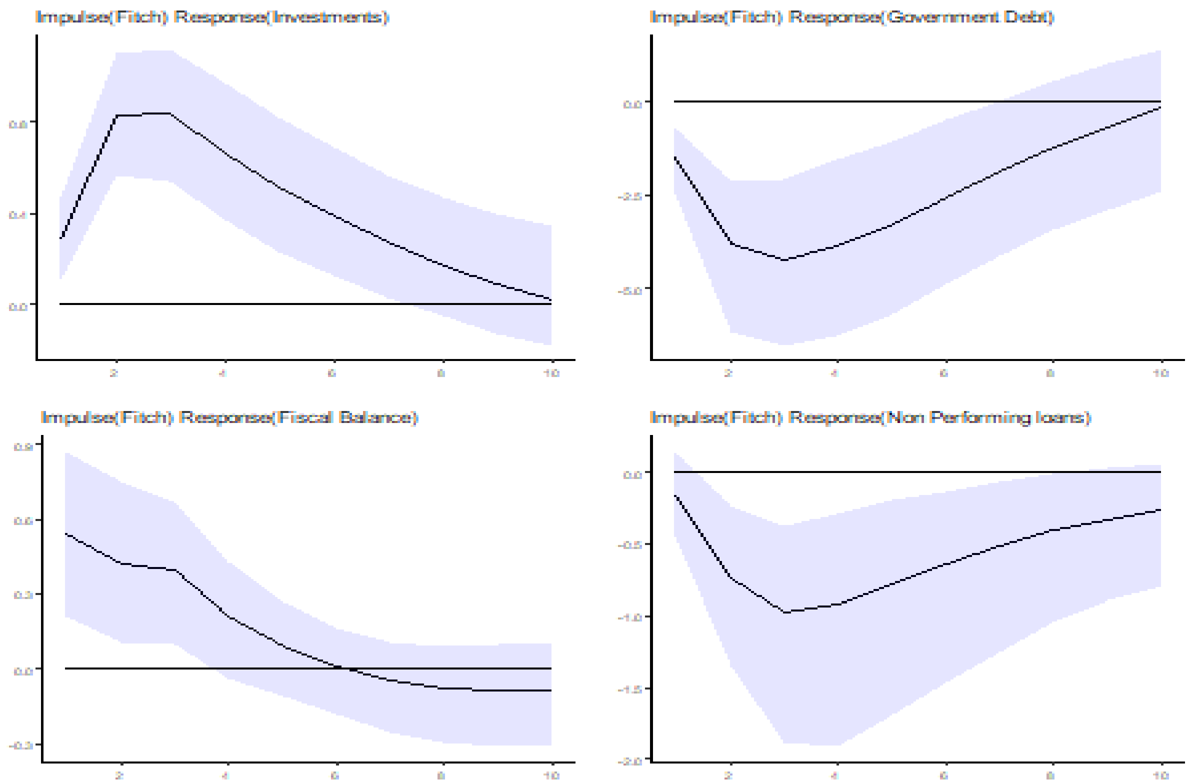

Notes: Shaded areas refer to the 95% confidence intervals based on 500 bootstrap replications. Generalized impulse response functions are based on estimates of the Panel Vector AutoRegressive (PVAR) model (3.2) in Section 3 of the chapter where the endogenous variables in our PVAR model are

$y_{i,t}$ = [Uncertainty, GDP growth, Investments, Debt, Fiscal Balance, NPLs, rating] using the rating of S&P's and the first difference transformation.

## Figure 3.4: Generalized impulse response functions for Fitch using first difference transformation



### Figure 3.4 (continued): Generalized impulse response functions for Fitch using the first difference transformation




Notes: Shaded areas refer to the 95% confidence intervals based on 500 bootstrap replications. Generalized impulse response functions are based on estimates of the Panel Vector AutoRegressive (PVAR) model (3.2) in Section 3 of the chapter where the endogenous variables in our PVAR model are

$y_{i,t}$ = [Uncertainty, GDP growth, Investments, Debt, Fiscal Balance, NPLs, rating] using the rating of Fitch and the first difference transformation.

Figure 3.5: Generalized impulse response functions for Moody's using expanding time windows

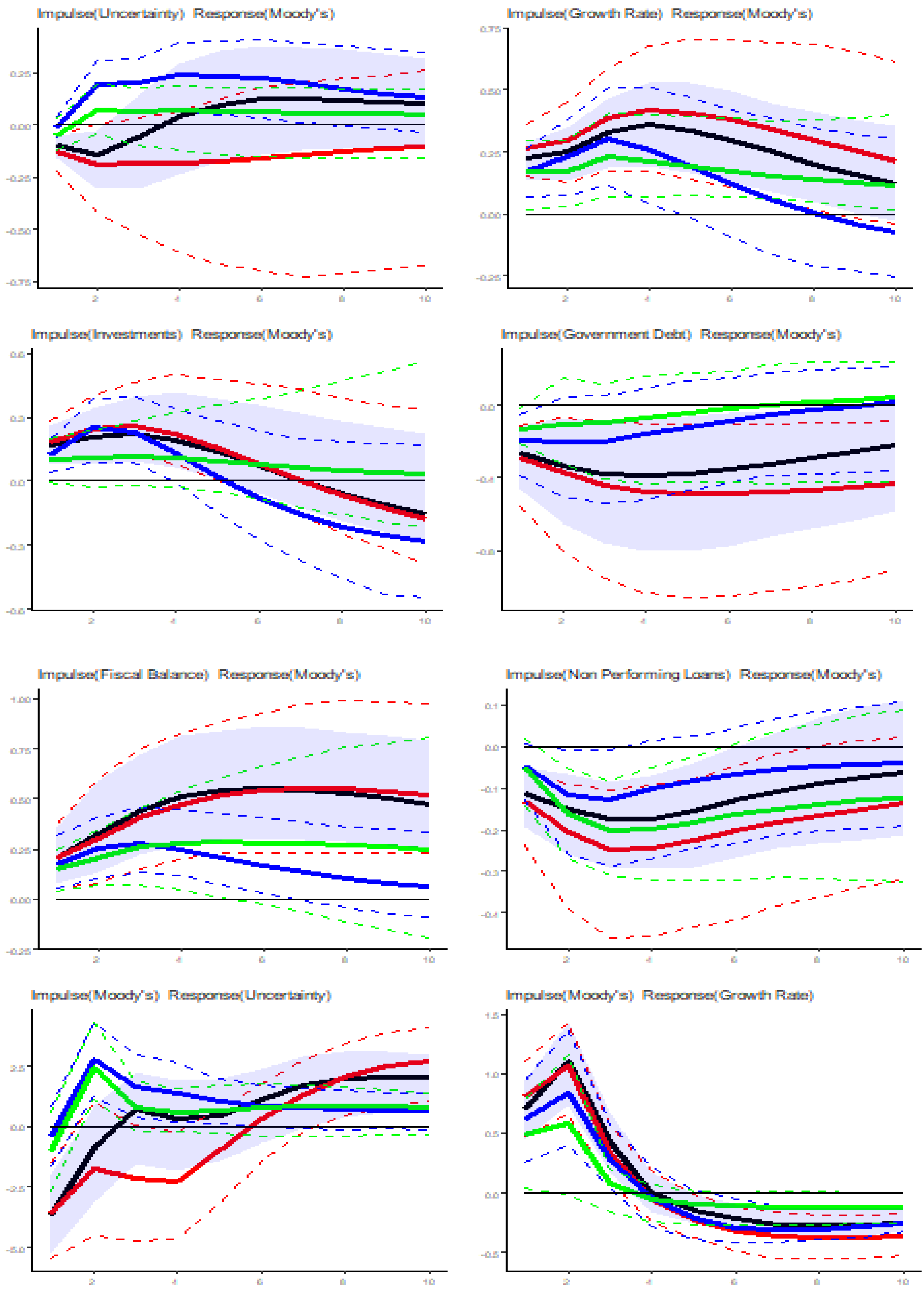
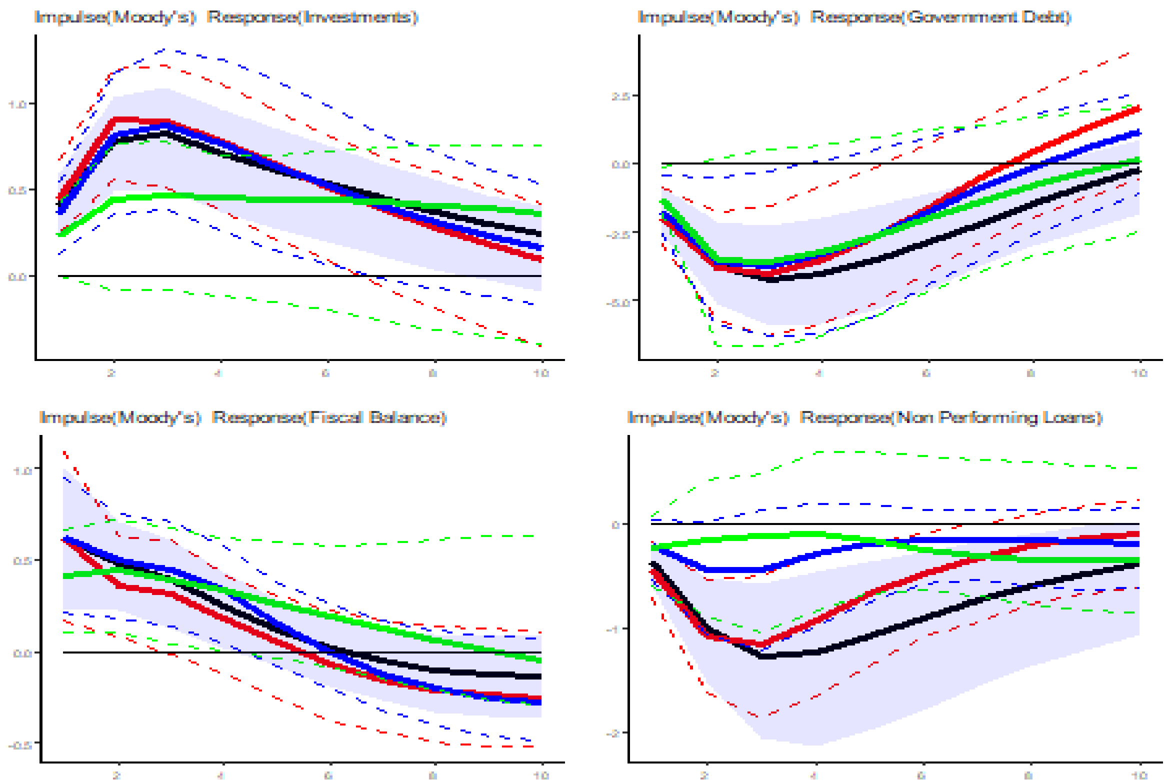


