University of New South Wales
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Honours Thesis

Sovereign Default Risk and the Fiscal Spending Multiplier

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Declaration

I declare that this thesis is my own work and that, to the best of my knowledge, it contains no material that has been published or written by another person(s) except where due acknowledgement has been made. This thesis has not been submitted for award of any other degree or diploma at the University of New South Wales or at any other educational institution. I declare that the intellectual content of this thesis is the product of my own work except to the extent that assistance from others is acknowledged.

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Calvin Yue He
28 October 2016

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A Guide to this Thesis

This thesis measures sovereign default risk, and characterises the effect of sovereign default risk on the fiscal multiplier. The thesis is divided into 2 Parts, each addressing one of these issues. This is done as it necessary to measure sovereign default risk prior to characterising its effects on the fiscal multiplier. In addition, creating a measure of sovereign default risk warrants an extensive exploration of the literature, methodology, and subsequent results. The same is true for characterising the effect of sovereign default risk on the fiscal multiplier. Therefore, the separation of these two Parts allows for clarity in addressing these two interrelated issues.

Each Part has its own setting and purpose. The thesis is designed so a reader can read each Part separately without too much loss of information.

In Part I, I create a new index for sovereign default risk based on sovereign credit default swaps. This index is designed to yield an accurate and meaningful measure of sovereign default risk that is applicable to further macroeconomic analysis.

In Part II, I use the index created in Part I to examine if sovereign default risk can drive non-linearities in the fiscal multiplier. Using a Threshold Vector Autoregression, I conclude that there is some evidence that higher levels of sovereign default risk result in lower fiscal multipliers. I also explore the transmission and implications of these findings.

Abstract

Recent events have placed sovereign default risk at the forefront of policy maker's minds. But its interaction with fiscal policy remain a relatively unexplored topic in the empirical literature. In this thesis, I will quantify sovereign default risk and its effects on expansionary fiscal policy. Using a new index constructed with data mining techniques to measure sovereign default risk (Part I), I examine if sovereign default risk can drive non-linearities in the fiscal multiplier (Part II). I find that high levels of sovereign default risk are associated with lower fiscal multipliers. These non-linearities can be partially explained by the dynamics of sovereign default risk itself. The results show an inverse relationship between sovereign default risk changes and the fiscal multiplier. Moreover, I find that sovereign default risk regimes are persistent following changes in fiscal spending. Taken together, this stresses the importance of considering sovereign default risk when making fiscal policy decisions. It also indicates that governments should consider sovereign default risk management as a long term policy objective to avoid situations where sovereign default risk renders fiscal spending impotent. I also find evidence that consumption is the underlying driver behind the output responses. This supports the notion that households face larger negative wealth effects from government expenditure when sovereign default risk is high. Whereas, when sovereign default risk is low I find that households are predominantly Ricardian.

Part I

A New Measure of Sovereign Default Risk: A Data Mining Approach

Chapter 1

Introduction

Sovereign default is a complex phenomenon. In 2015, Greece failed to make a 1.6bn Euro payment to the IMF triggering political and economic turmoil. Eighteen years earlier, Thailand required an IMF rescue package of over 17bn USD to prevent sovereign default. In both examples, countries had trouble paying their debts. However, the causes of these troubles were vastly different. The former was driven by the Global Financial Crisis of 2008 and subsequent recession, coupled with perpetual government deficits, and an inflexible monetary union. The latter was driven by speculative currency attacks, high foreign government debt, and a leveraged financial sector. This simple example illustrates the complex phenomenon of sovereign default risk.

The above example begs the question: How can we measure a country's sovereign default risk? This question has been answered partially by the literature. However, a unified approach in measuring sovereign default risk has not been achieved. In this Part, I will contribute to this literature by taking an agnostic data mining approach to create a new sovereign default risk index. The index does not seek to identify the drivers of sovereign default risk. Rather, it will simply provide a measure of market expectations of sovereign default risk.

There are four key contributions from my index. (1) I will exploit variations in sovereign credit default swap spreads to construct the index. Previous research has focused on realised sovereign default events, leaving only two states of the world (a default state and a non-default state). My index will exploit the rich continuum of information inherent in sovereign credit default swap spreads. (2) The index will be extrapolated beyond the sample size available for sovereign credit default swap spreads. This will yield a workable sample size for further analysis. (3) The index created has a quarterly frequency, rendering it more applicable to use in other macroeconomic analysis (as done in Part II). Most of the literature has thus far used data with annual frequency (Bruns and Poghosyan (2016) and Chakrabarti and Zeaiter (2014)). (4) The methodology employed combines techniques often used in index construction and data mining in economics. This combination of techniques has desirable properties, especially when working in small samples and with a large set of independent variables. It also yields strong results. To the best of my knowledge the methodology employed has not been used in the context of sovereign default risk.

I find that my sovereign default index yields strong in-sample and out-of-sample results. In-sample, my index yields strong fit and accuracy, and is able to beat common single-variable measures of sovereign default risk. Out-of-sample, my index is elevated in times where one would expect a high level of sovereign default risk. Moreover, alternative index construction methods yield similar results to my index. Overall, my index is able to capture movements in market expectations of sovereign default risk, and can be used in macroeconomic analysis involving sovereign default risk.

To further test my index, I analyse its effects in a fiscal policy setting by placing it into a standard fiscal Vector Autoregression. I find that there is significant relationship between sovereign default risk and fiscal policy variables. In particular, increases in sovereign default risk cause declines in both output and government revenue. This illustrates that sovereign default risk is a valid consideration when examining fiscal policy. In addition, these results speak to both the usability and validity of my index in providing a meaningful measure of sovereign default risk.

Chapter 2

Measuring Sovereign Default Risk: Credit Default Swaps

To measure sovereign default risk I will use sovereign credit default swap (SCDS) spreads. A SCDS is an over-the-counter financial instrument involving the transfer of default risk of government bonds between two parties. The buyer of the SCDS pays the seller a spread over a risk-free rate. In return, the buyer receives protection against sovereign default from the seller. A SCDS effectively allows the buyer to insure themselves against sovereign default.

An illustration of a SCDS is useful at this point. Say Agent A buys a 10-year U.S. government bond. To protect against default, Agent A also buys a 10-year SCDS from Agent B. Agent A will on a semi-annual basis pay a spread over a risk-free rate times the notional amount of the contract to Agent B. The payments will continue for 10-years unless there is an occurrence of a credit event (such as arrears, or sovereign default). In the case of a credit event, Agent A will first pay the accrued coupon for the period and will transfer the 10-year government bond to Agent B. Agent B will then give Agent A the par value of the bond (or alternatively, the difference between the par value and the market price of the government bond).

Given the SCDS market is trading on sovereign default risk it should come as no surprise that the price on the SCDS (the SCDS spread) measures the market's evaluation of sovereign default risk. This is the measure of sovereign default risk I will use in this thesis.

It is important to note that the sovereign default risk measured in SCDS spreads is broader than typical definitions of sovereign default risk. Typical definitions of sovereign default risk involve public debt default or restructuring, extreme financing constraints, large IMF-supported financing programs, or high inflation (see Baldacci, Petrova, Belhocine, Dobrescu, and Mazraani, 2011, and Reinhart and Rogoff, 2011a). These definitions are precise and may not capture the entirety of sovereign default risk. Though these factors are likely to be included in SCDS spreads, SCDS spreads may also account for other possible reasons for default. In particular, political factors may prevent the payment of public debt even if the government has the ability to pay the debts. For instance, the U.S. debt-ceiling crisis in 2011 significantly raised the default risk of the U.S. government without any significant deterioration in the government's financial position, or any actual default occurring. Being a continuous variable that is traded at a higher-frequency, SCDS spreads are not limited to binary states, and can capture variation between states, such as the U.S. debt-ceiling crisis. Therefore, it is important to remember that SCDS may represent not only the traditional default risk definitions, but also the state of political uncertainty and other possible reasons for sovereign default.[1]

Despite being a measure that should directly follow expectations of sovereign default risk, there is a question as to what the market participants are truly trading on. The existence of the SCDS market shows that sovereign default risk is real. But the features of market participants are unobserved, and their definition of sovereign default risk may not correspond to actual sovereign default risk. Despite this, it is likely that SCDS spreads are still highly correlated to an accurate measure of sovereign default risk. In addition, the use of other variables to measure sovereign default risk would not be accurate. This is as it is difficult to disentangle the sovereign default risk component of other variables often used in the literature (such as bond spreads, or debt-to-GDP ratios). Hence, using SCDS spreads as a measure of sovereign default risk is still appropriate, given the assumption is imposed that market participants are trading on accurate and rationale measures of sovereign default risk.

Like most financial instruments, SCDS are also subject to market liquidity. Badaoui, Cathcart, and El-Jahel (2013) show that SCDS spreads are more susceptible to liquidity factors than sovereign bond spreads. Despite this, Heinz and Sun (2014) show that SCDS spreads for European countries reflect not only liquidity conditions but also macroeconomic fundamentals and investor sentiment. This suggests that SCDS spreads incorporate fundamental information related to sovereign default risk. Also, relative to bond spreads, SCDS spreads adjust to new information faster in periods of stress (IMF (2013)). It has also been shown that when decomposing variations in SCDS spreads into a default risk or a risk premium component, the default risk component accounts for more than double the variation relative to the risk premium component (Longstaff, Pan, Pedersen, and Singleton, 2011). Taken together, these findings show that despite being subject to market liquidity, SCDS

[1]Simple regression analysis show that economic policy uncertainty in the U.S. explains approximately 10 per cent of the variation in the U.S. SCDS spreads (see section 7.1). This shows that political uncertainty may indeed be incorporated into SCDS spreads, but it still does not explain the majority of variation in this data.

spreads are an accurate and suitable measure of sovereign default risk.

Overall, SCDS spreads provide a rich, high-frequency and continuous measure of sovereign default risk. SCDS spreads are able to capture more information than simple binary state approaches. Simple binary state approaches are limited as they ignore sovereign default risk that can occur without a government defaulting on their debts. Being a continuous variable that is traded at high-frequency, SCDS spreads are not restricted to binary states and can capture variation between default and non-default states. Moreover, a broader array of information is encompassed in SCDS spreads that go beyond typical definitions of sovereign default risk, but may still be valid in evaluating sovereign default risk. SCDS spreads hence provide a richer continuum of information on sovereign default risk that is currently unexploited by the literature.

The primary issue with using SCDS spreads is the short sample size available. Data on SCDS spreads often does not go back further than 2008. This sample is too short for most macroeconomic analysis.[2] My index is designed to overcome this short sample issue by identifying factors associated with SCDS spreads in the available sample. I will now turn my attention to the literature's approach to measuring sovereign default risk, and methods commonly used for index construction.

[2] Appendix C provides more detail on the SCDS data.

Chapter 3

Literature review

3.1 Measuring Sovereign Default Risk

The literature on sovereign default risk is sizeable. In this section, I will focus on literature aimed at determining the variables that are associated with sovereign default risk. In this literature, there is still a lack of consensus regarding the set of variables related to sovereign default risk. This lack of consensus is largely because the variables driving sovereign default risk are broad and not easily identified.

In assessing sovereign default risk, the clear place to start is government finances. Baldacci et al. (2011) use a set of 12 fiscal variables and identify threshold values for each variable to help predict fiscal stress. They use both the minimization of misclassified errors, and maximization of the signal-to-noise ratio to determine the predictive power of each variable. This technique is designed to balance type I and type II error. An index is constructed based on the predictive power of the variable when the threshold value for each variable is exceeded. They identify that in advanced countries the gross financing needs and solvency risk of the government are the best predictors of fiscal stress out of the 12 variables considered. The findings are consistent with Reinhart and Rogoff (2011b) who find that changes in public debt-to-GDP ratios are statistically significant in explaining sovereign default. Taken together, these results lead to the intuitive conclusion that government finances are important in determining sovereign default risk.

Looking beyond government finances, economic fundamentals have been shown to be a key determinant of sovereign default risk. Collard, Habib, and Rochet (2015) construct a theoretical measure of maximum sustainable debt ratios and the probability of default for 23 OECD countries. They find that countries with higher and less volatile growth can sustain the same level of debt with lower probabilities of default. The results show that economic fundamentals are important in determining a country's sovereign default risk. Moreover, these fundamentals result in a wide variation in maximum sustainable debt ratios. The results are consistent with Reinhart, Rogoff, and Savastano (2003) who find debt tolerance levels often vary between developing countries based on default and inflation history. These results show that economic fundamentals can influence sovereign default risk. The results also highlights the fallacy of using a single-variable measure, such as debt-to-GDP, in identifying sovereign default risk as these measures can often fail to account for other factors such as economic fundamentals.

Sovereign debt crises are not mutually exclusive from other crises. Between 1970-2010 there have been 174 fiscal crises across over 81 countries. Of these fiscal crises, 42 have coincided with banking crises, 45 with currency crises, and 17 with both banking and currency crises (Bruns and Poghosyan, 2016). This illustrates the interrelation between fiscal crises and other forms of crises. This idea is consistent with empirical findings from Reinhart and Rogoff (2011b) who find that over a sample of 70 countries and 185 years, banking crises have significant power in predicting sovereign default. These results speak to the complexity and various sources of sovereign default risk.

Moreover, sovereign default risk appears to be influenced by an international component. SCDS spreads show significant co-movement across countries. Longstaff, Pan, Pedersen, and Singleton (2011) use principal component analysis to measure the level of co-movement in SCDS spreads across 26 countries. A single principal component on SCDS spreads from 2000 to 2010, accounts for 64 per cent of the variation in SCDS spreads. This is to say that from all the variation in SCDS spreads across countries and time, the majority of this variation is shared between countries. This research is built upon by Arghyrou and Kontonikas (2012) who use principal component analysis on government bond yield spreads across 10 Euro area countries. Using the second principal component to identify divergence between core and periphery country's default risk, they show that in recent times higher risk in periphery countries have corresponded with higher risk in core countries. This indicates the possibility of contagion in sovereign default risk, and suggests that when analysing sovereign default risk international variables should be considered. This is consistent with research on other forms of crises such as currency crises (see Eichengreen, Rose, and Wyplosz (1996)).

It has also been observed that sovereign default risk can be explained by domestic and international financial variables. Using a panel approach, Dieckmann and Plank (2012) show that the behaviour of SCDS spreads are significantly determined by country-specific financial variables such as the exchange rate with the U.S. dollar, and stock market volatility. The concept that financial variables determine sovereign default risk is also explored by Ang and Longstaff (2013). They identify sovereign default risk using the term structure of SCDS spreads. Using regression with global credit and financial variables, Ang and Longstaff find that these variables can explain 35 per cent of the variation in U.S. systemic risk, and 43 per cent of the Eurozone systemic risk. Taken together, this research stresses that financial components must also be considered when evaluating sovereign default risk.

The literature has identified many variables and factors that contribute to sovereign default risk. To address this broad set of variables, data mining techniques have been employed to measure sovereign default risk. These attempts in measuring sovereign default risk have thus far been the most comprehensive. Bruns and Poghosyan (2016) and Chakrabarti and Zeaiter (2014) use Extreme Bound Analysis (EBA) to identify the variables associated with fiscal distress. EBA regresses a variable of interest with controls against the relevant dependent variable, in this case sovereign default episodes. The set of controls is changed recursively to account for all possible combinations of controls. If the variable of interest remains significant a certain per cent of the time then it is deemed to be associated with the sovereign default episodes. This methodology is agnostic to the theory of sovereign default risk, and allows a research to test a broad set of variables. Using this methodology, Bruns and Poghosyan (2016) identify that variables related to macroeconomic performance, the government balance sheet, and trade performance and openness serve as leading indicators of sovereign default episodes. Similarly, Chakrabarti and Zeaiter (2014) find that macroeconomic performance, the government balance sheet, and trade performance are associated with default episodes. They also find that variables related to political and social indicators, such as democratic accountability, military involvement in politics, and ethnic tensions are robust in explaining sovereign default episodes. Jointly these papers speak to the broad set of variables that could be associated with sovereign default risk, and vindicates the use of data mining techniques to capture variation in sovereign default risk.

Given the vast set of variables that are thought to be associated with sovereign default risk, measuring it is challenging. This motivates the use of data mining techniques to identify the variables associated with sovereign default risk. I will now turn my attention to potential techniques that can be used for index construction.

3.2 Index Construction

Before constructing an index of sovereign default risk, it is useful to examine the literature's approach to index construction for fiscal distress and other indicators. In particular, the literature on constructing financial conditions indices is well developed and can be drawn upon to construct an index for sovereign default risk. Three common methods used for index construction are: Extreme Bound Analysis (EBA), Principal Component Analysis (PCA), and the Weighted-Sum Approach (WSA). Each has its merits and issues which I will now discuss.

As aforementioned, EBA has been used to design early warning signals for different types of crises. Studies that use EBA (or some variant of EBA) include Bruns and Poghosyan (2016), Chakrabarti and Zeaiter (2014), Christofides, Eicher, and Papageorgiou (2016) and, Ho (2015). From these, only Bruns and Poghosyan, and Chakrabarti and Zeaiter consider sovereign default risk. EBA considers a set of potential explanatory variables and uses complete subset regression to identify the variables that are associated with a given dependent variable, such as sovereign default crises. More specifically, in EBA one would have K variables and regress every combination of k ($< K$) variables against the dependent variable. By observing the significance of the coefficients of one variable over all the regressions, one can determine if the variable is consistently significant in explaining the dependent variable. EBA has many desirable properties. Firstly, the methodology is agnostic to theory. This allows the researcher to examine a large set of candidate variables. This, in a sense, allows the data to speak. And secondly, by using complete subset regression this ameliorates potential biases created from omitted variables or small samples. However, EBA is still subject to omitted variable bias as in each individual regression there is no way to control for all variables in a single regression, as it would likely overfit the data.

Principal component analysis is another tool used for index construction. The practice of using PCA is particularly common in constructing financial indices. PCA involves creating principal components (or factors) that explain common variation between a set of variables, whilst maintaining that the factors are orthogonal to each other (more in section 5.1). The Kansas City Federal Reserve Financial Stress Index (KCFSI) uses the first principal component from 11 financial variables as a measure of financial stress. Hakkio and Keeton (2009) show that the KCFSI aligns well with widely recognised episodes of financial stress, such as the collapse of Lehman Brothers. Building on this, Hatzius, Hooper, Mishkin, Schoenholtz, and Watson (2010) use a set of 45 financial variables to construct a financial conditions index. They choose a broader set of financial variables to capture financial conditions information that may be omitted by indices that use a more narrow set of variables. They show that the index constructed from the first principal component of the 45 variables outperforms the average of other financial indices in predicting future output growth. Similar to EBA, PCA allows for a large set of variables to be considered. However, by choosing only the first principal components this implicitly imposes that the shared variation between all variables selected can be used to explain the given variable of interest. This may not necessarily be the case. Moreover, there may be useful information captured in other components that are not used.

Another approach used to create financial conditions indices is the Weighted-Sum Approach. In this approach, variables are assigned weights according to their relative effect on a variable of interest, such as output. The methodology requires more discretion to be exercised in choosing the variables to include. Goodhart, Hofmann, et al. (2000) apply WSA to construct a financial conditions index for the U.K. A simple reduced-form demand regression is used to determine the weights assigned to four financial variables (the real interest rate, the real exchange rate, real property prices, and real share prices). They find their approach serves to better forecast inflation than other standard monetary conditions indices. Guichard and Turner (2008) construct a financial condition index using six financial variables. They assign weights using a Vector Autoregression (VAR) and evaluate the relative effect of a one unit change in each variable on output over four to six quarters. The approach identifies that the primary drivers in financial conditions are interest rate spreads and tightness of bank lending standards. The VAR approach better manages endogeneity, and focuses more on variable dynamics. Despite being simple and often leading to good results, WSA requires a significant amount of discretion from the researcher in variable selection. WSA does not allow for a large set of variables to be considered like in EBA or PCA. This makes the omission of important variables likely. This is an undesirable property when considering sovereign default risk, given the potentially large and unknown set of variables that could be associated with it.

In this Part, I construct my sovereign default risk index by applying a combination of elements from EBA and PCA. I will not use WSA as it requires too much discretion in the choice of variables. The methodology used gives significant flexibility in my choice of variables, whilst avoiding issues that occur in EBA or PCA.

Chapter 4

Data

I will not restrict my analysis to one country. Instead, I create the SCDS index for all OECD countries where the data permits it.[1] This is to show that the methodological contribution of this Part is robust in various settings.

4.1 SCDS spread

I obtain SCDS spreads from Datastream. Changes are taken to account for the potential presence of unit roots. Appendix C provides an account of the SCDS data.

4.2 Selection of variables

My methodology allows a large set of variables to be considered. I have hence used a set of over 70 variables that may be related to sovereign default risk. Moreover, different types of variables are used that include surveys, quantity and flow variables. Variables are chosen based on the following criteria: (1) The variable must have a history of at least 10 years. This is to extend the sample length of the index. (2) The variable should be related to sovereign default risk. (3) The variable must be available for many countries. With this three criteria, combined with my econometric approach I am able to create an index that has a longer history than the SCDS spreads, holistically characterises sovereign default risk, and can be applied to various countries.

Variables can broadly be defined into the following categories: Government finances, financial variables, international variables, domestic macroeconomic conditions, and expectations of future conditions. The broad range of variables is motivated by the literature that has identified that the variables pertaining to sovereign default risk are broad and not well defined.

[1]See Appendix A for a list of countries and relevant country codes.

All data is seasonally adjusted by source or using some variant of X-13. The first difference or first difference of logs is taken to account for the possible presence of unit roots. Moreover, when possible end of quarter observations are used to match the timing of measurement with stock variables.[2]

[2] Appendix B provides a comprehensive list of data and sources.

Chapter 5

Construction of index: A data mining approach

My index seeks to address three limitations of the data and previous attempts at measuring sovereign default risk. First, the short sample size of SCDS data limits its use in macroeconomic analysis. The index in this thesis is constructed with variables with a longer sample size than the SCDS spreads, hence extending the sample size. This renders the index applicable for use in further macroeconomic analysis (as done in Part II). Second, previous measures of fiscal distress only have an annual frequency. My index will have a quarterly frequency, giving it properties desirable in higher-frequency data. This is particular useful in structural identification in a Vector Autoregression setting (more in Part II Section 4.2). Lastly, the index uses SCDS data rather than realised sovereign default events. SCDS data is a desirable measure of sovereign default as it is a high-frequency and continuous financial variable. These properties yield a richer continuum of information than what is used in previous research (for example, Bruns and Poghosyan (2016)).

Adopting elements from both Hatzius et al. (2010), and Bruns and Poghosyan (2016) I use principal component analysis in conjunction with least squares, and Bayesian methods to construct an index for SCDS data. This methodology allows for significant flexibility in the choice of variables, and accommodates for the small sample of the SCDS spreads by exploiting the properties of PCA, and the use of Bayesian methods.

This chapter summarizes the methodology used to construct the index.

5.1 Econometric approach: Principal Component Analysis

Firstly, principal component analysis (PCA) is performed on the data for each country. This process yields principal components (or factors) that explain the variation in the data, and are also orthogonal to each other. The procedure effectively splits the data into factors, wherein each factor consists of a proportion of the common variation between all the variables. Taken together, the factors would explain 100 per cent of the variation in the data.

This procedure has two desirable properties. First, factors are constructed so they are (contemporaneously) orthogonal to each other. I can thus analyse each factor individually using least squares without concern for correlation with other factors that would result in omitted variable bias. Secondly, the extraction of common variation between variables yields a finer and more precise measure of the variables. Both of these properties are designed to overcome shortcomings of EBA. In particular, EBA ignores omitted variable bias and relies on recursive regression to manage these potential biases. The issue of omitted variable bias is managed in PCA as, by construction, each factor is orthogonal to one another. Moreover, EBA implicitly assumes all variation in a chosen variable is useful in potentially explaining the dependent variable. This is not necessarily true. For instance, there may be no reason a priori to assume all the variation in a government's debt-to-GDP ratio affects sovereign default risk. Sovereign default risk may in fact be driven by a latent exogenous shock that causes some (but not all) of the variation in the debt-to-GDP ratio and other variables. PCA accommodates for this possibility by extracting variation in variables. Each factor will only contain a proportion of the variation in a single variable, not all of it.

Factors are constructed as follows:

Let X be a $M \times N$ matrix representing the data for a country used in the index, where M is the number of periods (quarters) and N is the number of variables; let L represent the rank of matrix X, where $L \leq \min\{M, N\}$.

The principal components (or factor scores) are obtained using the singular value decomposition (SVD) of X:

$$X = P\Delta Q^T \tag{5.1}$$

where P is an $M \times L$ matrix containing the left singular vectors of X; Δ $L \times L$

diagonal matrix of the singular values of X i.e. the square root of the diagonal matrix of eigenvalues of $X^T X$; Q is a $N \times L$ matrix containing the right singular vectors of X.

The factor scores (denoted by F) are derived from the SVD in equation (5.1):

$$
\begin{aligned}
F &= P\Delta && (5.2)\\
&= P\Delta Q Q^T && (5.3)\\
&= XQ && (5.4)
\end{aligned}
$$

where F is an $M \times L$ matrix of factor scores.[1]

Each column of F represents one factor derived from the data. The first factor (column 1) explains the largest amount of shared variation in the data. The second factor (column 2) explains the largest amount of the remaining shared variation conditional on being orthogonal to the first factor. The remaining factors are constructed similarly to the second factor. Taking all factors together would explain 100 per cent of the variation in the data.

5.2 Econometric approach: Factor regressions

Following the estimation of factors, factor regressions are used to construct the index. This approach is motivated by Bai and Ng (2008) who identify that factors are accurate enough to be used in regression analysis. The result holds even if factors are constructed with a small sample.

The small sample size of SCDS spreads limits accuracy of statistical inference in regression analysis. To ameliorate this issue two adjustments are made. First, the SCDS spreads are regressed against only one factor at a time (with a constant). This minimises the possibility of over-fitting the data. Moreover, this approach will not yield any omitted variable bias as the factors are orthogonal to each other by construction. Second, parametric bootstrap simulations are used to check the significance of each factor. This is to ensure what is identified as statistically significant is not biased by the small sample of the regression.

This step of the index construction is designed to simultaneously exploit the benefits of EBA and PCA, whilst addressing some of the pitfalls of the PCA methodology. It

[1] For a more detailed description of PCA see Abdi and Williams (2010).

is common practice when using PCA to focus only on the first factor generated (for example Hatzius et al. (2010), and Hakkio and Keeton (2009)). The assumption is that the largest sources of common variation between the chosen variables are useful in explaining the variable of interest. However as mentioned earlier, the variables related to sovereign default risk are broad and not well defined. It would be difficult to conclude that the factor(s) that explain the largest amount of the variation in the data are the most useful in explaining sovereign default risk. For example, PCA will produce various factors. The first factor could be driven by fiscal variables, the second by financial variables, and the third by political risk. There is no reason a priori to assume that the first factor driven by fiscal variables contains all the information useful in explaining sovereign default risk. By only considering the first factor(s), one risks omitting important information on sovereign default risk. To mitigate this issue I adopt the recursive regression methodology from EBA. I will consider all factors generated from PCA as potential candidates in explaining sovereign default risk by regressing each factor individually against SCDS spreads. This ensures all important features of the data that are useful in explaining sovereign default risk are included in the index.

I also use a parametric bootstrap to overcome any bias from the small sample size of the SCDS spreads. In EBA, these biases are addressed by recursively estimating the regression with different combinations of independent variables. However, this procedure is subject to omitted variable bias. Using PCA factors as the independent variable in the regressions I avoid having significant omitted variable bias, and can use parametric bootstrapping to determine the statistical significance of each factor.

The procedure to create the index is as follows:

Let $f_{l,t}$ represents the lth column of the factor score matrix F at time t, where t is also the row of F; ε_t represent the residuals of the model that are uncorrelated with current and lagged values of $f_{l,t}$.

First, each individual factor is regressed against the change in SCDS spreads.

$$\Delta \text{ SCDS spread}_t = \beta_0 + \beta_{1,l} f_{l,t} + \varepsilon_t, \text{ where } l = 1 \ldots L \text{ and } t = 1 \ldots M \qquad (5.5)$$

If the coefficient on $\beta_{1,l}$ is insignificant at the 5 per cent level then the factor is dropped and the process is repeated for the next factor. If the coefficient on $\beta_{1,l}$ is significant at the 5 per cent level, then a normally distributed parametric bootstrap is performed to further test the significance of the factor.[2] If the bootstrap simulations

[2] See appendix D for details on the parametric bootstrap

still show the factor is significant at the 5 per cent level, the coefficient β_1 is stored as the factor weight used in the index.

Notice that I am using only contemporaneous variables as independent variables. This is as the SCDS spreads are a financial variable traded on a daily basis. Given that I am using a quarterly frequency, and assuming some level of market efficiency, it is unlikely that information from the previous quarter is significant in determining the contemporaneous value of SCDS spreads.

The final index is constructed by aggregating the significant factors weighted by the factor's coefficient estimated in equation 5.5.[3]

$$\text{Index}_t = \sum_{l=1}^{L} \beta_{1,l} f_{l,t} \tag{5.6}$$

The data length for each variable is different. Hence, choosing a different starting period will yield different factors and hence results. To account for this I perform the process using 22 different starting periods, from Q1:1984 to Q1:2005 with annual increments. Following the construction of the index for each starting period, I find the R-squared between the index (independent variable) and the SCDS data (dependent variable). I choose the time period that yields the highest R-squared as the optimal index for each country.

[3]It is worth mentioning a key assumption behind my econometric model is that factors that drive the SCDS spreads over the available sample period are also the drivers of SCDS spreads in the periods beforehand. This assumes that the factors behind SCDS spreads are constant over time. This is a reasonable assumption but may not necessarily be the case. However, due to data limitations this assumption must be imposed on the index.

Chapter 6

Results

6.1 In-sample metrics

This section details some in-sample metrics of the index. I have constructed these metrics by regressing the final index against the SCDS spread.

$$\Delta \text{ SCDS spread}_t = \alpha_0 + \alpha_1 \text{ Index}_t + \varepsilon_t \tag{6.1}$$

Overall, I will show that the index serves to satisfactorily capture the dynamics of SCDS spreads. All in-sample measures show a reasonable fit between the index and SCDS spreads. This indicates that the index constructed using my methodology is a suitable proxy of sovereign default risk for the countries examined.

6.1.1 Index versus SCDS spreads

A sample of graphs depicting the index against the realised SCDS spread are presented below. This represent a simple first parse at examining the performance of the index in capturing movements in the SCDS spreads. There a three key observations that can be made from these figures.

Firstly, overall the index performs well in tracking the movements in the SCDS spread. Upward/downward movements in the index tend to correspond with upward/downward movements in the SCDS spreads. This indicates that the index constructed performs well in capturing the general movements in the market perception of sovereign default risk, as measured by SCDS spreads.

Secondly, the index performs well in capturing extreme events. Key extreme events in the sample include the crash of Lehman Brothers in September 2008, American debt ceiling crises in 2011 and 2013, and the ongoing European debt crisis from 2010 onwards. These are reflected with higher changes in SCDS spreads. It can be observed that the index is, in general, at elevated levels during these periods. This indicates that the index performs well in capturing these periods of high sovereign default risk.

Lastly, the index appears to exhibit less volatility than the SCDS spreads. This is particularly the case during the times of high stress. The index often undershoots the extreme upwards and downward movements in the SCDS spreads. However, the volatility outside of these extreme movements appear to align well with the SCDS data. Hence, the index appears to capture variation outside extreme events well whilst still obtaining some of the variation of extreme movements.

Overall, this simple examination of the sample of graphs suggest that my index for sovereign default risk performs well in capturing the general movements in the SCDS spreads. I will now turn my attention to statistical measures of fit to further show that the general observations made in this sample of graphs hold across countries.

Figure 6.1: AUS- Index versus SCDS spreads

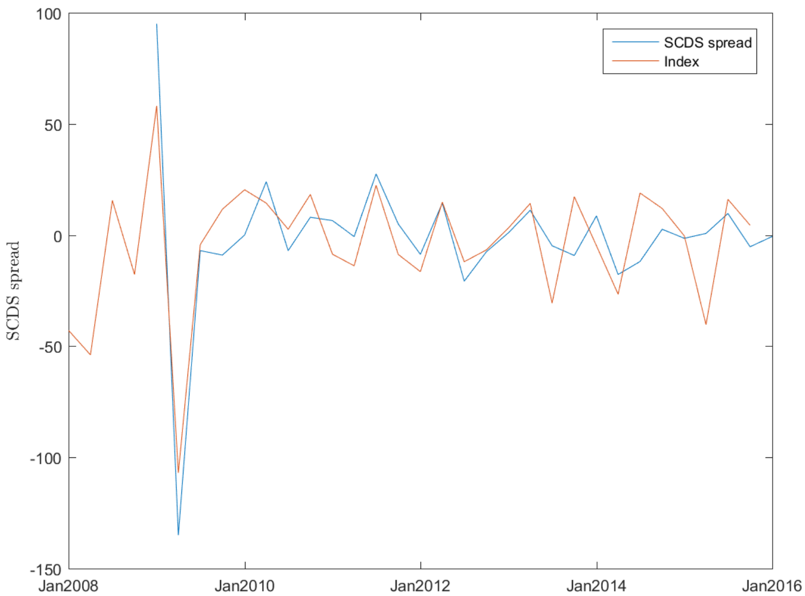


Figure 6.2: FRA- Index versus SCDS spreads

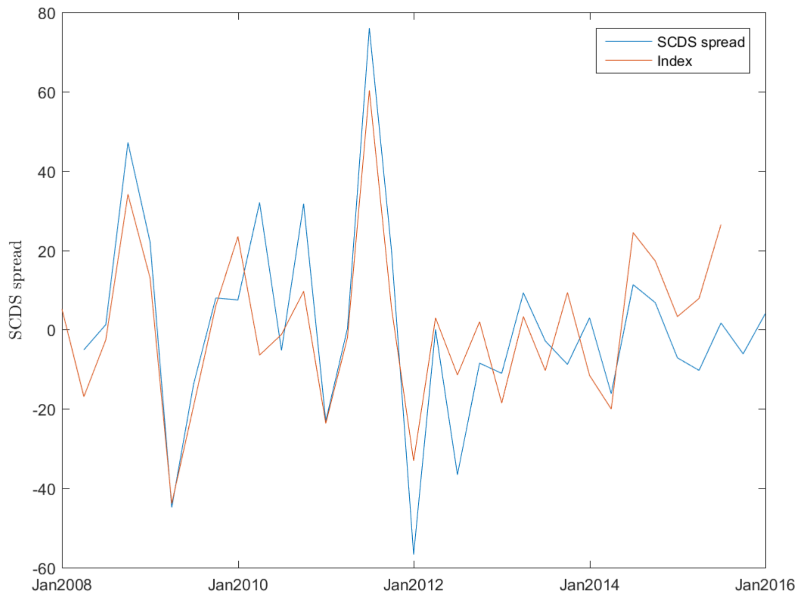


Figure 6.3: GER- Index versus SCDS spreads

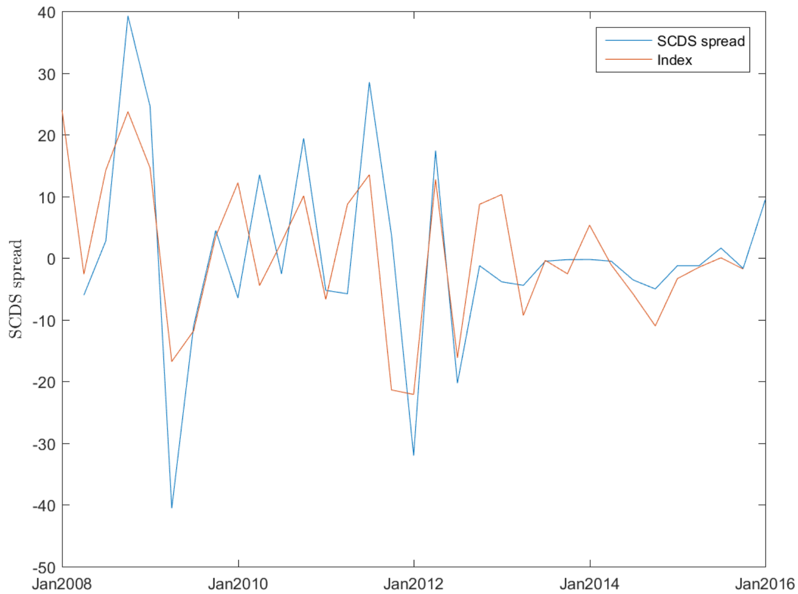


Figure 6.4: ITA- Index versus SCDS spreads

Figure 6.5: JAP- Index versus SCDS spreads

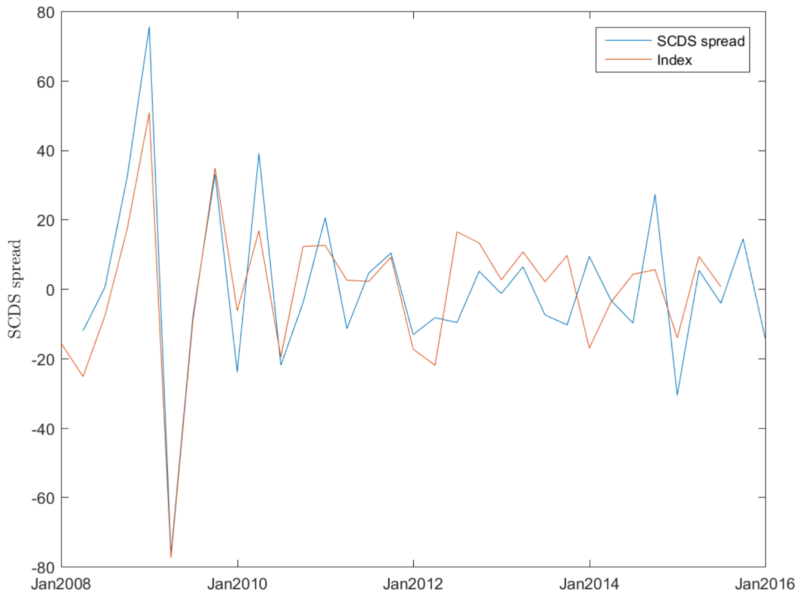


Figure 6.6: POR- Index versus SCDS spreads

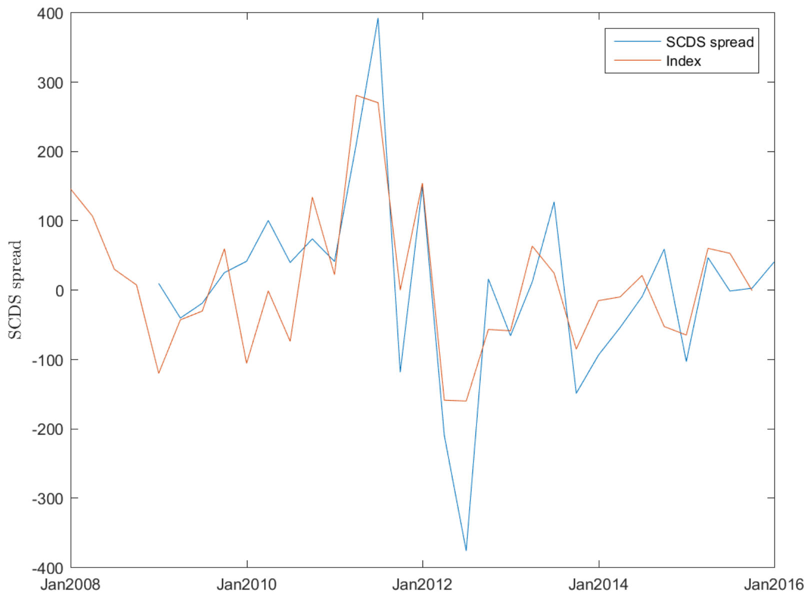


Figure 6.7: UNK- Index versus SCDS spreads

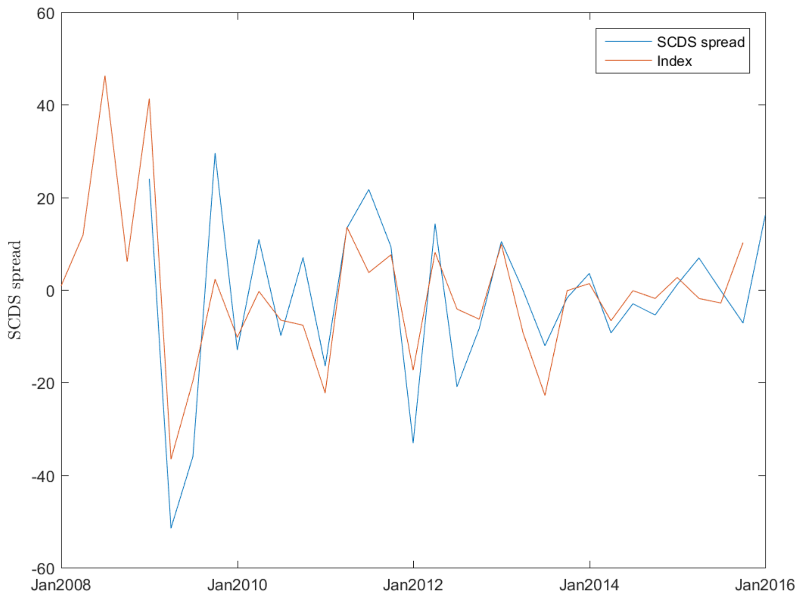
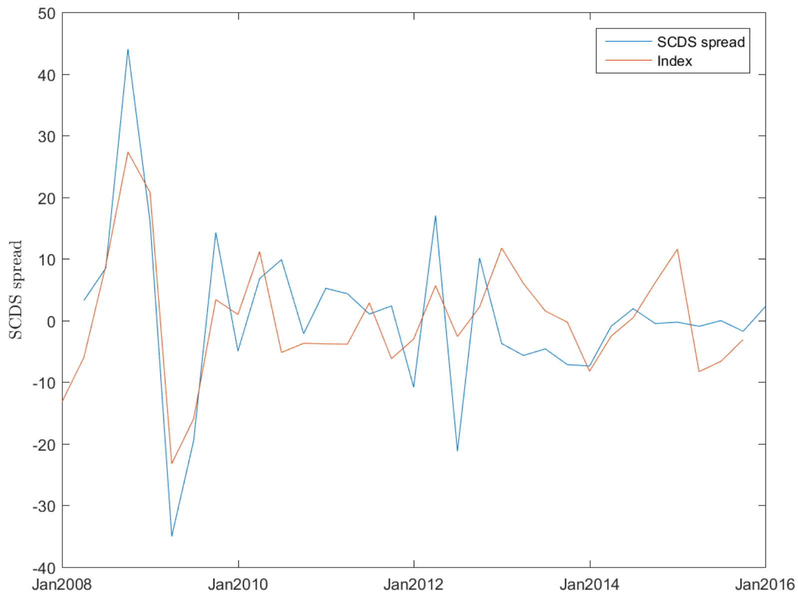


Figure 6.8: USA- Index versus SCDS spreads



6.1.2 R-squared

R-squared is used to measure the in-sample fit of the index to the SCDS spread data. It measures the amount of variation in the SCDS spread captured in my index. Table 6.1 shows the R-squared value from equation 6.1. The results show that across countries, the index often explains a significant portion of the variation in SCDS spreads.

The index for all countries captures at least 50 per cent of the variation in SCDS spreads. Moreover, the R-squared is often higher. For Australia, the index captures almost 70 per cent of the variation in the SCDS spread. The R-squared exceeds 80 per cent for Korea and Mexico. However, it is worth noting that there is large amount of variation in the R-squared across countries. For example, the U.S. index captures only 54 per cent of the variation in SCDS spread movements. This indicates that the index performs better for some countries and worse for others. Nonetheless, overall the results indicate that the index constructed for each country captures the majority of the variation in the SCDS spreads. This lends further support that my index can be considered a suitable proxy for SCDS spreads.

Table 6.1: Index R-squared

Country	R-squared
AUS	0.72
BEL	0.54
CHI	0.80
CZE	0.65
DEN	0.75
EST	0.70
FIN	0.66
FRA	0.66
GER	0.53
GRE	0.58
HUN	0.77
ICE	0.80
ISR	0.69
ITA	0.65
JAP	0.72
KOR	0.82
MEX	0.78
NET	0.72
NOR	0.72
POL	0.66
POR	0.61
SPA	0.57
SWE	0.80
TUR	0.63
UNK	0.61
USA	0.54

6.1.3 Root mean squared error

Examining the root mean squared error (RMSE) allows for a closer examination of the in-sample fit of the index. RMSE measures the average error the index makes in estimating the SCDS spread. A low RMSE indicates that the model fit is close to the actual value of SCDS spreads. The RMSE can be calculated as follows:

$$\text{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\text{SCDS spread}_t - \alpha_0 - \alpha_1 \text{Index}_t)^2} \tag{6.2}$$

where T is the sample length of regression equation 6.1.

Table 6.2 reports the RMSE for each country, and the RMSE as a proportion of one standard deviation of the SCDS spread. The latter is used to provide a standardised way of interpreting the RMSE across countries. Again, the lower the value the more accurate the model is in modelling the movements in SCDS spreads. There are two key takeaways from Table 6.2.

Firstly, all countries have a RMSE less than one standard deviation of the SCDS spread. This shows that on average the fitted value of the index is within one standard deviation of the realised value of the SCDS spreads. In fact, across countries the proportion of the RMSE to one standard deviation of the SCDS spreads is only 0.61. Hence, on average across countries the index is within 0.61 standard deviations of the realised SCDS spreads. This is an acceptable range of uncertainty to regard the index as a suitable and accurate proxy of sovereign default risk for the countries analysed.

Secondly, similar to the R-squared, there is a large range of accuracy between countries. The proportion of the RMSE to one standard deviation of the SCDS spread is as low as 0.45 for Korea, and as high as 0.78 for Austria. This again suggest that the index may be better suited to certain countries. Despite this, the overall results are still reasonably low to render the index applicable for further economic analysis.

Overall, the RMSE results demonstrate the accuracy of the index in fitting SCDS spread movements. The results speak to the ability of the index to not only capture the general movements of the SCDS spreads, but to do so with a certain level of precision. Taken together with the sample of graphs and the R-squared results, this shows that my index can be regarded as a suitable and accurate measure of sovereign default risk.

Table 6.2: Root mean squared error of Index

Country	RMSE	RMSE as a proportion of standard deviation
AUT	19.76	0.78
AUS	18.11	0.56
BEL	32.59	0.71
CHI	22.41	0.46
CZE	22.53	0.61
DEN	14.32	0.52
EST	30.19	0.56
FIN	12.02	0.62
FRA	15.22	0.62
GER	10.90	0.72
HUN	45.69	0.51
ICE	67.98	0.47
IRE	65.19	0.81
ISR	16.80	0.58
ITA	51.54	0.62
JAP	14.12	0.56
KOR	27.76	0.45
MEX	34.35	0.50
NET	15.56	0.56
NOR	5.02	0.55
POL	33.59	0.61
POR	87.49	0.66
SVK	28.21	0.68
SLO	41.88	0.77
SPA	41.45	0.69
SWE	8.17	0.47
TUR	27.75	0.64
UNK	11.51	0.64
USA	9.31	0.71

Chapter 7

Robustness

In this Chapter, I will undertake robustness tests for my constructed sovereign default risk index. However, I will focus my attention on the index constructed for the U.S. I do this for two reasons. (1) Recall that the U.S. index was one of the poorer performing indices from the in-sample metrics. Hence, robustness tests performed on the U.S index should be harder to meet. (2) I will continue to use the U.S. index in Part II of this thesis to analyse non-linearities in the fiscal multiplier.[1]

Overall, I find that the index of sovereign default risk for the U.S. fairs reasonably well against these robustness tests, and should be considered as a suitable measure of sovereign default risk applicable to macroeconomic analysis.

7.1 Index versus single variables

I measure the U.S. index performance against single variable measures commonly used to measure sovereign debt risk. In particular, I have used real output growth, the public debt-to-GDP ratio, an equity market index, the CBOE volatility index (VXO), the long term sovereign bond yield, and a U.S. economic policy uncertainty index (overall). These are variables commonly associated with and used to measure sovereign default risk. I find that none of these measures can reliably measure SCDS spreads, with the R-squared usually well below the R-squared of the index.

To measure my index against these variables I have performed the following regression:

$$\Delta SCDSspread_t = \beta_0 + \beta_1 X_t + \varepsilon_t \tag{7.1}$$

where X_t is one of the variables listed above.

Notice that as I am only including one variable in the regression. This is to manage

[1] A summary of the index constructed for the U.S. is presented in Appendix E.

the small sample size of the SCDS spreads, however this comes at the cost of leaving each individual regression susceptible to omitted variable bias.

As a measure of fit I once again use R-squared. For the regression defined by equation 7.1 the R-squared measures the proportion of the variation of the change in SCDS spread captured by the chosen variable.

Figure 7.1 summarises the R-squared for all the variables used for the U.S. SCDS spread. There are two notable features of Figure 7.1.[2]

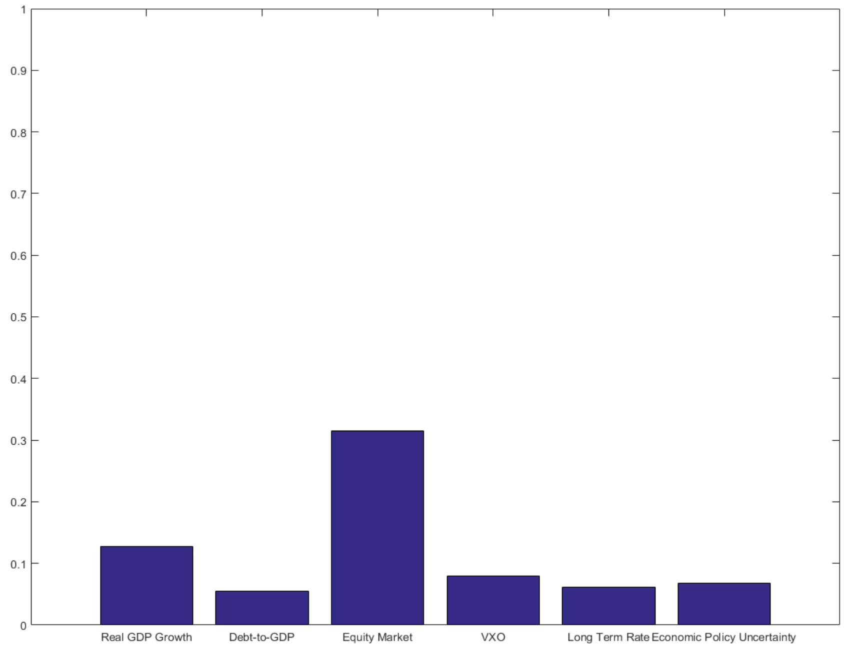
Firstly, overall a single variable measure of sovereign default risk often fails to capture the dynamics of SCDS spreads. This can be seen with the majority of single variable measures failing to explain more than 10 per cent of the variation in the SCDS spreads. Moreover, no measure exceeds an R-squared of 40 per cent. Recall that my index for the U.S. explained 54 per cent of the variation in the SCDS spreads. The lower R-squared of these single variable measures is consistent with the literature that which failed to produce a consistent set of sovereign default risk indicators. Moreover, this finding vindicates the use of data mining techniques that avoid the fallacy of using individual variables in measuring sovereign default risk.

Secondly, the equity market index is a notable outlier. The equity market index yields an R-squared of over 0.3, indicating it can explain over 30 per cent of the in-sample variation in the SCDS spreads. This result lends weight to the idea that financial markets are significant in determining sovereign default risk (Dieckmann and Plank (2012) and Ang and Longstaff (2013)). Despite having high R-squared relative to the other single-variable measures tested, it is still substantially lower than the R-squared of 54 obtained by the index. Hence, my index should still be considered a better measure of sovereign default risk than all single-variable measures.

Overall, the results show that single-variable measures fail to adequately capture sovereign default risk as measured by SCDS spreads. All single-variable measures tested perform worse than my index in explaining variation in the SCDS spread. Taken together, this supports the concept that the variables pertaining to sovereign default risk are broad, and it could be that latent factors that drive only certain portion of the variation in variables could be significant in explaining sovereign default risk. These findings suggest that the index constructed is an appropriate measure of sovereign default risk, and also illustrate the usefulness of my econometric approach that can draw upon many variables, and also has the ability to capture latent factors that may drive sovereign default risk.

[2] A full set of R-squared measures for all countries and variables tested is included in Appendix F

Figure 7.1: Single Variable R-squared



7.2 Case studies

So far the index has performed well using statistical metrics, but it is difficult to tell if statistical metrics can be easily translated to real-world experiences. In this section I will also show that when using real-world events the index still performs reasonably well. More specifically, the index exhibits elevated levels during these events.

I consider a set of key events from 1987 to 2008 (after which any event will be in-sample). The events considered are represented in Table 7.1.[3]

[3]The time periods are determined on an end of quarter basis. For instance, if an event occurred in July 1997 this is considered to be in Q3:1997. This is to align with how I have constructed my index.

Table 7.1: Case Studies

Number	Event	Date
1	Black Monday	Q4:1987
2	Junk Bond Collapse	Q1:1990
3	ERM Crisis	Q4:1992
4	Asian Crisis	Q3:1997
5	Dot-Com Bust	Q2:2000
-	NBER Recessions	Shaded in Grey

Figure 7.2: USA: Index case studies

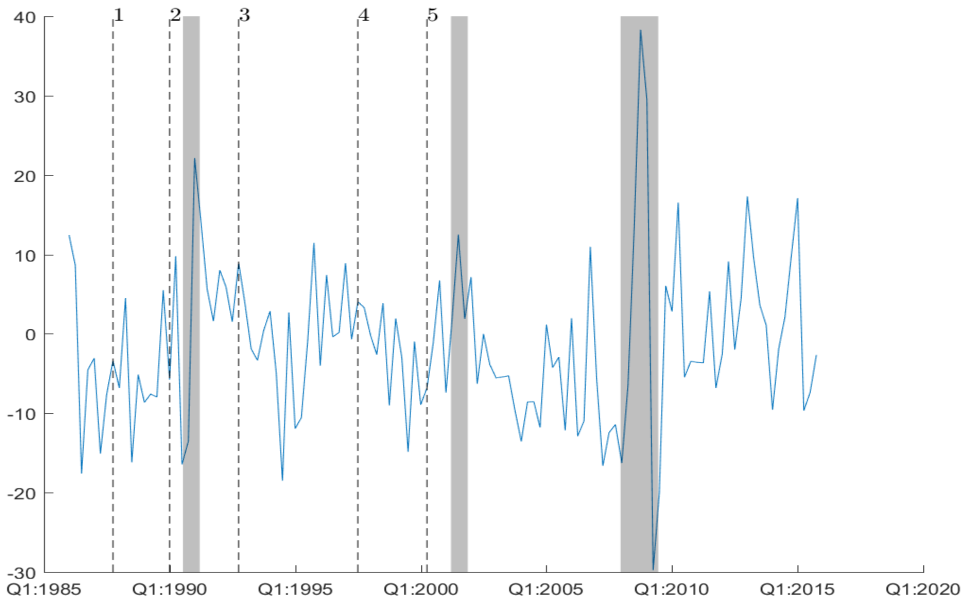


Figure 7.2 shows the U.S. index with the lines representing the events considered. The numbers on top of the lines align with the numbers in Table 7.1. As can be seen the lines generally correspond with times wherein the index is either elevated, or is quickly followed by an increase in the index level.

Events in which the index is already at an elevated level at the time of the event include: The Junk Bond Collapse, the ERM Crisis, and the Asian Crisis. These events are commonly associated with financial events, and given that the index is modelled off a financial variable it is unsurprising that the index responds contemporaneously with these events. However, it is worth noting that the index experiences elevated levels before the Asian Crisis. This does not correspond with any of the events considered.

Looking at other events, the Dot-Com bust aligns with a time wherein the index starts to experience an increase. This aligns well with economic events. The Dot-Com bust signalled the start of a recession (indicated in grey) and slow recovery for the U.S. It is likely that the increase in the index following the Dot-Com bust is capturing the effects the Dot-Com bust and subsequent recession had on sovereign default risk.

It appears that the index does not capture Black Monday in Q4:1987. This may be a signal missed by the index, or may indicate that Black Monday had few real effects on sovereign default risk. Regardless, this event is missed by the index, and may reflect the inability of the index to capture all episodes of high sovereign default risk.

Lastly, the index appears to capture all three recessions in the sample. During times of recession it is likely that government's experience higher levels of fiscal stress as these times are associated with lower tax revenue, and high expenditure in the form of automatic stabilisers. Hence, it is expected that sovereign default risk is higher in these times. My index is able to capture these recessions with the index experiencing elevated levels in recessions. This speaks to the ability for the index to capture the movements in sovereign default risk shaped by economic cycles.

Overall, I find that the U.S. index is able to capture real-world events that may drive increases in sovereign default risk. Despite not performing perfectly, the index is often times at elevated levels during these events. This speaks to the accuracy and usability of the index as a proxy for sovereign default risk.

7.3 Lasso regressions

For robustness I construct an index using Lasso regression. I find that the Lasso regression yields similar results to the index constructed using my preferred methodology. This lends further weight to the accuracy and usefulness of my econometric approach, and ultimately serves to support that my index is a suitable proxy for sovereign default risk.

A least absolute shrinkage and selection operator (Lasso) regression aims to shrink coefficients and set others to zero. Lasso estimation is commonly used to choose relevant explanatory variables, even when the number of parameters exceeds the number of observations (for example see Belloni, Chernozhukov, and Hansen (2014)). Moreover, Lasso regressions yields a model with variables that are easily interpreted and retains prediction accuracy (Tibshirani, 1996). The Lasso problem can be expressed as:

$$\min_{\beta_0,\beta} \left(\frac{1}{2N} \sum_{i=1}^{n} \left(y_i - \beta_0 - x_i^T \beta \right)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \right) \tag{7.2}$$

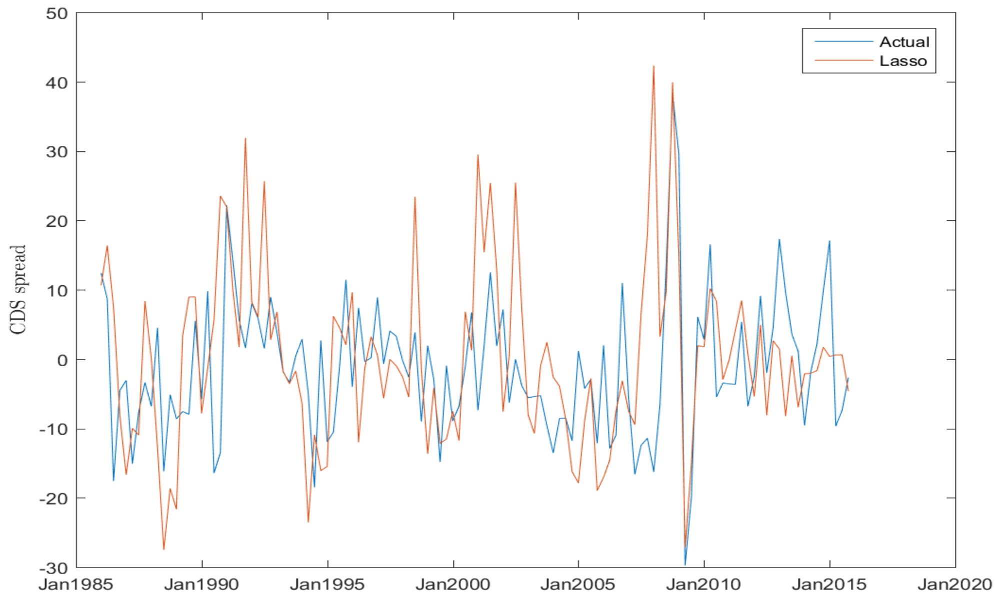
The coefficients are chosen to minimize the sum of squared residuals plus a penalty function. The penalty term, λ, penalizes the size of the model by the absolute size of the coefficients.

Under the condition that the dependent variable can be well-approximated with a small set of variables, Lasso regressions have been shown to be root-n consistent, and asymptotically normal (Belloni, Chen, Chernozhukov, and Hansen, 2012). Moreover, Lasso regression estimation of the mean regression function perform close to, or as well as, the oracle procedure in variable selection. That is, Lasso estimation can work as well as if the correct sub-model was known (Belloni et al. (2012), and Fan and Li (2001)). Together this makes Lasso regressions an appealing method in creating indices where the parameter space is large (as is the case in sovereign default risk).

I estimate the Lasso regression with SCDS spread as the dependent variable, and all variables used in the index as independent variables. I choose the value of the penalty term, λ, by performing 10-fold cross-validation and then choosing the penalty term that has the lowest mean squared error.

Figure 7.3 shows the index generated from the Lasso regression (orange) against the actual index (blue). It can be seen that the general movement of the Lasso index follows my constructed index well. The general upward/downward movements in the index correspond with upward/downward movements in the Lasso index. In fact, the two series have a correlation of 0.387. This confirms the observation that the two indices share similar movements. It is worth noting that the Lasso index appears more volatile than the actual index. It often overshoots the actual index value. This may represent that the Lasso regression uses all the variation in a chosen variable, whereas my index only uses a portion of the shared variation between variables. Nonetheless, the constructed with my preferred methodology holds up well against alternative index construction using Lasso regression. This speaks to the robustness of the econometric approach used to construct the index.

Figure 7.3: USA - Index versus Lasso



Chapter 8

The Index in a Fiscal VAR

To show the relationship between the sovereign default risk index and real economic variables I place the index in a standard fiscal Vector Autoregression (VAR). Conducting Granger-causality tests, and innovation accounting (variance decompositions and impulse response functions) I show that the sovereign default risk index constructed for the U.S. has real effects on the other variables. This indicates that sovereign default risk is a valid consideration in fiscal policy settings. In addition, the results shows that the index is both a useful and applicable measure of sovereign default risk.

8.1 Methodology and Identification

To show that the sovereign default risk index is a valid consideration in fiscal policy settings I will use a simple VAR setting. The model can be specified as follows.

Let Y_t represent a vector of endogenous variables (government expenditure, government revenue, output, and the sovereign default risk index) at time t[1]; Φ_0 be a vector of constants; $\Phi(L)$ be a matrix of coefficients representing the relationship between the lag of the endogenous variables to the contemporaneous value of the endogenous variables; and ε_t represent the residuals of the model.[2] The model can then be expressed as:

$$Y_t = \Phi_0 + \Phi(L)Y_{t-1} + \varepsilon_t \tag{8.1}$$

To achieve structural identification I will perform a Cholesky decomposition on the 4 variables in the system. I will perform a Cholesky decomposition with ordering of government expenditure, government revenue, output, and sovereign default risk. Hence, shocks to sovereign default risk have no contemporaneous effect on the other

[1] A detailed discussion on these variables and transformations can be found in Part II Chapter 5. Also, summary statistics are presented in Appendix M.

[2] A lag length of 1 is used. This is determined by the Akaike Information Criteria (AIC). This leaves 119 observations from Q3:1986 to Q4:2015.

3 variables; and can only affect them with a lag. The ordering of the first 3 variables is common in the fiscal VAR literature (see Blanchard and Perotti (1999)). I have ordered the sovereign default risk index last in the Cholesky ordering because it is based off a financial variable (SCDS spreads). Therefore, relative to the other variables, SCDS spreads are likely to respond faster to shocks. This is the rationale behind ordering the sovereign default risk index last.[3]

8.2 Granger-Causality

Prior to analysing the dynamics of the SVAR it is first important to understand the predictive relationships between the variables of interest. In this section, I will present Granger-causality tests as a preliminary analysis into the relationship between sovereign default risk and the other variables in the system. I find that the sovereign default risk index Granger-causes and is Granger-caused by both government revenue and output. This shows that the sovereign default risk index contains useful information in facilitating the prediction of government revenue and output. Further, the results provide evidence that there is significant interdependence between the sovereign default risk index and the other variables in the system.

Granger causality focuses only on predictive relationships. If lagged values of x Granger-cause values of y, variable x is said to Granger-cause variable y. This should not be mistaken for exogeneity. In the following Granger-causality tests I will be testing if certain variables are useful in predicting future values of the other variables. In these tests the null hypothesis is that the independent variable does not Granger-cause the dependent variable.[4]

Table 8.1 report the p-values from the Granger-causality tests for the VAR.[5]

The Granger-causality results suggest that the sovereign default risk index is Granger-caused by both government revenue and output. This indicates that predictions of the sovereign default risk index can be facilitated by past values of government revenue and output. However, there is not enough statistical evidence

[3]See Appendix L on the Cholesky decomposition. Also a more detailed discussion of structural identification is in Part II.

[4]I will use the 10 per cent level of significance to evaluate these tests. This is motivated by potential power issues driven by the relatively small sample size.

[5]To compliment this section I also conducted Granger-causality tests using the original SCDS spread in the VAR (in place of the sovereign default risk index). I find that there is no statistical evidence that any of the variables Granger-cause one another. This is likely to be driven by a power issue arising from the small sample size. These results add further weight to the usefulness of the index in generating an accurate and applicable measure of sovereign default risk. The results are presented in Appendix G

to suggest that government expenditure Granger-causes sovereign default risk. The results highlights that the variables in the fiscal VAR have predictive power in forecasting the sovereign default risk index. This indicates that the sovereign default risk index responds to lagged movements in the other endogenous variables. This is expected as these variables are generally considered to be significant indicators of sovereign default risk. Moreover, this further lends weight to the finding that the index is a meaningful measure of sovereign default risk.

Movements in sovereign default risk Granger-cause both government revenue and output. Moreover, despite being insignificant at the 10 per cent level it is worth mentioning the p-value for sovereign default risk Granger-causing government expenditure is close to the significance level used. These result provides some preliminary insight into how sovereign default risk could be managed. Primarily changes in revenue or expansionary fiscal policy to increase output may influence sovereign default risk. However, statements on the two-way relationship between variables are difficult to make as they neglect interactions with other variables in the multivariate system. Overall, the results show that government revenue and output can facilitate in the prediction of sovereign default risk.

The interdependence between sovereign default risk and the other variables is apparent from the Granger-causality results. This interdependence vindicates the use of the sovereign default risk index in analysing fiscal policy. In addition, the results illustrate the importance of using a multivariate setting to account for the full dynamics of the given variables.

Table 8.1: Granger-causality results

Independent variable	Dependent Variable			
	Expenditure	Revenue	Output	Index
Expenditure	-	0.00	0.08	0.25
Revenue	0.07	-	0.56	0.01
Output	0.51	0.00	-	0.00
Index	0.13	0.00	0.03	-

8.3 Variance Decompositions

(Forecast error) Variance decompositions provide a means to analyse the importance of different shocks to the forecast of each variable. Variance decompositions show the proportion (reported as a percentage) of movements in the sequence of a variable due to shocks to itself and shocks to other variables. To conduct this analysis it is necessary to impose structural restrictions. Recall from Section 8.1, the baseline set of restrictions have an ordering of government expenditure, government revenue, output, and the sovereign default risk index. I find that shocks to the sovereign default risk index explain over 10 per cent of the of the movements in government revenue, but fail to explain more than 5 per cent of the movements in government expenditure and output. Whereas, over 10 per cent of the forecast variance in the sovereign default risk index are explained by shocks in government expenditure. Taken together the results further illustrate the interdependence between sovereign default risk and the other variables in the system.