**Figure 3.5 (continued): Generalized impulse response functions for Moody's using expanding time windows**




Notes: The green line covers the 1998-2006 period. The blue line covers the 1998-2009 period. The red line covers the 1998-2012 period. The black line covers the whole 1998-2016 sample period. Dashed lines and shaded areas refer to 95% confidence intervals based on 500 bootstrap replications. Generalized impulse response functions are based on estimates of the Panel Vector AutoRegressive (PVAR) model (3.2) in Section 3 of the chapter where the endogenous variables in our PVAR model are

$y_{i,t}$ = [Uncertainty, GDP growth, Investments, Debt, Fiscal Balance, NPLs, rating] using the rating of Moody's and the first difference transformation.

**Figure 3.6: Generalized impulse response functions for S&P's using expanding time windows**

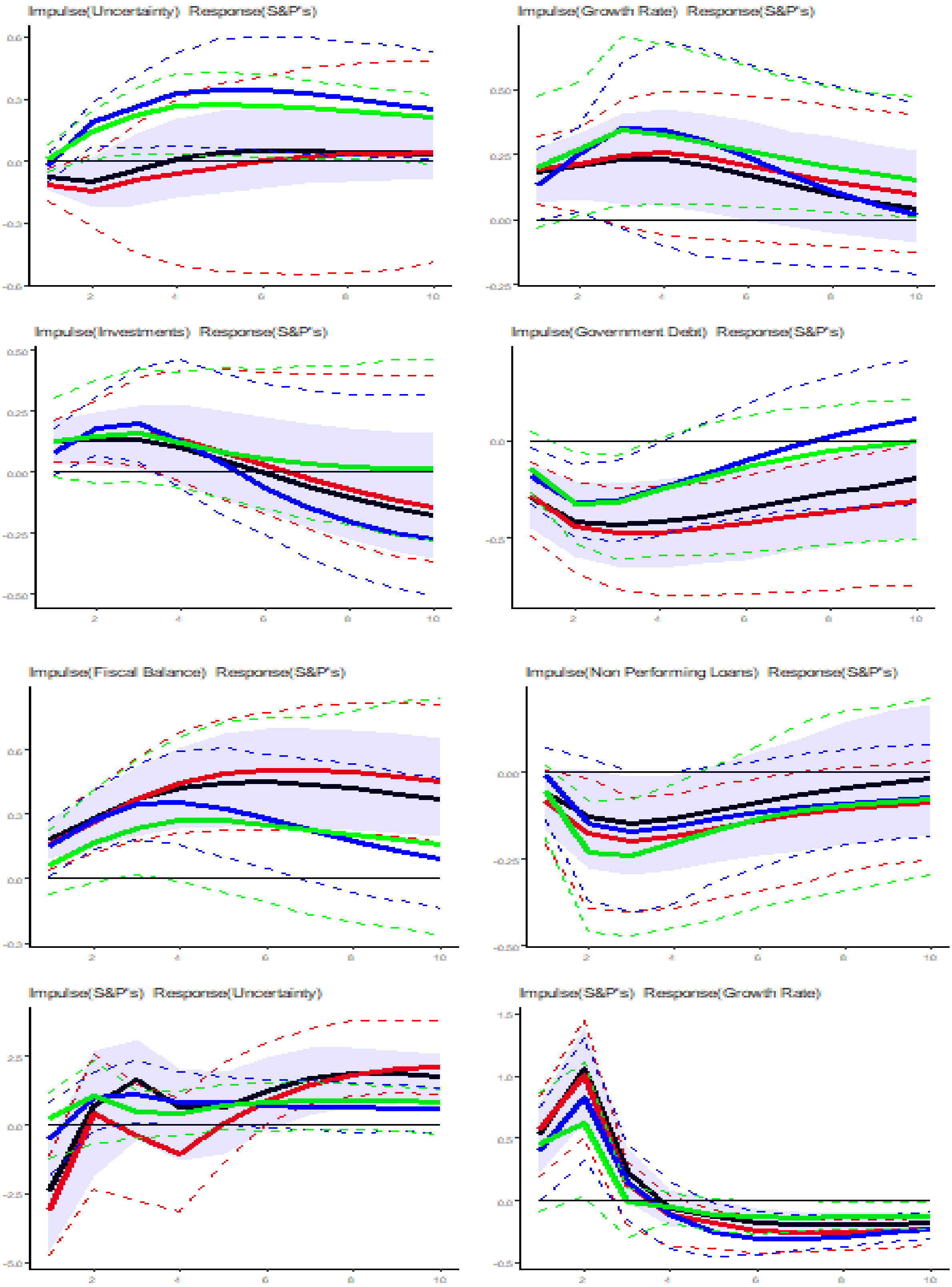
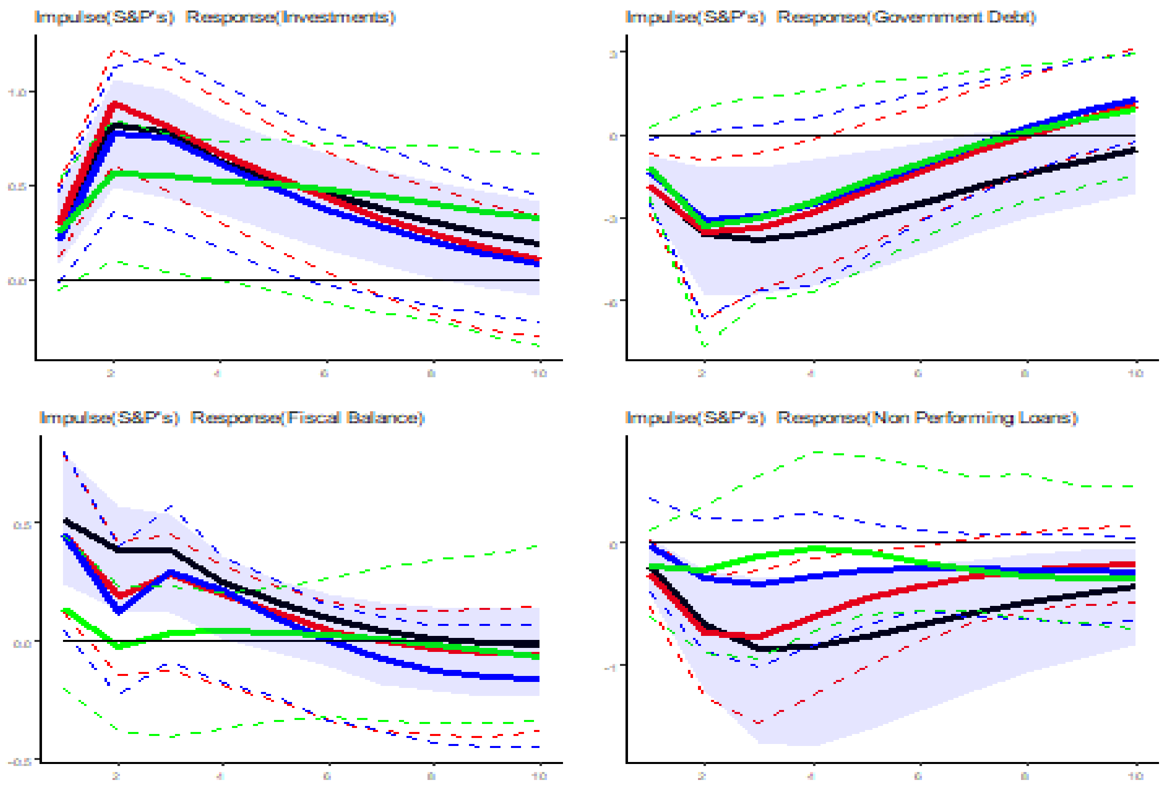


**Figure 3.6 (continued): Generalized impulse response functions for S&P's using expanding time windows**




Notes: The green line covers the 1998-2006 period. The blue line covers the 1998-2009 period. The red line covers the 1998-2012 period. The black line covers the whole 1998-2016 sample period. Dashed lines and shaded areas refer to 95% confidence intervals based on 500 bootstrap replications. Generalized impulse response functions are based on estimates of the Panel Vector AutoRegressive (PVAR) model (3.2) in Section 3 of the chapter where the endogenous variables in our PVAR model are

$y_{i,t}$ = [Uncertainty, GDP growth, Investments, Debt, Fiscal Balance, NPLs, rating] using the rating of S&P's and the first difference transformation.