Table 8.2 reports the variance decomposition of government expenditure to all variables over a horizon of 16 quarters.[6] The results indicate that government expenditure is mostly explained by its own shocks over the forecast horizon. In fact, by the 16th quarter more than 93 per cent of the variation in government expenditure forecasts are still driven by shocks to itself. This result provides support to the idea that government expenditure is largely discretionary and has little relation to the business cycle (Taylor, 2000).

Table 8.3 reports the variance decomposition of government revenue over a 16 quarter horizon. Shocks to government expenditure drive an immaterial proportion of government revenue. However, the forecast variation in government revenue can be explained by a mixture of itself, output growth, and changes to sovereign default risk. Output growth shocks drive approximately 23 per cent of the variation in government revenue from the 5th period onwards. This is expected given that government revenue is a direct function of output. Moreover, sovereign default shocks drive approximately 11 per cent of the forecast movements in government revenue. This is a reasonably large amount, and highlights that sovereign default risk can indeed drive dynamics in government revenue.

The variance decomposition of output growth is presented in Table 8.4. The results indicate that the forecast variance of output growth is largely determined by shocks to itself. Over the horizon the proportion of variation in output growth driven by

[6]Key: Exp= Government expenditure, Rev= Government revenue, Index= Sovereign default risk index.

shocks to itself falls from 83.28 to 80.08 per cent. This represents only a small decrease over the horizon. This is expected given that output growth is most likely largely determined by factors related to private consumption and investment.

Lastly, the variance decomposition of sovereign default risk is presented in Table 8.5. Overall, the forecast variance of sovereign default risk is determined by shocks to itself. However, shocks to government expenditure consistently drive over 10 per cent of the forecast variation in sovereign default risk. Counter to the Granger-causality results, this suggests that there is a nexus between government expenditure and sovereign default risk.

Overall, the variance decompositions indicate that sovereign default risk drive a large portion of movements in government revenue, but do not drive much of the dynamics in output and government expenditure. Moreover, the results show that over 10 per cent of the variation in the forecasts of the sovereign default risk are driven by shocks to government expenditure. Taken together, the results provide further evidence that the sovereign default risk index is interrelated with the other variables in the fiscal VAR. This again stresses that sovereign default risk is a valid consideration in this setting.

Table 8.2: Expenditure

	Exp	Rev	Output	Index
1	100.00	0.00	0.00	0.00
2	95.63	2.55	0.27	1.54
3	94.62	3.10	0.75	1.52
4	94.13	3.18	1.12	1.57
5	93.93	3.20	1.27	1.60
6	93.86	3.20	1.32	1.61
7	93.84	3.21	1.34	1.61
8	93.83	3.21	1.35	1.61
9	93.83	3.21	1.35	1.61
10	93.83	3.21	1.35	1.61
11	93.83	3.21	1.35	1.61
12	93.83	3.21	1.35	1.61
13	93.83	3.21	1.35	1.61
14	93.83	3.21	1.35	1.61
15	93.83	3.21	1.35	1.61
16	93.83	3.21	1.35	1.61

Table 8.3: Revenue

	Exp	Rev	Output	Index
1	0.83	99.17	0.00	0.00
2	0.62	71.07	18.00	10.31
3	0.74	66.61	21.79	10.86
4	0.81	65.52	22.74	10.93
5	0.83	65.16	23.04	10.96
6	0.84	65.04	23.15	10.97
7	0.85	65.00	23.18	10.97
8	0.85	64.99	23.20	10.97
9	0.85	64.98	23.20	10.97
10	0.85	64.98	23.20	10.97
11	0.85	64.98	23.20	10.97
12	0.85	64.98	23.20	10.97
13	0.85	64.98	23.20	10.97
14	0.85	64.98	23.20	10.97
15	0.85	64.98	23.20	10.97
16	0.85	64.98	23.20	10.97

Table 8.4: Output

	Exp	Rev	Output	Index
1	10.01	6.71	83.28	0.00
2	8.56	7.58	80.73	3.13
3	8.17	7.44	80.27	4.12
4	8.10	7.44	80.15	4.31
5	8.08	7.45	80.11	4.36
6	8.08	7.45	80.09	4.38
7	8.08	7.46	80.09	4.38
8	8.08	7.46	80.08	4.38
9	8.08	7.46	80.08	4.39
10	8.08	7.46	80.08	4.39
11	8.08	7.46	80.08	4.39
12	8.08	7.46	80.08	4.39
13	8.08	7.46	80.08	4.39
14	8.08	7.46	80.08	4.39
15	8.08	7.46	80.08	4.39
16	8.08	7.46	80.08	4.39

Table 8.5: Index

	Exp	Rev	Output	Index
1	11.79	0.01	0.04	88.15
2	10.83	2.07	6.22	80.88
3	10.79	2.06	6.50	80.65
4	10.79	2.07	6.54	80.61
5	10.79	2.07	6.55	80.60
6	10.78	2.07	6.55	80.59
7	10.78	2.07	6.56	80.59
8	10.78	2.07	6.56	80.59
9	10.78	2.07	6.56	80.59
10	10.78	2.07	6.56	80.59
11	10.78	2.07	6.56	80.59
12	10.78	2.07	6.56	80.59
13	10.78	2.07	6.56	80.59
14	10.78	2.07	6.56	80.59
15	10.78	2.07	6.56	80.59
16	10.78	2.07	6.56	80.59

8.4 Impulse response functions

Impulse response functions (IRFs) are used to measure the response of variables to an exogenous shock in other variables. Unlike Granger-causality tests, the IRFs are calculated using the entire multivariate system. This serves to more accurately capture the dynamics of each variable to a shock in another variable (or itself). In this section, I will analyse the effects of an increase in the sovereign default risk index on the variables in the system. I find that an increase in sovereign default risk drives significant losses in both output and government revenue. The result further supports of inclusion sovereign default risk in evaluating the dynamics of fiscal policy variables.

For all IRFs in this section I have employed the ordering as specified in Chapter 8.1. That is, government expenditure is ordered first, government revenue is ordered second, output is ordered third, and sovereign default risk is ordered last. Moreover, the shock imposed on the system is equivalent to a positive one-standard deviation of the sovereign default risk index. The approximate 90 per cent confidence interval bands are reported in red.[7] As all variables are in percentage changes, accumulated responses are reported.

[7]The confidence intervals are 1.645 multiplied by the standard error of the estimate. Under the assumption of normality, this would represent a 90 per cent confidence interval.

8.4.1 Shock to sovereign default risk

Figure 8.1 shows the IRFs of all variables in response to a positive one-standard deviation shock in the sovereign default risk index. The results can be interpreted as the response to an exogenous increase in sovereign default risk. The results indicate that increases in the sovereign default risk index shape both output and government revenue losses. This again speaks to the importance of considering sovereign default risk in a fiscal policy setting. It also indicates that the index constructed provides both an applicable and meaningful measure of sovereign default risk.

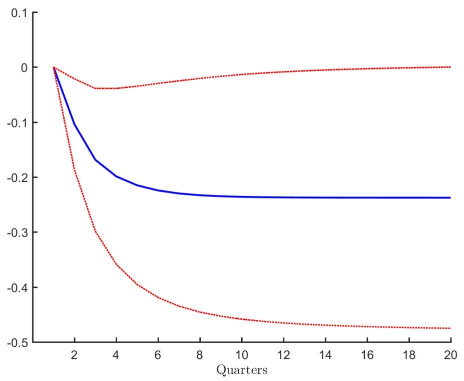
An exogenous increase in default risk drives a decline in output growth over the 20 quarter forecast horizon. Moreover, the effect is statistically different from zero in the third period. The result suggests that a one standard deviation increase in sovereign default risk defines a 0.23 per cent long run decline in output. This result is consistent with the literature identifying sovereign default as costly. In particular, this contributes to Yeyati and Panizza (2011) finding that the output costs of sovereign default are incurred prior to default, as agents anticipate the impending default. This result not only lends weight to the idea that agents respond prior to actual default, but suggests that the probability of default does not necessarily need to be a certainty to have output costs from sovereign default risk.

The shock in default risk also leads in a deterioration in the governments balance sheet. The response of government expenditure to a shock in sovereign default risk is statistically indistinguishable from zero. Moreover, the long-run accumulated response settles approximately at -0.04. This suggests that government expenditure responds very little (if at all) to shocks in sovereign default risk. On the other hand, there is a steep decline in government revenue from the shock to sovereign default risk. Government revenues initially declines by 2.15 per cent one period following the increase in sovereign default risk. The response stabilises at a long-run value of approximately -3.80 per cent. This response suggests that the one standard deviation shock in sovereign default risk drives government revenue down by 3.8 per cent in the long-run. Taken together, the results suggest that shocks to sovereign default risk can induce a deterioration in the government balance sheet through declines in government revenue.

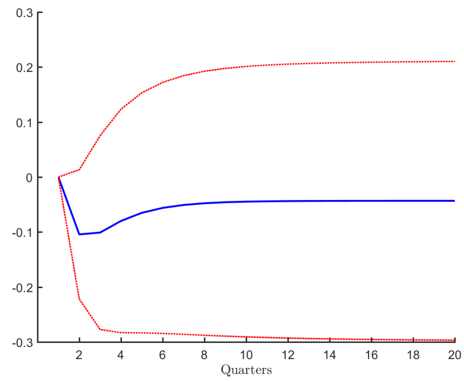
Lastly, a shock to default risk results in a permanently higher level of default risk. That is, that there is no reversion of sovereign default risk in this setting. Following the initial one-standard deviation increase in sovereign default risk, the sovereign default risk index increases by almost another 3 units to settle at a long-run accumulated response of 11.70. The confidence bands show that this result is statistically distinguishable from zero. This strongly suggests that shocks to sovereign default risk do not revert back automatically, and may require purposeful government policy to rein in sovereign default risk.

Taken together, the results show that the sovereign default risk index is a valid consideration in a fiscal setting. Shocks to sovereign default cause a significant negative response from both output and government revenue. This is indicative of the ability for sovereign default risk to drive economic dynamics, and stresses the consideration of sovereign default risk in fiscal policy settings. Moreover, the results again speak to the usefulness and applicability of the sovereign default risk index.

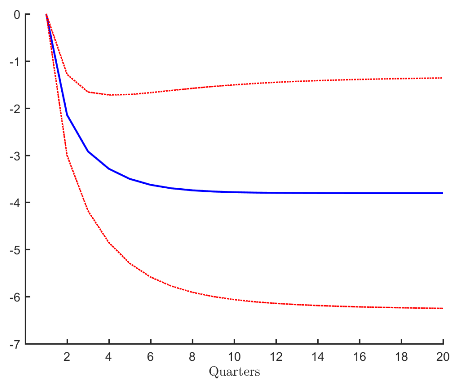
Figure 8.1: Shock to Sovereign Default Risk



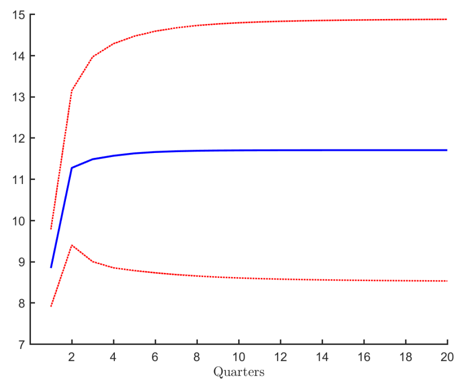
(a) Output



(b) Government Expenditure



(c) Government Revenue



(d) Sovereign Default Index

Chapter 9

Discussion and Concluding Remarks

9.1 Discussion and Further Research

In this thesis Part, I have constructed a usable and reliable measure of sovereign default risk. Unlike previous measures of sovereign default risk, I exploit the high-frequency and continuous nature of the SCDS spreads. To extend the sample size of the SCDS spreads to a usable length for macroeconomic analysis I utilise datamining techniques. The econometric approach of this Part combines elements from PCA, recursive regressions, and Bayesian methods. Together these techniques have desirable properties when dealing with small samples, and when identifying relevant factors when it is unclear which variables are significant. The latter is particularly useful when dealing with sovereign default risk because the variables related to sovereign default risk are broad and not well defined. To the best of my knowledge no similar methodology has been applied for sovereign default risk.

The index constructed using my methodology yields strong in-sample results. Across all applicable OECD countries I show that my index is able to capture the majority of the variation in the SCDS spread, and has less than a one standard deviation RMSE. These results speak to the accuracy of my index and the usefulness of the econometric approach.

Focusing on the U.S. index, I also show that other single-variable measures of sovereign default risk fail to capture as much variation in SCDS spreads as the index. Moreover, I show that real-world events often line up well with elevated levels of the sovereign default risk index. Lastly, I also show that other data mining techniques can be used to yield similar results to my index. Taken together, this shows my index is both a reliable and suitable measure of sovereign default risk.

To further show the practicable and applicability of my index I place it in a fiscal VAR. I show that sovereign default risk is in fact a valid consideration in this setting. Granger-causality tests, variance decompositions and the impulse response functions jointly illustrate the interrelations the sovereign default risk index has with the other variables in the system. This stresses that sovereign default risk is a valid consideration in fiscal policy settings. In addition, the results show that the sovereign default risk index is a meaningful measure that can generate real economic effects.

My index, though useful, fails to produce any meaningful economic interpretation. Factor scores represent shared variation over many variables, and interpreting what this shared variation represents is difficult. It could in fact represent movements in a latent variable. Despite not being the purpose of my research, it would be useful to derive more meaningful conclusions from the sovereign default risk index. This will facilitate in better understanding the drivers behind sovereign default risk. I have already made a small attempt at this by using Lasso regressions. However, more research in this field would be beneficial. In particular, Elliott, Gargano, and Timmermann (2015) proposes the use of complete subset regression (similar to EBA) and determining coefficients estimates using model averaging. An alternative method for index construction is to apply Bayesian shrinkage methods. One Bayesian method would be to apply a horseshoe estimator which has been shown to be have super-efficient rates of convergence (Carvalho, Polson, and Scott, 2010). These techniques can provide a more interpretable result in identifying drivers of sovereign default risk. My methodology can still be considered in these frameworks by serving as a benchmark.

Considering sovereign default risk measures beyond SCDS spreads would be worth further investigation. I have applied the use of SCDS spreads as by construction they should provide the market expectations of sovereign default risk. However, in practice there remains a question whether the participants of this market truly reflect the expectations of sovereign default. This is particularly the case with the U.S. which is often regarded as a risk-free as it issues debt in its own currency. This casts doubt over what the market participants are truly trading on. Moreover as mentioned earlier, SCDS spreads represent a relatively broad measure of sovereign default risk. Whether this information is useful in examining sovereign default risk is questionable. It may in fact act as a better proxy for political gridlock. Applying and then comparing other measures of sovereign default risk such as bond spreads, the yield curve, inflation swaps, and measures of government solvency may provide better measures of sovereign default risk, and ultimately further elucidate the true drivers behind sovereign default risk.

The sovereign default risk index and results from the fiscal VAR open the door to many new research possibilities. Given I have created a reliable and practical measure of sovereign default risk it can be used to further analyse the effects that sovereign default risk has on other economic variables. I have already established that increases in sovereign default risk drive lower economic growth and deteriorations in the government balance sheet. This reflects the ability of sovereign default risk to influence real economic outcomes. Further testing will yield a useful contribution to the literature that often focuses on the effects of actual sovereign default on the economy; rather than the effects of sovereign default risk. Appendices H and I together provide some preliminary analysis on this issue. I find that the output losses from increases in sovereign default risk are associated with investment losses. Moreover, I find that a potential transmission mechanism behind these investment losses is the increase in private risk and borrowing costs, driven by increases in sovereign default risk. That is, sovereign default risk translates to private risk and hence increases borrowing costs. Further research on these topics, such as examining the interaction between sovereign default risk and monetary policy, can build on the shallow understanding of the effects of sovereign default risk.

9.2 Concluding Remarks

Sovereign default risk is now of increasing concern for countries. This has made measuring and understanding sovereign default risk of increasing importance. The construction of this new sovereign default risk index represents a step in facilitating the measurement and understanding of sovereign default risk, and subsequently its implications. The key contribution of this index is the use of high-frequency and continuous financial data in the form of SCDS spreads. This renders the index more applicable to further macroeconomic analysis. Moreover, the methodology employed is unique and overcomes small sample issues that often arise in macroeconomic data. The sovereign default risk index constructed from this methodology performs well to in-sample and out-of-sample metrics, indicating that it is a meaningful measure of sovereign default risk. Moreover, I find that the index is also useful in empirical analysis of fiscal policy. This illustrates that sovereign default risk is a valid consideration when evaluating fiscal policy. Using this index, future research should attempt to build on this work, and ultimately untangle the complex phenomenon of sovereign default risk.

Part II

The Fiscal Multiplier in a Non-linear World: A Threshold Vector Autoregression Approach

Chapter 1

Introduction

From 2007 to 2016 the U.S. government's debt-to-GDP ratio increased from 42.0 per cent to 107.9 per cent. This represents a significant deterioration in the state of the U.S. government's finances. This experience has not been unique to the U.S. Over the same period, Ireland's debt-to-GDP ratio increased by a staggering 364 per cent from 24.8 per cent to 90.2 per cent. Greece is now near default as their debt-to-GDP ratio increased from 105.1 per cent to 171 per cent. As government finances across the globe deteriorate it begs the question of whether expansionary fiscal policy is an appropriate policy decision. In this Part, I will shed light on this issue by exploring whether different regimes of sovereign default risk can change the effectiveness of fiscal spending (government expenditure).

This recent deterioration of government finances coupled with subdued growth and constrained monetary policy has driven a renewed interest in the effectiveness of fiscal policy as a macroeconomic stabilisation tool. This renewed interest has prompted many attempts to reconcile the varying estimates of the fiscal (spending) multiplier. This has led the literature to consider that differing states of the world can affect the fiscal multiplier. In fact, the state of the business cycle has already been established as a driver of non-linearities in the fiscal multiplier (Auerbach and Gorodnichenko (2012), and Fazzari, Morley, and Panovska (2015)). This highlights the potential for fiscal spending to have non-linear effects. This research has shed light on the evaluation of policy tools available to governments. It has also opened the door to explore what can drive these non-linearities in the fiscal multiplier. In this Part, I will posit that differences in sovereign default risk can drive non-linearities in the fiscal multiplier.

The previous Part established that sovereign default risk is a valid consideration in the standard fiscal VAR. However, linear estimation, while useful, could be erroneous as it fails to consider potential non-linearities in the fiscal multiplier generated by different regimes of sovereign default risk. That is, the level of sovereign default risk could cause agents to respond differently to fiscal spending. To address this, I will use a non-linear setting. I will use my sovereign default risk index created in Part I as a threshold variable in a Threshold Vector Autoregression (TVAR) to identify if output responses to fiscal spending differ based on level of sovereign default risk.

The key contribution of this Part is the use of my sovereign default risk index as a threshold variable to capture non-linearities in the fiscal multiplier. Two regimes (high and low) will be defined based on the level of sovereign default risk. This will accommodate for different dynamics in variables depending of whether sovereign default risk is high or low. I will then evaluate the effectiveness of fiscal spending under each regime. Similar research in this area suggests that weak public finances can shape less effective fiscal spending (Perotti (1999) and Ilzetzki, Mendoza, and Vegh (2013)). These are findings that are supported by my results. I find that fiscal spending in periods of high sovereign default risk have large negative longer-term effects on output. This is in stark contrast to fiscal spending in periods of low sovereign default risk which have relatively neutral or slightly negative longer-term output effects. The results suggest sovereign default risk can cause non-linearities in the fiscal multiplier. However, the confidence intervals at times suggest that these non-linearities are not always statistically significant.

Exploration of my results suggest that these differences can be partially attributed to both the response of sovereign default risk, and the system's regime evolution over time. The results provide evidence of an inverse relationship between the response of sovereign default risk and the fiscal multiplier. In addition, I also find evidence that regimes are persistent. That is, an increase in fiscal spending is unlikely to drive a regime change. Taken together, the findings emphasise the importance of considering sovereign default risk when evaluating the effectiveness of fiscal spending. In addition, governments should also consider pre-emptive action against sovereign default risk to avoid situations wherein fiscal spending is rendered impotent by high levels of sovereign default risk.

Consumption appears to be the underlying driver behind the fiscal multiplier across regimes. Combining this result with the response of sovereign default risk suggests that wealth effects, and subsequent changes in credit constraints, drive the fiscal multiplier. In particular, I provide evidence that in times of high sovereign default risk, fiscal spending can have large negative effects on household wealth, hence driving lower multipliers. Lastly, fiscal spending when sovereign default risk is low results in mild decreases in consumption. This points to relatively more subdued declines in household wealth, and is consistent with the notion of Ricardian Equivalence.

Chapter 2

Literature review

The effects of changes in fiscal spending on the economy (the fiscal multiplier) has been the subject of a broad and expansive literature. Starting from analysis of the fiscal multiplier in linear settings, the empirical literature has recently evolved to investigating non-linearities in the fiscal multiplier that can be driven by various factors. Factors considered to be potential drivers of non-linearities in the fiscal multiplier include the state of the economy, credit regimes, and sovereign default risk. I will highlight some of these findings in the literature to contextualise my analysis of non-linearities in fiscal multipliers driven by sovereign default risk.

Overall, within the literature on fiscal multipliers there remains significant variation in estimation techniques, identification of spending shocks, and invariably, the estimates of the fiscal multiplier. In this literature review I will first detail fiscal multiplier estimates, then analyse the literature related directly to the relationship between sovereign default risk and the fiscal multiplier. Lastly, I will discuss identification strategies often used in the literature.

2.1 Fiscal multiplier estimates

The analysis of fiscal multipliers in empirical settings is well established. To a large extent this has been driven by Blanchard and Perotti (1999) who famously exploited higher frequency (quarterly) data and illustrated three features of fiscal spending shocks: (1) Multipliers are close to one. (2) Spending shocks cause persistent increases in spending. (3) Consumption increases, whereas investment decreases in response to an increase in fiscal spending. These findings have been extensively investigated in the literature since.

Despite the extensive literature that has been devoted to fiscal multipliers since Blanchard and Perotti (1999) there remains significant debate over the size of the fiscal multiplier. This range of estimates is highlighted in a review of the empirical literature by Ramey. She concludes that the fiscal multiplier “is probably between

0.8 and 1.5" (2011, pg. 673). This is supported by Gechert (2015) who compiles data over 104 studies and finds a range of fiscal multiplier estimates as high as 3.90 and as low as -1.75. As part of this meta-analysis, Gechert stresses that multipliers are heavily dependent on study design. This wide range of estimates is relative unhelpful in policy analysis, as a multiplier of 1 is considered the critical threshold after which fiscal spending is considered expansionary without decreasing other components of aggregate demand.[1]

This range and instability of estimates has motivated a growing branch of literature focusing on identifying non-linearities in the fiscal multiplier. The rationale behind this field is that the range of estimates from linear models can be attributed to potential factors that can change the size of the fiscal spending multiplier. This literature posits that linear estimation of fiscal multipliers produce erroneous estimates as it fails to account for how fiscal spending may interact with other economic variables in varying states. The evidence favouring non-linear analysis of the fiscal multiplier, over linear analysis, is growing. For example, Corsetti, Meier, and Müller (2012) consider non-linearities driven by exchange rate regimes, public indebtedness, and the health of the financial system. Comparing non-linear to linear results they conclude that non-linear estimation is more appropriate when examining the fiscal multiplier.

The relationship between the state of the business cycle and the fiscal spending multiplier has drawn significant attention. In a theoretical setting, Christiano, Eichenbaum, and Rebelo (2009) show how interest rates bounded by the zero-lower bound may increase the effectiveness of fiscal spending. In their new-Keynesian model, an increase in agent's desire to save drives the economy to the zero-lower bound. In this setting, any increase in fiscal spending will then define a fall in aggregate savings as agents (who drove the economy to the zero-lower bound by increasing savings) prefer to consumption smooth. This leads to larger multipliers relative to normal times. This highlights the potential for different economic settings to drive differences in the fiscal multiplier.

Motivated by these theoretical results, economic slack as a driver of non-linearities in the fiscal multiplier has also been examined empirically. Auerbach and Gorodnichenko (2012) use a Smooth-Transition Vector Autoregression (STVAR) to estimate the fiscal multiplier based on the state of the business cycle. They find significant differences in the size of the fiscal multiplier in expansions and recessions. Over five years, they find the multiplier is between 0 and 0.5 in expansions, and between 1 and 1.5 in recessions. The findings suggest fiscal policy is more effective

[1] A multiplier above 0 would indicate that fiscal spending is expansionary, but decreases other components of aggregate demand.

when the state of the business cycle is low. Building on this research, Fazzari, Morley, and Panovska (2015) use a Threshold Vector Autoregression (TVAR) to estimate state-dependent effects of fiscal policy. They employ a TVAR as opposed to an STVAR. They argue that the likelihood function could be flat when there is a relatively discrete threshold. A STVAR can therefore result in poor estimation of parameters. Despite the econometric differences, Fazzari et al. also find evidence of non-linearities in the fiscal multiplier over a variety of threshold variables related to economic slack. Using capacity utilisation as their primary threshold variable, they find that the fiscal multiplier is 0.8 points higher during the first two years when capacity utilisation is low, relative to when capacity utilisation is high. They point to consumption as the key driver behind this non-linear response to fiscal spending. More specifically, during recessions there are more credit constrained individuals. Therefore, increases in fiscal spending have a larger effect on output, as credit constrained individuals tend to have a higher marginal propensity to consume. Further, Bachmann and Sims (2012) reach similar findings regarding state-dependent fiscal multipliers but point to confidence as the primary transmission mechanism that drives larger multipliers when economic slack is high.

Looking beyond non-linearities generated from the state of the economy, credit regimes have also been found to drive non-linearities in the fiscal multiplier. Borsi (2016) identifies that financial conditions matter in determining the fiscal multiplier. Using data from 24 OECD countries, he finds that expansionary fiscal policy is more effective during credit crunches. He estimates a three year multiplier of around 2.69 in times of tighter credit, and 0.03 in times of credit expansion. Furthermore, similar to Fazzari et al. (2015) the larger output response in periods of tighter credit is driven by increases in consumption. This provides further support that credit constrained agents are a key determinant to the size of the fiscal multiplier. Other studies that examine credit or financial conditions as drivers of non-linearities include Corsetti et al. (2012), and Ferraresi, Roventini, and Fagiolo (2015). Both reach similar conclusions to Borsi (2016). That is, the fiscal multiplier is larger during times of tighter credit conditions. This not only provides evidence of non-linearities in the fiscal multiplier, but also lends weight to the proposition that credit constrained agents play a large role in driving these non-linearities.

The literature shows that non-linearities in the fiscal multiplier can arise under differing sets of conditions. In particular, economic and credit cycles have been identified as potential factors in driving these non-linearities. This literature has pointed to credit constraints as a potential determinant in driving non-linearities in the fiscal multiplier. In this Part, I will investigate whether sovereign default risk drives any non-linearities in the fiscal multiplier. While the literature on this issue is sparse, I will endeavour to explore this literature.

2.2 Sovereign default risk and the fiscal multiplier

The state of government finances in various settings has been shown to drive different economic dynamics. This provides evidence for the potential of sovereign default risk to drive non-linearities in the fiscal multiplier.

There is empirical evidence suggesting economic dynamics differ at different levels of public indebtedness. Kumar and Woo (2010) estimate a panel regression with 38 countries from 1970-2007. The focus of Kumar and Woo is based on initial debt-to-GDP levels. Using initial debt-to-GDP levels, they mitigate potential bias from reverse causality issues. Their estimates suggest that an increase of 10 per cent in initial debt-to-GDP ratios leads to a slowdown in output growth of around 0.26 per cent per year. In addition, they find some evidence of a larger negative output effects beyond the 90 per cent debt-to-GDP ratio threshold. Similar research has also been done by Checherita-Westphal and Rother (2012). This illustrates the potential for higher levels of public debt to drive different economic dynamics.

In theoretical settings, sovereign default risk is often accounted for by considering the government budget constraint, or spending rules that respond to the level of public debt. In a New Keynesian model, Corsetti, Kuester, Meier, and Müller (2010) illustrate the importance of considering the fiscal outlook when evaluating fiscal stimulus. Using a spending rule that responds to deviations in public debt, they show that current fiscal expansions coupled with prospective spending cuts can amplify the positive effects of fiscal stimulus. The amplification of fiscal stimulus comes from future expectations of lower public demand via expected future spending cuts. This expectation of lower public demand lowers the long term real interest rate, and hence boosts the stimulatory effects of fiscal spending. This model highlights that the fiscal outlook can be an important determinant in the size of the fiscal multiplier.

Looking more specifically at non-linearities in the fiscal multiplier driven by the state of government finances, Perotti (1999) considers a structural model wherein households can respond non-linearly to fiscal spending. The model considers an economy with both liquidity constrained and non-liquidity constrained households. The unconstrained households are able to internalise the government budget constraint in their decision making. Under these conditions, fiscal spending in periods of high public debt can be associated with lower private consumption. This response is generated from a negative wealth effect from expected future tax increases. The negative wealth effect is larger when public debt is higher, as higher debt levels imply higher future taxation. The model suggests that future tax distortions have a second order effect on wealth. Hence, higher public debt can amplify negative wealth effects (beyond the typical Ricardian effect) that may render fiscal spending impotent (or even counter-productive). Whereas, in periods where public debt is not a concern this non-linear wealth effect is subdued, and the changes in household wealth are dominated by typical Ricardian effects. That is, the present value of household wealth declines by the same amount as the increase in fiscal spending, this will necessarily lead to a reduction in consumption. Perotti then considers this model in an empirical framework. He estimates consumption growth from fiscal spending shocks over 19 OECD countries, and interacts the spending shock with a dummy variable indicating if the government is in 'bad times'. In support of his structural model, he finds that in the identified 'bad times' consumption responds negatively to fiscal spending increases. This highlights the ability of government finances to shape non-linearities the fiscal multiplier via non-linear household wealth effects.

More recent work has also shown that fiscal multipliers may depend on the state of government finances. Using quarterly data, Ilzetzki et al. (2013) investigate fiscal multipliers across 44 countries. They attempt to analyse the effect various economic variables have on the fiscal multiplier using panel VAR with country fixed effects. They find countries with debt-to-GDP ratios exceeding 60 per cent have lower fiscal multipliers, especially in the long run. They estimate a long-run multiplier of -2.3 for high debt countries, whereas the multiplier is positive for low debt countries. These findings are consistent with Perotti's finding that higher levels of public debt can shape lower fiscal multipliers. They also suggest that countries with higher sovereign default risk may in fact find fiscal spending counter-productive in promoting growth.

Similar to Ilzetzki et al. (2013), Nickel and Tudyka (2014) test for non-linearities driven by debt-to-GDP levels over a panel of 17 European countries. Their methodology incorporates a panel VAR and allows for non-linearities by interacting endogenous variables with the first lag of the debt-to-GDP ratio. Using Bayesian methods, they construct multipliers for various levels of debt-to-GDP. They find that the multiplier is positive when debt-to-GDP ratios are at or below 65 per cent. Beyond this threshold, the higher the level of debt-to-GDP the faster the fiscal multiplier goes to zero. The finding sheds light on potential non-linearities in the fiscal multiplier based on sovereign default risk. It is worth mentioning that both

Ilzetzki et al. (2013) and Nickel and Tudyka (2014) suffer from potential sample bias as they only include countries that have had debt-to-GDP ratios that have reached certain levels.

The literature has shown evidence of potential non-linear economic responses driven by sovereign default risk. In times of high sovereign default risk, fiscal spending appears to result in negative output responses that go beyond a typical Ricardian outcome. To explain these non-Ricardian effects, the literature has pointed to non-linear wealth effects generated from high sovereign default risk.

Most empirical analysis, including those mentioned above, use debt-to-GDP ratios as their chosen measure of sovereign default risk. Despite results indicating the presence of non-linearities in the fiscal multiplier, debt-to-GDP may not sufficiently capture all factors related to sovereign default risk. This was shown in Part I. I will build on the literature by considering my index as a measure of sovereign default risk, and examine whether it can define non-linearities in the fiscal spending multiplier.

2.3 Fiscal spending identification

To analyse the effect of fiscal spending on the economy, it is necessary to identify exogenous fiscal spending shocks. What constitutes a fiscal spending shock is still a contentious issue in the literature. However, there are currently two primary ways to identify fiscal spending shocks: the narrative approach, and the Structural Vector Autoregression (SVAR) approach. Each has its owns merits and disadvantages that I will now discuss.

2.3.1 The narrative approach

The narrative approach uses news and forecast data to facilitate the identification of exogenous fiscal spending shocks. The approach was pioneered by Ramey and Shapiro (1998) who use *Business Week* forecasts of defence spending to identify exogenous fiscal spending shocks. Episodes where forecasts suddenly increased due to major political events, and events unrelated to the state of the economy are classified as fiscal spending shocks. Using this approach Ramey and Shapiro identify three episodes of fiscal spending shocks: (1) The Korean War (2) The Vietnam War (3) The Carter-Reagan build-up. The rationale behind this identification strategy is that these shocks are less likely to be anticipated by agents, and are unlikely to be driven by the state of the economy, therefore making it less susceptible to endogeneity issues.

In Ramey (2009), she builds on the approach in Ramey and Shapiro (1998). Combining both *Business Week* forecasts and several newspaper sources Ramey constructs a new measure of military spending shocks. Using the identified shocks, Ramey estimates that the fiscal multiplier is between 0.6 and 0.8. This is generally smaller than the estimates found using the SVAR methodology.

This identification approach has some attractive features. Firstly, the spending shocks identified could be more exogenous than spending shocks derived from other methodologies. This is because this identification approach relies on real-world experiences, rather than (co-)variation in the data. Secondly, this identification method avoids the use of assumptions (or restrictions) that are inherent in the SVAR identification of fiscal spending shocks. Lastly, this identification allows a researcher to employ more flexible econometric methods. More specifically, a researcher can use single-equation methods and analyse many variables in these settings with less risk of over-parametrisation that often occurs in multivariate settings.

Despite the benefits, this identification approach can also be relatively restrictive. It heavily relies on only a few episodes of fiscal spending shocks. Estimates of the fiscal multiplier are hence generated from a small sample of spending shocks. Moreover, there is ambiguity over whether the economic effects of military spending can be generalised as similar to other forms of fiscal spending (Corsetti et al. (2012)). That is, it is ambiguous whether a defence spending shock would propagate across the economy in the same way as a government consumption shock.

2.3.2 The SVAR approach

Most of the fiscal multiplier literature employ SVAR models and apply short-run restrictions to identify fiscal spending shocks. From these identified shocks an estimate of the fiscal multiplier can be derived. This is the approach used in this thesis. Following Blanchard and Perotti (1999), fiscal spending shocks are identified by imposing short-run restrictions via a Cholesky decomposition of the residuals. In the standard fiscal VAR there are three variables: government expenditure (fiscal spending), government tax revenue, and output. The identifying restrictions allow output to respond contemporaneously to both government expenditure and government revenue shocks. However, government expenditure and government revenue only respond to output shocks with a lag. This is equivalent to ordering output last in the Cholesky decomposition. To justify this ordering, Blanchard and Perotti argue that the use of quarterly data eliminates the possibility of any discretionary adjustments to expenditure or revenue in response to unexpected output events within the quarter. That is to say that policy makers take more than a quarter to recognise an output shock, decide the appropriate measure to take, pass these measures through government, and finally implement the policy. Hence, output can be ordered last in the Cholesky decomposition. It is important to note that this form of identification relies critically on the use of quarterly data.

Further, Blanchard and Perotti remain agnostic on the relationship between government expenditure and revenue. That is, it is difficult to know whether government expenditure responds to government revenue, or whether government revenue responds to government expenditure. Therefore, the ordering of these two variables in the Cholesky decomposition can be switched to accommodate for both possible identification strategies. They find the correlation between government expenditure and revenue shocks to be small enough such that changing the ordering of these variables makes little difference to the results.

The primary critique of this identification strategy is that the identified shocks are not truly exogenous; but rather endogenous. Ramey (2009) shows that shocks identified through the narrative approach Granger-cause shocks generated from the SVAR approach. This finding suggests that shocks generated from an SVAR are largely anticipated and fail to capture the appropriate timing of the shock. Hence, the economic adjustment from an expenditure shock generated in an SVAR could already be taking place by the time the SVAR shock is identified. Nonetheless, this approach has been used extensively in the literature (see Perotti (2005), Fazzari et al. (2015), Gordon and Krenn (2010), and Auerbach and Gorodnichenko (2012)) and in this Part, I will be employing this identification strategy.

Chapter 3

Theoretical background

The literature has put forward various reasons to explain non-linearities in the fiscal multiplier. For example, fiscal spending alleviating credit-constraints of individuals driving larger output responses, confidence channels, and fiscal spending having non-Ricardian effects on household wealth as household's re-evaluate wealth differently in 'bad times', have all been proposed as candidate explanations behind non-linearities in the fiscal multiplier. To provide further insight on the potential for sovereign default risk to influence the fiscal multiplier I will consider a 2-period model. In this model, it can be shown that increases in sovereign default risk can cause declines in consumption. The model is set up as follows:

In period 0, a representative consumer is endowed with an exogenous amount of wealth, ω. The consumer can choose to consume the wealth or buy a one period government bond, D, that pays a real interest rate of R. There is no uncertainty in period 0.

In period 1, the consumer receives a fraction of the government bond back, $\theta_i D$, where $0 < \theta_i \leq 1$. This is less than unity if the government does not pay the entire amount. For simplicity, let the government have two choices, good ($i = G$) and bad ($i = B$). With probability π_G the government chooses θ_G, and with probability π_B the government chooses θ_B, where $0 < \theta_B < \theta_G \leq 1$. This indicates that if the government chooses the good state, it will pay back a larger proportion of the government bond to the consumer relative to if the government chooses the bad state. The consumer will take these states as given.

The representative consumer in this economy has log utility in both periods. The log utility necessarily imposes that $c_0, c_{1,i} > 0 \quad \forall i$. Also let β represent the consumer's discount factor, where $0 < \beta < 1$.

The consumer's maximisation problem can be expressed as follows:

$$\max_{c_0,B,\{c_{1,i}\}_{i\in\{G,B\}}} \quad \ln(c_0) + \beta \sum_{i\in\{G,B\}} \pi_i \ln(c_{1,i}) \tag{3.1}$$

$$s.t.$$

$$c_0 + \frac{1}{R}D = \omega \tag{3.2}$$

$$c_{1,i} = \theta_i D \quad \forall i \in \{G,B\} \tag{3.3}$$

The Lagrangian of the problem can be written as follows:

$$\mathscr{L} = \ln(c_0) + \beta \sum_{i\in\{G,B\}} \pi_i \ln(c_{1,i}) - \lambda_0(c_0 + \frac{D}{R} - \omega) - \sum_{i\in\{G,B\}} \lambda_i(c_{1,i} - \theta_i D) \tag{3.4}$$

To determine the consumer's optimal decision I take first order conditions. The first order conditions can be expressed as follows:

$$\frac{\partial \mathscr{L}}{\partial c_0} = \frac{1}{c_0} - \lambda_0 = 0 \tag{3.5}$$

$$\frac{\partial \mathscr{L}}{\partial c_{1,i}} = \frac{\beta\pi_i}{c_{1,i}} - \lambda_i = 0 \quad \forall i = G, B \tag{3.6}$$

$$\frac{\partial \mathscr{L}}{\partial D} = R \sum_{i\in\{G,B\}} \lambda_i\theta_i = \lambda_0 \tag{3.7}$$

Substituting equations 3.5 and 3.6 into equation 3.7 yields the Euler equation:

$$\beta R \sum_{i\in\{G,B\}} \frac{\pi_i\theta_i}{c_{1,i}} = \frac{1}{c_0} \tag{3.8}$$

$$\beta R \left(\frac{\pi_G\theta_G}{c_{1,G}} + \frac{(1-\pi_G)\theta_B}{c_{1,B}} \right) = \frac{1}{c_0} \tag{3.9}$$

The term inside the parentheses in equation 3.9 represents the expected value of the marginal utility across states, weighted by the proportion of the government bond repaid in each state. This equation dictates the adjustment to changes in the parameters.

To examine an increase in sovereign default risk I will define an increase in sovereign default risk as a decrease in the probability the government chooses the good state (a decrease in π_G). This represents a larger probability that the government will repay a lower fraction of the government bond, θ_B, to the consumer. For any given value of government bonds, where $D > 0$, this will necessarily decrease the expected value of wealth period 1. Performing comparative statics with respect to π_G it can be shown that this expected wealth decrease will cause consumption declines in both states.

Taking the derivative of the Euler equation (equation 3.9) with respect to π_G I can examine the effect of an increase in the probability of the government choosing the good state. The equation can be expressed as follows:

$$\frac{d}{d\pi_G}\beta R\left(\frac{\pi_G\theta_G}{c_{1,G}} + \frac{(1-\pi_G)\theta_B}{c_{1,B}}\right) = \frac{d}{d\pi_G}\frac{1}{c_0} \tag{3.10}$$

$$\frac{\theta_G}{c_{1,G}} - \frac{\theta_B}{c_{1,B}} = 0 \tag{3.11}$$

Equation 3.11 represents the effect of a marginal increase in the probability of the government choosing the good state. Assuming that θ_G and θ_B remain constant after the change in probability, the equation suggests that there needs to be an adjustment from either $c_{1,G}$ or $c_{1,B}$, or both.

Assuming that all adjustment to the change in π_G is done by $c_{1,G}$, by re-arranging equation 3.11 I can show that the adjustment will necessarily be positive.

$$c_{1,G} = \frac{\theta_G}{\theta_B}c_{1,B} > 0 \tag{3.12}$$

as θ_G, θ_B, and $c_{1,B} > 0$.

Similarly, assuming that all adjustment to the change in π_G is done by $c_{1,B}$, I can show that the adjustment will necessarily be positive.

$$c_{1,B} = \frac{\theta_B}{\theta_G}c_{1,G} > 0 \tag{3.13}$$

as θ_G, θ_B, and $c_{1,G} > 0$.

Together, equations 3.12 and 3.13 suggest that a decrease in the probability of the government choosing the good state will necessarily yield consumption decreases in period 1 across both states. The channel driving the decreases in consumption is from expected wealth declines as sovereign default risk increases. In this thesis, I will refer to this channel as the non-Ricardian effect. The model speaks to the ability of changes in sovereign default risk to reduce consumption. This result is reminiscent of Perotti (1999).

These results also suggest that if sovereign default risk responses to government expenditure are regime dependent then there will be non-linearities in the fiscal multiplier. These non-linearities would also be observed in consumption responses. More specifically, the model predicts an inverse relationship between sovereign default risk and consumption.

This model abstracts from any effects from credit constrained individuals. But it is important to note that there is a strong nexus between wealth and credit constraints. In fact, a low level of expected wealth may be the cause of credit constraints. Hence, any change in expected wealth from changes in the probability of default can influence credit constraints. More specifically, higher (lower) expected wealth driven by increases (decreases) in sovereign default risk will alleviate (tighten) credit constraints. This channel may serve to amplify the effects of changes in sovereign default risk in the above model.

In my analysis I will predominantly point to both non-Ricardian wealth effects and subsequent changes in credit constraints to explain non-linearities in the fiscal multiplier driven by regimes of sovereign default risk.

Chapter 4

Methodology

4.1 Threshold Vector Autoregression (TVAR)

Similar to Fazzari et al. (2015), this Part adopts a Threshold Vector Autoregression (TVAR) approach to assess the effect of sovereign default risk on the fiscal multiplier. The model accommodates for non-linearities by splitting the sample into two regimes based on values of the threshold variable (the sovereign default risk index) and then estimates the parameters for each sub-sample. This method generates two differing systems contingent on the regime of sovereign default risk (high or low). By considering these two systems, I can analyse the effect of fiscal spending in each regime of sovereign default risk.

Let Y_t represent a vector of endogenous variables (government expenditure, government revenue, output, and the sovereign default risk index) at time t; Φ_0 represent a vector of constants; Φ_1 represent a matrix of coefficients on the lags of the endogenous variables; ε_t represent the residuals of the model; q_{t-d} represent the threshold variable with a time delay of d. The time delay allows sovereign default risk to affect the system with a time delay; c be the critical value for the threshold variable wherein if the threshold variable exceeds the critical value the system is considered to be in a high regime; and let the superscripts h and l represent the high and low regimes. The model can be expressed as:

$$Y_t = \begin{cases} \Phi_0^h + \Phi_1^h(L)Y_{t-1} + \varepsilon_t^h, & \text{for } q_{t-d} > c \\ \Phi_0^l + \Phi_1^l(L)Y_{t-1} + \varepsilon_t^l, & \text{for } q_{t-d} \leq c \end{cases} \tag{4.1}$$

The top line of equation 4.1 represents the system in the high sovereign default risk regime. This line characterises the dynamics of the endogenous variables in the high regime. The bottom line of equation 4.1 represents the system in the low sovereign default risk regime. This line characterises the dynamics of the endogenous variables in the low regime. Each line taken alone is a linear VAR. Taken together, they constitute a non-linear system wherein the regime of the system depends on the threshold variable, q_{t-d}.

This methodology differs from the STVAR used in Auerbach and Gorodnichenko (2012). As highlighted by Fazzari et al. (2015), STVARs are subject to flat likelihood functions when the true state of the threshold variable is relatively discrete. This makes numeric maximisation difficult, and hence results in imprecise estimation. Moreover, sovereign default risk is conventionally thought in discrete terms. This is apparent in the sovereign default risk literature, wherein indicator variables are often used to identify times of fiscal distress. The use of indicators variables to identify times of fiscal stress is used by Perotti (1999), and Ilzetzki et al. (2013). Similar to this, the use of a discrete cut-off, as used in the TVAR, may be more appropriate when considering sovereign default risk.

To estimate this model I need to determine the number of (quarterly) lags to use (p), the delay that the threshold variable has on the system (d), and threshold value (c). Rather than using theoretical justifications to determine these values, I will allow these values to be endogenously determined by estimating the model over a range of values of p, d and c. I will consider up to 4 lags ($p = 1, 2, 3$ or 4), 4 delays ($d = 1, 2, 3$, or 4), and perform a grid search over different values of the threshold variable (a 4-period moving average of the sovereign default risk index) with a search interval of 0.05 and trimming the tails of the series by 15 per cent. The model with the lowest Akaike Information Criteria (AIC) is selected as the optimal model. This method of model selection is similar to Fazzari et al. (2015). Moreover, allowing these values to be determined endogenously by the data prevents bias being introduced by my own decision making.

4.2 Structural identification

To achieve structural identification I use a Cholesky decomposition similar to Blanchard and Perotti (1999). The ordering of the Cholesky decomposition is as follows: government expenditure, government revenue, output, and sovereign default risk. The first three variables are ordered the same as in Blanchard and Perotti (1999). This ordering allows for shocks to government expenditure to contemporaneously affect all other variables. Whereas, output shocks can only affect government expenditure and revenue with a lag. This ordering is motivated by the use of quarterly data, and the observation that discretionary spending and revenue changes often take time. That is, it takes a quarter or more for an output shock to be recognised, for discretionary fiscal policy to be formulated, passed through government, and then finally implemented.

I order the sovereign default risk index last. This allows sovereign default risk to respond contemporaneously to any shock in the system. The motivation for this is primarily that the sovereign default risk index is modelled off a financial variable; SCDS spreads. Hence, the sovereign default risk index is a 'fast' moving variable that should be able to respond contemporaneously to any of the shocks in the system.

I will also allow for the covariance-variance matrix to differ across regime. This allows for the interaction between residuals to change depending on the regime. For further details on the Cholesky Decomposition see Appendix L.

4.3 Generalised impulse response functions

In my system I am concerned with understanding the dynamics caused by changes in fiscal spending. However, as the model used contains two distinct regimes (high sovereign default risk and low sovereign default risk) the application of standard impulse response functions to analyse the effects of a shock on the system is not appropriate. I will therefore use Generalised Impulse Response Functions (GIRFs) in my non-linear analysis.

In a linear system, such as a VAR, impulse response functions are symmetric and scalable. That is, the effect of a 1 unit negative spending shock is double the direct inverse of a 0.5 unit positive spending shock. This is because the effects of a shock propagate through the system in a linear fashion. In a non-linear model, such as the TVAR used in this Part, shocks propagate through the system in different ways depending on the magnitude and direction of the shock, the initial conditions/regime, and any subsequent changes in regime. This renders standard impulse response functions inappropriate for non-linear analysis.

Generalised Impulse Response Functions developed by Koop, Pesaran, and Potter (1996) accommodate for the issues arising in non-linear systems. GIRFs simulate the path of all endogenous variables, given a starting period, both with and without an intervention. The simulated paths are calculated using two series of bootstrapped residuals. One set of bootstrapped residuals will contain the intervention (in my case a positive fiscal spending shock) and the other will not. As the path is simulated I will also allow for endogenous changes in regime. This allows the system to switch regimes as the process evolves. This process is iterated 500 times for a given starting period. After creating numerous simulated paths, the GIRF for this particular starting period is calculated as the difference in the mean of the simulations with the intervention, and the mean of the simulations without the intervention.

Let Y be the variable forecasted; n be the forecast period; v_t be the intervention/innovation imposed on the system in period t; ω_{t-1} represent the information up to and including period $t-1$; and k be the forecast horizon. The GIRF for variable Y can be expressed as follows:

$$\text{GIRF}_Y(n, v_t, \omega_{t-1}) = E(Y_{t+n}|v_t, \omega_{t-1}) - E(Y_{t+n}|\omega_{t-1}), \text{ for } n = 0, 1, \ldots k \tag{4.2}$$

The first component on the right-hand side of equation 4.2 represents the expected value of the variable given the intervention occurs. The second expression on the right-hand side of equation 4.2 represents the expected value of the variable given no intervention occurs. A logical measure of the effects of the intervention is captured by the difference between these two. Hence, the GIRF measures the difference in the variable generated from the intervention.

To evaluate the GIRFs for each regime the chosen starting period/history, t, is selected to be a time period that is a member of the particular regime of interest. To ensure the GIRF is representative of the dynamics of the regime (and not a single point in time), the GIRF is simulated over 500 histories within each regime. To account for this, the final GIRF for each regime is calculated by taking the average of the GIRFs from equation 4.2 over the 500 simulated histories. This is done for each regime to estimate a GIRF for the high regime, and a GIRF for the low regime. Appendix J details the complete Monte Carlo procedure used to generate GIRFs.

4.4 Multiplier calculation

Using the GIRFs of output and government expenditure I will construct the fiscal spending multiplier. In this thesis, I will use the cumulative fiscal spending multiplier. This approach is advocated by Spilimbergo, Schindler, and Symansky (2009) as it is a more complete representation of the dynamics between output and government expenditure. The cumulative fiscal spending multiplier is defined as the cumulative change in output divided by the cumulative change in government expenditure.[1]

Let t be the period of the fiscal spending intervention; n be the period ahead of t forecasted; k be the quarterly forecast horizon. I will use $k = 20$ in my analysis; $\Delta Output_{t+n}$ be the levels change in output n periods after the intervention; and ΔG_{t+n} the levels change in government expenditure n periods after the intervention. Then the cumulative multiplier can be expressed as follows:

$$\text{Cumulative Multiplier}_{t+n} = \frac{\sum_{n=0}^{k} \Delta Output_{t+n}}{\sum_{n=0}^{k} \Delta G_{t+n}} \tag{4.3}$$

As the data is in quarterly growth rates, to obtain the levels estimates for the cumulative multiplier I calculate the cumulative change in output by multiplying the cumulative percentage change in output by the mean of the level of output over the series. Similarly, I calculate the cumulative change in government expenditure by multiplying the cumulative percentage change in government expenditure by the mean of government expenditure across the time series.

By accounting for the cumulative changes in both output and expenditure over time, the cumulative multiplier provides the most holistic description of the dynamics of an expenditure shock on the economy. The literature also commonly uses two other multiplier measures; the impact multiplier and the peak multiplier. The impact multiplier is simply the response of output divided by the change in government expenditure at the time of the intervention. It describes the immediate output response to an expenditure shock. The peak multiplier is the largest value the multiplier takes during the forecast horizon. I will simply define this as the maximum of the cumulative multiplier over the forecast horizon.

When reporting government expenditure and revenue multipliers I will use the cumulative dollar-for-dollar change in government expenditure or revenue relative to the size of the initial expenditure shock. This is because the cumulative multiplier for expenditure is always unity. This can calculated as follows.

Let Y represent either the level of government expenditure or revenue; and the rest is defined as before. Then the government expenditure and revenue multiplier can be expressed as:

$$Y \text{ Multiplier}_{t+n} = \frac{\sum_{n=0}^{k} \Delta Y_{t+n}}{\Delta G_t} \tag{4.4}$$

[1] I will also report consumption and investment multipliers. These are calculated in the same way as the output multiplier. In this thesis, the output multiplier is also referred to as simply the multiplier. All other type of multipliers will be specifically labelled.

Chapter 5

Data

Due to data limitations I will focus my analysis on the U.S. This is as U.S. has a long history of quarterly tax data. This is crucial in the structural identification of the SVAR.

The data for government expenditure, government revenue, and output are obtained from the NIPA tables from the Bureau of Economic Analysis. These variables are defined as in Blanchard and Perotti (1999). Government expenditure is obtained from *Government Consumption Expenditures and Gross Investment.* Government revenues are defined as the sum of *Current tax receipts, Contributions for Government Social Insurance, Interest receipts, Current transfer receipts, and Capital transfer receipts*, less *Current transfer payments, Interest payments, Subsidies, and Capital transfer payments.* Lastly, output is obtained from *Gross domestic product.* These variables are seasonally adjusted by source and deflated using the *Implicit Price Deflater for Gross Domestic Product.* The first difference of the natural log of these 3 variables are taken to render the them stationary.

These measures of government expenditure and revenue are considered to be discretionary; purged of automatic stabilisation measures. Hence, my analysis will be focused on the discretionary components of fiscal policy.

To measure sovereign default risk I use my index constructed in the previous Part. However, I transform the sovereign default risk index by taking the 4 period moving average. This is to prevent excessive and unrealistic amounts of regime switching. Smoothing the series by taking a 4 period moving average effectively imposing some level of persistence in the sovereign default risk regimes. For example, if the government switches from the low to high regime, it is less likely to immediately switch back to the low regime. This approach is commonly used in the TVAR literature (see Balke (2000), Ferraresi et al. (2015), and Borsi (2016)). The moving average of a variable is taken as follows:

Let q represent the order of the moving average taken; x represent the original (untransformed) variable; and $\tilde{x}$ represent the variable after taking the moving average. Then:

$$\tilde{x}_t = \frac{\sum_{j=0}^{q} x_{t-j}}{q} \tag{5.1}$$

In this Part, I will refer to sovereign default risk as the sovereign default risk index created in Part I transformed using a 4 period moving average.

Lastly, for my robustness tests I will also use private consumption and private investment. Again all data is obtained from the NIPA tables from the Bureau of Economic Analysis. I measure private consumption as *Personal Consumption Expenditure*, deflated by the *Price Index for Personal Consumption Expenditures.* I measure private investment using *Private Fixed Investment*, deflated by *Price Index for Private Fixed Investment.* Both variables are seasonally adjusted by source. The first difference of the natural log are again taken to render the data stationary.

Summary statistics for all variables can be found in Appendix M. Unit root test results for all variables are presented in Appendix N.

Chapter 6

Results

In this Part, I conduct two baseline experiments to determine the response of the variables to increases in government expenditure. The positive expenditure shock imposed in both experiments is equivalent to one standard deviation of government expenditure growth. This can be thought of as a small government expenditure stimulus. In the first experiment (experiment 1), I will impose the positive expenditure shock and fix the regime to be the same as the initial regime of the chosen history. This experiment can be thought of as a situation wherein a government is perpetually either in the high sovereign default risk regime, or low sovereign default risk regime. In the second experiment (experiment 2), I will impose the positive expenditure shock but allow for endogenous regime switching as the system evolves. This experiment accounts for potential real-world dynamics wherein sovereign default risk regimes change over time.[1]

The purpose of these two experiments is to determine if the effects of government expenditure are dependent on the regime of sovereign default risk. Experiment 2 is more likely to represent the true dynamics of the economy as it is unlikely that the regime of sovereign default risk remains unchanged as the system evolves over time. However, experiment 2 may still not be able to truly capture the effects of sovereign default risk, as the system may switch immediately to the other regime and remain there. In this situation, the results will be reflective of only one regime. Amalgamating the information from these two experiments provides a more holistic account of the effectiveness of government expenditure in each regime of sovereign default risk. My results provide some evidence of non-linearities to the fiscal spending multiplier, with high levels of sovereign default risk associated with lower (and negative) fiscal multipliers. This indicates that households may respond in a non-Ricardian manner when sovereign default risk is high.

To explain the lower fiscal multiplier values when sovereign default risk is high

[1]The responses in experiment 1 are necessarily linear, hence linear impulse responses are calculated. Whereas, in experiment 2 the responses are non-linear. GIRFs are hence used for experiment 2.

I examine the response of the other 3 variables in the system: sovereign default risk, government expenditure, and government revenue. I find that the dynamics of sovereign default risk, and the evolution of the system's regime are dependent on the initial sovereign default risk regime. In particular, I find that there is an inverse association between the responses of sovereign default risk and output to the government expenditure shock. Moreover, I find that regime switching is rare following the expenditure shock. This indicates that increases in government expenditure are unlikely to define changes in regime. Together these findings illustrate that the response sovereign default risk and evolution of regime can partially explain the non-linearities observed in the fiscal multiplier. I also find little evidence that the dynamics of government expenditure or revenue drive the differences in the fiscal multiplier across regimes. That is, the response of government expenditure and (to a lesser extent) government revenues do not appear to be regime dependent.

Further investigating the discrepancy in multiplier results, I examine the consumption and investment responses to the same government expenditure shock. The results indicate that consumption is the likely underlying driver behind the fiscal multiplier response in both regimes of sovereign default risk. The consumption responses in the low regime supports the idea that consumers are Ricardian. Whereas, the consumption response in the high regime suggests that in the shorter-term when sovereign default risk is high, consumers may first respond to increases in wealth, and subsequent easing of credit constraints as sovereign default risk falls temporarily. This promotes consumption in the shorter-term. However, in the longer-term consumption falls as sovereign default risk increases. This supports theory that identifies wealth effects as an important determinant in consumption responses when sovereign default risk is high.

It is worth noting that for these baseline experiments I will abstract from the potential of having differing responses generated from the direction and size of the government expenditure shocks. I will only impose a reasonable small positive government expenditure shock in the baseline experiments. I will return to the issues of the direction and size of the expenditure shock later.

6.1 Parameter selection

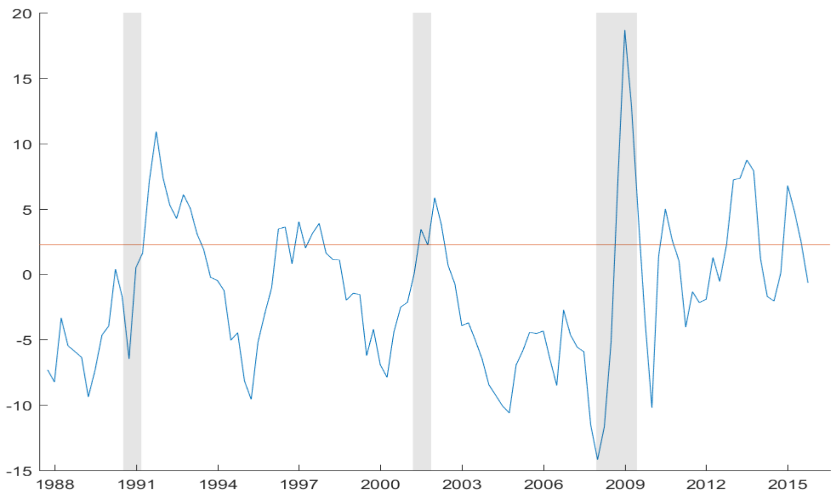
Following the parameter selection process outlined in section 4.1 I reach an optimal value of lags, p, delay of the threshold variable, d, and critical value, c, endogenously determined by the data. The model contains a sample size of 117 running from

1986Q4 to 2015Q4. The optimal model, chosen by AIC, has a lag length of 4 quarters, delay of 1 quarter, and the critical value of the threshold variable is 2.2571.

Figure 6.1 shows the threshold variable (sovereign default risk) over time with the horizontal line depicting the critical value determined by the data.[2] The model's critical value yields 20 regime changes over the sample period and indicates that approximately 27 per cent of the observations are in the high regime. This suggests that a high sovereign default risk regime is relatively uncommon, and the economy is most likely in the low sovereign default risk regime.

Comparisons of models with different lags and critical values are presented in Appendix O.

Figure 6.1: Threshold Variable



6.2 Fiscal Multiplier

Figures 6.2 and 6.3 display the fiscal spending multipliers for the two respective experiments. The solid lines represents the fiscal multiplier estimate, and the dotted lines show the 90 per cent confidence intervals.[3]

[2]The NBER recession bands are highlighted in grey. They show that out of the 3 recessions in the sample, 2 are considered to be a high sovereign default risk regime. Moreover, the majority of points in the high regime are not in these recessionary periods indicating that the sovereign default risk measure used is broader than the state of the business cycle.

[3]The 90 per cent confidence intervals will be report on all responses. For experiment 2, the confidence intervals are calculated by taking the 5th and 95th percentile of the GIRF multiplier simulations. Whereas, for experiment 1 , the confidence intervals are calculated using the Monte Carlo procedure detailed in Appendix K.

Overall, I find some evidence of non-linearities in the fiscal multiplier. In particular, the fiscal multiplier is lower when sovereign default risk is high. Over five-years, the fiscal multiplier estimates in the high sovereign default risk regime are below -4 in both experiments. Whereas the fiscal multiplier estimate is between 0 and around -1 for the low sovereign default risk regime. The findings support the concept that in the high sovereign default risk regime, increases in government expenditure may yield negative output effects as agents face larger declines in wealth. Whereas, in the low sovereign default risk regime these negative wealth effects are more subdued as concerns over sovereign default risk are lower. However, it is important to note that the confidence intervals suggest a degree of uncertainty surrounding some of the estimates.

6.2.1 Experiment 1 - Fixed regimes

When holding the regimes fixed, I find that the five-year multiplier is larger in the low sovereign default risk regime relative to the high sovereign default risk regime. In the low sovereign default risk regime, increases in government expenditure result in expansions to output over most of the forecast horizon. Whereas, in the high sovereign default risk regime increases in government expenditure result in large contractions in output over the forecast horizon. This suggests that non-Ricardian effects are present when sovereign default risk is high. The results also point to the potential perverse effects of perpetually being in the high sovereign default risk regime.

Figure 6.2 shows the multiplier response to a positive expenditure shock while fixing the given sovereign default risk regime. Table 6.1 provides a closer look at key multiplier statistics, with the 90 per cent confidence intervals reported in the parentheses.

Figure 6.2 suggests that over the longer-term increases in government expenditure when stuck in the high sovereign default risk regime can yield perverse output responses. The result illustrates the potential for government expenditure in times of high sovereign default risk to define large negative output effects, beyond what is predicted under the Ricardian equivalence. Initially, the output response in the high sovereign default risk regime yields a higher response than the low regime. The impact multiplier is 2.851, indicating that output initially increases by 2.851 times the initial increase in government expenditure. However, following the peak response, the multiplier quickly falls. After five years, the cumulative multiplier is -5.385; suggesting that total output contracts by over five times the level of the total changes in expenditure over the forecast horizon. This strongly suggests that government expenditure expansions in times of high sovereign default risk can yield large negative output responses. This reflects the perverse consequences of remaining in the high sovereign default risk regime, and is indicative of non-Ricardian responses from households when sovereign default risk is high.

It is worth noting that, the five-year multiplier estimate is outside of the range of estimates of the fiscal multiplier in the literature. However, by holding the regime in high sovereign default risk I am examining an extreme situation wherein the government is trapped in a high sovereign default risk regime. Hence, it is not surprising that the subsequent multipliers from this state are also extreme.

An increase in government expenditure when stuck in the low sovereign default risk regime yields a more subdued and atypical multiplier response than the high regime. More specifically, government expenditure defines a short-term increase in output, but over time this response gradually declines. The response is consistent with the Ricardian equivalence. The initial impact multiplier is 1.268. This indicates that there is a initial increase in output that is slightly larger than the expenditure shock itself. Over the forecast horizon, the multiplier response rises, with a peak response of 2.443. The multiplier then gradually declines with the five-year multiplier of -0.230. The five-year response is statistically insignificant from zero, indicating that the five-year multiplier is around zero. These results are comparable to Nickel and Tudyka (2014) who finds that the multiplier is likely to be positive and above 1 in the short-run, and close to 0 in the long-run. Hence, in the low regime, increases in government expenditure have a greater capacity to promote positive output responses relative to the high sovereign default risk regime. This is particularly the case in the shorter-term. These results vary from the multiplier response in the high regime, and may suggest that households respond to government expenditure in a Ricardian manner when sovereign default risk is low.

The estimates clearly suggest that the effects of government expenditure on output are larger when sovereign default risk is low. This is confirmed by the confidence intervals which do not overlap after approximately the two-year forecast horizon. This suggests the estimates are statistically distinguishable from one another. This illustrates the potential for non-linearities in the fiscal multiplier. In particular, government expenditure when stuck in the high sovereign default risk regime yield lower negative output responses. This reflects the potential perverse consequences of remaining in a high sovereign default risk regime. Overall, these responses are consistent with the theoretical model wherein consumption falls when sovereign default risk is high. Moreover, the results support the idea that in 'bad times' there may be a non-linear wealth effect that drives lower fiscal multipliers (Perotti, 1999).

Despite providing insight on potential non-linearities in the fiscal multiplier generated from sovereign default risk, this experiment does not allow for regime switching and may fail to account for these potential real-world dynamics. I will now turn to experiment 2 wherein I allow for regime switching.