**Figure 3.7: Generalized impulse response functions for Fitch using expanding time windows**

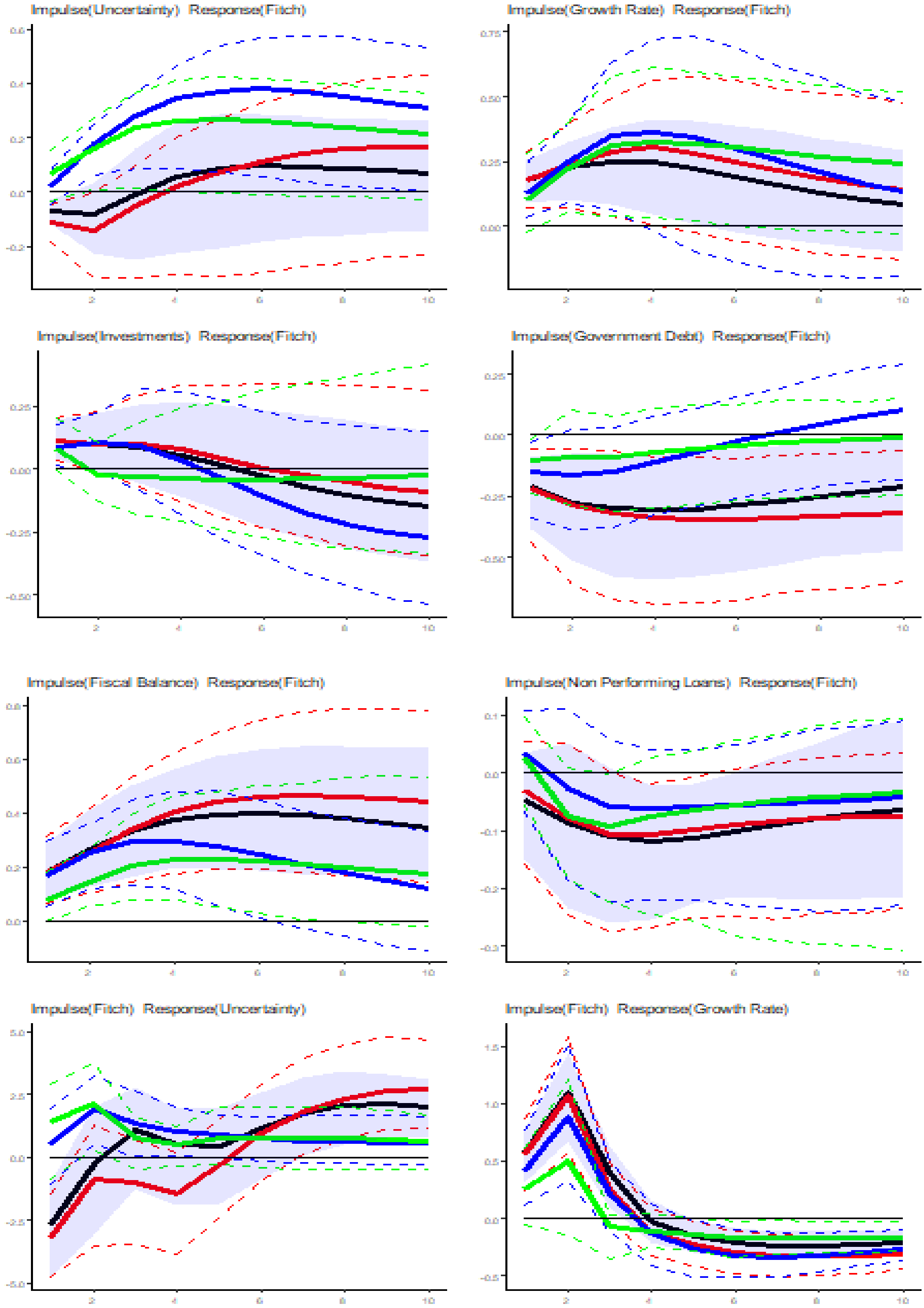
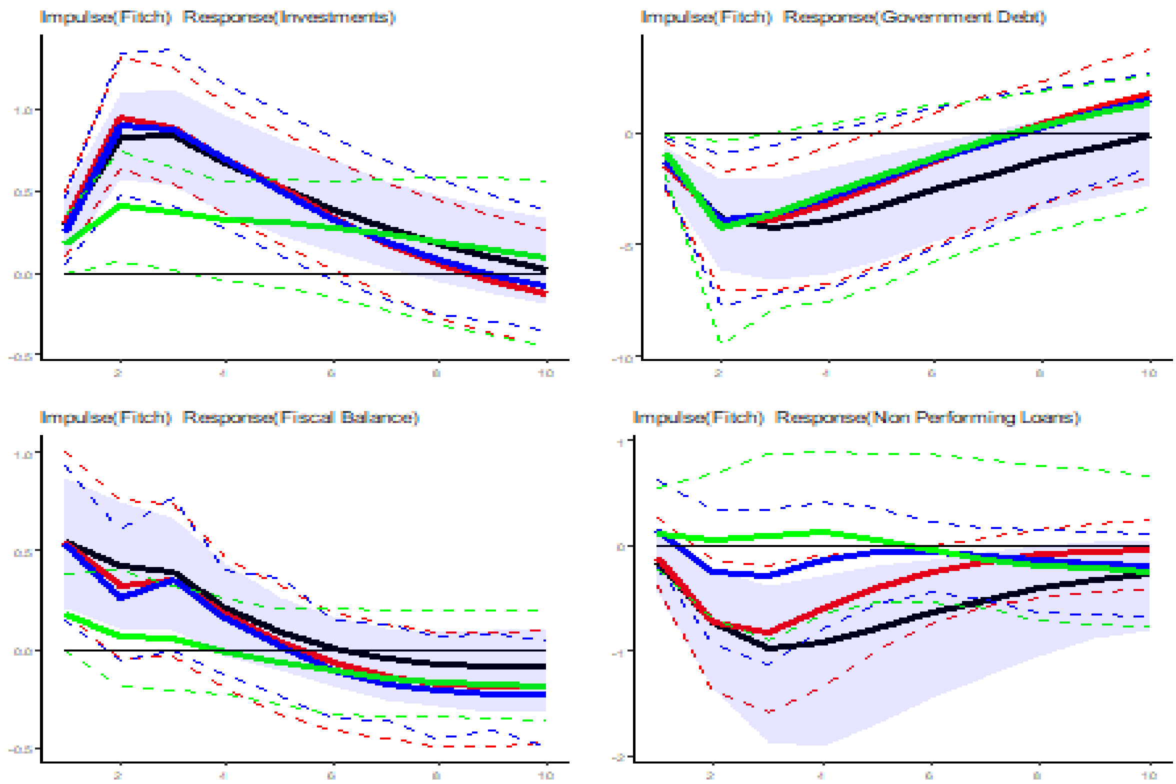


**Figure 3.7 (continued): Generalized impulse response functions for Fitch using expanding time windows**




Notes: The green line covers the 1998-2006 period. The blue line covers the 1998-2009 period. The red line covers the 1998-2012 period. The black line covers the whole 1998-2016 sample period. Dashed lines and shaded area refer to 95% confidence intervals based on 500 bootstrap replications. Generalized impulse response functions are based on estimates of the Panel Vector AutoRegressive (PVAR) model (3.2) in Section 3 of the chapter where the endogenous variables in our PVAR model are

$y_{i,t}$ = [Uncertainty, GDP growth, Investments, Debt, Fiscal Balance, NPLs, rating] using the rating of Fitch and the first difference transformation.