Figure 6.2: Experiment 1 - Multiplier

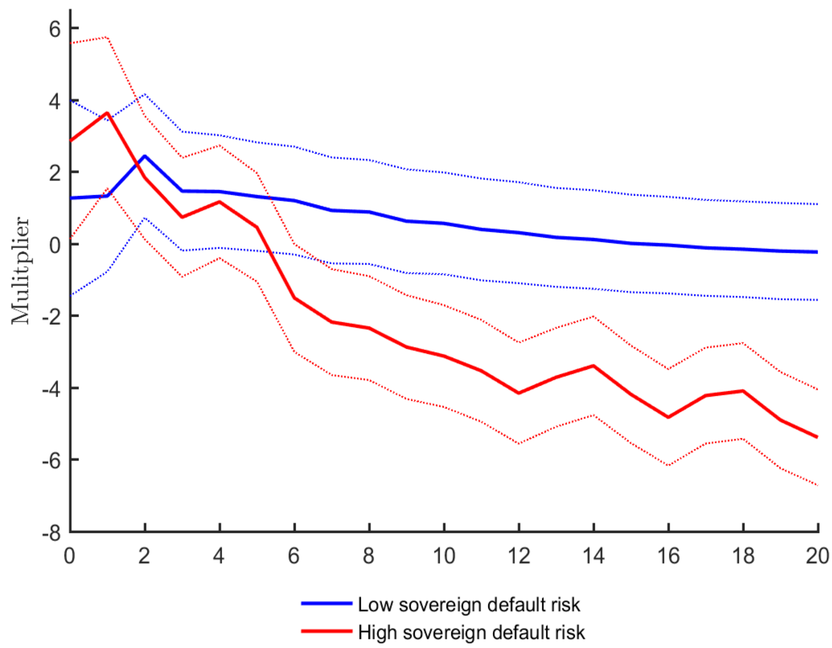


Table 6.1: Experiment 1 - Multiplier

	High	Low
Impact	2.851	1.268
	(0.129, 5.573)	(-1.454, 3.990)
Peak	3.641	2.443
	(1.539, 5.744)	(0.729, 4.156)
One-year	1.165	1.449
	(-0.401, 2.730)	(-0.117, 3.015)
Five-year	-5.385	-0.230
	(-6.716, -4.054)	(-1.561, 1.101)

6.2.2 Experiment 2 - Regime switching:

When allowing for regime switching, the multiplier responses provide some evidence of non-linearities based on the initial regime of sovereign default risk. The results point to higher fiscal multipliers if government expenditure occurs when sovereign default risk is low. The results are consistent with experiment 1. The results also support the idea that government expenditure in times of high sovereign default risk are associated with non-Ricardian effects that drive down the multiplier. Whereas, in the low regime these non-Ricardian effects are more subdued. However, despite the disparity in point estimates, the confidence intervals suggest that the differences observed cannot be considered statistically distinguishable from zero.

Figure 6.3 shows the fiscal multiplier when allowing for regime switching as the system evolves over the forecast horizon. Table 6.2 provides a more detailed account of the key multiplier statistics.

In the high regime, the dynamics of the fiscal multiplier suggest an increase in government expenditure can yield perverse economic consequences in the longer-term. Similar to experiment 1, the increase in expenditure causes an immediate strong increase in output. This short-term multiplier response under the high regime is once again larger than the equivalent response under the low regime. One period after the expenditure shock, the multiplier increases to a peak of 3.641, after which the multiplier declines precipitously. The five-year multiplier value is -4.154. This indicates that after five years output falls by over 4 times the cumulative change in government expenditure. This is a perverse economic outcome. These results provide further support that in the high sovereign default risk regime, government expenditure can increase output in the shorter-term. However, these short-term gains are heavily outweighed by large declines in output over the longer-term, as shown by the low five-year multiplier. This response is comparable to the multiplier response when holding the high regime constant. Recall that in experiment 1 the high regime multiplier was initially high then fell sharply to a five-year value of -5.385. Therefore, the results further point to the potential perverse economic effects of government expenditure when levels of sovereign default risk are high. In particular, the evidence lends weight to the idea that when sovereign default risk is high, agents respond in a non-Ricardian manner.

In the low regime, the fiscal multiplier dynamics show that government expenditure yields more sustained increases in output. The response shows that government expenditure can have a stimulatory effect in the short-run, but may shape a long-run decline in output. Similar to experiment 1, this response is consistent with a Ricardian response from agents, and a small impact from non-Ricardian effects. The impact multiplier in this setting is 1.268, and the peak response of 2.225 occurs two periods subsequent to the shock. Moreover, both are statistically distinguishable from zero. This indicates that government expenditure in the short-run can stimulate output by more than the increases in expenditure. Following the peak response, the multiplier declines gradually over the forecast horizon. After five-years the multiplier is -1.092. This estimate is also statistically different from zero. This suggests that in the longer-term output falls by approximately the cumulative changes in expenditure. It is worth noting this five-year multiplier response is lower than in experiment 1. This lower estimate indicates that once allowing for regime switching the multiplier value falls when in the low regime. This may be indicative that there may be some non-Ricardian effects from households even in the low sovereign default risk regime. Moreover, the five-year multiplier suggests that in the longer-term government expenditure is not worthwhile even in the low sovereign default risk regime. However, the short-term effects remain positive for longer than expenditure in high regime. Overall, the multiplier in the low regime indicates that government expenditure is less susceptible to the perverse economic effects that are exhibited in the high regime.

Taken together, the multiplier once allowing for regime switching affirm the results obtained when holding the regimes fixed. That is, the fiscal multiplier is lower if government expenditure occurs when sovereign default risk is high. These results are consistent with Ilzetzki et al. (2013) and Perotti (1999). When sovereign default risk is high, government expenditure results in perverse output effects with five-year multiplier estimates below -4. This suggests output falls by four times the total change in expenditure over five years. These negative output responses are much lower than a typical Ricardian response. Hence, the results lend further weight to the idea that when in the high sovereign default risk regime, increases in government expenditure can yield larger negative wealth effects from agents than a typical Ricardian response. This negative wealth effect results in lower fiscal multipliers. Whereas when sovereign default risk is low, the five-year multiplier responses is around -1. This indicates that relative to the high regime, increases in government expenditure do not lead to such large declines in household wealth. Lastly, government expenditure when sovereign default risk is low yields more prolonged output increases. The same is not true in the high regime. This highlights that government's have some ability to stimulate the economy in the shorter-term when sovereign default risk is low. However, despite the point estimates indicating there are non-linearities in the fiscal multiplier driven by sovereign default risk regimes, the 90 per cent confidence intervals often overlap suggesting that statistically these differences are indistinguishable from zero.

To provide insight into the non-linearities in the fiscal multiplier from both experiments, I will now turn my attention to the evolution of the sovereign default risk index, the probability of regime switching across the forecast horizon, and the response of both government revenue and expenditure. From analysing these responses, I can deduce candidate explanations for the non-linearities found in the fiscal multiplier.

Figure 6.3: Experiment 2 - Multiplier

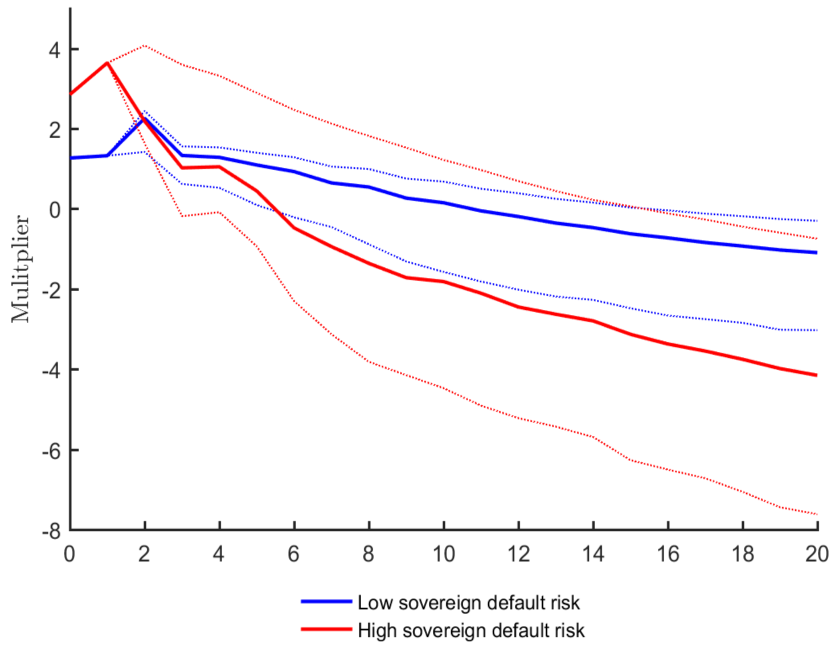


Table 6.2: Experiment 2 - Multiplier

	High	Low
Impact	2.851	1.268
	(2.851, 2.851)	(1.268, 1.268)
Peak	3.641	2.259
	(3.641, 3.641)	(1.419, 2.443)
One-year	1.050	1.285
	(-0.083, 3.318)	(0.526, 1.533)
Five-year	-4.154	-1.092
	(-7.618, -0.745)	(-3.026, -0.299)

6.3 Sovereign default risk response

Looking at the response of sovereign default risk after imposing the expenditure shock in both experiments (Figure 6.4) is useful in evaluating the driver of the non-linearities observed in the fiscal multiplier.[4] I find an inverse association between sovereign default risk and the fiscal multiplier. That is, when sovereign default risk falls the multiplier increases, and vice-versa. This suggests that the non-linearities in the multiplier could be partially attributed to differences in the response of sovereign default risk. The result lends further support to the notion that the lower multiplier in periods of high sovereign default risk could be driven by devaluations in household wealth.

First, consider experiment 1 where regimes are fixed. Recall, in this setting the fiscal multiplier is lower when sovereign default risk is high. Figure 6.4 shows the response of sovereign default risk to an increase in government expenditure and provides insight into the multiplier findings. Initially, following the increase in government expenditure, sovereign default risk falls by more in the high regime than in the low regime. However, the dynamics of sovereign default risk in the high regime over the forecast horizon are very volatile, with an overall increase in sovereign default risk over time. This implies the high regime is characterised by unstable sovereign default risk that ultimately increases following an increase in government expenditure. This is in stark contrast to the response of sovereign default risk in the low regime. In the low regime, the response of sovereign default risk indicates that government expenditure yields an initial decrease in sovereign default risk, with the peak negative effect occurring around three quarters following the expenditure shock. Sovereign default risk then gradually increases with the overall effect after five-years around 0. The responses across regimes are also commonly statistically distinguishable from each other. Taken together, these responses suggests that over five-years government expenditure in the low regime will not increase sovereign default risk, whereas government expenditure in the high regime will increase sovereign default risk, and hence implies government expenditure when sovereign default risk is high will be counter-productive to lowering sovereign default risk.

Once allowing for regime switching in experiment 2, the response of sovereign default risk exhibits similar dynamics to experiment 1 in low regime, whereas the response in the high regime is less volatile. In both regimes, initially after the expenditure increase sovereign default risk decreases. This is consistent with experiment 1. This initial decrease is again larger in the high regime. As the system evolves, the change in sovereign default risk in the high regime increases faster, and then exceeds the change in sovereign default risk under the low regime 7 periods following the initial shock. The change in the high regime's sovereign default risk remains higher

[4]The responses here represent the change in sovereign default risk; not the level. Hence, if the responses shared the same magnitude this would not mean that the level of sovereign default risk is the same. In fact, in this scenario the difference in the initial values of sovereign default risk would completely determine the difference in sovereign default risk.

thereafter. Overall, the sovereign default risk response settles at approximately 0 in the low regime, and 0.7 in the high regime. At this point the confidence intervals overlap indicating the difference is statistically indistinguishable from zero. The results suggest that government expenditure in both regimes result in unchanged or slightly higher levels of sovereign default risk.

The differences and dynamics of the response of sovereign default risk between regimes follow the fiscal multiplier response relatively closely. More specifically, the responses indicate that there is an inverse relationship between sovereign default risk and the fiscal multiplier. This supports the theoretical model wherein increases in sovereign default risk are associated with larger negative wealth effects.

Recall that the multiplier in the high regime was initially higher than the multiplier in the low regime, but then fell sharply. Whereas in the low regime, increases in government expenditure produced stimulatory output effects in the short-run which then gradually fell over the horizon. The larger impact multiplier in the high regime aligns with the larger fall in sovereign default risk in the high regime. This fall in sovereign default risk could represent an increase in household wealth that drives the larger multiplier. Also, the steep fall in the multiplier in the high regime corresponds with the period wherein sovereign default risk is increasing. This is particularly the case for experiment 1. Moreover, in the low regime, the relatively stable multiplier dynamics are consistent with the equivalent response of sovereign default risk. More specifically, the gradual decline in the multiplier in the low regime corresponds with the gradual increase in sovereign default risk. Overall, this provides evidence to suggest that the variations in the fiscal multiplier across regimes and experiment can be partially attributed to the responses of sovereign default risk. The results lends support to the possibility of non-linearities in the fiscal multiplier driven by the probability of default changing wealth, hence generating non-Ricardian effects.

Further exploring the role of sovereign default risk in determining the fiscal multiplier, I investigate the probability of being in each regime after the expenditure shock in experiment 2.[5] This is motivated by the idea that what matters is the regime of sovereign default risk, rather than the specific dynamics of sovereign default risk. I find evidence to suggest that regimes are persistent following expenditure shocks. This persistence is another candidate explanation in explaining the non-linearities in fiscal multiplier.

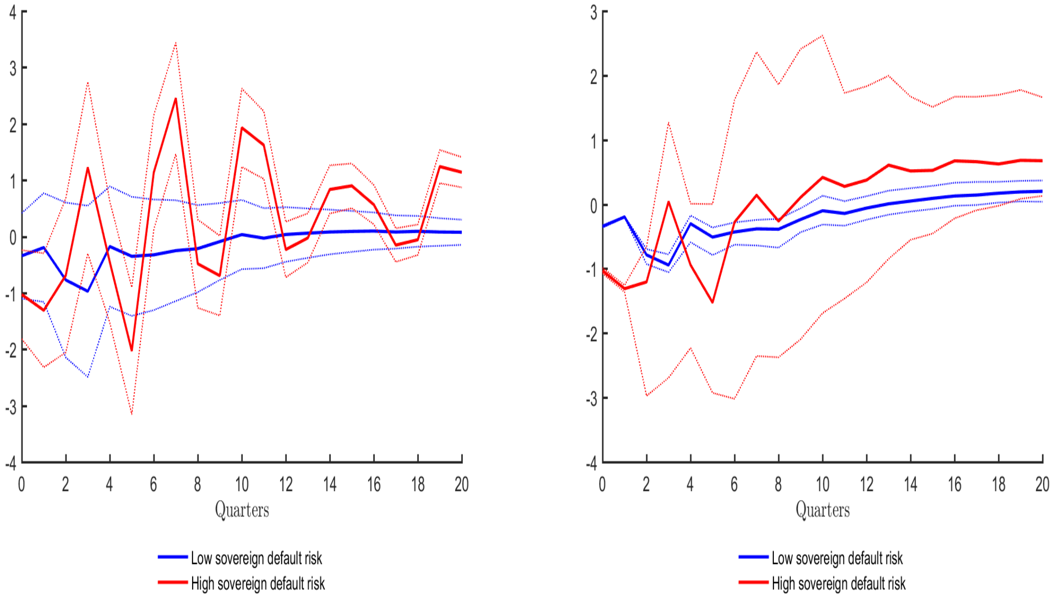
Figure 6.5 shows the probability of being in the high regime following an increase in government expenditure to each regime. This is calculated by determining the proportion of simulations that are in each regime over the forecast horizon. When

[5] There is no regime switching in experiment 1. Hence there is no probability of regime change.

sovereign default risk is low, a positive expenditure shock does not cause any change in regime. In fact, none of the simulated responses move to the high regime. In contrast, when sovereign default risk is high a positive expenditure shock initially drives a reduction in the probability of being in the high regime. For around two years following the expenditure shock, approximately 20 per cent of the simulations are in the low regime. However, after five-years all simulations are back in the high-regime. This indicates that government expenditure is unlikely to drive sovereign default risk from the high regime to the low regime. These probabilities shed further light on why the fiscal multiplier exhibits non-linearities. More specifically, the lack of regime switching suggests that the regime of the system itself is important in determining the fiscal multiplier.

Combining the information from the response of sovereign default risk under both regimes and experiments, and observing the probability of regime switching yields evidence that sovereign default risk influences the fiscal multiplier. In particular, the longer-term changes in sovereign default risk after the expenditure shock in the high regime are in general higher than the low regime's. This corresponds to the lower multiplier when sovereign default risk is high. Further, the larger increase in sovereign default risk from the expenditure shock in the high regime suggests that expansionary fiscal policy may be impotent in lowering sovereign default risk. Building on this, I find that regime switching is rare, indicating that the initial conditions of sovereign default risk drive persistent differences in regimes. This is another candidate explanation to the non-linearities in the fiscal multiplier. Taken together, this indicates that both the dynamics of sovereign default risk and the regime of sovereign default risk are important in determining the multiplier. These results lend weight to the basic finding of the theoretical model that when sovereign default risk increases, consumption decreases. This is also consistent with Perotti (1999) who argues that households have larger declines in wealth from government expenditure during 'bad times'.

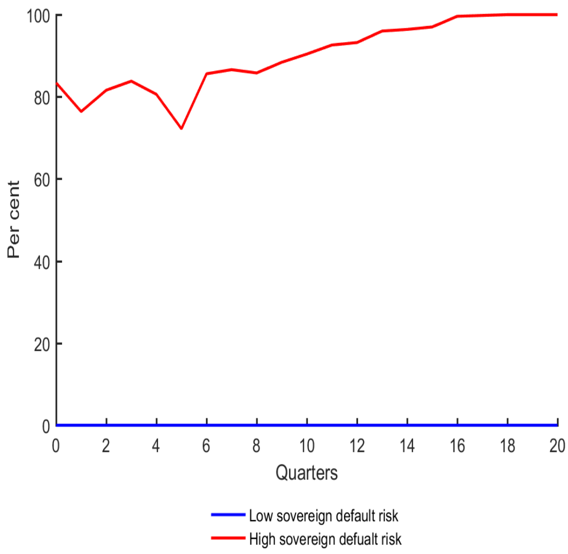
Figure 6.4: Sovereign Default Risk Response



(a) Experiment 1

(b) Experiment 2

Figure 6.5: Probability of High Regime



6.4 Fiscal policy response

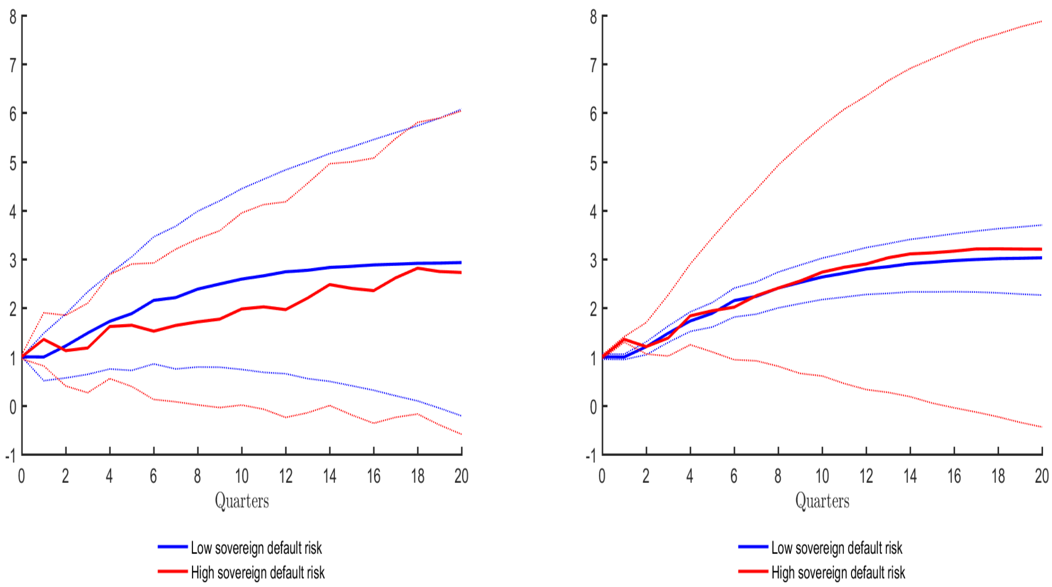
Analysing the responses of fiscal policy variables (government expenditure and revenue) to the shock in government expenditure provides further insight into the non-linear multipliers observed across regimes. I find little evidence that the differences in multiplier responses are driven by differences in government expenditure and revenue responses.

From Figure 6.6 it is clear that government expenditure increases persistently following a shock to itself. The figures present the cumulative dollar-for-dollar change in government expenditure relative to the size of the initial expenditure shock. The government expenditure response share similar dynamics and magnitudes across both regimes and experiments. The peak and longer-term response of government expenditure is around 3. This indicates that following an increase in expenditure, government expenditure continues to increase until the cumulative increase in expenditure is approximately 3 times the initial expenditure shock. This response is larger than that obtained by Blanchard and Perotti (1999) and Fazzari et al. (2015), highlighting the differences in models once considering sovereign default risk. However, they do lend weight to the finding in Blanchard and Perotti (1999) that government expenditure persistently increases following a positive shock to itself. Overall, the similar response of government expenditure to its own shock across regimes and experiments indicates that government expenditure responses are not regime dependent. Hence, the regime dependence in the multiplier cannot be explained by government expenditure.

Figure 6.7 shows the cumulative dollar-for-dollar change in government revenue relative to the size of the initial expenditure shock. Following the shock, revenue declines in both regimes and experiments. However, the decline in the low regime is more subdued than the decline in the high regime. In both experiments, the five-year revenue response when in the low regime is approximately 0. This indicates that government revenues do not change following increases in expenditure in the low regime. The five-year revenue response when in the high regime is -0.625 and -0.424 when holding the regime fixed and allowing for regime switching. The differences across regimes yields some evidence that the differences in the multiplier across regimes can be partly attributed to government revenue responses. However, the discrepancies in revenue responses across regimes are relatively small and the confidence intervals also overlap. This indicates there is only weak evidence of regime dependence in government revenue.

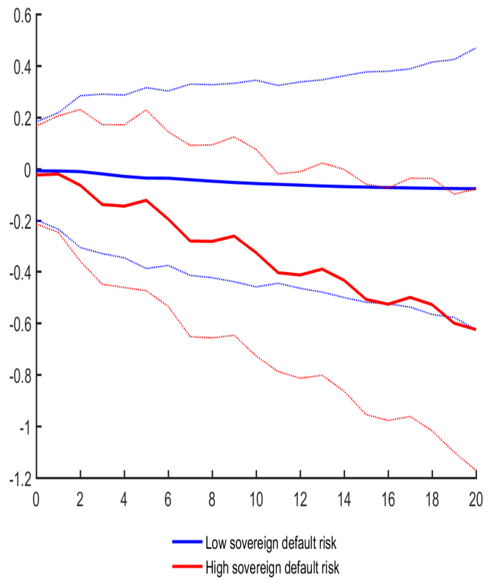
Overall, when considering the response of government expenditure and revenue in explaining the non-linearities in the multiplier across regime there is only weak evidence that the non-linearities can be attributed to government revenue responses. I find no evidence that the non-linearities in the multiplier can be attributed to government expenditure. This is consistent with Fazzari et al. (2015) who also find little evidence that non-linearities in the multiplier are driven by economic slack can be explained by government revenue and expenditure responses. This suggests that the differences in the multiplier across regimes are largely associated with the differences in the response of sovereign default risk, and subsequent regime switching as explained in the previous section. This further illustrates the importance of considering sovereign default risk in government expenditure decisions.

Figure 6.6: Goverment Expenditure Multiplier

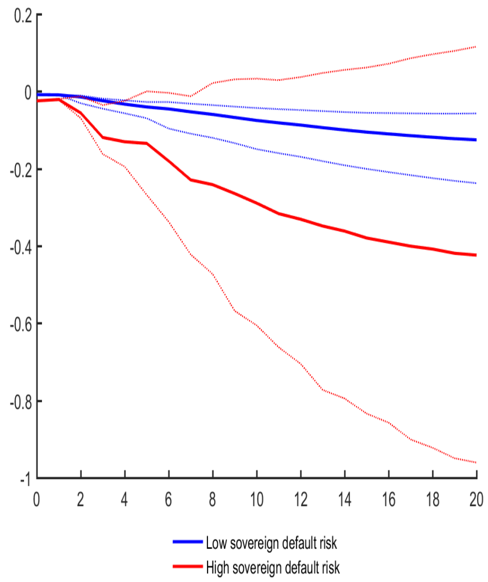


(a) Experiment 1 (b) Experiment 2

Figure 6.7: Government Revenue Multiplier



(a) Experiment 1



(b) Experiment 2

6.5 Components of Aggregate Demand: Consumption and Investment

In this section I will analyse the response of private consumption and private investment to a shock in government expenditure using the same two experiments (experiment 1 and experiment 2). These responses will help yield a more refined understanding of what drives the non-linearities in the fiscal multiplier between regimes of sovereign default risk. The results suggest that private consumption is the underlying driver behind the dynamics of the multiplier. This provides support for the notion that higher levels of sovereign default risk can produce negative wealth effects that define lower consumption. Moreover, the investment responses show evidence of a crowding-out of private investment independent of the sovereign default risk regime. This helps explain the lower than usual multiplier estimates from the model.

The estimation is done by replacing output growth with private consumption or investment growth in the TVAR. I use the same critical value of the threshold variable, but allow the delay and lag length to vary. This is as components of aggregate demand may have different time lags in responding to sovereign default risk.[6]

6.5.1 Consumption Multipliers

Figures 6.8 and 6.9 show the cumulative multiplier of output and private consumption for the two experiments. The output multiplier is shown for ease of reference. The dynamics of the consumption multiplier are similar to the dynamics of the output multiplier. The estimates suggest that in the low regime, the Ricardian Equivalence dominants consumer decisions. Whereas in the high regime, there is a short-run expansionary consumption effects due to wealth increases from the decrease sovereign default risk, but this is outweighed in the longer-term by negative wealth effects as sovereign default risk increases again.

In the low regime, an increase in government expenditure reduces consumption. In both experiments, the impact consumption multiplier is approximately -0.5. This indicates that consumption falls by around half the size of the initial expenditure increase. When holding the low regime fixed, the consumption multiplier does not display much dynamics, staying around the value of -0.5 over the forecast horizon. When allowing for regime switching, the dynamics of consumption exhibit a gradual decline over the forecast horizon with a five-year value of -1.018. In both experiments, the relatively stable path of consumption is consistent with the stable path of the output multiplier. This is particularly the case when allowing for regime switching, wherein the gradual decline in the consumption multiplier is consistent with the gradual decline in the output multiplier. Moreover, the subdued decline in consumption to an expenditure increase is consistent with predictions of Ricardian equivalence. In fact, the consumption multiplier when allowing for regime switching suggests consumers are almost perfectly Ricardian as consumption falls by almost exactly the size of the expenditure changes over the longer-term. These responses provide evidence that consumption responses are important in understanding the output multiplier. In addition, I find evidence to suggest that when sovereign default risk is low consumers may in fact be predominately Ricardian.

In the high regime, an increase in government expenditure, in both experiments, produce a consumption multiplier that is consistent with the output multiplier. The results again point to consumption as the driver of the output multiplier. Moreover, the results point to a possible increase in household wealth and subsequent easing of credit constraints in the shorter-term, that are outweighed in the longer-term as household wealth then declines. When holding the regimes fixed, consumption initially has a strong positive response, with a peak response of 1 around one period

[6] Model comparisons can be found in Appendix O.

following the expenditure shock. This indicates that consumption increases by the same amount as the changes in expenditure. However, this response declines sharply over the forecast horizon. The five-year consumption multiplier is -2.273. This suggests that over five-years consumption falls by over 2 times the cumulative changes in expenditure. This is well below a typical Ricardian response under which consumption should fall by 1 times the cumulative change in expenditure. Therefore, this points to the presence of non-Ricardian outcomes when sovereign default risk is high. When allowing for regime switching, the consumption response becomes more subdued. Again there is an initial positive consumption multiplier that quickly deteriorates over time. The peak response is approximately 0.5, and the long-run response is approximately -1.4. This more subdued outcome is consistent with the differences observed in the output multiplier in the high regime between experiments. In addition, notice again that the longer-term consumption multiplier is below what a typical Ricardian response would be. Overall, these results indicate that consumption dynamics in the high regime are consistent with the corresponding output responses. This adds further evidence to consumption being the underlying driver behind output responses from government expenditure.

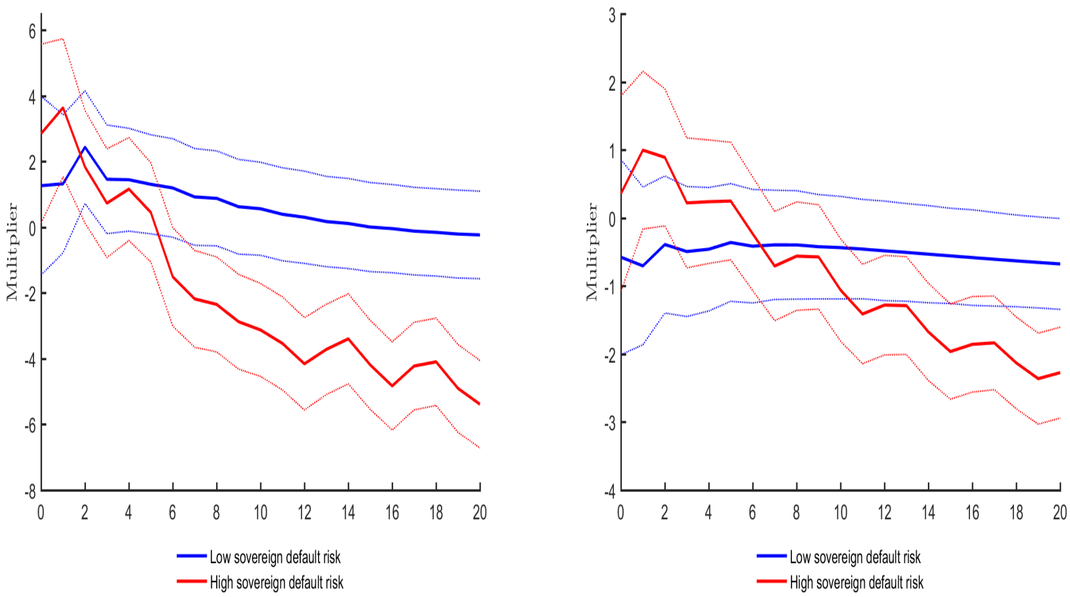
Combining the information from the consumption responses with the non-linearities observed in the sovereign default risk responses is illuminating in understanding the transmission of government expenditure in different regimes of sovereign default risk.

In the high regime, the initial increase then sharp decrease in consumption following the government expenditure shock tells a mixed story. The initial increase in consumption aligns with the large fall in sovereign default risk following a positive expenditure shock in the high regime. This decline in sovereign default risk can increase expected wealth, and hence consumption as shown in the theoretical model. Moreover, this increase in consumption can be amplified if the increases in expected wealth alleviates credit constraints. This can explain the larger initial consumption response in the high regime relative to the low regime. However, in the longer-term recall that sovereign default risk increased beyond its initial level. This would yield the previous positive effects as temporary. In addition, it would also drive the decline in consumption as the increase in sovereign default risk cause a large decline in expected wealth, and also subsequently tighten credit constraints. This is consistent with the sharp decline in consumption observed in the high regime.

In the low regime, the consumption response exhibit mild declines with subdued dynamics over the forecast horizon. This aligns well with the movements in sovereign default risk which initially fall slightly, then gradually increases to a value of 0, implying no change in sovereign default risk in the longer-run. The absence of large movements in sovereign default risk subdues any non-Ricardian wealth effects as there are only small changes and in probability of default. As a result, in this setting consumers are predominantly Ricardian. Taking these together indicates that the non-Ricardian effects are more likely to occur when the government is in a high sovereign default risk regime. This is because these times may be associated with larger variations and increases in sovereign default risk in response to changes in government expenditure, and hence larger non-Ricardian changes in wealth.

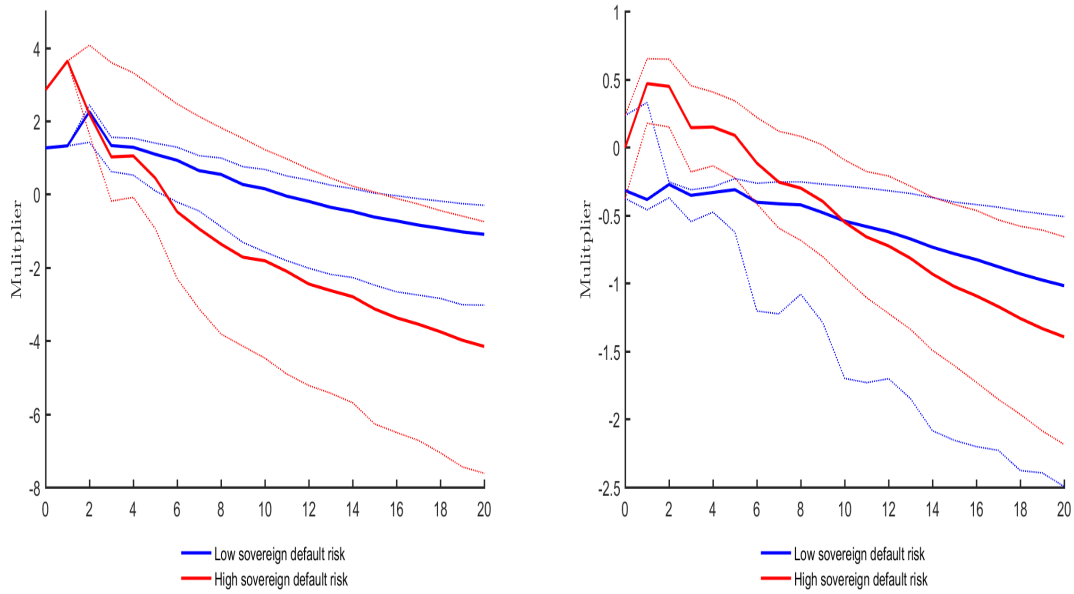
Overall, I find evidence that consumption is a key driver behind the output multiplier. Hence, consumption theories should facilitate the understanding of the non-linearities in the multiplier generated from regimes of sovereign default risk. I provide some evidence to suggest that when in the low sovereign default risk regime the Ricardian Equivalence dominates consumer decisions. Whereas, when in the high sovereign default risk regime the shorter-term consumption multiplier indicates that household decisions may be dictated by increases in wealth, and an easing of credit constraints as sovereign default risk initially falls. However as sovereign default risk increases in the longer-term, there is a large decrease in consumption. This decrease may be attributed to large negative wealth effects coupled with a tightening of credit constraints. This drives consumption lower than a typical Ricardian response.

Figure 6.8: Experiment 1



(a) Output (b) Consumption

Figure 6.9: Experiment 2



(a) Output

(b) Consumption

6.5.2 Investment Multipliers

Figures 6.10 and 6.11 show the private investment multiplier in the two experiments. The investment multiplier across regimes indicate that increases in government expenditure crowd out investment. In the respective experiments, the dynamics of investment do not correspond well with output. This further suggests that the dominant driver of the fiscal multiplier is consumption.

When holding the regime fixed, the investment responses in both regimes show extreme dynamics. More specifically, government expenditure in the low regime yields an initial fall in investment. Over the forecast horizon, the investment multiplier continues to fall, with a five-year multiplier value of -9.5. This suggests that investment falls by 9.5 times the cumulative increase in government expenditure. When in the high regime, the increase in government expenditure initially drives an increase in investment with a peak response of approximately 5. However, following the peak response the investment multiplier falls sharply. The five-year investment multiplier is approximately -11. Overall, this provides some evidence that government expenditure reduces, and hence crowds out, private investment. However, these estimates are lower than standard estimates, and may reflect the inability of linear systems to capture the dynamics of investment. I will now turn my attention to experiment 2 which accounts for non-linearities by allowing for regime switching.

Once allowing for regime switching, the investment responses in both regimes are more subdued but still suggest that government expenditure crowds out private investment. In the low regime, investment falls slightly following an increase in government expenditure. Similar to experiment 1, there is a gradual decline in the investment multiplier over the forecast horizon, with a five-year multiplier of -2. This value is also statistically different from zero. This indicates that over five-years private investment falls by twice the total change in government expenditure. This response highlights the ability for government expenditure to crowd out private investment, even when sovereign default risk is low. In the high regime, an increase in government expenditure initially increases investment with a peak response of 0.678. Following the peak, the response falls gradually over the forecast horizon with a five-year multiplier value of -1.591. This suggests over the longer-term private investment falls by around 1.5 times the increases in government expenditure. Between the high and low sovereign default risk regimes, the longer-term dynamics of the investment multiplier yield no evidence of regime dependence. Moreover, both five-year multipliers suggest that increases in government expenditure crowd out private investment. This is consistent with Blanchard and Perotti (1999) who also finds that government expenditure crowds out private investment.

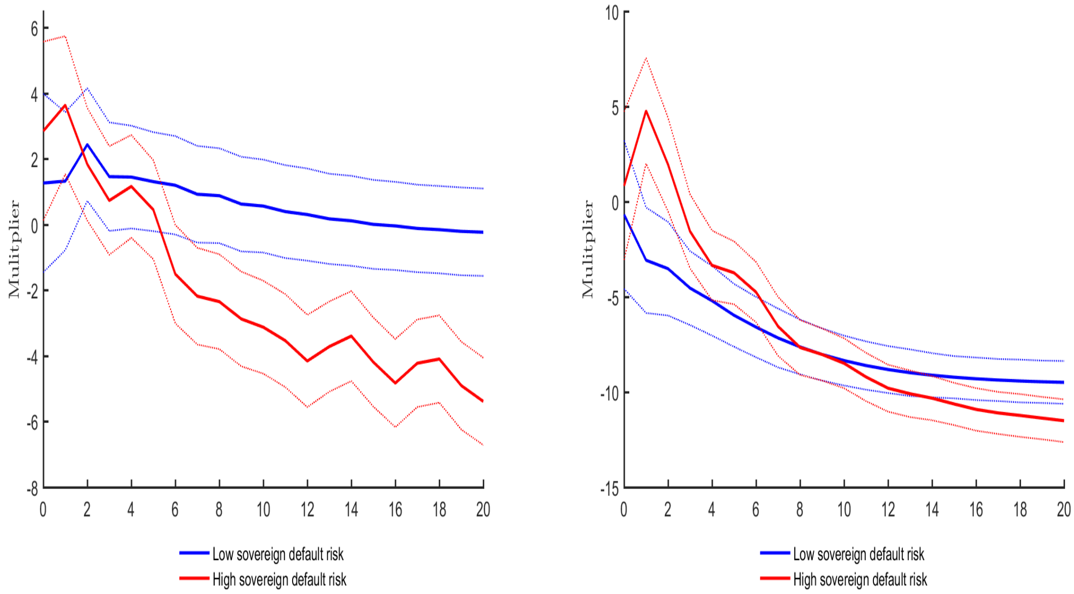
In facilitating the understanding of the dynamics of the output multiplier, the investment multiplier provides little information. There are significant discrepancies between the investment and output multipliers both between regime and experiment. This indicates that investment largely fails to explain the dynamics in output. However, consistent with the output multiplier, in the high regime investment shows an initial positive response. This is also consistent with consumption responses. This may indicate that credit constraints may also loosen for investors in the high regime. This would particularly be the case if borrowing costs fell for both consumers and investors as wealth increases due to the initial large fall in sovereign default risk.[7] However, aside from this small similarity, the investment responses between regimes and experiments fail to explain the output multiplier dynamics. This indicates that consumption is the likely key underlying driver to the output multiplier.

Despite this, the response of investment to an increase in government expenditure still provides some useful insight into the response of investors under varying regimes of sovereign default risk. In particular, the results suggest that government expenditure in the longer-term leads to a crowding out of private investment regardless of the sovereign default risk regime. This provides some insight into

[7] I find some evidence to support the argument that reductions in public risk drive down private firm borrowing costs in a linear setting. The results can be found in Appendix I.

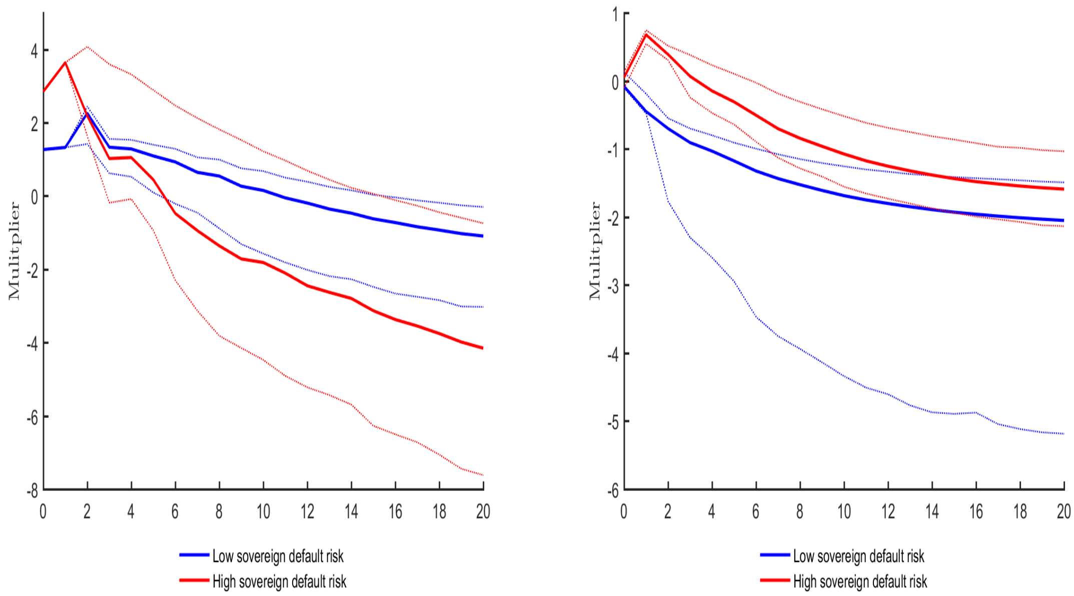
why my multiplier estimates are lower than standard estimates of the multiplier. However, caution should be exercised when interpreting these estimates as some are outside the typical range of standard estimates.

Figure 6.10: Experiment 1



(a) Output (b) Investment

Figure 6.11: Experiment 2



(a) Output (b) Investment

Chapter 7

Extensions and Robustness

In this Chapter, I will extend my baseline analysis and also address some of the limitations inherent in the analysis.

To address the possibility that non-linearities may depend on the direction and/or size of the expenditure shock I will conduct 2 extensions. Firstly, I will examine the multiplier using a negative expenditure shock rather than a positive expenditure shock. Secondly, I will examine the multiplier response to a larger expenditure shock.

In addition, I will also explore the possibility that government revenues respond to shocks in government expenditure with a lag, I will change the Cholesky ordering used to identify government expenditure shocks. Lastly, to account for different values of the critical value, I will examine the multiplier when using the median of the sovereign default risk index as the critical value. This extension is designed to account for the potential over-parametrisation inherent in the TVAR approach.

7.1 Fiscal consolidation: A negative expenditure shock

For my baseline analysis I imposed a positive expenditure shock. This represented a small government expenditure stimulus. This was done as the fiscal multiplier literature focuses on the effects of fiscal expansion. This is even the case in non-linear settings. However, in the context of sovereign default risk it may be more appropriate to consider a fiscal expenditure consolidation, rather than expansion. For example, a government close to the government budget constraint would be unable to even consider a fiscal expansion, and may only be able to consider an unchanged level of expenditure or declines in expenditure (fiscal consolidation). In fact, it may be optimal for governments to pay down their debts to exit a crisis zone (Cole and Kehoe, 2000). Moreover, given that a TVAR is a non-linear system it is possible that negative expenditure shocks yield different outcomes than the inverse of positive expenditure shocks. I will now turn my attention to the multiplier following a negative government expenditure shock equivalent to one standard deviation of government expenditure growth.[1]

I find the multiplier responses from a decrease in government expenditure to be close to the inverse of the multiplier responses following an increase in government expenditure. These similarities are likely attributed to the lack of regime switching after imposing the expenditure shock. The results indicate that fiscal consolidation when sovereign default risk is high could yield positive output effects, whereas the effects when sovereign default risk is low are less clear.

Figure 7.1 shows the multiplier to a negative expenditure shock and Table 7.1 shows key multiplier estimates. As the expenditure shock imposed is negative the interpretation of the multiplier is different. The interpretation of the multiplier to a negative expenditure shock is inverted relative to the interpretation of a positive expenditure shock. For instance, a multiplier of 1.5 following a negative expenditure shock can be interpreted as an output contraction equivalent to 1.5 times the absolute value of the cumulative changes in government expenditure.

In the low regime, the multiplier dynamics indicates that a negative expenditure shock is contractionary in the shorter-term, but may yield positive output effects in the longer-term. The decrease in government expenditure immediately defines a contraction in output of 1.268 times the size of the expenditure contraction. This effect becomes more contractionary, with a peak response of 2.174 two periods after the expenditure shock. This is indicative of the shorter-term contractionary effects of fiscal consolidation. However, over the forecast horizon the multiplier gradually declines, and the five-year output multiplier is -1.428. The five-year response is also statistically different from zero at the 10 per cent level of significance. Overall, this response indicates that fiscal contractions result in output losses in the shorter-term, but over time lead to output gains.

In the high regime, the multiplier dynamics closely follow the dynamics after imposing a positive expenditure shock. The results indicate that fiscal consolidation during high sovereign default risk could promote economic growth over the longer-term. Following the negative expenditure shock, output contracts. The peak response is 3.649 indicating that at the peak, output contracts by over 3.5 times the absolute cumulative changes in expenditure. Following the peak response, the multiplier falls relatively sharply. The five-year multiplier is around -5. This suggests

[1] I will only analyse the case of experiment 2, as by holding the regimes fixed (as in experiment 1) the results will be necessarily linear. Hence, the output responses to a negative shock in experiment 1 will be the direct inverse of a positive government expenditure shock.

that output increases by five times the cumulative absolute change in government expenditure. The five-year cumulative output multiplier is also statistically distinguishable from -1. The results provide support for fiscal consolidation in the form of government expenditure cuts during times of high sovereign default risk. This is consistent with Cole and Kehoe (2000).

It is important to note that similar to when imposing a positive expenditure shock the 90 per cent confidence intervals of the multiplier in each regime overlap. This suggests that the difference in multipliers cannot be statistically distinguishable from zero. This is similar to the baseline experiment. Despite this, the large difference in the point estimates, especially in the five-year cumulative multiplier, still suggest that governments should consider potential asymmetries in the multiplier due to sovereign default risk regimes.

The multiplier dynamics in each regime after a negative expenditure shock is similar to the multiplier dynamics after a positive expenditure shock. This illustrates that there may not be asymmetries in the fiscal multiplier driven by the direction of the government expenditure shock. That is, a positive and negative expenditure shock will yield inverted output outcomes given the sovereign default risk regime.

Looking further into these similarities I find that the evolution of regime after the negative expenditure shock is similar to when imposing a positive expenditure shock. Recall that in the low regime, following a positive expenditure shock there was no change in the regime, whereas in the high regime there were a minority of simulations that switched regimes, but over five-years all the simulations were back in the high regime. When imposing a negative expenditure shock, the probability of regime switching for either regime is very low. This is shown in Figure 7.2. Given that regimes appear very persistent when imposing either positive or negative expenditure shocks, it is not surprising that the multiplier dynamics are similar.

Hence, imposing a negative expenditure shock does not change the analysis from the baseline experiments. Moreover, the responses indicate that fiscal consolidation can have positive output effects when sovereign default risk is high. These results serve to complement the findings of the baseline experiments, and further suggest that there is some evidence of sovereign default risk defining non-linearities in the fiscal multiplier.

Figure 7.1: Negative Expenditure Shock - Multiplier

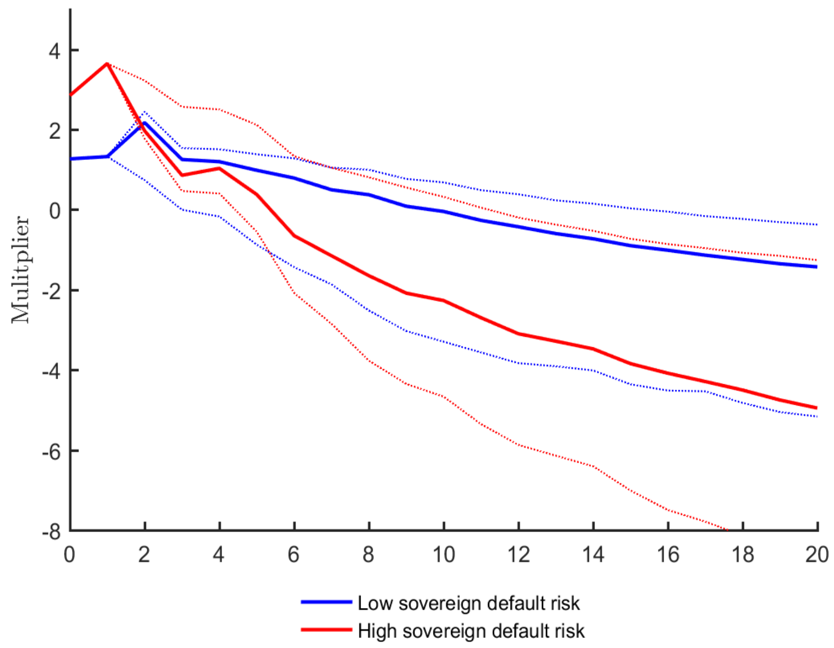
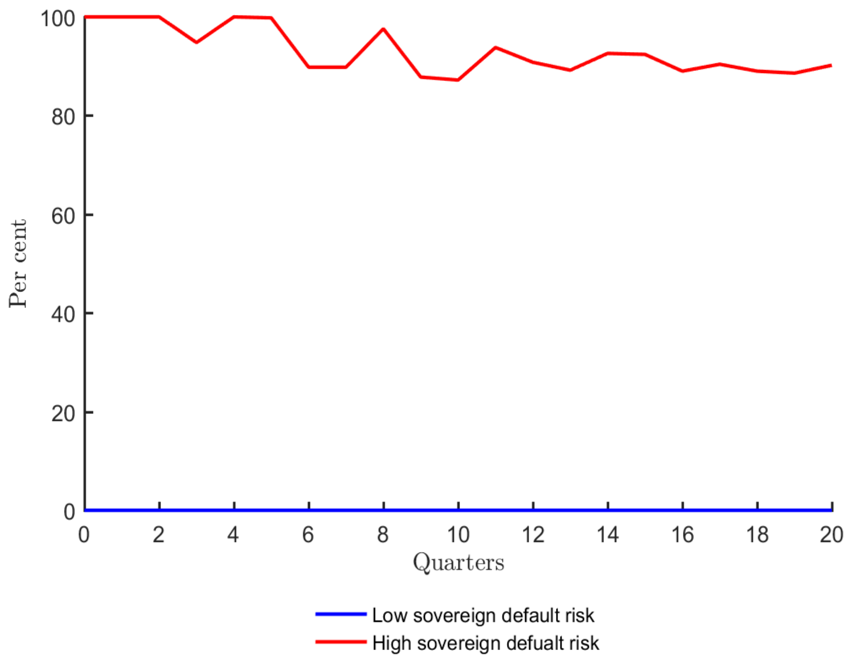


Table 7.1: Negative Expenditure Shock - Multiplier

	High	Low
Impact	2.851	1.268
	(2.851, 2.851)	(1.268, 1.268)
Peak	3.649	2.174
	(3.649, 3.649)	(0.737, 2.446)
One-year	1.032	1.198
	(0.403, 2.502)	(-0.172, 1.509)
Five-year	-4.953	-1.428
	(-8.657, -1.258)	(-5.164, -0.372)

Figure 7.2: Negative Expenditure Shock - Probability of High Regime



7.2 A large expenditure shock

In the baseline experiments a positive expenditure shock, equivalent to one standard deviation of government expenditure growth, was imposed on the system. This shock represented a small fiscal stimulus. However, as the system is non-linear the response of the variables also depend on the size of the shock imposed. Hence, different dynamics may be observed if the shock imposed is larger (or smaller). In this section I will instead impose a positive shock to government expenditure equivalent to 1 per cent of GDP.[2] This is similar to the shock size used in Fazzari et al. (2015). This expenditure intervention can be thought of as a large fiscal stimulus.[3,4]

When imposing a large positive expenditure shock the multiplier exhibits similar

[2]To create a government expenditure shock equivalent to 1 per cent of GDP, I create a new series that is 1 per cent of GDP divided by the level of government expenditure at that time. I then average this series to create a government expenditure growth shock equivalent to 1 per cent of GDP.

[3]I will once again only examine the response when allowing for regime switching, as the multiplier when holding the regimes fixed will be unchanged.

[4]In the high regime, such a large fiscal stimulus is consistent with the idea of 'gambling for redemption' wherein a country finds it optimal to increase debt levels in times of crisis, as the benefit of smoothing consumption is larger than the potential costs of higher risk premiums and a self-fulfilling crisis (Conesa and Kehoe, 2015).

dynamics across regimes. This can be observed in Figure 7.3. In both regimes, a large positive expenditure shock defines an initial increases in output, and following the peak response the multipliers declines gradually. In the low regime, the multiplier dynamics are comparable to those observed in the baseline experiment. Whereas, the dynamics in the high regime differ substantially from the baseline experiment. Recall that in the baseline experiment in the high regime, following the peak effect the fiscal multiplier falls sharply. However, when imposing a large positive expenditure shock in the high regime, following the peak response the fiscal multiplier experiences a gradual, rather than a sharp, decline. In fact, the multiplier follows the dynamics of the low regime multiplier closely. In addition, the five-year fiscal multiplier in the high regime is larger than the fiscal multiplier in the low regime (see Table 7.2). This suggests that after a large expenditure shock the fiscal multiplier is larger when sovereign default risk is initially high. This is in contrast to the baseline experiment. Overall, the similarities in the multiplier dynamics across regimes after imposing a large expenditure shock indicate that the dynamics and non-linearities in the fiscal multiplier are contingent on the size of the expenditure shock.

Looking into this result, I find the change in the multiplier dynamics from the baseline specification can be partially attributed to the evolution of regime. Figure 7.4 displays the probability of being in the high regime following the large positive spending shock. Similar to the baseline experiment, a large expenditure shock in the low sovereign default risk regime does not define a change in regime for any of the simulations over the entire forecast horizon. This is useful in explaining why the response in the low regime is similar after imposing a small or large positive spending shock. Whereas, a large positive expenditure shock in the high regime immediately lowers the probability of being in the high regime to below 10 per cent. The number of simulations in the high regime remains low for over half the forecast horizon. This result highlights the ability of government expenditure drive a change from the high to the low regime. However, this change in regime appears temporary with the probability of being in the high regime returning to 100 per cent by the end of the forecast horizon. The evolution of regime is in stark contrast to the baseline experiment wherein the majority of simulations stayed in the high regime over the entire forecast horizon. The disparity in results between the baseline experiment and the large expenditure shock indicates that the difference in the fiscal multiplier in the high regime, between experiments, can be partially attributed to the changes (or lack-there-of) in regimes from the different expenditure shocks.

Overall, the results provide evidence that large enough government expenditure increases can neutralise the negative effects of sovereign default risk on the fiscal multiplier observed in the baseline experiments. In addition, I find that this neutralisation of the negative effects can be partially attributed to a highly probable regime switch, from the high regime to the low regime. Despite these positive effects, the results also indicate that this may not be a sustainable strategy as it is very likely that the economy returns to the high sovereign default risk regime in the longer-term. These results highlight that the non-linearities in the multiplier observed in the baseline experiments are also subject to the size of the expenditure shock.

Figure 7.3: Large Expenditure Shock - Multiplier

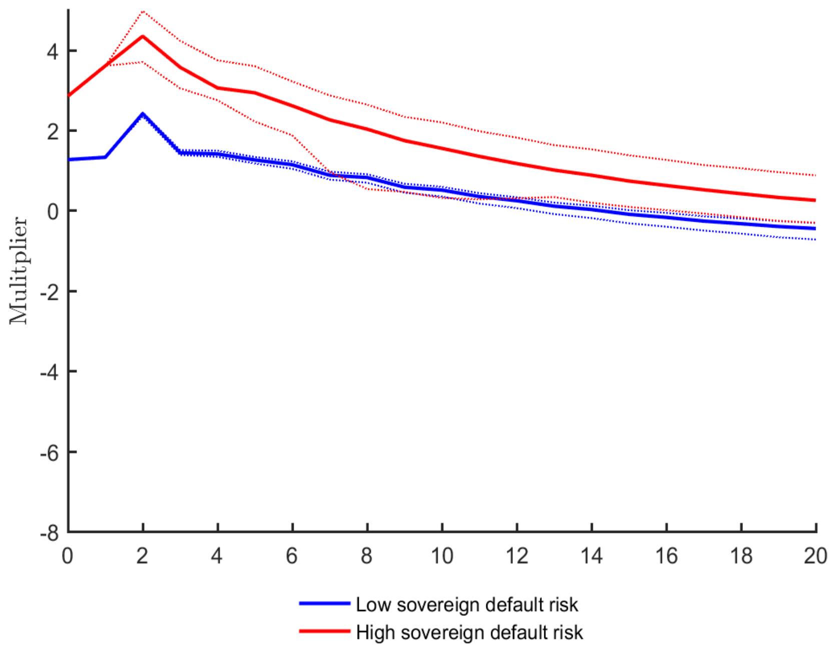
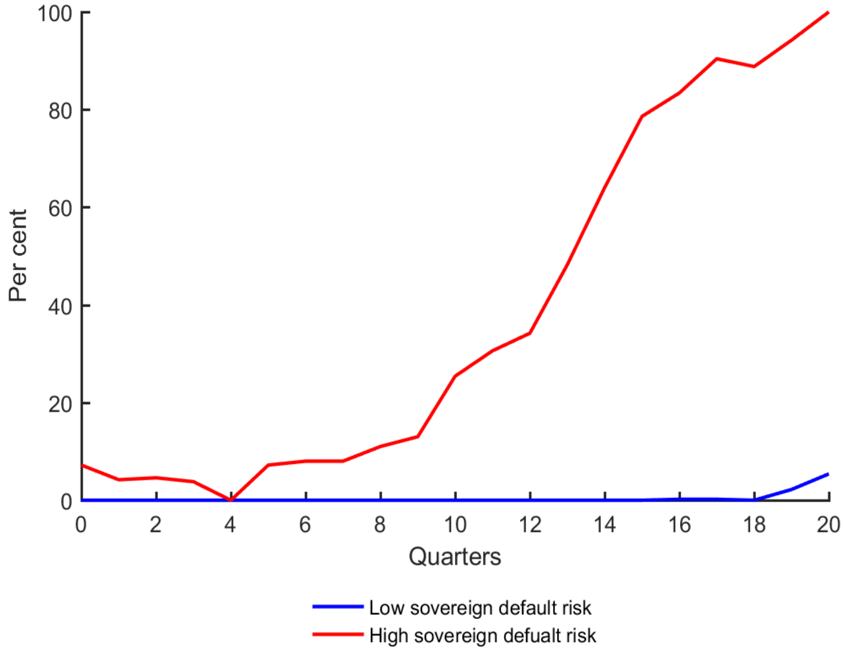


Table 7.2: Large Expenditure Shock - Multiplier

	High	Low
Impact	2.851	1.268
	(2.851,2.851)	(1.268,1.268)
Peak	4.345	2.416
	(3.670,4.973)	(2.348, 2.446)
One-year	3.055	1.410
	(2.749,3.055)	(1.338, 1.492)
Five-year	0.254	-0.449
	(-0.305,0.876)	(-0.722, -0.313)

Figure 7.4: Large Expenditure Shock - Probability of High Regime



7.3 An alternative identification scheme

In my baseline analysis, I identify government expenditure shocks using a Cholesky decomposition with government expenditure ordered first. This allows government expenditure innovations to contemporaneously affect government revenue, output and sovereign default risk. However, as previously mentioned, the relationship between government expenditure and revenue is ambiguous. It is unclear whether government expenditure affects revenue first, or vice-versa (Blanchard and Perotti, 1999). To account for this, I will now analyse the fiscal multiplier in each regime of sovereign default risk by ordering government revenue first in the Cholesky decomposition. This identification scheme will restrict the government expenditure shock to only affect government revenue with a lag. All other variables will still be able to respond contemporaneously to the government expenditure shock. I find that the magnitudes of the fiscal multiplier change under this identification strategy relative to the baseline identification. However, the overall finding that government expenditure in the high sovereign default risk regime drive lower fiscal multipliers remains robust.

Figure 7.5 shows the fiscal multiplier response when holding the regimes fixed following a government expenditure shock under the new identification strategy. Table 7.3 shows key multiplier statistics in more detail.

The results indicate that when perpetually in the low regime an increase in government expenditure can promote output expansions in the shorter-term, however in the longer-term output falls. Following the expenditure shock, the peak multiplier response is around 1 and the five-year cumulative multiplier is around -1. Similar to the baseline identification scheme the multiplier responses still indicate that government expenditure has the potential to drive positive output responses in the shorter-term, but these responses become negative in the longer-term. It is worth noting that the short-run response has become lower, suggesting that the positive output responses from government expenditure may be lower than estimates suggest under the baseline specification.

The results under the new identification scheme when perpetually in the high regime yield more extreme output responses in the longer-term than the baseline identification scheme. Recall that under the baseline identification scheme the multiplier, following an initial increase, fell sharply with a five-year value of -5.385. When changing the identification scheme, the multiplier still exhibits a sharp decrease (albeit without the initial increase). However, the five-year multiplier is lower than before at -9.021. This represents a substantial change in the five-year multiplier estimate, illustrating the sensitivity of the estimates from changes in identification.

Despite the differences in estimates the multiplier in the high regime is still lower than the multiplier in the low regime. Moreover, the confidence intervals do not overlap. This indicates that the five-year multipliers are statistically distinguishable from each other at the 10 per cent level of significance. Hence, the baseline finding that the fiscal multiplier is lower when sovereign default risk is high is robust to this change in identification.

The results when allowing for regime switching and under this change in identification do not define substantial changes, relative to the baseline identification scheme, in the dynamics of the multiplier and the long-run multiplier estimates. Overall, the output responses from a government expenditure increase under the new identification scheme again suggest that the multiplier is lower when sovereign default risk is high. Figure 7.6 shows the fiscal multiplier dynamics when allowing for endogenous regime switching with the new identification strategy. Table 7.4 shows the key multiplier statistics in more detail.

In the low regime, similar to the baseline identification scheme, government expenditure defines expansionary output responses in the short-term, but the output response gradually becomes negative. More specifically, the peak response in the low regime is 0.842, and the five-year multiplier is -1.539. These estimates are similar to the baseline identification wherein the five-year multiplier was -1.092. Looking at the high regime, the increase in government expenditure defines some short-run stimulatory effects. However, similar to the baseline identification scheme, the multiplier response falls relatively sharply with a five-year multiplier of -4.046. This is comparable to the five-year multiplier value of -4.154 under the baseline identification scheme. Combining the multiplier responses in both regimes indicates that the multiplier is lower when sovereign default risk is high, relative to when sovereign default risk is low. Moreover, the responses indicate that in the low regime government expenditure has a greater potential to yield a more sustained increase in output than in the high regime. These conclusions are similar to those obtained under the baseline identification scheme. Therefore, the findings lend further weight to the notion that higher levels of sovereign default risk can drive lower fiscal multipliers through non-Ricardian negative household wealth effects. However, also similar to the baseline identification scheme, the 90 per cent confidence intervals under each regime overlap indicating that there still remains significant doubt over these estimates.

The impact multipliers under the new identification strategy and allowing for regime switching are more subdued than the baseline impact multipliers, this is particularly the case in the high regime. Recall that in the baseline identification strategy the impact multipliers were 2.851 and 1.268 for the high and low regime. Whereas the new identification strategy, the impact multipliers are 0.268 and 0.186. This indicates that the initial response of output are sensitive to identification. The result casts doubt over the proposition that the high impact multiplier observed in the high regime in the baseline experiments are driven by wealth increases as a result of decreases in sovereign default risk.

Overall, after changing the identification scheme the fiscal multiplier in both experiments yield similar findings to the baseline identification scheme. That is, government expenditure in the high sovereign default risk regime is more likely to yield lower and negative fiscal multipliers, relative to government expenditure in the low sovereign default risk regime. The similarity in results between identification schemes are consistent with Blanchard and Perotti (1999) and Perotti (2005) who find that the correlation between government expenditure and revenue shocks to be sufficiently low such that the ordering between them yields little change in results. Moreover, the similarities lend further weight to the concept that high levels of sovereign default risk are associated with non-Ricardian negative household wealth responses, whereas when sovereign default risk is low these non-Ricardian responses are more subdued.

Figure 7.5: Alternative Identification Scheme - Experiment 1 - Multiplier

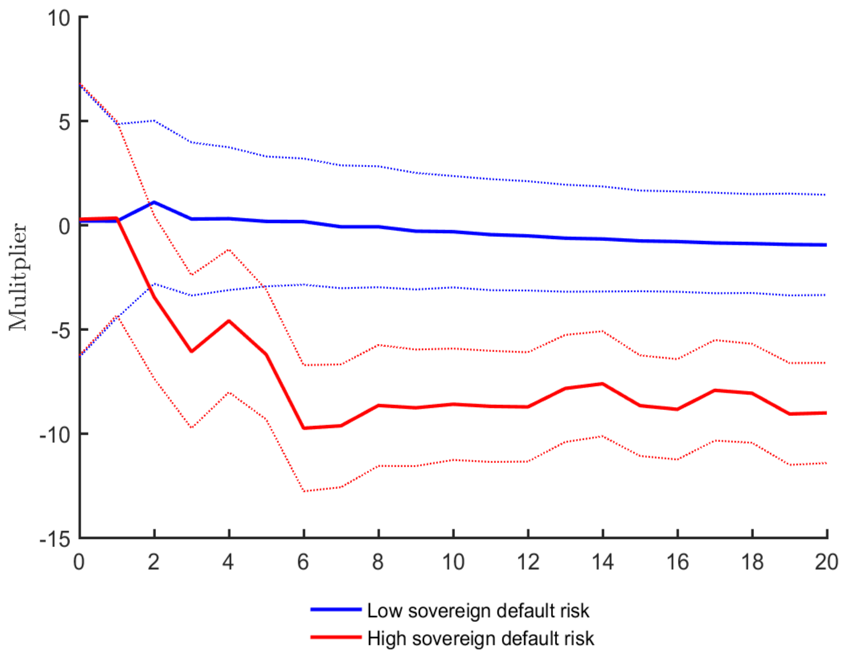


Table 7.3: Alternative Identification Scheme - Experiment 1 - Multiplier

	High	Low
Impact	0.268	0.186
	(-6.267, 6.803)	(-6.349, 6721)
Peak	0.324	1.087
	(-4.328, 4.976)	(-2.824, 4.997)
One-year	-4.600	0.297
	(-8.025, -1.175)	(-3.128, 3.722)
Five-year	-9.021	-0.960
	(-11.424, -6.619)	(-3.364, 1.442)

Figure 7.6: **Alternative Identification Scheme - Experiment 2 - Multiplier**

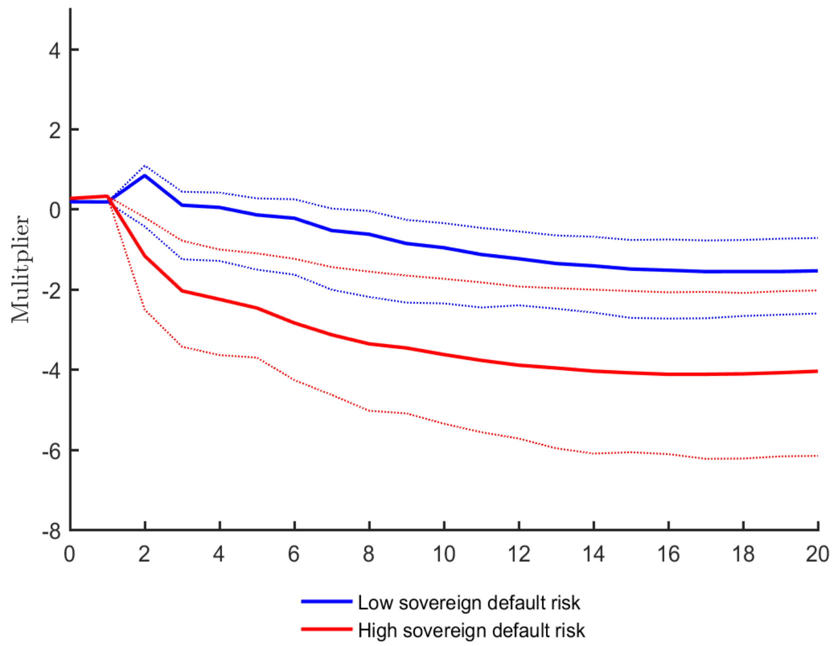


Table 7.4: Alternative Identification Scheme - Experiment 2 - Multiplier

	High	Low
Impact	0.268	0.186
	(0.268, 0.268)	(0.186, 0.186)
Peak	0.324	0.842
	(0.324, 0.324)	(-0.434, 1.087)
One-year	-2.250	0.044
	(-3.643, -1.007)	(-1.291, 0.413)
Five-year	-4.046	-1.539
	(-6.158, -2.028)	(-2.604, -0.720)

7.4 Median as critical threshold

I will now use the median value of sovereign default risk as the critical value of the threshold variable. This will necessarily impose half the observations to be in each regime. This effectively imposes the assumption that the government is in the high sovereign default risk regime for half of the sample period. Despite being an unrealistic assumption, increasing the number of periods in the high regime to some extent addresses the issue of over-parametrisation, driven by the small number of periods in the high regime. In fact, Auerbach and Gorodnichenko (2012) argue that TVAR estimates can be imprecise when there are a small number of observations in a certain regime. They therefore favour the STVAR methodology which does not split the sample like a TVAR.