**Figure 3.8: Linear and logistic transformation of sovereign credit ratings for Moody's**

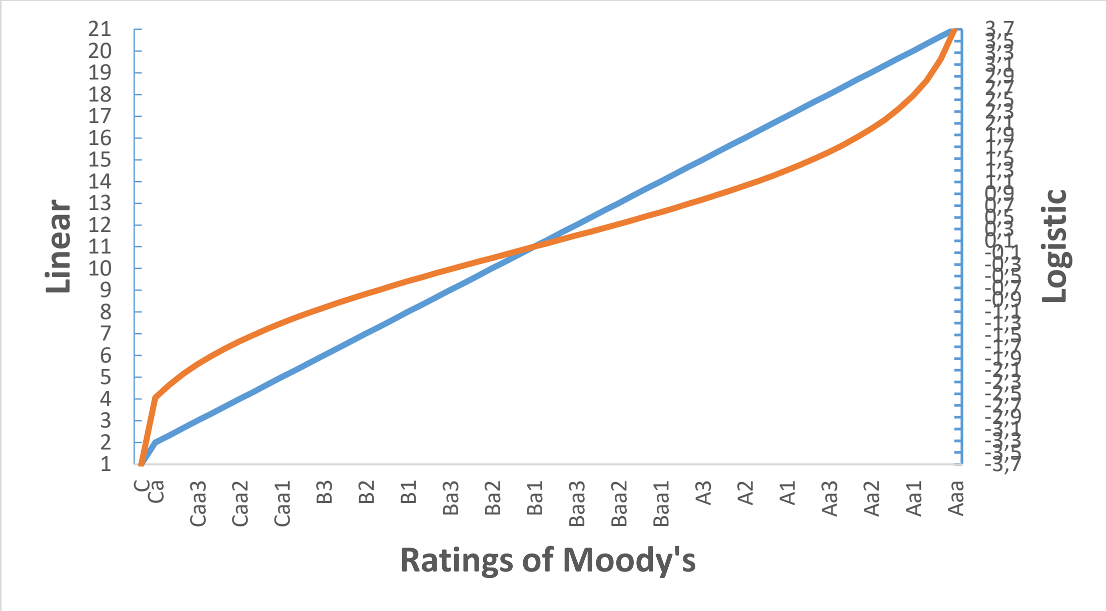


**Figure 3.9: Generalized impulse response functions for Moody's using logistic transformation of sovereign ratings**

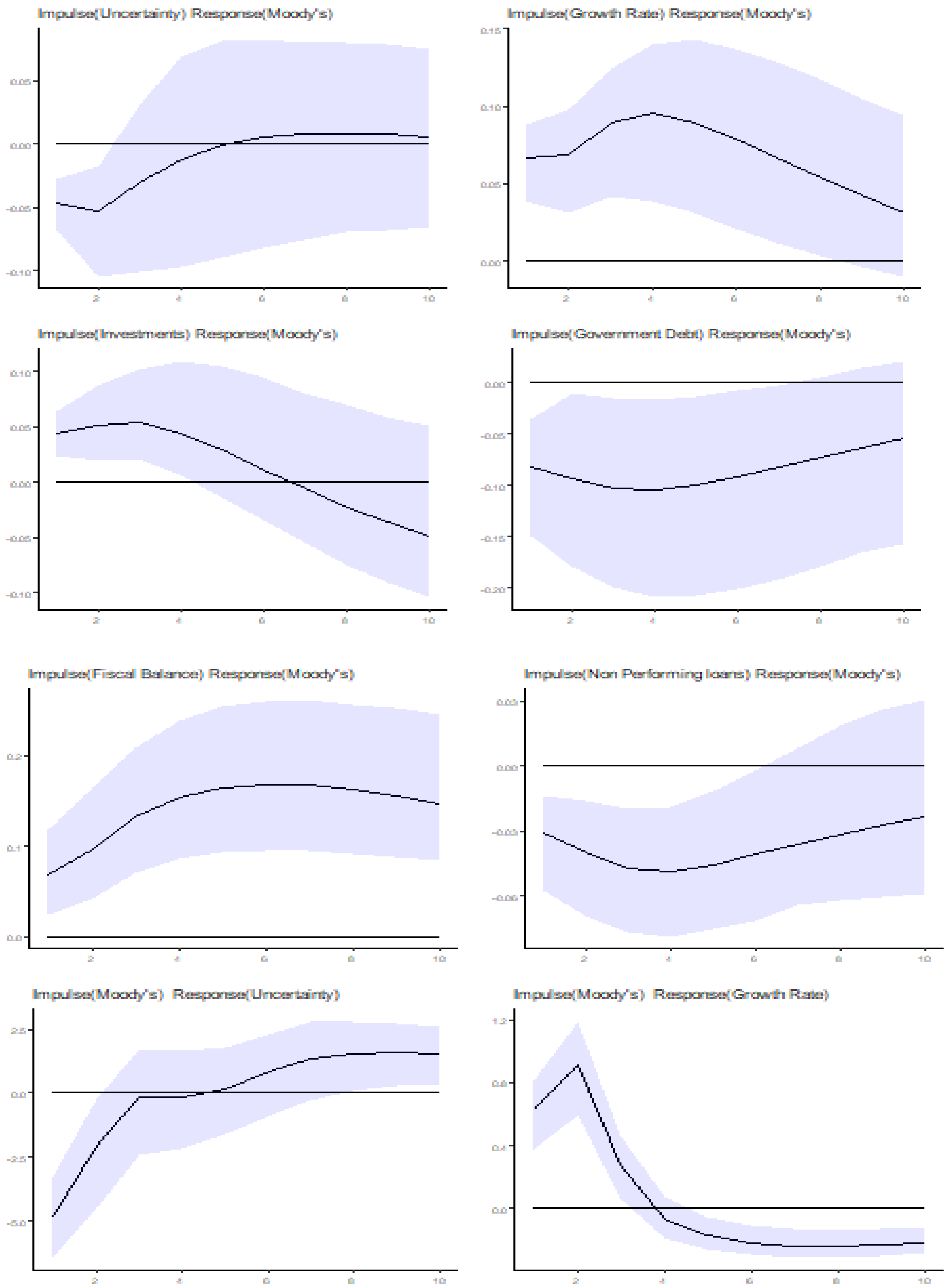
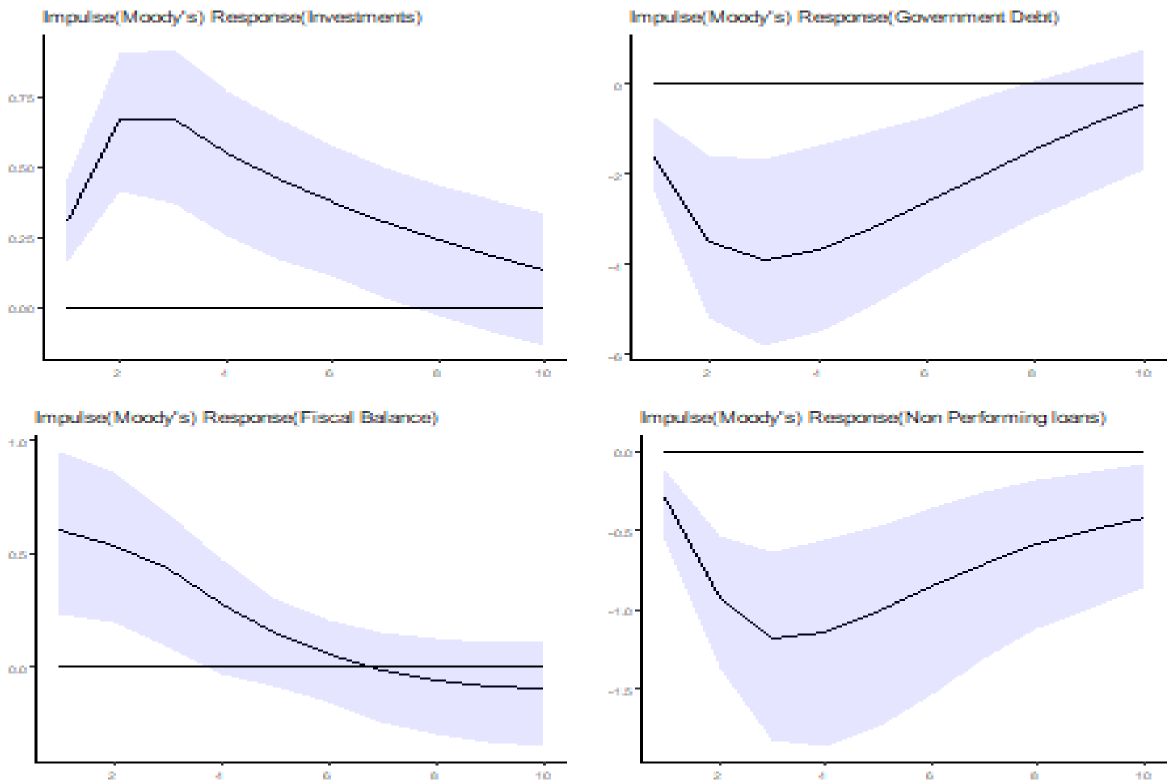


**Figure 3.9 (continued): Generalized impulse response functions for Moody's using a logistic transformation of sovereign ratings**

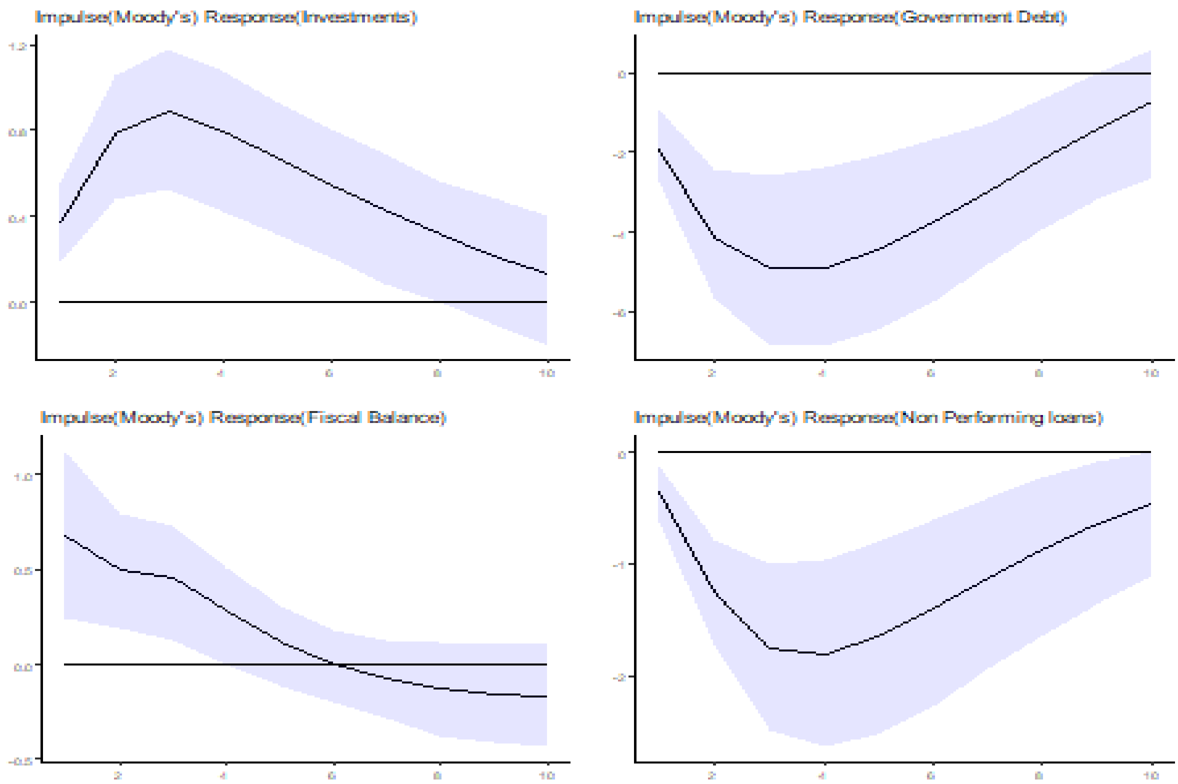



Notes: Shaded areas refer to the 95% confidence intervals based on 500 bootstrap replications. Generalized impulse response functions are based on estimates of the Panel Vector AutoRegressive (PVAR) model (3.2) in Section 3 of the chapter (using the first difference transformation) where the endogenous variables in our PVAR model are

$y_{i,t}$ = [Uncertainty, GDP growth, Investments, Debt, Fiscal Balance, NPLs, rating] using the logistic transformation of the rating of Moody's.

**Figure 3.10: Generalized impulse response functions for Moody's using stock price volatility**

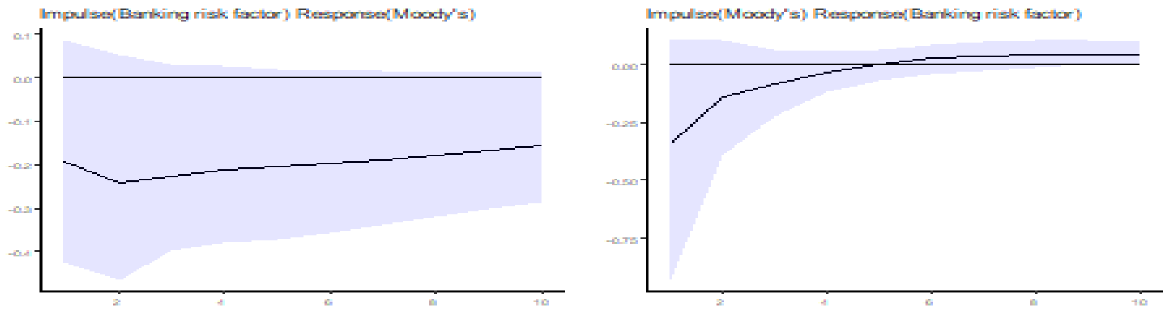
**Figure 3.10 (continued): Generalized impulse response functions for Moody's using stock price volatility**




Notes: Shaded areas refer to the 95% confidence intervals based on 500 bootstrap replications. Generalized impulse response functions are based on estimates of the Panel Vector AutoRegressive (PVAR) model (3.2) in Section 3 of the chapter where the endogenous variables in our PVAR model are

$y_{i,t}$ = [Stock price volatility, GDP growth, Investments, Debt, Fiscal Balance, NPLs, rating] using the rating of Moody's and the first difference transformation.

**Figure 3.11: Generalized impulse response functions for Moody's using the banking risk factor**




Notes: Shaded areas refer to the 95% confidence intervals based on 500 bootstrap replications. Generalized impulse response functions are based on estimates of the Panel Vector AutoRegressive (PVAR) model (3.2) in Section 3 of the chapter where the endogenous variables in our PVAR model are

$y_{i,t}$ = [Uncertainty, GDP growth, Investments, Debt, Fiscal Balance, banking risk factor, rating] using the rating of Moody's and the first difference transformation.

### Table 4.1 Transformation of sovereign and corporate credit ratings

This table presents the conversion of S&P's credit rating notation to a numerical scale.

| Numerical Rating | S&P's Rating |
|---|---|
| 22 | AAA |
| 21 | AA+ |
| 20 | AA |
| 19 | AA- |
| 18 | A+ |
| 17 | A |
| 16 | A- |
| 15 | BBB+ |
| 14 | BBB |
| 13 | BBB- |
| 12 | BB+ |
| 11 | BB |
| 10 | BB- |
| 9 | B+ |
| 8 | B |
| 7 | B- |
| 6 | CCC+ |
| 5 | CCC |
| 4 | CCC- |
| 3 | CC |
| 2 | C |
| 1 | SD/D |

### Table 4.2 Changes in corporate ratings around sovereign downgrades

| | **Corporate Credit Rating** | | |
|---|---|---|---|
| | Year before Downgrade | Year of Downgrade | Difference |
| Treated Firms | 15.837 | 13.103 | -2.734 |
| Control Firms | 12.766 | 12.497 | -0.299 |
| Difference | -3.071*** | -0.606** | -2.465*** |
| | (0.089) | (0.254) | (0.269) |

**Table 4.3 Sovereign Credit Rating Downgrades by Country and Year**

This table provides the initial sample of sovereign credit rating downgrades used in the study and the number of treated firm-year observations by country and year throughout 1990-2017.

| Country of Domicile | Year of a sovereign downgrade | Number of treated firms |
|---|---|---|
| Argentina | 2000 | 5 |
| | 2001 | 5 |
| | 2008 | 4 |
| | 2012 | 2 |
| | 2013 | 3 |
| | 2014 | 3 |
| Brazil | 1999 | 4 |
| | 2002 | 8 |
| | 2014 | 6 |
| | 2015 | 18 |
| | 2016 | 24 |
| Canada | 1992 | 1 |
| China | 2017 | 1 |
| Colombia | 2017 | 2 |
| Czech Republic | 1998 | 1 |
| Greece | 2011 | 3 |
| | 2015 | 8 |
| Hong Kong | 1998 | 2 |
| | 2017 | 1 |
| Hungary | 2006 | 1 |
| | 2012 | 1 |
| Indonesia | 1997 | 1 |
| | 1998 | 4 |
| Ireland | 2011 | 2 |
| Italy | 2004 | 1 |
| | 2006 | 2 |
| | 2011 | 2 |
| | 2012 | 2 |
| | 2013 | 7 |
| | 2014 | 9 |
| Japan | 2001 | 1 |
| | 2002 | 4 |
| | 2011 | 13 |
| | 2015 | 13 |
| Jordan | 2017 | 1 |
| Mexico | 1995 | 2 |
| | 2009 | 4 |
| Philippines | 2005 | 4 |
| Portugal | 2010 | 1 |
| | 2011 | 2 |

| | | |
|---|---|---|
| | 2012 | 4 |
| Russia | 2014 | 5 |
| | 2015 | 13 |
| Saudi Arabia | 2015 | 1 |
| | 2016 | 3 |
| South Korea | 1997 | 1 |
| Spain | 2012 | 2 |
| Taiwan | 2002 | 1 |
| Thailand | 1997 | 1 |
| | 1998 | 2 |
| Turkey | 2001 | 2 |
| | 2016 | 6 |
| United States | 2011 | 4 |