I re-estimate the TVAR using the median value of sovereign default risk as the critical value. In this re-estimation I allow the delay and lags to be re-determined.[5] The fiscal multiplier following an increase in government expenditure, in both experiments, yields different results to the baseline findings. This is likely driven by model misspecification from choosing the particular critical value.

When holding the regimes fixed (experiment 1), the fiscal multiplier dynamics contradict the baseline results. Figure 7.7 and Table 7.5 show the fiscal multiplier dynamics over the forecast horizon and key multiplier statistics. In the low regime, the multiplier initially shows that output responds positively to increases in government expenditure. However, following this increase there is a steep decline in the multiplier with the five-year multiplier being -4.179. This indicates that in the low regime, output contracts by over 4 times the cumulative change in government expenditure. This suggests that there are low fiscal multipliers when sovereign default risk is low. This is starkly different from the baseline model wherein the multiplier in the low regime experienced a gradual decline to its five-year value of -0.230. Furthermore, the high regime multiplier also display different dynamics to the baseline model. In the high regime, an increase in expenditure defines a sustained increase in output. The peak multiplier is 3.651 and the five-year multiplier is 1.781. The estimates suggest that government expenditure in the high regime can sustainably increase output by more than the cumulative changes in expenditure. This is again in contrast to the baseline model wherein the multiplier in the high regime fell sharply, and was below the low regime multiplier. These differences in multiplier results from the baseline experiments indicate the sensitivity of the estimation to changes in the critical value, and may also reflect poor estimation based on choosing the incorrect critical value.

When allowing for regime switching (experiment 2), the fiscal multiplier dynamics change from the baseline specification and, ultimately suggest that the multiplier in each regime share similar dynamics. Figure 7.8 displays the multiplier dynamics after imposing a positive government expenditure shock and allowing for regime switching. In this setting the multiplier dynamics across regime are very similar. More specifically, in both regimes there is initially a positive response in output following the increase in government expenditure, and this response gradually

[5] Model comparisons can be found in Appendix O.

declines over the forecast horizon. This aligns well with the low regime multiplier dynamics in the basline model. However, the high regime multiplier in this new setting differs from the baseline specification wherein the high regime fiscal multiplier declined sharply. From Table 7.6, the five-year multiplier is -1.558 in the high regime, and -2.491 in the low regime. This suggests that in both regimes government expenditure in the longer-term is contractionary. The point estimates also indicate that the government expenditure is more effective (or less contractionary) in the high sovereign default risk regime. However, the confidence intervals of each regime very clearly contain at least the point estimate of the multiplier of the other regime. This suggests that there is little evidence of regime dependent fiscal multipliers based on sovereign default risk. This is similar to be baseline specification, however in this new specification the multiplier dynamics are more similar across regime than in the baseline specification.

Overall, once changing the threshold value to be the median of the threshold variable the results change. This suggests that the estimation of the TVAR is sensitive to the chosen critical value of the threshold variable. Despite this, it should be recognised that imposing the government is in each regime for half of the period is a relatively strong assumption that may yield erroneous estimation and results.

Figure 7.7: Median Critical Value - Experiment 1 - Multiplier

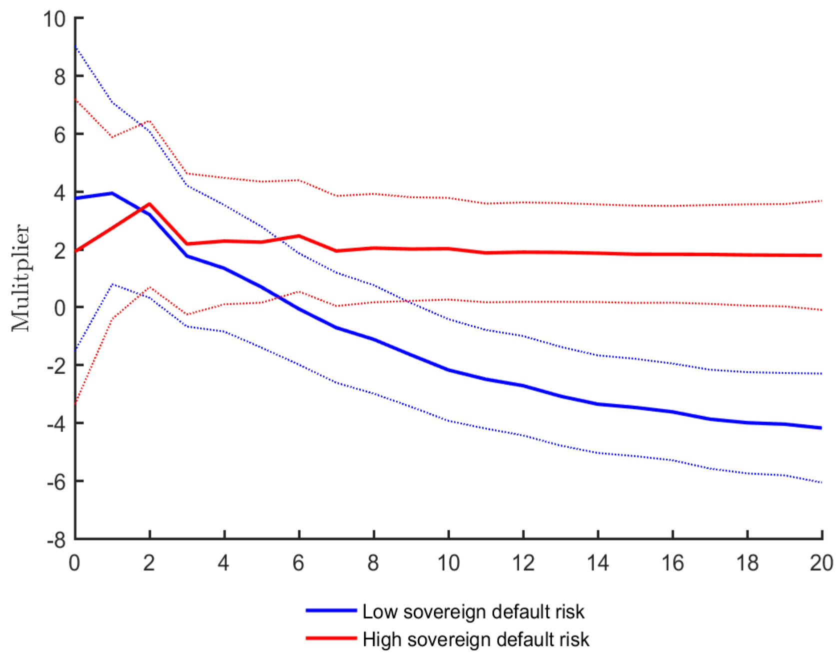


Table 7.5: Median Critical Value - Experiment 1 - Multiplier

	High	Low
Impact	1.910	3.749
	(-3.365, 7.185)	(-1.526, 9.025)
Peak	3.651	3.926
	(0.689, 6.433)	(0.786, 7.065)
One-year	2.275	1.334
	(0.091, 4.459)	(-0.849, 3.519)
Five-year	1.781	-4.179
	(-0.102, 3.664)	(-6.066, -2.300)

Figure 7.8: Median Critical Value - Experiment 2 - Multiplier

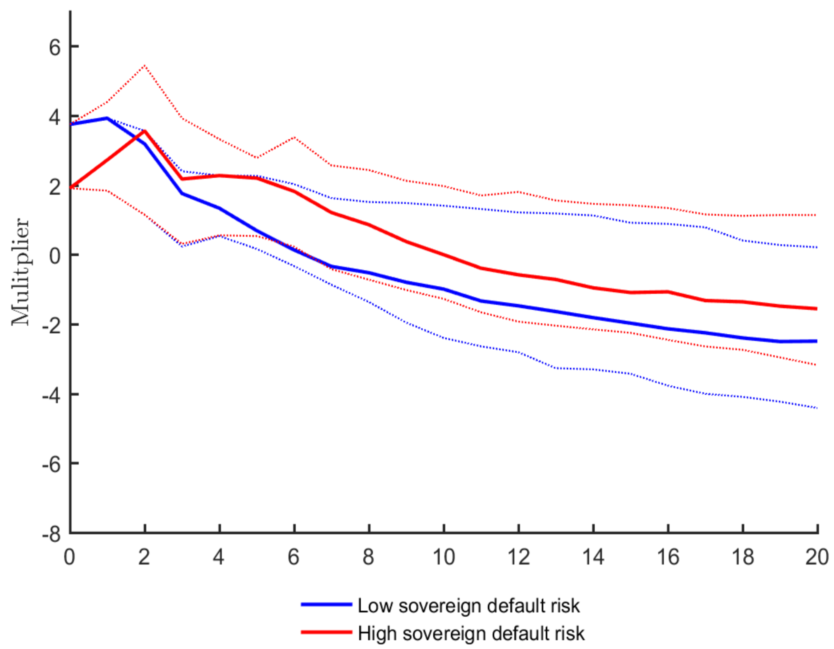


Table 7.6: Median Critical Value - Experiment 2 - Multiplier

	High	Low
Impact	1.910	3.749
	(1.910, 3.749)	(3.749, 3.749)
Peak	3.561	3.925
	(1.148, 5.442)	(1.840, 3.926)
One-year	2.275	1.335
	(0.555, 3.322)	(0.532, 2.276)
Five-year	-1.558	-2.491
	(-3.179, 1.139)	(-4.414, 0.211)

Chapter 8

Discussion and Concluding Remarks

8.1 Discussion and Implications of Results

In this thesis Part, I have examined the effectiveness of government expenditure under different regimes of sovereign default risk. I extend the standard fiscal VAR from Blanchard and Perotti (1999) to include my sovereign default risk index created in Part I. In my baseline experiments, I find some evidence that government expenditure in times of high sovereign default risk yield perverse long-run economic outcomes. More specifically, I find that long-run multipliers lower than -4 when sovereign default risk is high. The equivalent multiplier when sovereign default risk is low is between 0 to -1. The large negative response in the high sovereign default risk regime is indicative of a non-Ricardian response from households. Moreover, the stark differences in these estimates indicate that governments should evaluate the level of sovereign default risk prior to making fiscal policy decisions. However, it is important to note that the confidence intervals at times overlap suggesting that the non-linearities are not always statistically significant.

Looking into the other non-linear results of the system, I find that the response of sovereign default risk also exhibits regime dependence. The evidence suggests that increases in government expenditure when in the high sovereign default risk regime actually define higher longer-term levels of sovereign default risk. This is in contrast to the low regime wherein I find no evidence that sovereign default risk experiences a longer-term increase following an increase in government expenditure. These responses appear to have an inverse association with the multiplier responses. That is, when sovereign default risk increases the multiplier decreases, and vice-versa. These results provide evidence of non-linearities in the response of sovereign default risk to an increase in government expenditure. This indicates that sovereign default risk responses are a reasonable candidate in explaining the disparity in multiplier results across regime. Moreover, looking at the evolution of the regime I find that regimes are persistent following expenditure shock. That is, the system is likely to stay in the prevailing regime following an increase in government expenditure. Taking the response of sovereign default risk together with the result that regimes are persistent yield important policy implications. This persistence in sovereign default risk regimes is concerning to policy makers. It suggests that longer-term sovereign default risk may be outside the immediate control of government expenditure. This implies that precautionary measures should be used to avoid high levels of sovereign default risk. More specifically, governments should take active policy steps towards managing sovereign default risk to avoid the perverse effects government expenditure has on the economy when sovereign default risk is high. Such steps could include maintaining levels of fiscal space, or credible commitments to sustainable budgeting. These steps can serve to avoid situations wherein governments are concerned about both economic output and sovereign default risk.

To determine the demand component driving the multiplier I examine the responses of consumption and investment to the same positive expenditure shock. I find that consumption responses exhibit strong similarities to the equivalent output responses. These similarities are not present when comparing the investment multiplier to the output multiplier. These results speak to the theory underlying the effects of government expenditure. I find some evidence that in the shorter-term, government expenditure increases can promote consumption in when sovereign default risk is high. This increase corresponds to a large decrease in sovereign default risk, and suggests that there is an increase in the expected wealth value of households that could cause higher levels of consumption. Moreover, this increase in consumption could be amplified if the increase in wealth also alleviates credit constraints on households. However, in the longer-term these gains are temporary as sovereign default risk increases beyond its initial level. The consumption responses provide evidence that during this period households experience large negative wealth effects (beyond standard Ricardian effects) as predicted by my theoretical model. Whereas in the low regime, these wealth effects are not as strong as the changes in sovereign default risk are more subdued. The findings suggests that households are predominantly Ricardian when sovereign default risk is low. This indicates that households experience larger declines in wealth following increases in government expenditure the higher sovereign default risk is. This because the higher the initial level of sovereign default risk, the larger the dynamics sovereign default risk exhibit to a expenditure increase. This result is consistent with the findings of Perotti (1999) and my theoretical model. This transmission of sovereign default risk into household wealth expectations should be further investigated in more theoretical settings.

I find that my results are robust to changes in identification scheme, and changes in the direction of the government expenditure shock. This lends further weight to the baseline findings that sovereign default risk can define non-linearities in the fiscal multiplier. Moreover, the results of the negative expenditure shock imply that in times of high sovereign default risk, measures to cut expenditure could in fact yield expansionary output outcomes. This indicates that there may be output gains in reversing some of the negative wealth effects experienced by households when sovereign default risk is high.

Lastly, the results are sensitive to changes in the threshold value, and the size of the expenditure shock imposed. This is unsurprising given that changing the threshold value is likely to lead to misspecification of the TVAR, and imposing a large expenditure shock is not always a realistic proposition that is captured in the data. Despite this, the instability in results does leave my analysis open to further refinement.

Overall my findings indicate that there is some evidence of non-linearities in the fiscal multiplier driven by different regimes of sovereign default risk. High regimes of sovereign default risk are associated with lower (and negative) longer-term multipliers than times of low sovereign default risk. Taken with my other findings, the results suggest that governments should not only consider sovereign default risk when making government expenditure decisions, but also actively seek to prevent sovereign default risk from moving to a high regime in the first place. Precautionary measures to prevent sovereign default risk from moving to the high regime will maintain the effectiveness of government expenditure as non-Ricardian household wealth effects from government expenditure become more subdued (or negligible) when sovereign default risk is low.

8.2 Further Research

Given the nascent nature of literature on the effects of sovereign default risk on the fiscal multiplier, my research is open to further development and refinement. Further research on my analysis would be beneficial to improve the understanding of the effects sovereign default risk have on fiscal policy. Further analysis will also build on the existing literature identifying drivers of non-linearities in the fiscal multiplier. An immediate extension to my methodology is to use an STVAR. An STVAR can address two issues. Firstly, an STVAR will partially overcome the risk of over-parametrisation that is inherently present in TVARs. This is especially the case with the small number of observations in the high sovereign default risk regime. However, as argued by Fazzari et al. (2015) STVARs may result in poor estimation if the true critical value is more discrete than continuous. Secondly, an STVAR is more appropriate if one considers sovereign default risk to affect the system in a more continuous manner. That is, the regimes of sovereign default risk are more continuous than binary. STVAR analysis would hence be useful to examine this differing setting.

In the same vain, my analysis could also benefit from the usage of Bayesian methods. Bayesian methods, in particular state-space modelling, can be used to estimate the appropriate cut-off value of the threshold variable. Moreover, the use of a Bayesian Vector Autoregression can be used to not only incorporate prior information, but also avoid over-parametrisation. The following two are both logical extensions of my empirical work that will elucidate the robustness of my analysis.

Another useful extension to my work would be to consider the effects of tax changes on the system. This would facilitate in building a more holistic understanding of fiscal policy effects in certain regimes of sovereign default risk. However, the identification of tax rate shocks is more difficult as the data only shows tax revenue, and the movements in tax revenue are largely endogenous. One would need to identify changes in the tax rate to properly analyse the effects of tax changes on the economy. This would yield a more holistic analysis of regime dependent fiscal multipliers from sovereign default risk, and could elucidate the appropriate fiscal policy response in times of high and low sovereign default risk.

Analysis using other countries would also provide substantive insight. In this thesis, due to data limitations I have restricted my analysis to the case of the U.S. Given the U.S. issues public debt in its own currency and is generally considered a risk free borrower the non-linearities identified in this thesis may have different dynamics other countries. This may particularly be the case where governments do not issue debt in their own currency. Applying the same analysis using these countries could provide deeper insight into the effects of sovereign default risk on the fiscal multiplier. Unfortunately, the current data in other countries is limiting. To overcome this a panel setting, similar to Nickel and Tudyka (2014), could be adopted.

I have used my index as a measure of sovereign default risk. The refinement of the index or alternative measures of sovereign default risk can also be used as threshold variables to test the robustness of my analysis. Variables such as government financing needs, debt-to-GDP ratios and bond yields may provide further information on whether sovereign default risk can drive non-linearities in the fiscal multiplier.

I have proposed that credit constraints via changes in household wealth play a role in the shorter-term for both consumers and investors. To investigate this further, the exploration of the relationship between fiscal policy, sovereign default risk, and interest rates is warranted. This analysis can elucidate the role that borrowing costs and credit constraints play in determining the fiscal spending multiplier. I have already provided some evidence that sovereign default risk can define higher borrowing costs for firms in Appendix I. Further exploration of this in a more complete non-linear setting is warranted.

In this Part, I also have argued that negative non-Ricardian wealth effects is the primary driver behind the lower multiplier when sovereign default risk is high. However, empirical methods are limited in providing deeper insight on this issue. Future research should focus on incorporating sovereign default risk and the non-Ricardian household wealth effects into theoretical settings. This can provide further insight if such settings can produce the non-linearities in the fiscal multiplier that I have observed in the data.

8.3 Concluding remarks

Recent macroeconomic events that have placed both fiscal policy and sovereign default risk at the forefront of policy discussion. My results provide a timely analysis on a key policy question. I have shown that there is some evidence of non-linearities in the fiscal multiplier driven by levels of sovereign default risk. Increases in government expenditure in times of high sovereign default risk yield low and negative multipliers. Whereas, government expenditure when sovereign default risk is low is associated with subdued or slightly negative multipliers. However, the confidence intervals at times suggest that these non-linearities are not always statistically significant. This indicates that the analysis could benefit from further research. I also provide evidence illustrating that the non-linearities in the multiplier are driven by negative households wealth effects that are more prominent when sovereign default risk is high. Overall, the results indicate that sovereign default risk is a valid consideration when evaluating government expenditure decisions. In fact, my findings also show that government expenditure in times of high sovereign default risk may be counter-productive not only in stimulating output, but also in reducing the longer-term level of sovereign default risk. Together, the results speak to the need for governments to consider sovereign default risk management as a long term objective. Without such actions, governments risk rendering expansionary fiscal policy impotent.

Appendix A

Country Code Key

Table A.1 shows the country code key and notes for all OECD countries.

Table A.1: Country Code Key

Country Code	Country	Notes
AUT	Austria	
AUS	Australia	
BEL	Belgium	
CAN	Canada	SCDS data unavailable
CHI	Chile	
CZE	Czech Republic	
DEN	Denmark	
EST	Estonia	
FIN	Finland	
FRA	France	
GER	Germany	
GRE	Greece	SCDS no longer traded
HUN	Hungary	
ICE	Iceland	
IRE	Ireland	
ISR	Israel	
ITA	Italy	
JAP	Japan	
KOR	Korea	
LUX	Luzembourg	SCDS data unavailable
MEX	Mexico	
NET	Netherlands	
NZE	New Zealand	SCDS data unavailable
NOR	Norway	
POL	Poland	
POR	Portugal	
SVK	Slovak Republic	
SLO	Slovenia	
SPA	Spain	
SWE	Sweden	
SWI	Switzerland	SCDS data unavailable
TUR	Turkey	
UNK	United Kingdom	
USA	United States	

Appendix B

Index Data

Tables B.1 and B.2 show all the data used for the index across countries. I have noted the transformation of the variable to render them stationary. Moreover, the results of the p-values of the Augmented Dickey-Fuller tests are presented for the U.S. data. The lag length is chosen using AIC.

All data (except financial and survey data) are either seasonally adjusted by source or by some variance of X-13. Also, when possible I use end of quarter figures. This ensures consistentcy as all stock variables are reported as end of quarter.

The data sources used are taken from sources that have international data to ensure the index can be constructed across various countries. Sources include: International Financial Statistics from the International Monetary Fund (IMF), Oragnisation of Economic Co-operation and Development (OECD), the Bank of International Settilement (BIS), Thompson Reuters Datastream (Datastream), Bloomberg (Bloomberg), and the Federal Reserve Economic Data (FRED).

Table B.1: Index data

Number	Data title	Transformation	Source	Units	Start	End	P-value	Lag
1	General government debt to gdp	Difference	BIS	Per cent of gdp; market value	Q2:1980	Q4:2015	0.006	4
2	Real effective exchange rate	Log difference	BIS	Index	Q2:1970	Q1:2016	0.001	1
3	Debt to gdp Non-financial corporations	Difference	BIS	Per cent of GDP; market value	Q2:1970	Q4:2015	0.006	2
4	Debt to gdp; Households & NPISHs	Difference	BIS	Per cent of GDP; market value	Q2:1970	Q4:2015	0.169	4
5	Debt to gdp; Non financial sector	Difference	BIS	Per cent of GDP; market value	Q2:1970	Q4:2015	0.021	8
6	Debt to gdp; private sector; creditor- domestic banks	Difference	BIS	Per cent of GDP; market value	Q2:1970	Q4:2015	0.025	4
7	Survey of professional forecasters 3month tbill (current)	Difference	Bloomberg	Per cent	Q4:1981	Q1:2016	0.001	7
8	Survey of professional forecasters 10yr tbill (current)	Difference	Bloomberg	Per cent	Q2:1992	Q1:2016	0.001	2
9	Survey of professional forecasters anxious index (current)	Difference	Bloomberg	Index	Q2:1970	Q1:2016	0.001	8
10	Survey of professional forecasters unemployment (current)	Difference	Bloomberg	Per cent	Q2:1970	Q1:2016	0.001	1
11	Survey of professional forecasters CPI (current)	Difference	Bloomberg	Per cent	Q4:1981	Q1:2016	0.001	7
12	Survey of professional forecasters ECB HICP (current)	Difference	Bloomberg	Per cent	Q2:1999	Q1:2016	0.001	1
13	Survey of professional forecasters ECB growth (current)	Difference	Bloomberg	Per cent	Q2:1999	Q1:2016	0.001	1
14	VXO	Difference	Datastream	Index	Q1:1986	Q1:2016	0.036	8
15	Citi macro risk index- long term	Difference	Datastream	Index	Q1:1999	Q1:2016	0.001	1
16	U.S. economic policy uncertainty index - overall nadj	Difference	Datastream	Index	Q2:1985	Q1:2016	0.004	8
17	U.S. economic policy uncertainty index - news based nadj	Difference	Datastream	Index	Q2:1985	Q1:2016	0.001	8
18	Equity risk premium	Difference	Datastream	Per cent	Q3:1988	Q1:2016	0.001	2
19	Equity risk premium World	Difference	Datastream	Per cent	Q3:1988	Q1:2016	0.001	1
20	Equity risk premium U.S.	Difference	Datastream	Per cent	Q3:1988	Q1:2016	0.001	2
21	Equity risk premium Eurozone	Difference	Datastream	Per cent	Q3:1988	Q1:2016	0.001	1
22	Europe economic policy uncertainty news based	Difference	Datastream	Index	Q2:1987	Q1:2016	0.001	8
23	Equity risk premium western europe	Difference	Datastream	Per cent	Q2:1988	Q1:2016	0.001	1
24	OE WES: Expected inflation rate	Difference	Datastream	Per cent	Q2:1991	Q1:2016	0.001	1
25	WES public deficits	Difference	Datastream	Survey (1-10)	Q4:1991	Q1:2016	0.001	2
26	WES foreign debts	Difference	Datastream	Survey (1-10)	Q4:1991	Q1:2016	0.001	4
27	WES insufficient demand	Difference	Datastream	Survey (1-10)	Q4:1991	Q1:2016	0.001	1
28	WES economic situation 6 months	Difference	Datastream	Survey (1-10)	Q2:1989	Q1:2016	0.004	7
29	WES economic situation	Difference	Datastream	Survey (1-10)	Q2:1989	Q1:2016	0.001	7
30	WES domestic share price	Difference	Datastream	Survey (1-10)	Q3:1998	Q1:2016	0.001	3
31	WES trade balance	Difference	Datastream	Survey (1-10)	Q2:1989	Q1:2016	0.001	2
32	WES expected st rate	Difference	Datastream	Survey (1-10)	Q1:1989	Q1:2016	0.010	7
33	WES expected long term rate	Difference	Datastream	Survey (1-10)	Q3:1998	Q1:2016	0.001	6
34	Financial stability index	Difference	FRED	Index	Q2:1994	Q1:2016	0.001	1
35	Ted spread	Difference	FRED	Per cent	Q2:1986	Q1:2016	0.001	1
36	Moody's Seasoned BAA Corp Bond yield	Difference	FRED	Per cent	Q2:1986	Q1:2016	0.001	1
37	Moody's Seasoned BAA Corp Bond spread	Difference	FRED	Per cent	Q2:1986	Q1:2016	0.001	1
38	Moody's Seasoned AAA Corp Bond yield	Difference	FRED	Per cent	Q2:1970	Q1:2016	0.001	3

Table B.2: Index data continued

Number	Data title	Transformation	Source	Units	Start	End	P-value	Lag
39	Moody's Seasoned AAA Corp Bond spread	Difference	FRED	Per cent	Q2:1983	Q1:2016	0.001	1
40	Leading index for US	Difference	FRED	Index	Q2:1982	Q1:2016	0.001	3
41	Equity market-related economic uncertainty index	Difference	FRED	Index	Q2:1985	Q1:2016	0.001	8
42	Economic Policy Uncertainty Index for US	Difference	FRED	Index	Q1:1985	Q1:2016	0.006	8
43	Economic Policy Uncertainty Index for Europe	Difference	FRED	Index	Q2:1987	Q1:2016	0.001	8
44	Industrial production	Log difference	IMF	Index	Q2:1970	Q4:2015	0.001	1
45	Total reserves excluding gold	Log difference	IMF	USD	Q2:1970	Q4:2015	0.003	8
46	Official reserve assets	Log difference	IMF	USD	Q2:1970	Q1:2016	0.001	2
47	Monetary base to broad money	Difference	IMF	Per cent	Q2:1970	Q4:2015	0.001	1
48	Treasury bill rate (country specific)	Difference	IMF	Per cent per annum	Q2:1970	Q1:2016	0.001	7
49	Direct investment	Log difference	IMF	USD	Q2:1973	Q4:2015	0.001	3
50	Libor	Difference	IMF	Per cent per annum	Q2:1970	Q1:2016	0.001	5
51	Openess	Log Difference	IMF	USD	Q1:1973	Q4:2015	0.001	8
52	GDP deflator	Log Difference	IMF	Index	Q2:1970	Q1:2016	0.041	2
53	Real effective exchange rate by unit labour cost	Log Difference	IMF	Index	Q2:1992	Q4:2015	0.001	1
54	Producer price index , all commodities	Log Difference	IMF	Index	Q2:1970	Q1:2016	0.001	1
55	Export Price Index, All Commodities, Index	Log Difference	IMF	Index	Q2:1970	Q1:2016	0.001	1
56	Import Price Index, All Commodities, Index	Log Difference	IMF	Index	Q2:1970	Q1:2016	0.001	1
57	Assets, Direct investment, US Dollars	Log Difference	IMF	USD	Q2:2006	Q4:2015	0.001	1
58	Liabilities, Direct investment, US Dollars	Log Difference	IMF	USD	Q2:2006	Q4:2015	0.001	1
59	Central Bank, Total Gross Assets, National Currency	Log Difference	IMF	National currency	Q1:2002	Q1:2016	0.001	1
60	General Government, Expense, Interest, 2001 Manual, Noncash, National Currency	Log Difference	IMF	National currency	Q2:2001	Q4:2015	0.001	1
61	General Government, Revenue, Tax, 2001 Manual, Noncash, Euros	Log Difference	IMF	National currency	Q2:2001	Q4:2015	0.004	2
62	General Government, Total expenditure, Noncash, National Currency	Log Difference	IMF	National currency	Q2:2001	Q4:2015	0.001	1
63	Capacity utilisation	Difference	OECD	Per cent	Q2:1970	Q1:2016	0.001	8
64	OECD Standardised BCI, Amplitude adjusted (Long term average=100), sa	Difference	OECD	Index	Q1:1970	Q1:2016	0.001	5
65	Current account as a % of GDP, s.a.	Difference	OECD	Per cent of GDP	Q2:1970	Q4:2015	0.001	1
66	Exports of goods and services	Log Difference	OECD	USD constant prices, constant PPPs	Q2:1970	Q1:2016	0.001	1
67	Gross domestic product - expenditure approach	Log Difference	OECD	USD constant prices, constant PPPs	Q2:1970	Q1:2016	0.001	1
68	General government final consumption expenditure	Log Difference	OECD	USD constant prices, constant PPPs	Q2:1970	Q1:2016	0.001	1
69	Gross fixed capital formation	Log Difference	OECD	USD constant prices, constant PPPs	Q2:1970	Q1:2016	0.001	1
70	Imports of goods and services	Log Difference	OECD	USD constant prices, constant PPPs	Q2:1970	Q1:2016	0.001	1
71	Interbank rate	Difference	OECD	Per cent	Q2:1970	Q1:2016	0.001	8
72	Private final consumption expenditure	Log Difference	OECD	USD constant prices, constant PPPs	Q2:1970	Q1:2016	0.001	1
73	Harmonised unemployment rate: all persons, s.a.	Difference	OECD	Per cent	Q2:1970	Q1:2016	0.001	1
74	Share price index	Log Difference	OECD	Index (base year=2010)	Q2:1970	Q1:2016	0.001	1
75	Lt rate	Difference	OECD	Per cent	Q2:1970	Q1:2016	0.001	1
76	CPI: all items	Log Difference	OECD	Index	Q2:1970	Q1:2016	0.064	3

Appendix C

SCDS data

Table C.1 shows the sample length for the differenced SCDS spreads across all countries analysed. The p-value of the Augmented Dickey Fuller is also presented. The lag length is determined by AIC. Most p-values show that the data is stationary at the 10 per cent level of significance. However, there are a few countries wherein the SCDS data is non-stationary. This is most likely due to power issues related to the small sample size of the data.

Table C.1: SCDS data description

Country	Start	End	P-value	Lags
AUT	Q3:2009	Q2:2016	0.09	4
AUS	Q1:2009	Q2:2016	0.24	5
BEL	Q1:2008	Q2:2016	0.25	5
CHI	Q2:2008	Q2:2016	0.05	6
CZE	Q2:2008	Q2:2016	0.14	6
DEN	Q1:2009	Q2:2016	0.15	5
EST	Q1:2009	Q2:2016	0.04	6
FIN	Q3:2008	Q2:2016	0.16	5
FRA	Q2:2008	Q2:2016	0.11	4
GER	Q2:2008	Q2:2016	0.14	5
HUN	Q1:2008	Q2:2016	0.18	5
ICE	Q4:2008	Q2:2016	0.02	6
IRE	Q1:2009	Q2:2016	0.25	6
ISR	Q2:2008	Q2:2016	0.23	6
ITA	Q1:2008	Q2:2016	0.19	5
JAP	Q2:2008	Q2:2016	0.00	0
KOR	Q1:2008	Q2:2016	0.05	6
MEX	Q2:2008	Q2:2016	0.09	5
NET	Q3:2008	Q2:2016	0.24	5
NOR	Q1:2009	Q2:2016	0.16	5
POL	Q2:2008	Q2:2016	0.21	6
POR	Q1:2009	Q2:2016	0.02	3
SVK	Q1:2009	Q2:2016	0.08	4
SLO	Q1:2008	Q2:2016	0.13	4
SPA	Q1:2008	Q2:2016	0.13	4
SWE	Q1:2009	Q2:2016	0.14	6
TUR	Q2:2008	Q2:2016	0.08	5
UNK	Q1:2009	Q2:2016	0.03	4
USA	Q2:2008	Q2:2016	0.01	4

Appendix D

Parametric Bootstrap

If the given factor in equation 5.5 is significant at the 5 per cent level of significance, a parametric bootstrap is performed to ensure the value is significant after accounting for the small sample. This is done to overcome the power issues that arise from the small sample period of the SCDS spreads. The full procedure can be described as follows:

1. Perform the factor regression for a given factor, and check the significance of the $\beta_{1,l}$ coefficients

$$Y_t = \beta_0 + \beta_{1,l} f_{l,t} + \varepsilon_t, \text{ where } l = 1 \dots L \text{ and } t = 1 \dots M \tag{D.1}$$

2. If $\beta_{1,l}$ is significant at the 5 per cent level, store the coefficients, factor, and obtain the RMSE of the regression
3. Randomly sample n residual terms, $e_t \sim N(0, RMSE^2)$
4. Generate data $Y_t^{[j]}$ using the bootstrapped residuals, coefficients, and factor

$$Y_t^{[j]} = \beta_0 + \beta_{1,l} f_{l,t} + \epsilon_t \tag{D.2}$$

5. Repeat the regression in Step 1 except with the simulated data in the previous step as the dependent variable, and store the estimated value of $\beta_{1,l}$
6. Repeat steps 3 to 5, M (1000) times
7. Obtain the 2.5 and 97.5 percentile of the distribution of $\beta_{1,l}$. These are the cutoffs of the distribution.
8. Check if the coefficient obtained from the original regression in Step 1 lies between these two cutoffs.
   - If Yes, then keep the factor and the relevant $\beta_{1,l}$ to be used in the index
   - If No, the factor is considered insignificant and not used in the index

Appendix E

U.S. index

Figure E.1 shows the sovereign default risk index for the US. And Table E.1 shows the key summary statistics for the index.