**Table 4.4 Variable Definition**

This table defines each variable used throughout this chapter

| *Variable* | *Definition* | *Data Source* |
|---|---|---|
| Sovereign Credit Rating | Long-term foreign currency rating assigned to the sovereign by S&P's | Bloomberg |
| Corporate Credit Rating | Long-term foreign currency rating assigned to the corporation by S&P's | Bloomberg |
| Size | Natural logarithm of total assets (AT) | Compustat Global Datastream |
| Investment | Annual capital expenditures to lagged net property, plant, and equipment | Compustat Global Datastream |
| Tobin's Q | Total assets plus market capitalization minus common equity to total assets | Compustat Global Datastream |
| Cash | Cash and short-term investment to total assets | Compustat Global Datastream |
| Cash Flow | Annual operating income plus depreciation and amortization to lagged total assets | Compustat Global Datastream |
| Leverage | Total debt to total assets | Compustat Global Datastream |
| Sales /Assets | Total sales to total assets | Compustat Global Datastream |
| Sales/VAIP | Sales to the value of assets in place (VAIP) as calculated in Loderer et al. (2017) | Compustat Global Datastream |
| SGA/Sales | Selling, general and administrative costs to total sales | Compustat Global Datastream |
| Sales growth | Natural logarithmic difference in total sales | Compustat Global Datastream |
| ROA | Earnings before interest, taxes, depreciation and amortization to total assets | Compustat Global Datastream |
| OROA | Earnings before interest and taxes to total assets | Compustat Global Datastream |

**Table 4.5 List of treated firms**

| Country | Year of sovereign downgrade | Company | Corporate Rating: Before Downgrade | Corporate Rating: After Downgrade |
|---|---|---|---|---|
| Brazil | 2014 | Ambev Sa | A | A |
| | | Eletrobras-Centr Eletr Bras | BBB | BBB- |
| | | Embraer Sa | BBB | BBB |
| | | Petroleo Brasileiro Sa- Petr | BBB | BBB- |
| | 2015 | Ambev Sa | A | A- |
| | | Braskem Sa | BBB- | BBB- |
| | | Brf Sa | BBB- | BBB |
| | | Eletrobras-Centr Eletr Bras | BBB- | BB+ |
| | | Embraer Sa | BBB | BBB |
| | | Gerdau Sa | BBB- | BBB- |
| | | Klabin Sa | BBB- | BBB- |
| | | Localiza Rent A Car Sa | BBB- | BBB- |
| | | Transmissora Alianca De Ener | BBB- | BB+ |
| | | Ultrapar Participacoes Sa | BBB | BBB- |
| | 2016 | Braskem Sa | BBB- | BBB- |
| | | Brf Sa | BBB | BBB |
| | | Eletrobras-Centr Eletr Bras | BB+ | BB |
| | | Embraer Sa | BBB | BBB |
| | | Hypera Sa | BB+ | BB+ |
| | | Jbs Sa | BB+ | BB |
| | | Klabin Sa | BBB- | BB+ |
| | | Localiza Rent A Car Sa | BBB- | BB+ |
| | | Rio Paranapanema Com | BBB- | BB |
| | | Sao Martinho Sa | BB+ | BB+ |
| | | Ultrapar Participacoes Sa | BBB- | BB+ |
| | | Vale Sa | BBB | BBB- |
| China | 2017 | China Shenhua Energy Co Ltd | AA- | A+ |
| Greece | 2015 | Titan Cement Co Sa | BB | BB |
| Hong Kong | 2017 | Mtr Corp Ltd | AAA | AA+ |
| Ireland | 2011 | Medtronic Plc | AA- | AA- |
| Italy | 2011 | Terna Spa | A+ | A |
| | 2012 | Terna Spa | A | A- |
| | 2014 | Atlantia Spa | BBB+ | BBB+ |
| | | Terna Spa | BBB+ | BBB |
| Japan | 2011 | Elec Power Development Co | AA | A+ |
| | | Okinawa Electric Power Co | AA | AA- |
| | | Osaka Gas Co Ltd | AA | AA- |
| | | Takeda Pharmaceutical Co | AA | AA- |
| | | Tokyo Gas Co Ltd | AA | AA- |
| | 2015 | Canon Inc | AA | AA |
| Mexico | 2009 | America Movil Sa De Cv | BBB+ | BBB+ |

| | | | | |
|---|---|---|---|---|
| | | Grupo Bimbo Sa De Cv | BBB+ | BBB |
| | | Grupo Televisa Sab | BBB+ | BBB+ |
| Russia | 2014 | Federal Grid Co Of The Unif | BBB | BBB- |
| | | Transneft Pjsc | BBB | BBB- |
| | 2015 | Federal Grid Co Of The Unif | BBB- | BB+ |
| | | Gazprom Neft Pjsc | BBB- | BB+ |
| | | Mmc Norilsk Nickel Psjc | BBB- | BBB- |
| | | Novatek Jsc | BBB- | BB+ |
| | | Rosseti Pjsc | BBB- | BB+ |
| | | Transneft Pjsc | BBB- | BB+ |
| | | Uralkali Pjsc | BBB- | BB- |
| Spain | 2012 | Enagas Sa | AA- | BBB |
| | | Red Electrica Corp Sa | AA- | BBB |
| Turkey | 2016 | Koc Holding As | BBB- | BBB- |
| | | Turk Sise Cam | BB+ | BB |
| | | Turk Telekomunikasyon As | BBB- | BBB- |
| | | Turkcell Iletisim Hizmet | BBB- | BBB- |
| United States | 2011 | Automatic Data Processing | AAA | AAA |
| | | Exxon Mobil Corp | AAA | AAA |
| | | Johnson & Johnson | AAA | AAA |
| | | Microsoft Corp | AAA | AAA |

**Table 4. 6 Summary Statistics**

This table presents the median and means of nonrated, rated, treated and control groups. Treated firms have a credit rating equal to or above the sovereign rating in the year before a sovereign downgrade. Control firms are matched firms using the Abadie and Imbens matching estimator. The covariates are country, year, size, investment, Tobin's Q, cash flow, cash, and leverage.

| | Median | | | | Mean | | | |
|---|---|---|---|---|---|---|---|---|
| | Non rated | Rated | Treated | Control | Non rated | Rated | Treated | Control |
| Tobin's Q | 1.23 | 1.58 | 1.17 | 1.08 | 1.65 | 1.34 | 1.30 | 1.21 |
| Size | 6.84 | 8.68 | 11.13 | 10.88 | 7.02 | 8.37 | 11.47 | 11.28 |
| Cash Flow | 0.13 | 0.19 | 0.17 | 0.18 | 0.12 | 0.18 | 0.18 | 0.18 |
| Investment | 0.17 | 0.22 | 0.15 | 0.15 | 0.15 | 0.17 | 0.17 | 0.18 |
| Cash | 0.10 | 0.09 | 0.14 | 0.12 | 0.16 | 0.06 | 0.14 | 0.13 |
| Leverage | 0.19 | 0.34 | 0.35 | 0.36 | 0.22 | 0.32 | 0.38 | 0.36 |

### Table 4.7 Linear regression on Asset turnover

This table presents regression estimates of the effect of a sovereign downgrade on Asset turnover of firms that have a pre-downgrade rating at or above the sovereign bound (i.e., treated firms) relative to non treated firms. The dependent variable is the ratio of Sales to the book value of total assets. Bound is a dummy variable that takes the value of one if a firm has a credit rating equal to or above the sovereign rating in year $t-1$, and Sovereign Downgrade is a dummy variable that takes the value of one if a firm's country rating is downgraded in year t. Robust standard errors are reported in parentheses. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% level, respectively.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Sovereign Downgrade | -0.127*** | 0.038*** | 0.030*** | -0.001 | -0.015** |
| | (0.016) | (0.007) | (0.007) | (0.007) | (0.007) |
| Bound | -0.273*** | -0.004 | 0.004 | 0.002 | 0.007 |
| | (0.016) | (0.010) | (0.009) | (0.011) | (0.011) |
| Sovereign Downgrade*Bound | 0.038 | 0.014 | 0.034 | 0.005 | 0.023 |
| | (0.050) | (0.02) | (0.022) | (0.024) | (0.024) |
| Tobin's Q | | | | 0.0027*** | 0.002*** |
| | | | | (0.0006) | (0.001) |
| Size | | | | -0.070*** | -0.066*** |
| | | | | (0.001) | (0.001) |
| Cash Flow | | | | 0.362*** | 0.349*** |
| | | | | (0.005) | (0.005) |
| Investment | | | | -0.024*** | -0.026*** |
| | | | | (0.001) | (0.001) |
| Cash | | | | -0.374*** | -0.374*** |
| | | | | (0.005) | (0.005) |
| Leverage | | | | -0.089*** | -0.075*** |
| | | | | (0.004) | (0.004) |
| Constant | 0.932*** | 0.928*** | 0.973*** | 1.518*** | 1.496*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| | | | | | |
| Firm FE | NO | YES | YES | YES | YES |
| Year FE | NO | NO | YES | NO | YES |
| Observations | 455,643 | 471,111 | 471,111 | 322,025 | 322,025 |
| R-squared | 0.001 | 0.000 | 0.011 | 0.055 | 0.063 |
| Number of Firms | | 46,654 | 46,654 | 38,167 | 38,167 |

## Table 4.8 Linear regression on Sales growth

This table presents regression estimates of the effect of a sovereign downgrade on Sales Growth of firms that have a pre-downgrade rating at or above the sovereign bound (i.e., treated firms) relative to non treated firms. Sales Growth is defined as the logarithmic difference between Sales and Lag Sales. Bound is a dummy variable that takes the value of one if a firm has a credit rating equal to or above the sovereign rating in year $t-1$, and Sovereign Downgrade is a dummy variable that takes the value of one if a firm's country rating is downgraded in year t. Robust standard errors are reported in parentheses. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% level, respectively.

| | (2) | (3) | (4) | (5) |
|---|---|---|---|---|
| Sovereign Downgrade | 0.252*** | 0.042 | 0.046 | 0.026 |
| | (0.036) | (0.036) | (0.035) | (0.035) |
| Bound | 0.0447 | -0.0447 | -0.212*** | -0.210*** |
| | (0.052) | (0.051) | (0.057) | (0.056) |
| Sovereign Downgrade*Bound | -0.248** | -0.068 | -0.080 | 0.015 |
| | (0.116) | (0.114) | (0.118) | (0.117) |
| Tobin's Q | | | 0.150*** | 0.150*** |
| | | | (0.003) | (0.003) |
| Size | | | 0.638*** | 0.705*** |
| | | | (0.004) | (0.005) |
| Cash Flow | | | 0.643*** | 0.498*** |
| | | | (0.031) | (0.030) |
| Investment | | | 0.115*** | 0.107*** |
| | | | (0.007) | (0.007) |
| Cash | | | -0.296*** | -0.290*** |
| | | | (0.031) | (0.031) |
| Leverage | | | -0.206*** | -0.240*** |
| | | | (0.026) | (0.026) |
| Constant | 4.845*** | 4.164*** | -0.0234 | -0.577*** |
| | (0.002) | (0.024) | (0.032) | (0.040) |
| Firm FE | YES | YES | YES | YES |
| Year FE | NO | YES | NO | YES |
| Observations | 265,459 | 265,459 | 207,827 | 207,827 |
| $R^2$ | 0.000 | 0.033 | 0.127 | 0.142 |
| Number of Firms | 40,375 | 40,375 | 34,825 | 34,825 |

### Table 4.9 Linear regression on Sales to Value of Assets in Place ratio

This table presents regression estimates of the effect of a sovereign downgrade on Sales to Value of Assets in Place of firms that have a pre-downgrade rating at or above the sovereign bound (i.e., treated firms) relative to non treated firms. The dependent variable is the ratio of Sales to Value of Assets in Place. Bound is a dummy variable that takes the value of one if a firm has a credit rating equal to or above the sovereign rating in year $t-1$, and Sovereign Downgrade is a dummy variable that takes the value of one if a firm's country rating is downgraded in year t. Robust standard errors are reported in parentheses. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% level, respectively.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Sovereign Downgrade | -0.033 | 0.008 | 0.045 | 0.087** | 0.046 |
| | (0.061) | (0.039) | (0.040) | (0.040) | (0.041) |
| Bound | -0.865*** | -0.134** | -0.102* | -0.0317 | -0.0200 |
| | (0.061) | (0.055) | (0.055) | (0.067) | (0.067) |
| Sovereign Downgrade*Bound | -0.011 | 0.095 | 0.115 | -0.034 | 0.040 |
| | (0.199) | (0.129) | (0.130) | (0.142) | (0.142) |
| Tobin's Q | | | | 0.032*** | 0.032*** |
| | | | | (0.003) | (0.004) |
| Size | | | | 0.082*** | 0.060*** |
| | | | | (0.005) | (0.006) |
| Cash Flow | | | | -0.415*** | -0.458*** |
| | | | | (0.034) | (0.035) |
| Investment | | | | -0.025** | 0.033*** |
| | | | | (0.009) | (0.010) |
| Cash | | | | -0.963*** | -0.956*** |
| | | | | (0.036) | (0.036) |
| Leverage | | | | 1.280*** | 1.281*** |
| | | | | (0.031) | (0.031) |
| Constant | 2.085*** | 2.072*** | 2.236*** | 2.751*** | 2.667*** |
| | (0.004) | (0.003) | (0.022) | (0.039) | (0.047) |
| | | | | | |
| Firm FE | NO | YES | YES | YES | YES |
| Year FE | NO | NO | YES | NO | YES |
| Observations | 311,157 | 322,483 | 322,483 | 228,394 | 228,394 |
| R-squared | 0.001 | 0.000 | 0.003 | 0.018 | 0.021 |
| Number of Firms | | 37,194 | 37,194 | 30,256 | 30,256 |

**Table 4.10 Linear regression on Selling, General and Administrative Expenses to Sales ratio**

This table presents regression estimates of the effect of a sovereign downgrade on Selling, General and Administrative Expenses to Sales of firms that have a pre-downgrade rating at or above the sovereign bound (i.e., treated firms) relative to non treated firms. The dependent variable is Selling, General and Administrative Expenses scaled by total Sales. Bound is a dummy variable that takes the value of one if a firm has a credit rating equal to or above the sovereign rating in year $t-1$, and Sovereign Downgrade is a dummy variable that takes the value of one if a firm's country rating is downgraded in year t. Robust standard errors are reported in parentheses. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% level, respectively.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Sovereign Downgrade | -0.130*** | -0.001 | -0.001 | -0.002 | -0.001 |
| | (0.016) | (0.010) | (0.010) | (0.002) | (0.007) |
| Bound | -0.124*** | 0.001 | -0.003 | 0.001 | 0.002 |
| | (0.016) | (0.0137) | (0.0137) | (0.0121) | (0.0121) |
| Sovereign Downgrade*Bound | 0.094* | -0.002 | 0.001 | -0.006 | -0.004 |
| | (0.048) | (0.031) | (0.031) | (0.024) | (0.024) |
| Tobin's Q | | | | 0.006*** | 0.006*** |
| | | | | (0.001) | (0.001) |
| Size | | | | -0.016*** | -0.024*** |
| | | | | (0.001) | (0.001) |
| Cash Flow | | | | -0.432*** | -0.418*** |
| | | | | (0.006) | (0.006) |
| Investment | | | | 0.0192*** | 0.0193*** |
| | | | | (0.002) | (0.001) |
| Cash | | | | 0.153*** | 0.152*** |
| | | | | (0.006) | (0.006) |
| Leverage | | | | -0.057*** | -0.045*** |
| | | | | (0.005) | (0.005) |
| Constant | 0.298*** | 0.293*** | 0.271*** | 0.401*** | 0.420*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Firm FE | NO | YES | YES | YES | YES |
| Year FE | NO | NO | YES | NO | YES |
| Observations | 415,550 | 430,030 | 430,030 | 302,652 | 302,652 |
| R-squared | 0.000 | 0.000 | 0.001 | 0.025 | 0.027 |
| Number of Firms | | 43,481 | 43,481 | 35,993 | 35,993 |

**Table 4.11 Linear regression on Return on Assets**

This table presents regression estimates of the effect of a sovereign downgrade on Return on Assets of firms that have a pre-downgrade rating at or above the sovereign bound (i.e., treated firms) relative to non treated firms. Return on Assets is the ratio of Earnings Before Interest, Taxes, Depreciation, and Amortization to the book value of Assets. Bound is a dummy variable that takes the value of one if a firm has a credit rating equal to or above the sovereign rating in year $t-1$, and Sovereign Downgrade is a dummy variable that takes the value of one if a firm's country rating is downgraded in year t. Robust standard errors are reported in parentheses. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% level, respectively.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Sovereign Downgrade | 0.056*** | -0.002 | -0.001 | 0.003* | 0.003* |
| | (0.003) | (0.002) | (0.002) | (0.002) | (0.002) |
| Bound | 0.089*** | 0.004 | 0.005* | 0.000 | -0.001 |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| Sovereign Downgrade*Bound | -0.075*** | -0.009 | -0.005 | -0.004 | -0.002 |
| | (0.010) | (0.006) | (0.007) | (0.006) | (0.006) |
| Tobin's Q | | | | 0.007*** | 0.007*** |
| | | | | (0.002) | (0.002) |
| Size | | | | 0.005*** | 0.003*** |
| | | | | (0.000) | (0.000) |
| Cash Flow | | | | 0.312*** | 0.310*** |
| | | | | (0.001) | (0.001) |
| Investment | | | | 0.005*** | 0.004*** |
| | | | | (0.000) | (0.000) |
| Cash | | | | -0.0191*** | -0.020*** |
| | | | | (0.001) | (0.001) |
| Leverage | | | | 0.002** | 0.004*** |
| | | | | (0.001) | (0.001) |
| Constant | 0.059*** | 0.061*** | 0.074*** | 0.064*** | 0.062*** |
| | (0.000) | (0.000) | (0.001) | (0.001) | (0.002) |
| Firm FE | NO | YES | YES | YES | YES |
| Year FE | NO | NO | YES | NO | YES |
| Observations | 450,434 | 465,344 | 465,344 | 321,709 | 321,709 |
| R-squared | 0.002 | 0.000 | 0.008 | 0.150 | 0.156 |
| Number of Firms | | 46,573 | 46,573 | 38,051 | 38,051 |