Figure E.1: USA Index

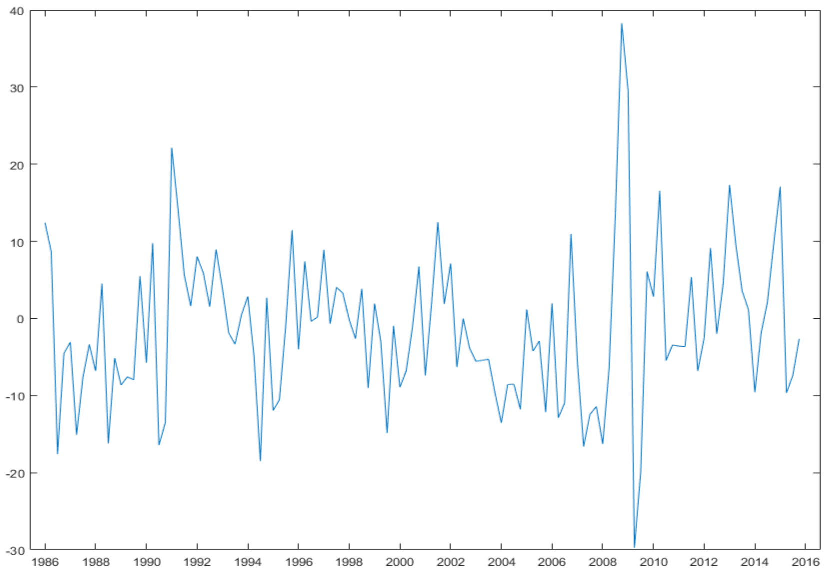


Table E.1: U.S. - SCDS Index summary statistics

Statistic	Value
Mean	-1.336
Median	-2.577
Maximum	38.291
Minimum	-29.758
Standard deviation	10.08
Skewness	0.631
Kurtosis	4.724
Observations	120
Start	Q1:1986
End	Q4:2015

Appendix F

Single Variable Measures

A more detailed analysis of the R-squared of single variable measures across the countries examined is exhibited in Table F.1. In all tests the benchmark index performs better than the single variable approach.

Table F.1: R-squared of single variable measures

	Variable					
Country	Output	Debt-to-GDP	Equity Index	VXO	Long term rate	U.S. Economic policy uncertainty
AUT	0.071	0.002	0.091	0.038	0.203	0.193
AUS	0.011	0.104	0.252	0.037	0.230	0.230
BEL	0.017	0.007	0.059	0.096	0.021	0.024
CHI	0.152	0.000	0.000	0.004	0.019	0.019
CZE	0.047	0.107	0.000	0.221	0.000	0.000
DEN	0.020	0.163	0.017	0.000	0.081	0.082
EST	0.000	0.051	0.000	0.001	0.000	0.000
FIN	0.286	0.003	0.014	0.053	0.101	0.101
FRA	0.002	0.000	0.055	0.060	0.238	0.244
GER	0.137	0.000	0.020	0.105	0.052	0.051
HUN	0.083	0.020	0.000	0.136	0.067	0.066
ICE	0.000	0.000	0.000	0.038	0.002	0.002
IRE	0.000	0.000	0.002	0.000	0.007	0.002
ISR	0.113	0.000	0.000	0.013	0.021	0.023
ITA	0.360	0.002	0.003	0.007	0.000	0.000
JAP	0.016	0.207	0.014	0.274	0.001	0.000
KOR	0.010	0.000	0.637	0.560	0.627	0.627
MEX	0.000	0.000	0.566	0.075	0.031	0.031
NET	0.306	0.003	0.050	0.004	0.055	0.061
NOR	0.040	0.038	0.001	0.041	0.267	0.223
POL	0.148	0.000	0.000	0.074	0.343	0.334
POR	0.058	0.003	0.032	0.056	0.039	0.046
SVK	0.000	0.009	0.000	0.026	0.003	0.000
SLO	0.000	0.000	0.000	0.009	0.016	0.008
SPA	0.082	0.010	0.000	0.008	0.060	0.060
SWE	0.005	0.118	0.131	0.037	0.192	0.188
TUR	0.000	0.000	0.000	0.090	0.124	0.128
UNK	0.003	0.011	0.083	0.010	0.392	0.364
USA	0.128	0.054	0.316	0.079	0.062	0.068

Appendix G

Granger Causality Test using SCDS spreads

Table G.1 shows the Granger-causality tests when using the SCDS spread in the VAR described in Part I Chapter 8. Unsurprisingly, there is no evidence of Granger-causality between any combination of the variables. These results should not be interpreted at face-value as they likely suffer from power issues generated from the small sample size of the SCDS spreads. More specifically, the tests are constructed with only 28 observations. Overall, these results give little information and lends weight to the usefulness of my sovereign default risk index facilitating meaningful macroeconomic analysis.

Table G.1: Granger-causality tests with SCDS

Independent variable	Dependent Variable			
	Expenditure	Revenue	GDP	SCDS
Expenditure	-	0.98	0.56	0.40
Revenue	0.59	-	0.68	0.79
GDP	0.95	0.68	-	0.77
SCDS	0.59	0.84	0.59	-

Appendix H

Decomposing the Output Loss: Consumption versus Investment

In Part I Chapter 8 I established that increases to the sovereign default risk increase drove output losses. To further understand the output losses I re-estimate the baseline VAR but replace output growth with components of output growth, namely private consumption growth, and private investment growth.[1,2] This will provide a more refined understanding of how the output losses from increases in sovereign default risk occur. I find evidence that investment responses are the dominant driver of the output responses.

Figure H.1 presents the impulse response of consumption growth from a one-standard deviation increase in sovereign default risk. The dynamics of consumption growth do follow the response of output. Recall that output declined following the shock and settled at a long-run value of -0.23. Whereas, in response to a shcok in sovereign default risk consumption growth actually increases, with an accumulated long-run value of around 0.36 per cent. This is clearly far from the negative output response. From this it is unlikely that that negative output response from sovereign default risk is driven by changes in private consumption.

Looking over to investment, figure H.2 shows the impulse response of private investment to a one-standard deviation increase in sovereign default risk. It is easy to see that the response of private investment follows closely to the impulse response of output growth from before. More specifically, the one-standard deviation shock to sovereign default risk causes a long run decline in investment of around -0.67 per cent. This helps explain the contributing factors to the declines in output. Moreover, the responses in government expenditure and revenues, and sovereign default risk show very similar dynamics both in shape and magnitude to the baseline model. The adds further weight that the dynamics in the baseline model are driven by

[1]Data is obtained from the NIPA tables from the U.S. Bureau of Economic Analysis.

[2]Lag length for each model is determined by AIC. A lag length of 3 quarters is chosen for the VAR containing consumption, and a 1 quarter lag is determined for the investment VAR.

responses to the investment component of output.

Figure H.1: Consumption VAR

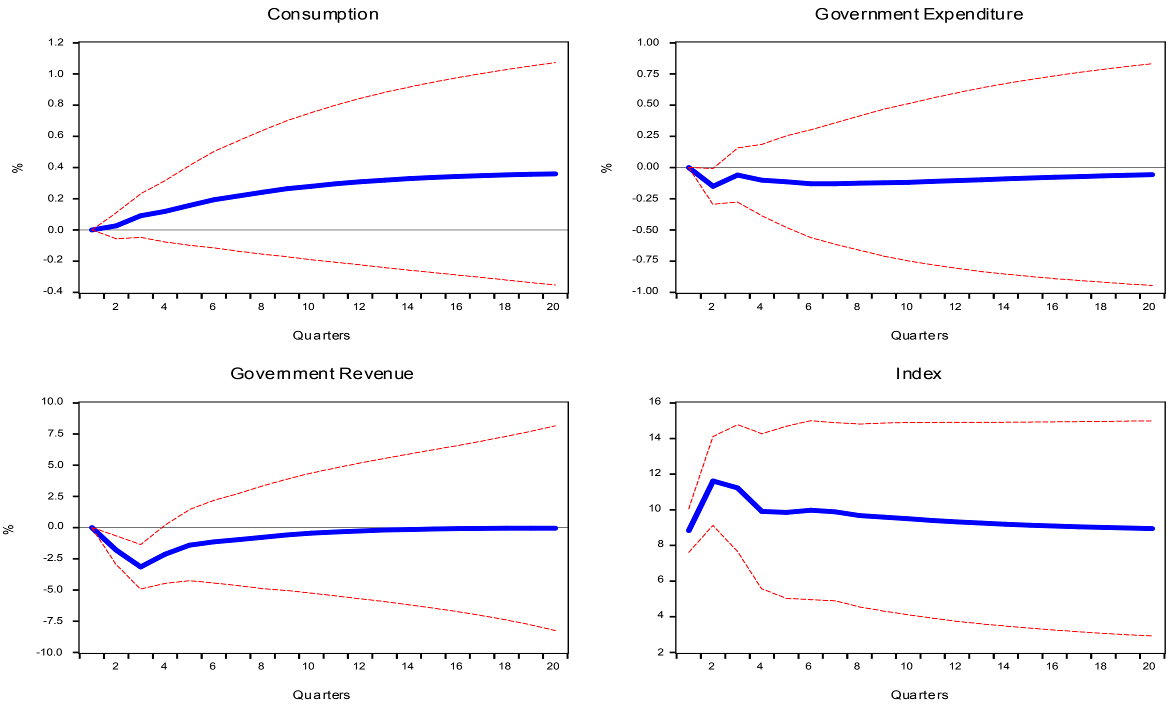
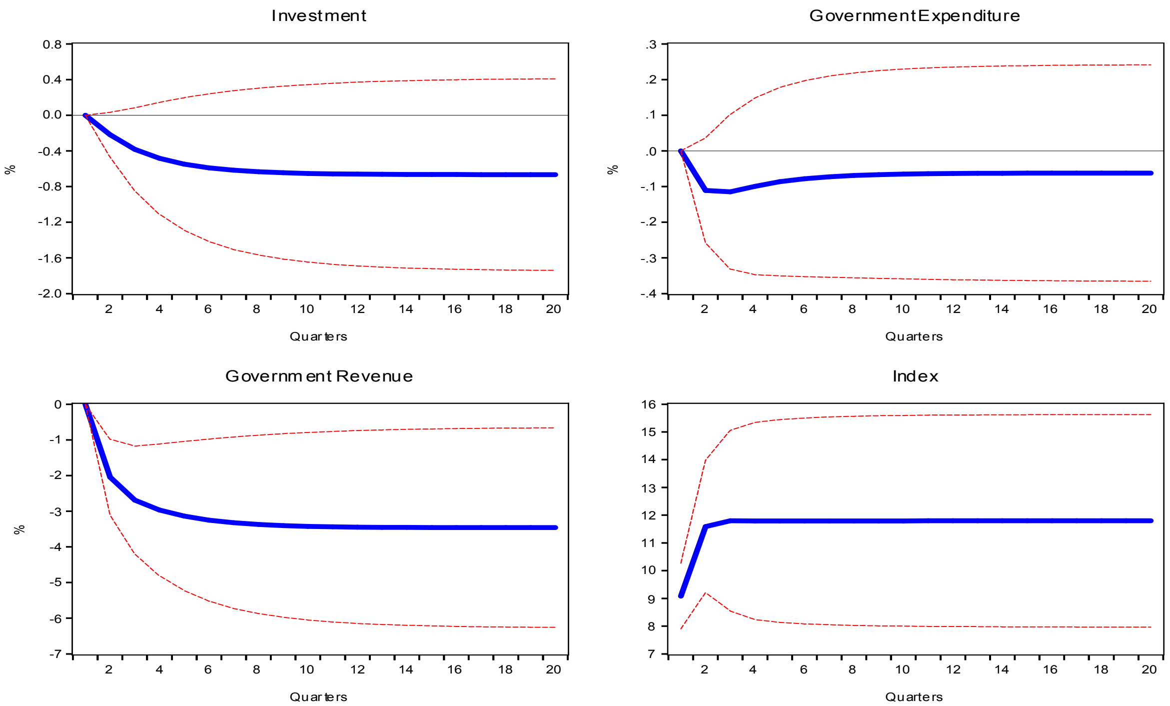


Figure H.2: Investment VAR



Appendix I

In search for a transmission mechanism: The sovereign risk premium

Armed with the knowledge that output losses from sovereign default risk are partly driven by investment responses (Appendix H) I will now examine if the sovereign risk premium can be considered a reasonable transmission mechanism in which sovereign default risk propagates through the economy.

Much of the sovereign default and debt literature has focused primarily on measuring output losses without econometrically identifying many transmission mechanism (see Checherita-Westphal and Rother (2012)). I will contribute to further the discussion on output losses through an examination of the sovereign risk premium.

I.1 The sovereign risk premium

The sovereign risk premium can be considered to be the addition in borrowing costs for both private firms and public institutions generated from sovereign default risk. In this set-up a private firm's interest rate on borrowing (i) can be de-constructed intro three components. (1) A risk free rate (r) (2) a sovereign risk premium (θ) (3) A private spread (τ).

$$i = r + \theta + \tau \tag{I.1}$$

The risk-free rate (r) is a latent variable. In practice, the risk-free rate is proxied by the U.S Treasury bond rate. This proxy makes the assumption that the U.S. government is risk-free. However, given that I am analysing sovereign default risk in the U.S it would be erroneous to consider this proxy as a reliable measure of the risk-free rate. It is likely to be a combination of the risk-free rate and the sovereign risk premium. Disentangling the two is difficult given the many factors that determine the U.S. treasury bond rate. I will focus on measurements of τ which may in fact include or interact with θ.

It is worth noting that the sovereign risk premium is a supply-side argument to the downward output and investment response to shocks in sovereign default risk. A higher sovereign risk premium indicates that creditors are less willing to loan funds to a debtor (in this case, a private firm). This represents a lower supply of loanable funds, rather than any change in the demand for loanable funds.

In this Appendix I will use corporate bond spreads as a measure of corporate risk.[1] The questions are as follows: (1) Does public risk translate into private risk or vice-versa? (2) Does public risk increase the borrowing costs of private firms by more than the increase in rates to government bonds i.e. does the corporate bond spread increase to changes in sovereign default risk.

I.2 Granger Causality

To understand the directional relationship between the corporate bond spread and sovereign default risk I conduct a Granger-causality tests. The purpose of these tests are to determine the predictive direction between corporate bond spreads and sovereign default risk.

Table I.1 presents the results from the Granger-causality tests. Both possible null hypotheses are tested. That is, sovereign default risk does not Granger-cause corporate bond spreads, and corporate bond spreads do not Granger-cause sovereign default risk. The Granger-causality tests show that sovereign default risk Granger-causes corporate bond spreads at the 5 per cent level of significance. Moreover, there is not enough statistical evidence to suggest that corporate bond spreads Granger-cause sovereign default risk.

The results suggest that public risk are translated into private risk, but private risk do not translate into public risk. The result is expected given that government risk is likely to be determined by a complex web of factors, whereas government risk is likely to pose a systemic risk to all firms in the economy. Overall, these Granger-causality tests show that when considering the sovereign risk premium channel the causal direction cannot go from private risk to public risk. This may lend weight to the argument that high debt causes low growth.

[1]Data obtained from FRED under series title *BofA Merrill Lynch US Corporate 7-10 Year Option-Adjusted Spread*. The time period used is from Q1:1997 to Q4:2015.

Table I.1: Pairwise Granger-causality: U.S. long term yield spread and sovereign default risk

Null	observations	F-statistic	p-value
Sovereign default risk does not GC spreads	74	4.52	0.01
Spread does not GC sovereign default risk		1.11	0.33
Lags: 2			

I.3 Impulse responses

To further analyse the relationship between sovereign default risk and the sovereign risk premium I examine the dynamics by estimating impulse response functions. The ordering of the Cholesky decomposition is sovereign default risk first, and corporate bond spreads second. This is motivated by the Granger-causality results and allows corporate bond spreads to respond contemporaneously to shocks in sovereign default risk.

Figure I.1 shows the accumulated impulse response of the sovereign default risk index to a one-standard deviation positive shock in corporate bond spreads. The shock can be thought as an exogenous increase in private risk. The response of sovereign default risk indicate that increases in private risk also lead to increases in sovereign default risk. However, the confidence intervals suggest that the response of sovereign default risk cannot be statistically distinguished from zero. This suggests that shocks to corporate bond spreads do not cause a significant change in sovereign default risk. This consistent with both the Granger-causality test that found corporate bond spreads do not Granger-cause or drive much of the forecast variation in sovereign default risk.

Figure I.2 shows the impulse response of sovereign bond spreads to a positive one standard deviation shock in sovereign default risk. The initial effect of the shock is positive at 0.20. Moreover, the response is statistically distinguishable from zero. This response remains statistically distinguishable from zero for one more quarter; after which the response cannot be distinguished from zero. The impulse response suggests that a one-standard deviation shock drives a total of around a 0.4 per cent increase in corporate bond spreads over the first two quarters. This represents over 20 per cent increase over the mean value of corporate bond spreads. This result are consistent with both the Granger-causality and variance decompositions results. Recall that sovereign default risk not only Granger-caused corporate bond spreads, but also explained over 10 per cent of the forecast error variance of corporate bond spreads.

The finding that sovereign default risk shapes an increase in corporate bond spreads indicates that sovereign default risk translates into private risk. That is, the burden of higher sovereign default risk is not only carried by the government borrowing costs, but can also be transmitted to private borrowing costs. Moreover, the results highlights a potential transmission mechanism for the decrease in investment and output found in the thesis. As sovereign default risk rises, creditors demand higher yields to compensate for the perceived additional risk to the private firm generated from sovereign default risk. This drives up corporate bond spreads. A firm's cost of investment is now higher, hence causing investment to fall.

Figure I.1: Response of index to shock in spread

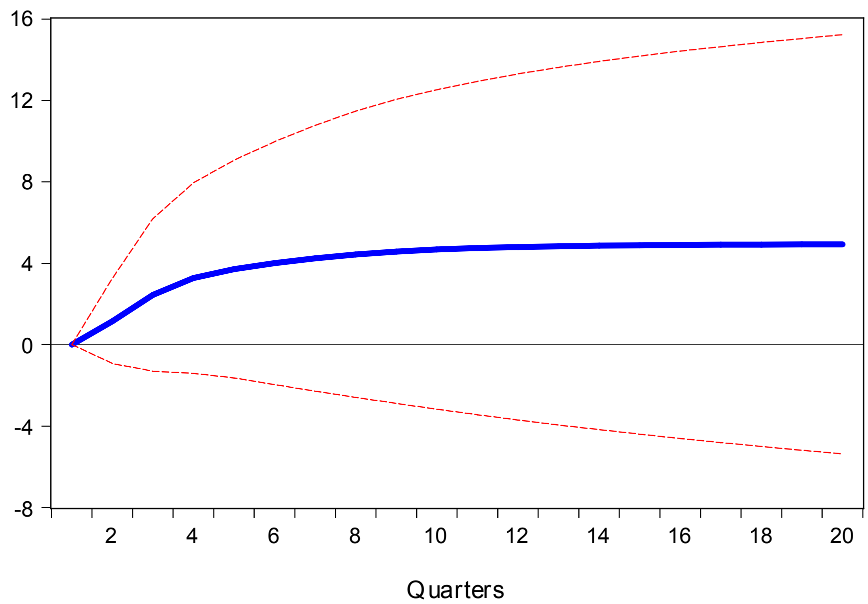
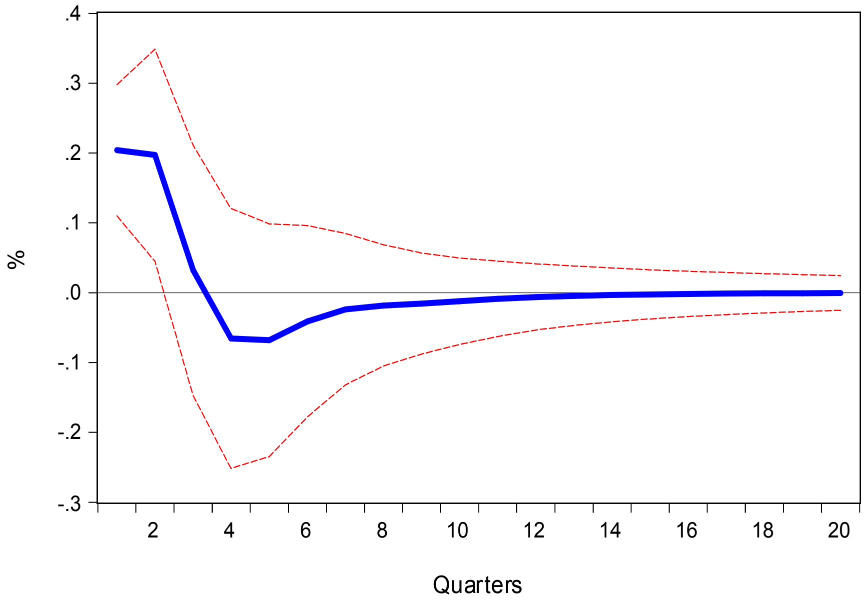


Figure I.2: Response of spread to shock in index



Appendix J

Generalized Impulse Response Functions

The calculation of Generalised Impulse Response Functions used in this thesis is adopted from Koop et al. (1996). The Monte Carlo procedure can be detailed as follows:

Let the TVAR be denoted with the following notation:

$$Y_t = \begin{cases} \Phi_0^h + \Phi_1^h(L)Y_{t-1} + \varepsilon_t^h, & \text{for } q_{t-d} > c \\ \Phi_0^l + \Phi_1^l(L)Y_{t-1} + \varepsilon_t^l, & \text{for } q_{t-d} \leq c \end{cases} \tag{J.1}$$

Also allow Σ^r where $r = h, l$ represent the covariance-variance matrix of each regime; B^r where $r = h, l$ be the lower-triangular matrix obtained from the Cholesky-Decomposition of Σ^r; ϵ_t^r be the innovations obtained for each regime following the Cholesky decomposition; k be the desired forecast horizon.

1. Choose a regime r
2. Choose a history that corresponds to the given regime, $t = 1, \ldots, T$
3. Randomly sample $(k + 1) \times m$ innovations from ϵ_t^r, $t = 1, \ldots, n$. Let this sample of innovations be called ζ_b
4. Impose the government expenditure shock in the initial period of ζ_b. Call this set of innovations ζ_s
5. Both set of innovations are transformed back into reduced-form by pre-multiplier the innovations by B^r. Let the the resulting residuals be called: ε_b and ε_s
6. From the chosen history, variables are forecasted forward k periods with the both sets of residuals and the system described in equation J.1. At each period in k the regime is checked using the delayed value of sovereign default risk. The variables are then calculated based on the given regime.

7. The difference between responses is calculated as the GIRF for this particular simulation in this particular history i.e $GIRF_j^r, h$

8. Steps 3 to 6 are repeated 500 times and the average of the GIRF over all simulations is the GIRF for this history

$$GIRF_h^r = \frac{1}{500}\sum_{j=1}^{500} GIRF_j^r, h \quad , for j = 1, \ldots, 500 \tag{J.2}$$

9. Step 2 to 7 are repeated for 500 different histories in the chosen regime.

10. The average of the GIRF over these 500 histories is the GIRF for the given regime

$$GIRF^r = \frac{1}{500}\sum_{h=1}^{500} GIRF_h^r \tag{J.3}$$

11. Steps 2 to 7 are then repeated for all remaining regimes.

It is worth mentioning that linear impulse responses can be calculated using Steps 3 to 7. In Step 6 is unnecessary to check the regime over each forecast period. Moreover, any random history can be used.

Appendix K

Monte Carlo Confidence Intervals for Impulse Responses in a VAR

To reflect the uncertainty surrounding the estimation of the VAR system, I construction confidences for the multiplier using the following Monte-Carlo procedure:

Let the linear VAR system be denoted by:

$$Y_t = \Phi_0 + \Phi_1(L)Y_{t-1} + \varepsilon_t \tag{K.1}$$

And denote the estimated parameters using hats i.e.$\hat{\Phi_0}, \Phi_1\hat{(}L), \hat{\varepsilon_t}$. Let T represent the sample size.

1. Randomly sample T residuals from $\hat{\varepsilon}$
2. Forecast T periods forward (using a random starting period) using the estimated system and the randomly sampled residuals
3. Re-estimate the model in equation K using the simulated data
4. Using the re-estimated model calculate the impulse response of each variable over the selected forecast horizon
5. Calculate and store the relevant multipliers over the forecast horizon
6. Repeat steps 1 to 5, 10,000 times
7. I approximately construct the 90 per cent confidence bands for the relevant multiplier by taking 1.645 times the standard deviation over the 10,000 simulations for each forecast period.

Appendix L

Cholesky Decomposition

Given m endogenous variables, and a time-series of length T the SVAR model can be expressed as follows:

$$BY_t = \Gamma_0 + \Gamma(L)Y_{t-1} + \varepsilon_t \tag{L.1}$$

where Y_t is a $m \times 1$ matrix of endogenous variables. Y_{t-1} represent lagged values of the endogenous variables. α is an $m \times 1$ vector of constants.Matrix B has a diagonal of 1, and represents the contemporaneous effects the endogenous variables have on each other; Γ_0 represents a vector of constants; and $\Gamma(L)$ is a matrix characterising the relationship between lagged values of the endogenous variables to contemporaneous values of the endogenous variables; and ε_t is an $m \times 1$ matrix of innovations for each variable.

To estimate the SVAR I must first estimate a reduced-form VAR which has the following specification:

$$Y_t = B^{-1}\Gamma_0 + B^{-1}\Gamma(L)Y_{t-j} + B^{-1}\varepsilon_t \tag{L.2}$$

$$= \Phi_0 + \Phi(L)Y_{t-j} + e_t \tag{L.3}$$

To achieve identification I must take the observed values of e_t and impose restrictions to the system to recover the innovations (ε_t). Notice the difference between equation L.1 and L.3 is the B matrix. Once the B matrix is identified one can recover the innovations.

Let Σ represent the variance-covariance matrix from equation (L.3). Σ contains $\frac{(n^2+n)}{2}$ distinct elements. Whereas B contains $n^2 - n$ unknown values. There are also n unknown values of variance. This leaves a total of n^2 unknown values in the SVAR but only $\frac{(n^2+n)}{2}$ known independent variables from Σ. It is necessary to impose $\frac{n^2-n}{2}$ restrictions on the structural model. The restrictions imposed through the Cholesky Decomposition render the matrix B to be lower triangular with one's on the diagonal, and zeros in the upper triangular region. These restrictions effectively impose a timing structure on the variables. In particular, contemporaneous innovations to one variable may or may not have a contemporaneous effect on other variables. This depends on whether the relevant element in the B matrix is 0 or non-zero.

The B matrix is obtained through an Cholesky (or LDL) Decomposition of the observed variance-covariance matrix from the reduced form VAR, Σ.

To recover the innovations simply match the innovations in equation L.2 with the reduced form residuals in equation L.3. i.e.

$$\varepsilon_t = B \times e_t \tag{L.4}$$

Appendix M

Data for Vector Autoregressions

Table M.1 shows the summary statistics of government expenditure growth, government revenue growth, output growth, private consumption growth, private investment growth, and the sovereign default risk index after taking the 4-period moving average. These variables are used in both the VAR and TVAR in this thesis.

Table M.1: Summary Statistics

	Government Expenditure	Government Revenue	Output	Private Consumption	Private Investment	Index
Mean	0.459	0.544	0.628	0.689	0.749	-1.380
Median	0.413	0.931	0.673	0.697	1.099	-1.689
Maximum	2.169	21.577	1.871	1.860	3.996	18.682
Minimum	-1.400	-35.779	-2.135	-1.211	-8.046	-14.188
Std. Dev.	0.814	6.953	0.603	0.515	1.892	5.704
Skewness	-0.026	-1.896	-1.211	-0.598	-1.575	0.434
Kurtosis	2.285	11.388	6.679	4.469	7.688	3.348
Observations	117	117	117	117	117	117.000
Start Date	Q4:1987	Q4:1987	Q4:1987	Q4:1987	Q4:1987	Q4:1987
End Date	Q4:2015	Q4:2015	Q4:2015	Q4:2015	Q4:2015	Q4:2015

Appendix N

Unit Root Tests

Table N.1 shows the results from the Augmented Dickey-Fuller Test. I have used BIC to choose the optimal lag length and used the 10 per cent level of significance to account for the relatively small sample size used.

Table N.1: Unit Root Tests

Variable	Transformation	Specification	Lags	P-value	Stationary
Government expenditure	Log difference	Constant	2	0.07	Yes
Government revenue	Log difference	Constant	8	0.03	Yes
Output	Log difference	Constant	4	0.00	Yes
Sovereign default risk	4-period moving average	Constant	8	0.03	Yes
Private Consumption	Log difference	Constant	2	0.05	Yes
Private Investment	Log difference	Constant	2	0.03	Yes

Appendix O

Model Comparisons

Table O.1 to O.4 show the AIC of the TVARs across delay and lag. The optimal model is has its AIC in bold.

Table O.1: Baseline Model Comparison

		Delay			
		1	2	3	4
Lag	1	3.882	3.953	3.780	3.843
	2	3.501	3.564	3.611	3.608
	3	3.262	3.399	3.457	3.494
	4	**3.177**	3.293	3.450	3.572

Table O.2: Consumption Model Comparison

		Delay			
		1	2	3	4
Lag	1	3.719	3.776	3.696	3.819
	2	3.185	3.277	3.396	3.288
	3	**2.268**	3.096	3.010	3.000
	4	2.876	3.081	2.777	2.883

Table O.3: Investment Model Comparison

		Delay			
		1	2	3	4
Lag	1	5.770	5.802	5.577	5.672
	2	**5.163**	5.388	5.421	5.482
	3	5.163	5.430	5.377	5.457
	4	5.356	5.421	5.600	5.590

Table O.4: Median Model Comparison

		Delay			
		1	2	3	4
Lag	1	3.853	3.840	3.736	3.945
	2	3.589	3.716	3.631	3.663
	3	**3.420**	3.474	3.467	3.530
	4	3.425	3.612	3.842	3.923

Appendix P

Estimation of TVAR

The TVAR can be expressed as follows:

$$Y_t = \begin{cases} \Phi_0^h + \Phi_1^h(L)Y_{t-1} + \varepsilon_t^h, & \text{for } q_{t-d} > c \\ \Phi_0^l + \Phi_1^l(L)Y_{t-1} + \varepsilon_t^l, & \text{for } q_{t-d} \leq c \end{cases} \tag{P.1}$$

The TVAR is estimated for each sub-sample. So ignoring the superscripts the equation estimated can be written as follows:

$$Y_t = \Phi_0 + \Phi_1(L)Y_{t-1} + \varepsilon_t \tag{P.2}$$

$$Y_t = \Gamma_0 + \Gamma_1 Y_{t-1} + \Gamma_2 Y_{t-2} + \ldots + \Gamma_p Y_{t-p} + \varepsilon_t \tag{P.3}$$

$$\tag{P.4}$$

Now let the covariance matrix be Σ which is calculated as follows:

$$\Sigma = \frac{1}{T}\varepsilon_t \varepsilon_t^{\mathsf{T}} \tag{P.5}$$

The log likelihood can be expressed as follows:

$$\begin{aligned} \text{Log Likelihood} = \text{constant} + \frac{T}{2}\log|\Sigma^{-1}| \\ - \frac{1}{2}\sum_{t=1}^{T}\big((Y_t - \Phi_0^l - \Phi_1^l(L)Y_{t-1})^{\mathsf{T}}\Sigma^{-1}(Y_t - \Phi_0^l - \Phi_1^l(L)Y_{t-1})\big) \end{aligned} \tag{P.6}$$

I also impose stationarity conditions on the coefficients. To do this

$$[I_n - \Phi_1(L)]Y_t = \Phi_0 + \varepsilon_t \tag{P.7}$$
$$\Phi(L)Y_t = \Phi_0 + \varepsilon_t \tag{P.8}$$

If the Y_t is covriance-stationary then the mean of the process μ can be expressed as:

$$\mu = (I_n - \Phi_1(L))^{-1}\Phi_0 \tag{P.9}$$

Writing the VAR in terms of deviations from the mean:

$$Y_t - \mu = \Phi_1(L)(Y_{t-1} - \mu) + \epsilon_t \tag{P.10}$$
$$Y_t - \mu = \Gamma_1(Y_{t-1} - \mu) + \Gamma_2(Y_{t-2} - \mu) + \ldots + \Gamma_p(Y_{t-p} - \mu) + \epsilon_t \tag{P.11}$$

We can now re-express the VAR(p) into a VAR(1) as follows:

$$\zeta_t = F\zeta_{t-1} + v_t \tag{P.12}$$

where,

$$\zeta_t = \begin{bmatrix} Y_t - \mu \\ Y_{t-1} - \mu \\ . \\ . \\ . \\ Y_{t-p+1} - \mu \end{bmatrix} \tag{P.13}$$

$$F = \begin{bmatrix} \Gamma_1 & \Gamma_2 & \Gamma_3 & \ldots & \Gamma_{p-1} & \Gamma_p \\ I_n & 0 & 0 & \ldots & 0 & 0 \\ 0 & I_n & 0 & \ldots & 0 & 0 \\ . & . & . & \ldots & . & . \\ . & . & . & \ldots & . & . \\ . & . & . & \ldots & . & . \\ . & . & . & \ldots & I_n & . \end{bmatrix} \tag{P.14}$$

$$v_t = \begin{bmatrix} \varepsilon_t \\ 0 \\ . \\ . \\ . \\ 0 \end{bmatrix} \tag{P.15}$$

The eigenvalues of the matrix F from equation P.14 are calculated. If the absolute value of any of the eigenvalues is above 1 a very large penalty is added to the log-likelihood, equation P.7, to prevent the the VAR from displaying non-stable dynamics. This means what I have estimated are the coefficients that yield the lowest log-likelihood given that the estimates meet stationarity conditions.

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