### Table 4.12 Linear regression on Operating Return on Assets

This table presents regression estimates of the effect of a sovereign downgrade on Operating Return on Assets of firms that have a pre-downgrade rating at or above the sovereign bound (i.e., treated firms) relative to non treated firms. Operating Return on Assets is the ratio of Earnings Before Interest and Taxes to the book value of Assets. Bound is a dummy variable that takes the value of one if a firm has a credit rating equal to or above the sovereign rating in year $t-1$, and Sovereign Downgrade is a dummy variable that takes the value of one if a firm's country rating is downgraded in year t. Robust standard errors are reported in parentheses. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% level, respectively.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Sovereign Downgrade | 0.052*** | -0.001 | 0.000 | 0.005*** | 0.004* |
| | (0.003) | (0.002) | (0.002) | (0.00205) | (0.00207) |
| Bound | 0.077*** | 0.000 | 0.002 | -0.0001 | -0.001 |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| Sovereign Downgrade*Bound | -0.068*** | -0.008 | -0.005 | -0.005 | -0.001 |
| | (0.010) | (0.007) | (0.007) | (0.006) | (0.006) |
| Tobin's Q | | | | 0.008*** | 0.008*** |
| | | | | (0.000) | (0.000) |
| Size | | | | 0.001*** | 0.001*** |
| | | | | (0.001) | (0.001) |
| Cash Flow | | | | 0.296*** | 0.296*** |
| | | | | (0.001) | (0.001) |
| Investment | | | | 0.003*** | 0.002*** |
| | | | | (0.000 | (0.000) |
| Cash | | | | 0.010*** | 0.008*** |
| | | | | (0.002) | (0.002) |
| Leverage | | | | -0.010*** | 0.006*** |
| | | | | (0.001) | (0.001) |
| Constant | 0.020*** | 0.022*** | 0.043*** | 0.018*** | 0.021*** |
| | (0.000) | (0.000) | (0.001) | (0.001) | (0.002) |
| Firm FE | NO | YES | YES | YES | YES |
| Year FE | NO | NO | YES | NO | YES |
| Observations | 450,510 | 465,393 | 465,393 | 321,271 | 321,271 |
| R-squared | 0.002 | 0.000 | 0.010 | 0.132 | 0.139 |
| Number of Firms | | 46,553 | 46,553 | 38,020 | 38,020 |

**Table 4.13 DiD on Sales to Assets ratio around a Sovereign Downgrade**

This table presents difference-in-differences matching estimators in the Sales to Assets ratio around a sovereign downgrade. Treated firms have a credit rating equal to or above the sovereign rating in the year before a sovereign downgrade. Control firms are matched firms using the Abadie and Imbens matching estimator. The covariates are country, year, size, investment, Tobin's Q, cash flow, cash, and leverage. The sample consists of 64 treated and control observations. Robust standard errors are reported in parentheses. ***,**, and * indicate significance at the 1%, 5%, and 10% level, respectively.

| | Year before Downgrade | Year of Downgrade | Difference |
|---|---|---|---|
| Treated Firms | 0.566 | 0.585 | 0.019 |
| Control Firms | 0.752 | 0.642 | -0.110 |
| Difference | -0.186 | -0.057 | |
| | (0.123) | (0.091) | |
| Difference in Difference | | | 0.129 |
| | | | (0.153) |

**Table 4.14 DiD on Sales growth around a Sovereign Downgrade**

This table presents difference-in-differences matching estimators in Sales growth around a sovereign downgrade. Treated firms have a credit rating equal to or above the sovereign rating in the year before a sovereign downgrade. Control firms are matched firms using the Abadie and Imbens matching estimator. The covariates are country, year, size, investment, Tobin's Q, cash flow, cash, and leverage. The sample consists of 64 treated and control observations. Robust standard errors are reported in parentheses. ***,**, and * indicate significance at the 1%, 5%, and 10% level, respectively.

| | Year before Downgrade | Year of Downgrade | Difference |
|---|---|---|---|
| Treated Firms | 8.602 | 7.852 | -0.750 |
| Control Firms | 7.071 | 7.703 | 0.632 |
| Difference | 1.531 | 0.149 | |
| | (0.636) | (0.469) | |
| Difference in Difference | | | -1.382* |
| | | | (0.79) |

### Table 4.15 DiD on Sales to Value of Assets in Place ratio around a Sovereign Downgrade

This table presents difference-in-differences matching estimators in Sales to Value of Assets in Place ratio around a sovereign downgrade. Treated firms have a credit rating equal to or above the sovereign rating in the year before a sovereign downgrade. Control firms are matched firms using the Abadie and Imbens matching estimator. The covariates are country, year, size, investment, Tobin's Q, cash flow, cash, and leverage. The sample consists of 64 treated and control observations. Robust standard errors are reported in parentheses. ***,**, and * indicate significance at the 1%, 5%, and 10% level, respectively.

| | Year before Downgrade | Year of Downgrade | Difference |
|---|---|---|---|
| Treated Firms | 1.013 | 1.276 | 0.263 |
| Control Firms | 1.675 | 1.769 | 0.094 |
| Difference | -0.662 | -0.493 | |
| | (0.341) | (0.251) | |
| Difference in Difference | | | 0.169 |
| | | | (0.423) |

### Table 4.16 DiD on Selling, General and Administrative Expenses to sales ratio around a Sovereign Downgrade

This table presents difference-in-differences matching estimators in SGA to Sales ratio around a sovereign downgrade. Treated firms have a credit rating equal to or above the sovereign rating in the year before a sovereign downgrade. Control firms are matched firms using the Abadie and Imbens matching estimator. The covariates are country, year, size, investment, Tobin's Q, cash flow, cash, and leverage. The sample consists of 64 treated and control observations. Robust standard errors are reported in parentheses. ***,**, and * indicate significance at the 1%, 5%, and 10% level, respectively.

| | Year before Downgrade | Year of Downgrade | Difference |
|---|---|---|---|
| Treated Firms | 0.204 | 0.166 | -0.038 |
| Control Firms | 0.155 | 0.145 | -0.010 |
| Difference | 0.049 | 0.021 | |
| | (0.032) | (0.024) | |
| Difference in Difference | | | -0.028 |
| | | | (0.04) |

**Table 4.17 DiD on Return on Assets around a Sovereign Downgrade**

This table presents difference-in-differences matching estimators in Return on Assets around a sovereign downgrade. Treated firms have a credit rating equal to or above the sovereign rating in the year before a sovereign downgrade. Control firms are matched firms using the Abadie and Imbens matching estimator. The covariates are country, year, size, investment, Tobin's Q, cash flow, cash, and leverage. The sample consists of 64 treated and control observations. Robust standard errors are reported in parentheses. ***,**, and * indicate significance at the 1%, 5%, and 10% level, respectively.

| | Year before Downgrade | Year of Downgrade | Difference |
|---|---|---|---|
| Treated Firms | 0.150 | 0.124 | -0.026 |
| Control Firms | 0.132 | 0.109 | -0.023 |
| Difference | 0.018 | 0.015 | |
| | (0.017) | (0.013) | |
| Difference in Difference | | | -0.003 |
| | | | (0.021) |

**Table 4.18 DiD on Operating Return on Assets around a Sovereign Downgrade**

This table presents difference-in-differences matching estimators in Operating Return on Assets around a sovereign downgrade. Treated firms have a credit rating equal to or above the sovereign rating in the year before a sovereign downgrade. Control firms are matched firms using the Abadie and Imbens matching estimator. The covariates are country, year, size, investment, Tobin's Q, cash flow, cash, and leverage. The sample consists of 64 treated and control observations. Robust standard errors are reported in parentheses. ***,**, and * indicate significance at the 1%, 5%, and 10% level, respectively.

| | Year before Downgrade | Year of Downgrade | Difference |
|---|---|---|---|
| Treated Firms | 0.103 | 0.087 | -0.016 |
| Control Firms | 0.095 | 0.074 | -0.021 |
| Difference | 0.008 | 0.013 | |
| | (0.015) | (0.011) | |
| Difference in Difference | | | 0.005 |
| | | | (0.019) |